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Efficient localization for large-scale underwater sensor networks ☆

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ABSTRACT

In this paper, we study the localization problem in large-scale underwater sensor networks. The adverse aqueous environments, the node mobility, and the large network scale all pose new challenges, and most current localization schemes are not applicable. We propose a hierarchical approach which divides the whole localization process into two sub-processes: anchor node localization and ordinary node localization. Many existing techniques can be used in the former. For the ordinary node localization process, we propose a distributed localization scheme which novelly integrates a 3-dimensional Euclidean distance estimation method with a recursive location estimation method. Simulation results show that our proposed solution can achieve high localization coverage with relatively small localization error and low communication overhead in large-scale 3-dimensional underwater sensor networks.

1. Introduction

Recently, there has been a rapidly growing interest in monitoring aqueous environments for scientific exploration, commercial exploitation and coastline protection. The ideal vehicle for this type of extensive monitoring is a distributed underwater system with networked wireless sensors, referred to as Underwater Wireless Sensor Network (UWSN) [2,3]. In less than two years after the inception of the concept of UWSN, a certain amount of research work has been conducted in this interesting research area. Readers can refer [2–5] for challenges and states-of-art for UWSN research.

New routing and MAC protocols were proposed in [6–11] to accommodate the unique characteristics of UWSN. The authors of [12] investigated the synchronization problem for long delay acoustic channels of UWSN. In [13], the authors addressed the energy issues in UWSN and proposed methods to estimate the battery lifetime and power cost of shallow water networks.

For most UWSNs, localization service is an indispensable part. For example, in the long-term non-time-critical aquatic monitoring service [3,14], localization is a must-do task to get useful location-aware data. Location information is also needed for geo-routing which is proved to be more efficient than pure flooding in UWSNs [7]. In this paper, we investigate the localization issue for large-scale UWSNs.

Localization has been widely explored for terrestrial wireless sensor networks, with many localization schemes being proposed so far. Generally speaking, these schemes can be classified into two categories: range-based schemes and range-free schemes. The former covers the protocols that use absolute point-to-point distance (i.e., range) estimates or angle estimates to calculate locations [15–20], while the latter makes no assumptions about the availability or validity of such range information [21–25]. Although range-based protocols can provide more accurate position estimates, they need additional hardware for distance measures, which will increase the network cost. On the other hand, range-free schemes do not need additional hardware support, but can only provide coarse position estimates. In

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this paper, we are more interested in accurate localization, which is requested by a range of applications, such as estuary monitoring and pollutant tracking [3]. Moreover, in UWSNs, acoustic channels are naturally employed, and range measurements using acoustic signals are much more accurate than using radio [3,7]. Thus, range-based schemes are potentially good choice for UWSNs. Due to the unique characteristics (such as low communication bandwidth, node mobility, and 3-dimensional node deployment) of UWSNs [2,3], however, the applicability of the existing range-based schemes is yet to be investigated.

There are also several schemes proposed for the localization service in underwater acoustic networks [26–31]. These solutions are mainly designed for small-scale networks (usually with tens of nodes or even less). For large-scale UWSNs, hundreds or thousands of sensor nodes are deployed in a wide underwater area. Directly applying these localization schemes proposed for small-scale underwater networks in large-scale networks is often inefficient and costly.

In this paper, for the first time, we explore the localization problem in large-scale UWSNs. We propose a hierarchical approach, dividing the whole localization process into two sub-processes: anchor node localization and ordinary node localization. Many existing approaches can be used in anchor node localization. For ordinary node localization, we propose a novel distributed method based on a 3-dimensional Euclidean distance estimation method and a recursive location estimation method. Simulation results show that our localization scheme can achieve high localization coverage with accurate location estimation and low communication overhead in large-scale 3-dimensional underwater sensor networks.

The rest of this paper is organized as follows. In Section 2, we discuss the challenges for localization in large-scale UWSNs. In Section 3, we describe our new localization scheme. Simulation results are then presented in Section 4. And finally we draw conclusions in Section 5.

