Passive-Event-Assisted Approach for the Localizability of Large-Scale Randomly Deployed Wireless Sensor Network

Zhiguo Chen, Guifa Teng*, Xiaolei Zhou, and Tao Chen

Abstract: Localizability in large-scale, randomly deployed Wireless Sensor Networks (WSNs) is a classic but challenging issue. To become localizable, WSNs normally require extensive adjustments or additional mobile nodes. To address this issue, we utilize occasional passive events to ease the burden of localization-oriented network adjustment. We prove the sufficient condition for node and network localizability and design corresponding algorithms to minimize the number of nodes for adjustment. The upper bound of the number of adjusted nodes is limited to the number of articulation nodes in a connected graph. The results of extensive simulations show that our approach greatly reduces the cost required for network adjustment and can thus provide better support for the localization of large-scale sparse networks than other approaches.

Key words: network localizability; random deployment; Wireless Sensor Networks (WSNs); passive event

1 Introduction

The localizability of sparse networks is a classic but still challenging issue encountered by large-scale, low-power Wireless Sensor Networks (WSNs), particularly randomly deployed networks. Strict requirements on network density continue to limit the practical applications of large-scale WSNs despite the innovations in cooperative localization[1–4] that have been achieved over the past two decades. Hardware costs and topology control mechanisms prevent the deployment of sparse networks as large-scale networks.

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Manuscript received: 2017-05-09; revised: 2017-06-06; accepted: 2017-06-07

In addition, the overall distribution and localizability of randomly deployed networks may be affected and degraded by terrain, weather, and other external factors.

Nevertheless, the demand for randomly deployed large-scale sensor networks has continued to grow during the last decade. Many large-scale WSN applications, such as environmental monitoring[5], precision agriculture[6], and military applications, have adopted the random deployment scheme to rapidly release thousands of inexpensive, tiny sensors through aircrafts or drones to the field of interest. This deployment method generates extensive nonlocalizable networks that fail to satisfy the conditions of 3-connection and redundant rigidity for network localizability[7]. Furthermore, those networks require either massive adjustment operations or additional nodes to become localizable. Therefore, time and hardware costs complicate localizability in randomly deployed networks.

Conventional approaches for localizing non-localizable networks enhance the level of network localizability by deploying extra nodes or beacons to create abundant internode distance constraints. These approaches, however, have two shortcomings. First, finding an efficient redeployment plan is difficult

when all node locations are unknown. Second, terrain limits may preclude the practical implementation of an available detailed redeployment plan. Several other approaches have been proposed, including (1) mobile-assisted approaches (e.g., robots[8], passive events[9]), which utilize some mobile nodes in the sensor field to provide thorough information for localization and (2) network adjustment[10], which dynamically adjusts the power of the sensor node to obtain additional distance measurements and therefore achieve localizability. However, the application scenarios of the above approaches remain limited. Zhou et al.[11] utilized moving events to help localize non-localizable nodes in a randomly deployed WSN. In this approach, however, the occasional availability of moving events increases the total time cost of achieving network localizability beyond functionality. The above issues motivate us to refocus on the localizability problem to improve support for randomly deployed large-scale of WSNs.

In this work, we first focus on utilizing static events in the field to achieve localizability in randomly deployed large-scale WSNs. Moreover, we also prove the condition for adjusting arbitrarily connected networks to achieve network localizability. On the basis of theoretical findings, we propose a novel approach, WindTalker, which uses passive events in the sensor field to obtain additional distance measurements.

Our major contributions are summarized as follows.

• To the best of our knowledge, this work is the first to utilize the occasional passive event to ease the burden of localization-oriented network adjustment. Our approach drastically reduces the amount of effort necessary to achieve network localizability. Thus, compared with other approaches, our approach can better support the random deployment of large-scale WSNs.

• We propose the sufficient condition for *network localizability* and *node localizability* and design the corresponding adjustment algorithm in polynomial time. The upper bound of the adjusted nodes is the number of articulation nodes in the network.

• We evaluate our approach through extensive experiments. Compared with the *state-of-the-art* approach[10], our approach greatly reduces the total cost required to achieve network localizability.

The rest of this paper is organized as follows: Related works are summarized in Section 2. Section 3 presents a brief introduction to graph rigidity and localizability. Section 4 illustrates the sufficient

conditions for node and network localizability in theory and the detailed design of WindTalker with corresponding algorithms. The results of the extensive simulations that we performed to evaluate our approach are presented in Section 5. Finally, we conclude this work in Section 6.

2 Related Work

Localizability is a classic and challenging issue that has been persistently encountered by randomly deployed WSNs over the last two decades. This section summarizes recent works that are related to this topic. In general, the foci of related work can be broadly categorized into (1) positioning in WSNs, (2) localizability in partially localizable networks, and (3) localization-orientated network adjustment.

2.1 Positioning in WSNs

Positioning in WSNs aims to provide accurate positions for each sensor through range-based[1,2,12] or range-free[13–15] approaches. Range-based approaches utilize internode distances to estimate the physical positions of unknown nodes. Moreover, these approaches integrate multiple physical measurements, such as Radio Signal Strength (RSS)[12], Time Difference of Arrival (TDoA)[16,17], and angle of arrival, with different positioning models, such as multilateration, multidimensional scaling, and Semidefinite Programing[18]. The range-free approach estimates the coarse-grained locations of sensors on the basis of neighboring information, such as hop number[13,14] and node connectivity[15]. The majority of innovations on positioning techniques for WSNs are highly dependent on the density of the deployed nodes. Specifically, they can only localize nodes with high connectivity and not other nodes. Non-localizable nodes directly motivate studies on the localizability of sparse networks.

2.2 Localizability in sparse network

Studies on localizability utilize graph rigidity theory to determine the localizability of a network or its node. Eren et al.[7] first utilized graph rigidity to propose the condition for network localizability. This has been validated by Refs. [19, 20]. Goldenberg et al.[21] first proposed the nontrivial, necessary, and sufficient condition for node localizability. Yang et al.[22] further proposed the currently optimal necessary and sufficient conditions for node localizability. These

innovations fundamentally distinguish the localizable components or nodes of randomly deployed WSNs. However, the localizability of the remaining non-localizable components remain challenging. This issue has spurred studies on localization-oriented network adjustments.

2.3 Localization-orientated network adjustment

Interest in the localization-oriented network adjustment of the non-localizable components of randomly deployed networks has continued to increase. Mobility-assisted adjustment approaches utilize mobile nodes[8, 23–25] to generate additional distance relations for non-localizable nodes and hence increase the connectivity of non-localizable nodes to achieve localizability. However, the availability of the controllable mobile robot is too strict for the large-scale applications of WSNs. The extra hardware cost of the mobile nodes should not be overlooked. Other works have focused on dynamically tuning the transmission power of sensor nodes to manipulate network topology and finally convert a non-localizable network into a localizable one. Anderson et al.[26] proposed the first graph manipulation method to assure network localizability. Given that such an approach does not distinguish nodes with connectivity, a large proportion of nodes require adjustment, which increases costs. Chen et al.[10] proposed a finer-grained adjustment approach to reduce the total cost for network adjustment. In this work, we further utilize the external and passive event in the sensor field to reduce the number of adjusted nodes. The utilization of the passive event fundamentally changes the topology of the deployed networks and drastically reduces the costs required to localize a randomly generated sparse network.

3 Graph Rigidity and Network Localizability

Given a distance graph G, *localizability* is used to determine whether a graph or its nodes can be localized. In graph theory, *rigidity* provides the foundation of the localizability of the nodes and the entire network. We briefly introduce localizability to help readers better understand our work.

As previously proved by numerous researchers[7, 19, 27–30], network localizability is intertwined with the *rigidity* of the graph. In a rigid graph, the distance between any pair of vertices

remains unchanged with the continuous movement of the nodes.

A distance graph $G = (V, E)$ can be considered as a mapping p that maps the vertices in G to an Euclidean space, where V denotes a set of vertices, and E denotes a set of edges. A mapping p is called a *realization* if each edge $(i, j) \in E$ satisfies $d(i, j) = ||p(i) - p(j)||$. Two realizations are *equivalent* to each other if they are identical after a series of translations, rotations, and reflections. A distance graph G has at least one feasible realization that represents the ground truth of the corresponding network. A distance graph G is *generically rigid* if it cannot continuously deform its realizations while preserving all distance constraints among nodes[27, 31].

A distance graph G is *globally rigid* if all of its realizations are identical after a series of translations, rotations, and reflections, i.e., all of those realizations are equivalent.

A distance graph G is *redundantly rigid* if it remains *rigid* after removing any edge in G. A node is localizable if its location can be uniquely determined.

Theorem 1[21] A graph with $n \geqslant 4$ vertices is globally rigid in $\mathbf{R}^2$ if and only if it is 3-connected and redundantly rigid, where $\mathbf{R}^2$ means two-dimensional Euclidean space.

A graph $G = (V, E)$ is called k-connected (for $k \in N$) if $|V| > k$ and $G - X$ is connected for every set $X \subseteq V$ with $|X| < k$[32], where N is the number of vertices, and X is the subset of V. In other words, any pair of vertices in G is not separated by less than k other vertices.

Eren et al.[7] further proved that a network is uniquely localizable if and only if its distance graph is globally rigid and it contains at least three beacons.

A node is localizable if its location can be uniquely determined. Yang et al.[22] proposed the sufficient condition of the node localizability, as presented in Theorem 2.

Theorem 2[22] In a distance graph $G = (V, E)$, where a set $B \subset V$ of $k \geqslant 3$ vertices denotes beacons, any vertex is localizable if it is contained in a redundantly rigid component and has at least three vertex-disjoint paths to three distinct beacons in such a component.

We further consider the localizability from the *node* and *network* with the events available in the sensor field. The network is modeled as a distance graph as follows.

Consider a randomly deployed sensor networks of n

sensor nodes in an Euclidean space $\mathbf{R}^2$. m beacons are present with known positions among those nodes. In such a network, each node measures the distances to its neighbors with RSS, and sends the probed results to the sink node in the network. Therefore, the network can be formalized as a distance graph $G = (V, E)$. Any two vertices $v_i, v_j \in V$, $(v_i, v_j) \in E$ is located at known locations (e.g., beacons) or is separated by a measurable, which is denoted as $d(v_i, v_j)$.

Note that vertex is a specific term of the node in graph G. To ease presentation, the following pairwise terms are synonymous: (1) vertex and node, (2) network and graph, (3) block and 2-connected component, and (4) cut node and articulation node.