2. Challenges

Localization in large-scale UWSNs is largely unexplored. The adverse aqueous environment, the node mobility and the network scale pose grant challenges. We next discuss how these factors challenge the existing localization schemes.

2.1. Range-free localization schemes

Since radio does not work well in water, UWSN has to employ acoustic communications. Due to its unique features of large latency, low bandwidth and high error rate, the underwater acoustic channel poses many constraints on localization schemes. Traditional range-free localization schemes which adopt message flooding [22,23] are inefficient because of their huge communication overhead. In addition, unlike the nodes in most terrestrial sensor networks, underwater sensor nodes are continuously moving due to water current and other activities (such as shipping and fishing) [14]. The localization procedure needs to be repeated from time to update node locations. This further increases the communication overhead. Moreover, range-free localization schemes can only provide coarse location estimates, which is usually not desirable by many applications (such as estuary monitoring and pollutant tracking).

2.2. Range-based localization schemes

As mentioned earlier, range-based localization schemes have potentials for UWSNs since acoustic signals can help to significantly improve the accuracy of range estimates. In general, range-based localization schemes can be further divided into two categories: centralized and distributed. Centralized localization schemes usually need a global central node or several local centers to collect all the needed information from other nodes. Then these central nodes use some optimization methods to estimate the node locations based on the available information. MDS [32,33], SDP [17], and convex programming methods [34,35] belong to this category. It is evident that centralized localization schemes are not good candidates for large-scale UWSNs since they will introduce relatively large communication overhead and cannot respond timely to node location changes.

Multilateral methods presented in [36,19], and graph theory based methods discussed in [20] are distributed range-based localization schemes. All these schemes are proposed for two-dimensional terrestrial sensor networks, and cannot be directly applied into three dimensional UWSNs since in two-dimensional sensor networks, a sensor node only needs to know its distance to three anchors to determine a unique position, while for three dimensional UWSNs, in order to get a unique location, a sensor node has to know its distances to at least four anchors. This will also put high requirements on the connectivity of the networks [37]. Furthermore, the localization method proposed in [20] is based on the graph rigidity theory [38,39]. With minimal robust quads as the basic localization unit, a distributed algorithm is used for location transformation among different quads. For three dimensional underwater sensor networks, however, this method is not applicable, because the rigidity theory for three or more dimensional graph has not been well established [38,39].

2.3. Small-scale underwater localization systems

As we know, common GPS cannot work in the underwater environment. In order to get the absolute location information for the underwater objects, "underwater GPS" systems, such as GIB (GPS Intelligent Buoys) [26] and PARADIGM [27], have been proposed. Normally, these underwater GPS systems depend on the surface buoys to provide absolute position information and these buoys act as the satellites of the common GPS. All nodes within the communication ranges of these buoy nodes can get to know their absolute positions by estimating their distances to at least three buoy nodes. For large-scale underwater sensor networks, we cannot assume that all of these sensor nodes can get their absolute positions from the underwater GPS systems for the following two reasons. First, this needs all sensors to be equipped with some costly hardware, which may not be feasible in practice. Second, the surface buoys need to guarantee that all sensors can receive their messages. This requires large transmission power and therefore shorten the buoys' lifetimes since these buoys are also powered by batteries in most cases.

Different from underwater GPS systems, a distributed localization protocol is proposed for multi-hop underwater robot networks in [28]. This protocol is based on the iterative multilateral methods and is only suitable for small-scale underwater networks because of its slow convergence time.

In [27], the authors propose a localization scheme for small underwater vehicle networks. Their scheme is based on buoys moored to the seafloor and all underwater vehicles need to communicates directly with these buoys to get their locations. For large-scale underwater sensor networks, this method is not suitable since it requires all nodes to communicate directly with these fixed buoys.

Recent years have witness the active research in the localization for UWSNs. A range-free area based localization scheme for underwater networks has been proposed in [30], which can provide coarse location estimates. In [40], the authors propose a silent positioning scheme for UWSNs, and it relies on the time-difference of arrivals measured locally for location calculation. This scheme is designed for one-hop localization and all sensor nodes should be in the communication ranges of the anchor nodes. In [41], the authors study the localization problem in sparse 3-D underwater sensor networks. They transform the 3-D underwater positioning problem into its two-dimensional counterpart via a projection technique. Depth information of every node is requisite in their scheme. Mobility behavior of underwater sensor nodes has been considered in [42]. In this work, a collaborative localization scheme that effectively compensates for node motion with the ranging epoch has been proposed. In [43], the authors propose to use an AUV to aid the localization process. In this scheme, the AUV works as a mobile satellite and could localize the nodes within its communication range. A follow-up work is presented in [44]. In this study, multiple mobile beacon nodes which can sink and rise in the water are expected to send out messages to localize sensor nodes. For the schemes with mobile beacons, the localization time of every node is in large part dependent on the mobility behavior of the beacon nodes. Thus the convergence time of these schemes may be slow and the performance will degrade in the environment with mobile sensor nodes.

Clearly, large-scale UWSNs demand novel localization solutions. A desired scheme should give relatively accurate location estimates with communication overhead as low as possible. It must be fully distributed and can converge fast to cope with the node mobility. In the next section, we present our proposed localization scheme for large-scale UWSNs.

3. Localization for large-scale UWSNs

3.1. Overview

We consider a typical UWSN environment as shown in Fig. 1. There are three types of nodes in the network: surface buoys, anchor nodes, and ordinary nodes. Surface buoys are nodes that drift on the water surface. These buoys are often equipped with common GPS and can get their absolute locations from GPS or by other means. Anchor nodes are those who can directly contact the surface buoys to get their absolute positions. These nodes can also communicate with ordinary nodes and assist them to do localization. Ordinary nodes are those who cannot directly talk to the surface buoys because of cost or some other constraints but can communicate with the anchor nodes to estimate their own positions.

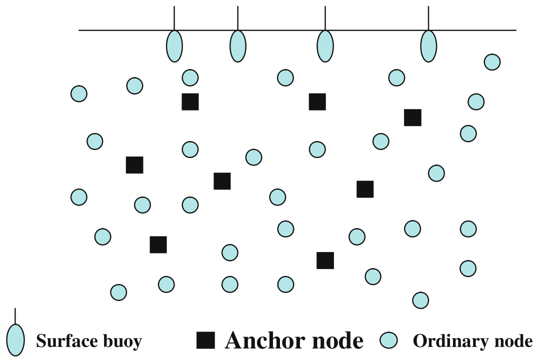


Fig. 1. A typical underwater sensor network setting.

To handle the large-scale of UWSNs, we propose a hierarchical localization approach. In this approach, the whole localization process is divided into two sub-processes: anchor node localization and ordinary node localization. At the beginning, only the surface buoys know their locations through common GPS or by other means. Four or more buoys are needed in our system. These buoys work as the "satellites" for the whole network, and anchor nodes can be localized by these surface buoys. Using surface buoys to locate underwater objects has been extensively investigated and many existing systems, such as [26,27], can be employed in the anchor node localization process. Simulation and experiment results show that with advanced signal processing technologies, these underwater "GPS" usually can provide position estimates with centimetric accuracy even for mobile underwater nodes [45–49]. And so, it is safe for us to assume that anchor nodes can always get perfect location estimation from the surface buoys. In this paper, we will not contribute to this part. Instead, we mainly tackle the problem of ordinary node localization, for which we propose a distributed range-based scheme, novelly integrating a 3-dimensional Euclidean distance estimation method and a recursive location estimation method. We describe this scheme in the following section.