4 Design of WindTalker

This section focuses on the exploitation of passive events in the sensor field to transform a non-localizable network to a localizable one. We first use an illustrative example to explain the involved passive events and then demonstrate the conditions for network and node localizability with available events in the field. Finally, we propose the corresponding network adjustment approach to localize an originally non-localizable network.

4.1 Passive events

Passive events have been widely utilized for localization. Those events emit certain kinds of signals that can be detected by sensors. *Range-free* approaches[15] take events from different directions to derive the orders of the sensors in the field and to construct multiple sequences of these events to estimate their relative locations. *Range-based* approaches take the signals emitted by events to construct additional distance constraints to localize nodes.

Various events exist in the sensor field. These events include animal sounds, bomb explosions during combat, and train and vehicle noise. However, only some events can be utilized to assist network localization. We first impose the following constraints on the events.

● Detectable. The signal emitted by the events should be detectable and identifiable by sensors. Usually, the type of detectable signals depends on the actual settings of WSN applications. To ease presentation in this work, we use an acoustic event as a representative example of a passive event because numerous current WSN applications are integrated with on-board acoustic chipsets.

● High-powered. The transmission power of the event should be high enough to cover the majority of the sensors in the field. To simplify this problem, we assume that all of the sensors in the field can receive the signals emitted by the sensors. In other words, the event is fully covered by the disc model. We also discuss the case of partial coverage in Section 4.3.

● External and passive. The event is not generated by the deployed network and is thus not associated with any extra hardware cost. Moreover, the location and occasion of the event are uncontrollable.

We illustrate an example of a passive event in Fig. 1, wherein solid balls denote beacons, blank balls denote ordinary nodes, and the star denotes the passive event. The event emits acoustic signals that can be received by the sensor in the field. This example involves three different roles, i.e., event, beacons, and ordinary nodes. The events can be detected and identified by all sensors, including beacons and normal nodes. Beacons are special sensors that are aware of their own locations. Usually, the locations of the beacons are enabled by on-board Global Navigation Satellite System (GNSS) blocks, such as GPS and Beidou. Except for the awareness of locations, the hardware settings of the beacons are exactly the same as those of ordinary sensor nodes. The passive event is distinct from the beacons. Although the signals emitted by the event can be detected by the sensors, it is not a part of the network hardware.

The localization of the acoustic source is a heavily studied problem[33]. It has also been called as *acoustic source localization* and is well supported by numerous innovative works. Zhou et al.[11] proposed a near synchronization-free approach for event detection and localization. Given the page limitations of this paper, we suggest that interested readers refer to the previous publication for detailed information. We assume that the location of the event source is known and focus on the utilization of these events to help localize initially non-localizable networks.
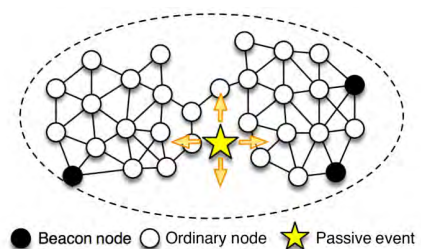

Fig. 1 Example of passive event in sensor field.

4.2 Event-assisted localizability

In practice, a sparse network generated through random deployment seldom satisfies the condition of *global rigidity*. The localization of a large network is complicated. To address this complex issue, we propose the theoretical foundations that underlie the utilization of static events in the sensor field to localize an initially non-localizable network.

The grounded graph of a network shows that an event adds edges to a network, as shown in Fig. 2. The solid ball shows the localizable node B_1 at the initial stage, whereas the blank balls, labeled $L_1, L_2, ..., L_n$ represent non-localizable nodes. To ease presentation, we designate the distance graph without the event as the *original graph* and the distance graph with the event as the *generated graph*. Through Theorem 3, we prove that at least one more edge is added for each vertex in the generated graph.

Theorem 3   Given that an event E occurs at a known position, for each node L_i under the coverage of E, an edge exists between L_i and E in the distance graph if a path exists between B_1 and L_i.

Proof   When the signal emitted by event E achieves B_1 and L_1, the TDoA and the difference in distance between EB_1 and EL_1 can be derived. Given that EB_1 can be directly computed on the basis of positions of E and B_1, the distance between E and L_1 can be estimated. Similarly, EL_2 can be computed.   ■

As shown in Theorem 3, the passive event fundamentally changes the underlying graphical model of the network. Thus, each unknown vertex in a connected graph adds one edge to the event in the generated graph. The additional edges improve the connectivity of the underlying graph, as proven in Theorem 4.

Theorem 4   Given an event E at a known position, any connected network in the coverage of the event is 2-connected.

Proof   Consider the connected graph in Fig. 3, where the balls denote the nodes in the network and the
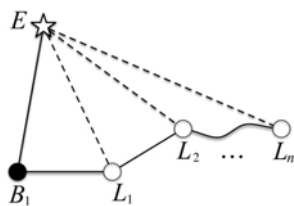

Fig. 2   Event brings one additional edge to each non-localizable node.
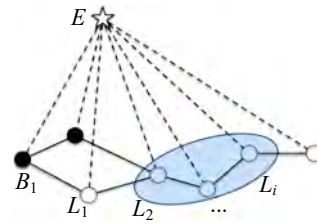

Fig. 3   A connected graph.

solid lines denote the distances between those nodes. The dotted lines represent the distance between the event and any nodes in the network. In such a connected network, each node has at least one simple path to one beacon.