3.2. Ordinary node localization

In 3-dimensional UWSNs, for a range-based localization scheme, ordinary nodes have to estimate their distances to more than 4 anchor nodes and calculate their locations by triangulation methods, which are commonly used in GPS systems. In a large-scale UWSN, however, not all ordinary nodes can directly measure their distances to 4 or more anchor nodes, thus some multi-hop distance estimation methods have to be developed.

In [19], the authors proposed and compared three multi-hop distance estimation methods: DV-Hop, DV-Distance and Euclidean. Even for two-dimensional terrestrial sensor networks, the performance of DV-Hop and DV-Distance degrades dramatically in anisotropic topologies, while the Euclidean method can achieve much more accurate results and behave more consistently in both anisotropic and isotropic networks than other methods [19]. In a UWSN, since the sensor nodes are constantly moving due to many environment factors, the network topology may change unpredictably with time and space. Thus, the Euclidean method is expected to be more suitable for UWSNs than other approaches.

In our scheme, we employ a hybrid approach based on a 3-dimensional Euclidean distance estimation method and a recursive location estimation method to get the ordinary node positions. When combined with the recursive method, the inherent problems of the Euclidean method such as high communication cost and low localization coverage can be greatly alleviated. Next, we will first describe overall process for the ordinary node localization. Then, we will discuss its two key components, 3-dimensional Euclidean distance estimation and recursive location estimation. After that, we will give some discussions and analysis.

3.2.1. Ordinary node localization process

In the ordinary node localization process, there are two types of nodes: reference nodes and non-localized nodes. In the *initialization phase*, all anchor nodes label themselves as reference nodes and set their confidence values to 1. All the ordinary nodes are non-localized nodes. With the advance of the localization process, more and more ordinary nodes are localized and become reference nodes. There are two types of messages: localization messages and beacon messages. Localization messages are used for information exchange among non-localized nodes and reference nodes, while beacon messages are designed for distance estimates. During the localization process, each node (including reference nodes and non-localized nodes) periodically broadcasts a beacon message, containing its id. And all the neighboring nodes which receive this beacon message can estimate their distances to this node using techniques, such as TOA (time of arrival). We describe the actions of the two types of nodes as follows.

Reference nodes: Each reference node periodically broadcasts a localization message which contains its coordinates, node id, and confidence value.

Non-localized nodes: Each non-localized node maintains a counter, n, of localization messages it broadcasts. We set a threshold N (referred to as "*localization message threshold*") to limit the maximum number of localization messages each node can send. In other words, N is used to control the localization overhead. Besides, each non-localized node also keeps a counter, m, of the reference nodes to which it knows the distances. Once the localization process starts, each non-localized node keeps checking m. There are two cases:

(1) $m < 4$. The non-localized node broadcasts a localization message which contains all its received reference nodes' locations and its estimated distances to these nodes. Its measured distances to all one-hop neighbors are also included in this localization message. Besides, this node uses the *three dimensional Euclidean distance estimation*, which will be described in details in Section 3.2.2, to estimate its distances to more non-neighboring reference nodes. After this step, the set of its known reference nodes is updated. Correspondingly, m is updated and the node returns to the m-checking procedure.
(2) $m \geqslant 4$. The non-localized node selects 4 non-collinear reference nodes with the highest confidence values for location estimation. After it gets its location, it will calculate its confidence value. If its confidence value is larger than a predefined threshold, this node is localized and labels itself as a new reference node. Then, it broadcasts a localization message which contains its coordinates, node id, and confidence value. Such a *recursive location estimation* process will be described in details in Section 3.2.3.

The complete localization procedure of an ordinary node is illustrated in Fig. 2. We next describe the two key modules: three dimensional Euclidean distance estimation and recursive location estimation.

3.2.2. Three dimensional euclidean distance estimation

In [19], a Euclidean distance propagation method is proposed for two-dimensional sensor networks. Here, we extend it into 3-dimensional networks.

The basic idea of Euclidean distance estimation is to estimate the distance between two non-neighboring nodes

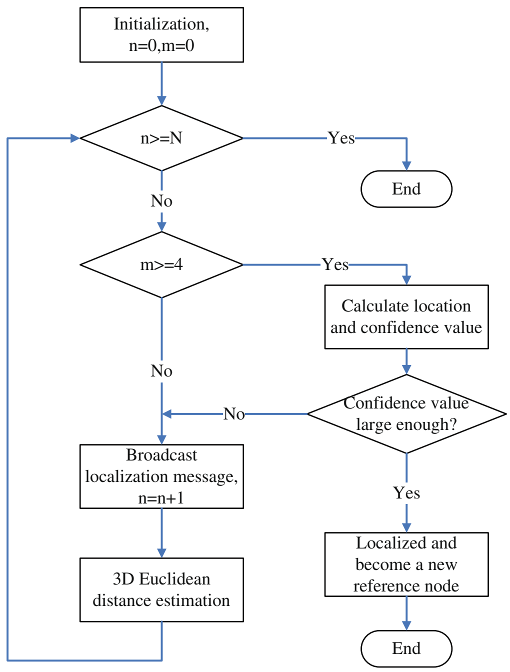


Fig. 2. Ordinary node localization process.

from its known one-hop distance measurements. In this way, non-localized nodes may get to know its distance to some localized reference nodes which might be multiple hops away from them.

We use an example to illustrate the method. Referring to Fig. 3, if an ordinary node *E* wants to estimate its distance to anchor node *A* which is two-hop away, Node *E* needs to know at least three one-hop neighbors (e.g., *B*, *C*, and *D*) which have distance estimates to *A*. Note that nodes *A*, *B*, *C* and *D* should not be co-plane and any three nodes out of *A*, *B*, *C*, *D* and *E* should not be co-line. Moreover, *E* should have the length information of *EB*, *BA*, *EC*, *CA*, *ED*, *DA*, *DB*, *DC*, and *BC*. The 3-dimensional Euclidean distance estimation works as follows: First, node *E* uses edge *BA*, *CA*, *BC* to construct the basic localization plane. Since the lengths of edges *DB*, *DA* and *DC* are already known (to *E*), the position of *D* can be easily estimated. There exist at most two possible positions for *D*. Because *E* knows the lengths of edges *ED*, *EB* and *EC*, corresponding to the two possible positions of *D*, there will be at most four possible solutions for *E*'s position. The choice among these four possibilities is made locally by voting when *E* has more immediate neighbors with estimates to *A*. If it cannot be decided, the distance estimate to *A* is not available until *E* gets more information from its neighbors.

3.2.3. Recursive location estimation

In [36], the authors propose an iterative framework to extend the position estimation from a few reference nodes throughout the whole network. System coverage increases recursively as nodes with newly estimated positions join the reference node set, which is initialized to include anchor nodes.

This recursive location estimation method is illustrated in Fig. 4. In the figure, node 1 can get its location information from four neighboring anchor nodes *A*, *B*, *C* and *D*. If the location estimation error is small enough, node 1 can be regarded as a new reference node for other nodes. Then, it will broadcast its own location information. When another node (node 2 in this example) gets to know the locations of *C*, *D*, *E* and 1 as well as the distances to these nodes, it can calculate its own location. On the other hand, if the location estimation error is large, node 1 cannot be treated

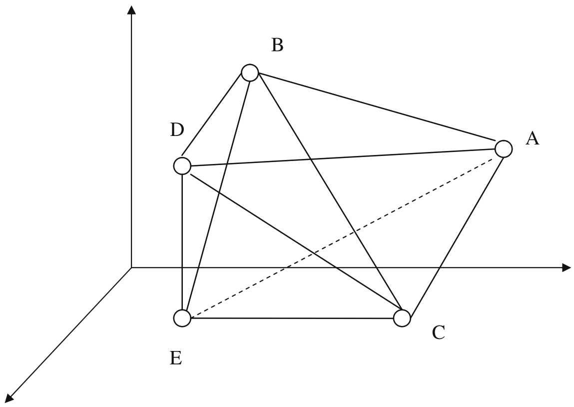


Fig. 3. 3-Dimensional Euclidean estimation.