Therefore, in accordance with Theorem 3, an additional edge exists between the event and the node. Removing the event from such a graph shows that it is connected. Specifically, if any node in the original graph is removed, at least one path exists between any node pair through the event. Such a graph remains connected. If we remove the event and any of the three nodes in the blue area, the graph is no longer connected. Therefore, the graph in Fig. 3 is 2-connected.   ■

The passive event transforms any connected network within its coverage to a 2-connected network. Although such a network does not satisfy the condition for *network localizability*, i.e., 3-connected and globally rigid, the improvement in connectivity enlarges the localizable nodes. We take the network in Fig. 4 as an example. In this figure, the star, and solid and blank balls denote the event, beacon, and node at unknown locations, respectively. The original network is a 2-connected ring. When the event is available, the generated network appears as a *wheel* graph, which has already been proved as globally rigid[22]. With more than three vertices at known positions (one event and two beacons), the generated graph is localizable.

In the above case, the event turns a non-localizable ring into a localizable graph. Following this lead, we further propose the significant condition for *node localizability* to identify the localizable nodes in the generated graph.
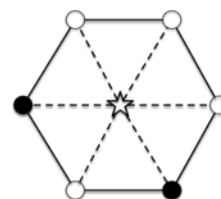

Fig. 4   An example of Wheel graph with 7 nodes.

Theorem 5 (Network Localizability) Given an event E at a known position and k ($k \geqslant 2$) beacons, the generated graph is localizable if the original graph is 2-connected.

Proof We first prove that the generated graph is 3-connected if the original graph is 2-connected. The definition of a 2-connected graph states that the original graph remains connected after the removal of any two vertices. Given that event E has at least one edge to any nodes in the original graph, it is 3-connected if it remains connected after the arbitrary removal of three vertices. Given that the original graph is 2-connected, we only have to consider the different cases for the third vertex. Supposing that the three vertices are two vertices in the original graph and the event, the remainder of the generated graph is definitely connected. Supposing that the three vertices all belong to the original graph, the remainder of the original graph is no longer connected. However, those vertices are connected by the event in the generated graph. Therefore, the generated graph is 3-connected.

We further prove that the generated graph is globally rigid. Given that the event has at least one edge to any vertex in the original graph and the original graph is 2-connected, the generated graph presents a wheel form with the event at the centroid. The wheel graph has already been proved as globally rigid. Therefore, the generated graph is globally rigid.

Therefore, the generated graph is 3-connected and globally rigid with at least three vertices at known positions. In accordance with Theorem 1, the generated graph is localizable. ∎

Theorem 5 is used to differentiate the localizable and non-localizable components of the original graph. However, the condition in Theorem 5 requires information on global topology to identify 2-connected components in the original graph. When the scale of the randomly deployed network is large, the identification of the 2-connected components incurs massive communication and computation costs that consume scare on-board resources. In addition, the time span from deployment to functionalization will be too large for time-sensitive applications. In reference to Theorem 5, we further propose the sufficient condition for node localizability in Theorem 6 to facilitate the design of distributed localization.

Theorem 6 (Node Localizability) Given an event E at a known position and k ($k \geqslant 2$) beacons, any vertex in the original graph is localizable if it has two disjoint simple paths to two different beacons.

Proof We first divide the original graph into several 2-connected components and connected subgraphs. Theorem 5 states that given event E, the generated graphs of any 2-connected components are localizable. Therefore, any vertex in the 2-connected subgraphs of the original graph is localizable. Any vertex in the original graph with two disjoint simple paths to two different nodes is definitely contained in a 2-connected component of the original graph. ∎

Given that one edge always exists between an arbitrary beacon pair, we can easily prove that the condition in Theorem 6, i.e., two disjoint paths to two different beacons are equivalent to those contained in 2-connected components with at least two beacons. To ease presentation, the paths mentioned in this paper are all simple paths, i.e., paths that lack loops. Algorithm 1 describes the identification of the localizable component in a connected graph. We first derive all of the 2-connected components of graph G, also known as *blocks*, with Tarjan Algorithm[34]. We check the localizability of each block in G in accordance with Theorem 5. If a block contains two or more beacons, it is labeled as localizable.

4.3 Adjustment for non-localizable nodes

The condition of the 2-connected graph for localizability remains too strict for sensor networks generated through random deployment. First, external factors, such as terrain and weather, result in uneven sensor distribution in the deployment field. In addition, the topology control mechanism limits sensor density. Therefore, in this subsection, we further consider the localization of nodes that are not contained in any 2-connected components.

Our key idea to locate non-localizable nodes is to

Algorithm 1 Network localizability

Require: Given original graph $G = (V, E)$, set of beacons $B \subset V$ and $|B| \geqslant 2$

Random select $b_i \in B$

$[BlockSet, CutVertices] = Tarjan(b_i)$ % return all 2-connected components and cut vertices as subgraphs with Tarjan Algorithm

for each $block \in BlockSet$ **do**

    if $block$ contains two or more beacons **then**

        $block.localizability = true$

    else $block.localizability = false$

    end if

end for

dynamically augment the transmitting power of some non-localizable nodes to ensure that they satisfy the node localizability condition. To date, most of the sensor nodes support the dynamic augmentation of their transmitting power. For example, the radio frequency output power of TelosB with the CC2420 chipset is programmable. Its output power is divided into 31 levels from the minimum to the maximum. The tunable transiting power expands the ranging radius of RSS-based ranging techniques. Under various output power levels, the ranging distance varies from tens of centimeters to over 100 m.

We define the operation of vertex augmentation as follows.

Definition 1   (**Vertex augmentation**[10]) In a graph $G = (V, E)$, the k times vertex augmentation of $v \in V$ is to connect vertex v and its i-hop neighbors in G for any $i \leqslant k$, denoted as v^k.

In practice, k times vertex augmentation is realized by increasing ranging capacity for vertex v by k times. We only consider 2-time vertex augmentation in this work. For brevity, we denote 2-time vertex augmentation as v^2.

We then consider the location of non-localizable nodes in the original graph. Figure 5 shows an example of a randomly deployed sparse network. According to the condition for *node localizability* stated in Theorem 6, i.e., two disjoint paths to two different beacons, the nodes that are not located in gray circles are all converted to localizable with a passive event in the field. Under the condition for emphnode localizability, the nodes in the path between two different beacons are all identified as localizable.

The three gray circles show three different cases of non-localizable nodes: (1) not contained in any 2-connected component (Case 1 in Fig. 5), (2) contained in a 2-connected component with one beacon (Case 2 in Fig. 5), and (3) contained in a 2-connected component without any beacon (Case 3 in Fig. 5).
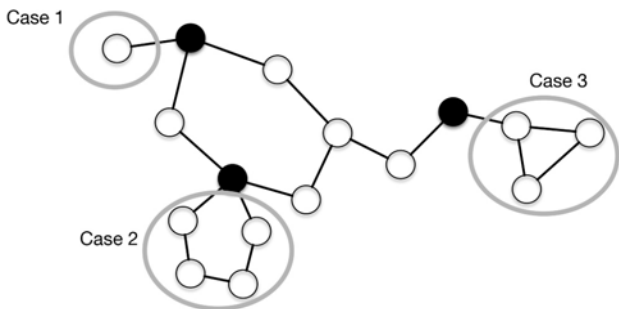
In the above three cases, if we conduct vertex augmentation v^2 for each non-localizable node in the gray circles, at least two disjoint paths to two different beacons will exist. Therefore, those nodes are converted to localizable. On the basis of this case study, we then prove node adjustment in Theorem 7.

Theorem 7 (**Node adjustment**) For a given connected original graph $G = (V, E)$ and a passive event, any non-localizable vertex v in the generated graph is localizable after performing vertex augmentation v^2 for all non-localizable vertices.

Proof According to the definition of node localizability proposed in Theorem 6, non-localizable nodes are all not contained in any 2-connected components with at least two beacons. We divide the original graph into a combination of several localizable (2-connected components with at least two beacons) and non-localizable (a connected subgraph that consists of all non-localizable nodes) components. Note that non-localizable components may also be 2-connected, e.g., Case 3 in Fig. 5. Given that the original network is connected, any non-localizable component is directly connected to at least one localizable component.

To simplify the presentation of the proof, we show a pair of non-localizable component G_1 and localizable component G_A in Fig. 6a. Any node in G_1 lacks two disjoint paths to two different beacons; hence the nodes in G_1 are all non-localizable. On the other hand, G_A is a 2-connected graph with two beacons. Therefore, G_A is localizable.

After subjecting each node in G_1 to vertex augmentation, one extra edge exists between nodes in G_1 and their two-hop neighbors. The added edges are shown as dotted lines in Fig. 6b. As such, G_1 is 2-connected after vertex augmentation. In addition, at least one extra edge is added between localizable and non-localizable components. Therefore, the graph of G_1 and G_A is 2-connected with at least two beacons. ∎
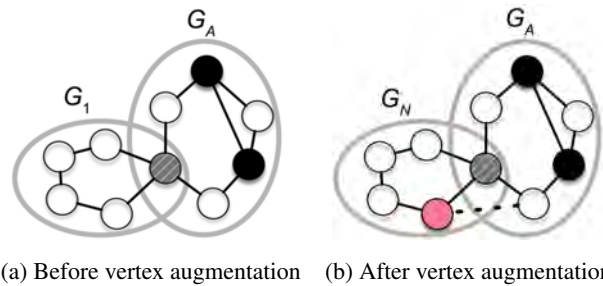

Fig. 5   An example for non-localizable nodes.

(a) Before vertex augmentation   (b) After vertex augmentation

Fig. 6   Network adjustment with vertex augmentation.

On the basis of Theorem 7, we propose the network adjustment algorithm in Algorithm 2. Such an algorithm initializes G_A with the largest localizable block identified in Algorithm 1. An arbitrary articulation node cv in G_A is selected. We perform vertex augmentation to one of its non-localizable one-hop neighbors, denoted as v_n^2. The corresponding block is added to G_A. The algorithm is terminated when $G_A = G$.

Using Algorithm 2, we can easily find that the upper bound of the adjusted nodes is equal to the number of articulation nodes in G. With finite vertex augmentations, all the non-localizable nodes in the graph are converted to localizable nodes. We then prove that after performing Algorithm 2, the network can be localized with *Sweeps*[2]. The actual design of the localization algorithm is beyond the scope of this paper.

Proposition 1 Given the locations of the passive event and localizable nodes, any non-localizable node v in a connected graph $G = (V, E)$ can be localized by *Sweeps*[2] after performing Algorithm 2.