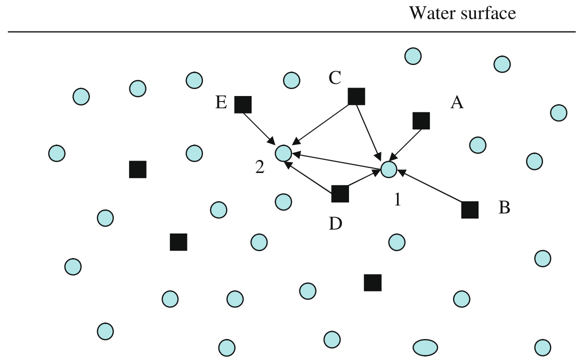


Fig. 4. Recursive location estimation.

as a reference node and will not broadcast its location. In our scheme, the following formula is used to estimate the *location error* δ:

$$\delta = \sum_i \left|(u - x_i)^2 + (v - y_i)^2 + (w - z_i)^2 - l_i^2\right|, \quad (1)$$

where (u, v, w) are the estimated coordinates of the unknown node, (x_i, y_i, z_i) are the reference node *i*'s location, l_i is the measured distance between the unknown node and node *i*.

In order to alleviate the error propagation effect, every reference node in the system has a *confidence value* η. For the initial reference nodes (i.e., the anchor nodes), η is set to be the largest, while for a new reference node, η is associated with its location error. In our scheme, η is calculated as follows

$$\eta = \begin{cases} 1 & \{\text{if node is the initial anchor}\}, \\ 1 - \frac{\delta}{\sum_i (u-x_i)^2 + (v-y_i)^2 + (w-z_i)^2} & \{\text{others}\}, \end{cases} \quad (2)$$

We can see that η is essentially a normalized δ. A critical value λ (referred to as "*confidence threshold*" later) is set. When $\eta > \lambda$, the unknown node can become a reference node. Otherwise, it will continue to be non-localized. When a node gets to know its distances to more than four nodes, it will choose four according to their η values and calculate its location.

3.3. Discussions

Advantages: Our proposed scheme has the following advantages. First, it is fully distributed with no central control unit. Second, Because our scheme is based on recursive and 3-D Euclidean distance estimation, it is robust to the anisotropic network topology [19]. Third, since all communication is done locally, it is expected to converge fast and can well cope with the node mobility. Fourth, it can achieve accurate results without much communication overhead. The latter two points will be confirmed by the simulation results presented in Section 4.

Location error: In order to localize a node, basically, two types of distance estimates are used: the direct measured distance and the distance estimated by three dimensional

Euclidean distance estimation method. Inevitably, there will be some errors in these distance measurements. Since we use the recursive method, errors will accumulate in the system. This means that the farther a node from the anchor nodes, the more the error for its location estimation. In order to alleviate the error accumulation, we need to carefully plan the anchor node placement to ensure that all nodes are not so far away from anchor nodes. If anchor nodes can actively move as underwater autonomous vehicles (AUVs), some adaptive methods can be used to guide these anchor movement. We leave this issue as our future work.

Communication cost: In a localization process, every node needs to broadcast a beacon message to get to know its neighbors' information. Every node also needs to broadcast at most N localization messages which contains its calculated location or its known one-hop neighbor information. The total number of localization messages of the whole network is bounded by $O(nN)$, where n is the number of nodes in the network. Some enhancements can also be made to lower the communication costs. For example, a node can decide whether to broadcast its localization message or not according to its communication environment. If a node senses the channel occupancy rate is high, it will not broadcast its localization message if this message is not so helpful to others. The node can also decide whether to broadcast messages according to its energy parameters in order to save energy.