Proof Suppose a connected graph $G = (V, E)$ contains m 2-connected components and the largest component with more than two beacons is denoted as G_A. Given the location of the passive event, any node in G_A is localizable. A bilateration order B_A can be constructed by starting at any beacons with breadth-first order for G_A. Therefore, any node in G_A can be localized with *Sweeps* according to Ref. [2].

Suppose the neighboring 2-connected component of G_A is G_1, and the articulation node is cv_1. After subjecting vertex augmentation to v_n, an arbitrary one-hop neighbor of cv_1 in G_1, the nodes in G_1 are all localizable. We construct an order by starting at v_n with breadth-first order, denoted as B_1. Given that v_n is directly connected to two nodes in G_A, the new order

$B_A \cup B_1$ is a bilateration order. Therefore, any node in $G_A \cup G_1$ can be localized with *Sweeps* according to Ref. [2]. The above processes are conducted iteratively until all of the 2-connected components are localizable. As a result, the generated order $B = B_A \cup B_1 \cup \cdots \cup B_{m-1}$ is a bilateration order. Any nodes in B can be localized with *Sweeps*. ∎

4.4 Event with partial coverage

Partial coverage is a highly challenging issue encountered in this work. When one available event exists, the connected components in the coverage of such an event can be adjusted into localizable. In other words, all the nodes in the coverage of available events are localizable. Such a localizable component greatly enhances the size of localizable nodes and connectivity in the original network. Although we cannot directly convert the entire network into localizable, the remaining effort has been drastically reduced. The adjustment of the remaining non-localizable nodes is dependent on the coverage range and locations of the event. If the event covers most of the nodes in the field, then only a few vertex augmentations are required to turn every non-localizable node into a localizable one. By contrast, if most of the nodes are not covered by such an event, exploiting the event is difficult. In the worst case, i.e., no node is covered by the event, then our problem is equivalent to the problem in LAL_H[10].

5 Performance Evaluation

This section first focuses on two specific instance of a connected network to validate the correctness of our proposal. Then, we conduct a large-scale simulation for 200 instances of randomly deployed networks, to evaluate the performance of our approach. We select the *state-of-the-art* work, LAL_H[10], as a benchmark for our approach.

5.1 Case study for WindTalker

We first randomly release 20 nodes to generate a connected graph, as shown in Fig. 7a. Nodes #5, #10, and #12 are three beacons in the network. The distance graph is constructed by adding edges between an arbitrary pair of beacons, as shown in Fig. 7b. Then, we identify 2-connected components (labeled with different colors) in Fig. 7c where the highlighted nodes are cut nodes. The distance graph consists of seven blocks, i.e., 2-connected components, as shown in Fig. 7d.

Algorithm 2 Network adjustment

Require: Given all the blocks and cut vertices of the original graph G as $BlockSet$ and $CutVertices$

  Let G_A denotes a localizable *block*

  while $G_A ! = G$ **do**

    for each cv $\in$ CV $\cap$ G_A **do**

      Randomly select a one-hop neighbor of cv as v_n

      Perform v_n^2

      $AdjacentBlock = FindAdjacentBlock(G_A, cv)$

      $AdjacentBlock.localizability = true$

      $G_A = G_A \cap AdjacentBlock$

      Remove cv from CV

    end for

  end while

(a) Topology   (b) Distance graph   (c) Biconnected components and cut nodes
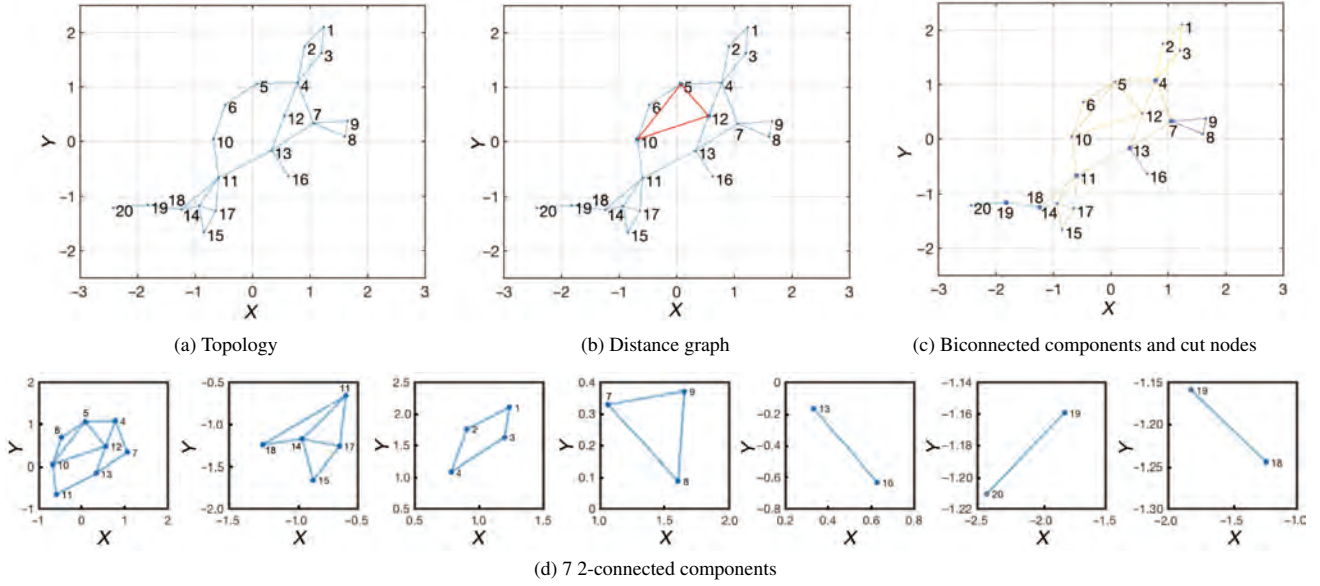
(d) 7 2-connected components

Fig. 7   Topology of a 20-node connected graph (near the origin of coodinates in $\mathbf{R}^2$).

WindTalker begins with the block that contains at least two beacons. Given that the beacons are connected in the distance graph, at least one block satisfies the above condition. We randomly select a one-hop neighbor of an arbitrary cut node of such a block and perform vertex augmentation v^2. The neighbor block is therefore adjusted to be localizable.

In the above instance, WindTalker begins with the 1st component in Fig. 7d. This component consists of three beacons and five unknown nodes. Such a block satisfies the condition of *network localizability* imposed by Theorem 5 when the passive event is available. Therefore, we initialize G_A in Algorithm 2 with such a block. Then, we find the neighboring block of G_A with the largest cardinality, i.e., the 2nd block in Fig. 7d. An arbitrary one-hop neighbor v_n (node #14 in Fig. 8) of the cut node (node #11 in Fig. 8) is selected to perform vertex augmentation v^2. Next, an extra edge will always be added between v_n and its two-hop neighbors. As a result, the 2nd block and the G_A consist of a new 2-connected component. We update G_A with the new component. WindTalker is performed iteratively until all blocks are contained in the generated component.

The final topology of the graph is plotted in Fig. 8, where the black nodes denote beacons, blue nodes denote cut nodes, red nodes denote nodes that perform vertex augmentation, and red dotted lines denote added edges. To facilitate presentation, we only plot one extra edge for each node that performs vertex augmentation and omit the other edges from their two-hop neighbors. In our case study, six nodes perform
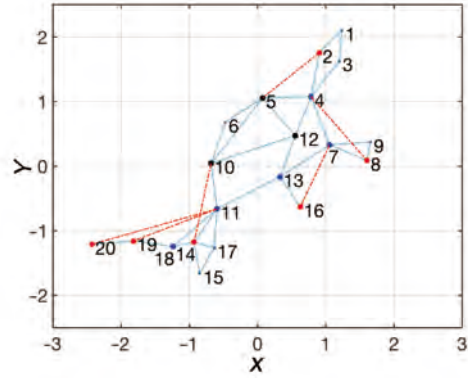

Fig. 8   Topology of graph after performing *WindTalker*.

vertex augmentation. The upper bound of the nodes that require vertex augmentation is $b_n - 1$, where b_n denotes the number of the contained blocks.

We further validate the correctness of *WindTalker* with a randomly generated connected graph with 1000 nodes in a 1×1 area. The distribution of such a network is shown in Fig. 9a. The average connectivity of the network is 4.742. We subject this network to *WindTalker* and subject 56 nodes to vertex augmentation to obtain the localizable network. The nodes that require vertex augmentation are highlighted with red in Fig. 9b, whereas the cut nodes are highlighted with blue.

5.2   Large-scale experiments

We further evaluate the performance of *WindTalker* through large-scale experiments. We select the proportion of the nodes that require vertex augmentation as the metric to evaluate the cost

(a) Original distribution　　　　　　　　　　(b) Adjusted
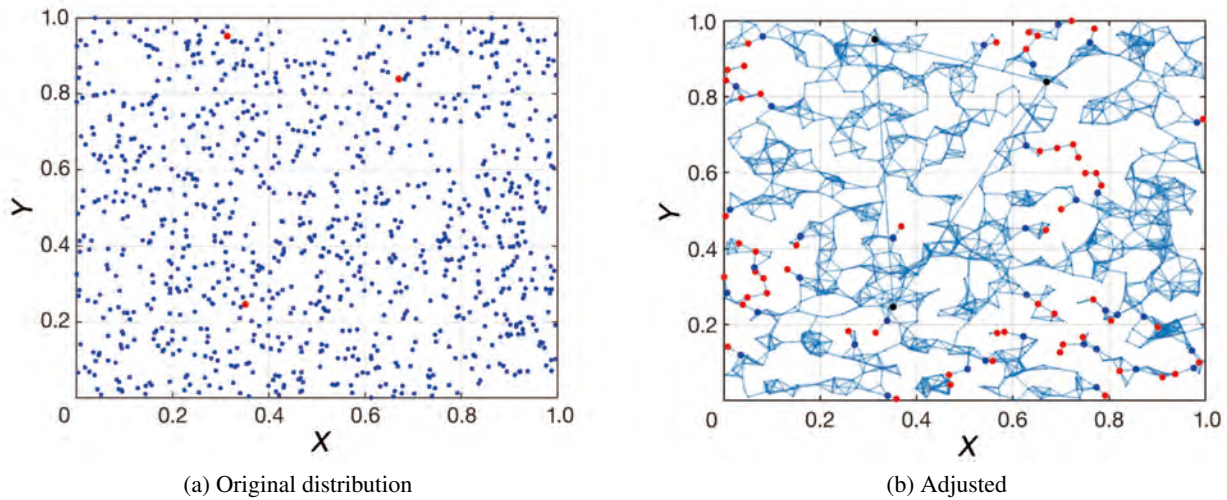
Fig. 9　Case study for a randomly generated 1000-node connected graph (in the unit region of $\mathbf{R}^2$).

required to convert a randomly deployed network into a localizable network. We generate 200 instances in our experiment. The first 100 instances are randomly generated in a 1×1 square with the same communication radius $r = 0.045$, whereas the second 100 instances are based on the same node distribution with different communication radius $r = [0.04, 0.05]$ with step length 0.0001. We then describe the results for these two experiments. We select the *state-of-the-art* work, LAL_H, in Ref. [10], as the benchmark for our approach.

The major objective of the first experiment is to evaluate the performance our approach under different node distributions. We randomly release 1000 nodes into the 1×1 square with a given communication radius r and select the giant connected component to construct the network. Given that the radius is constant, the average node degrees for these instances negligibly vary. Under the above settings, the average node degree is approximately 5 for each instance. The experimental results obtained by *WindTalker* and LAL_H for these instances are shown in Fig. 10. The proportion of the nodes that require vertex augmentation in WindTalker is significantly less than that in LAL_H because of the utilization of the passive event. Owing to the passive event in the field, our approach achieves finer-grained adjustment than LAL_H.

In addition, the distribution range of the Cumulative Distribution Function (CDF) curve for our approach is narrower than that of the CDF curve for the LAL_H approach. It shows that the costs required to achieve localizability under different scenarios are similar to each other. In other words, compared with other
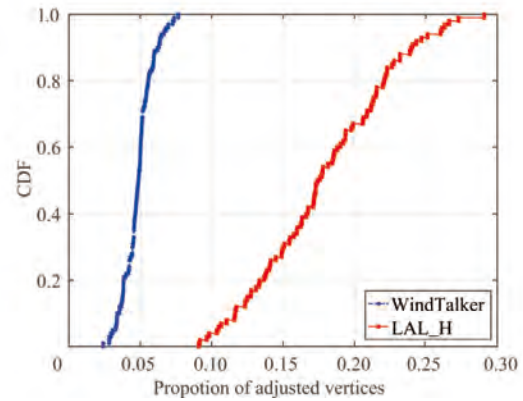
Fig. 10　CDF of the proportion of the adjusted nodes in 100 instances with same communication radius.

approaches, our approach shows better robustness to different patterns of sensor node distribution. Such a characteristic can provide improved support for the large-scale random deployment of WSNs.

We further evaluate the performance of our approach for the same distribution with different communication radii. We increase r from 0.4 to 0.5 with a step length of 0.0001 to simulate different connectivity conditions. The experimental results are shown in Fig. 11. When $r = 0.4$, our approach requires the augmentation of 14.2% of the nodes in the network to achieve localizability. This requirement decreases as the radius increases to 0.042 and reaches 0 when $r = 0.0426$. When our approach requires no further adjustment, the LAL_H approach still requires the adjustment of nearly 40% of the nodes to achieve localizability. Therefore, we can confidently conclude that utilizing passive events greatly reduce the efforts required to adjust a randomly deployed WSN for localization purpose.
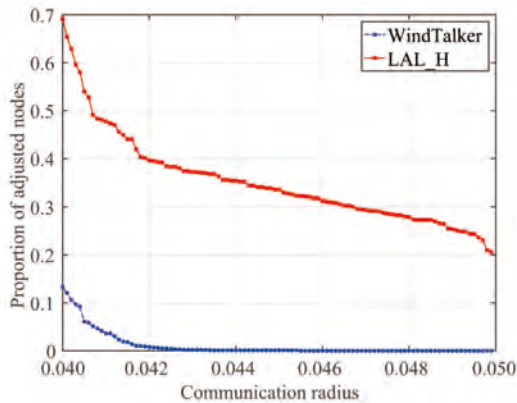
Fig. 11 Proportion of the adjusted nodes in 100 instances with different communication radii.

6 Conclusion

This work focuses on achieving localizability in large-scale randomly deployed WSNs. We propose *WindTalker*, a novel approach that utilizes occasional passive events to guide the adjustment of non-localizable nodes in a network. Compared with other current fine-grained approaches for network adjustment, our approach, which uses passive events, considerably relaxes the conditions for node and network localizability. Therefore, our approach greatly eases the burden of localization-oriented network adjustment.

We prove the sufficient condition for node and network localizability and design the corresponding algorithms for minimizing the number of nodes to be adjusted. The upper bound of the adjusted nodes is limited to the number of articulation nodes in a connected graph. The results of extensive simulations show that our approach greatly reduces the cost for network adjustment and hence can better support localization in large-scale sparse networks than other approaches.

To the best of our knowledge, we are the first to utilize the occasional passive event to reduce the cost of localization-oriented network adjustment. We believe our approach can greatly help various WSN applications.

Our approach encounters two crucial challenges despite its advantages. First, the assumption of the full coverage of the passive event is too strict. Given that the deployed field is usually massive in practice, the availability of a high-power passive event seems difficult. We plan to further study the event-assisted adjustment approach under partial coverage. Second, our approach is performed in a centralized manner, which may result in considerably communication overhead. Nevertheless, our node localizability condition has considerable potential for extensive implementation. In our future work, we will design the corresponding algorithms in a distributed manner with the proper leveraging of the message mechanism.

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