Convergence analysis: Here, we say that the localization scheme *converges* if all localizable nodes get their locations in the localization process. And the *convergence time* is defined as the time for the localization scheme to converge. It is clear that when our scheme reaches convergence, the localization coverage will not increase any more no matter how many more localization messages to be sent. Therefore, if we get to know the convergence property of our localization scheme, we can stop localization message transmission at the convergence point. In this way, the communication cost can be saved.

Corollary 1. *Our localization scheme converges at the lth round localization message broadcasting, where l equals to the number of hops from the last localizable node to its farthest related anchor node.*

Proof. Referring to Fig. 5, let's assume node m is the last localizable node in the network, and it gets localized in the lth round. Let's assume that node m_{r1} is the last known reference node to node m for its localization. If node m_{r1} is k_1 hops away from node m, m_{r1} gets localized and becomes reference nodes in $(l-k_1)$th round. This can be proved by the contradiction as follows.

If node m_{r1} is one-hop neighbor of node m, then, m_{r1} becomes a new reference node in the $(l-1)$th round. This can be verified by the contradiction as follows. If node m_{r1} becomes a reference node before $(l-1)$th round, then, in the worst case, node m can get to know this reference node m_{r1} and get localized in the $(l-1)$th round because m_{r1} is the last reference node for its localization purpose. This will be in contradiction with our basic assumption that node m gets localized in the lth round. While if node m_{r1} is $k_1 > 1$

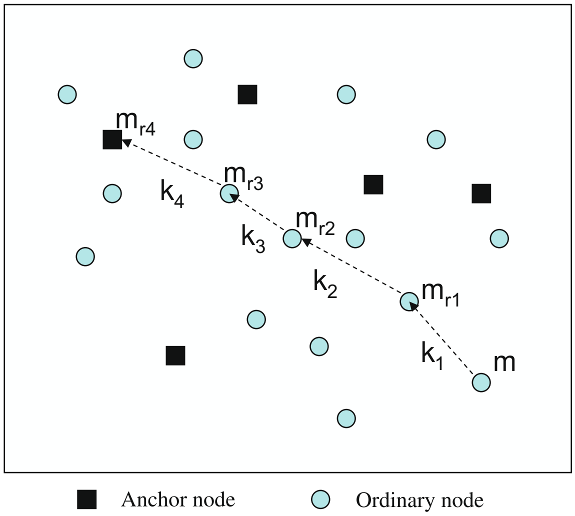


Fig. 5. Convergence process.

hops away from node m, node m must get to know this reference node m_{r1} through 3-D Euclidean distance estimation method, and k_1 round message broadcastings are needed to propagate the information of node m_{r1} to node m. Since m_{r1} is the latest known reference node to node m, in the same way, we can prove that node m_{r1} must become a reference node in the $(l-k_1)$th round by contradiction.

If reference node m_{r1} is not the original anchor node, for node m_{r1} to become a reference node in the $(l-k_1)$th round. In the same way, we can prove that its last known reference node m_{r2} should be localized and become a reference node in $(l-k_1-k_2)$th round, where k_2 is the hop count from m_{r2} to m_{r1}. Following this way, finally, we can reach one of the original anchor nodes with known location. The message round for this node to get localized should be $\sum k_i$ which equals to the hops from this node m to the furthest related anchor node. □

For a *random network*, since the anchor nodes as well as the ordinary nodes are randomly distributed, it is hard to get the exact value of message rounds for the convergence. However, we can get some approximate upper bound. For example, for a dense network with radius of R, if the communication range of every node is r, this upper bound can be $\frac{R}{r}$.

It is clear that the convergence property of our scheme is closely related to the localization message threshold N in our scheme. When N is much larger than the message rounds for the convergence, the communication cost will be increased significantly without any improvement in the localization coverage. On the other hand, a very small N cannot achieve the desired localization coverage.[1]

[1] For mobile underwater networks, the whole localization process needs to be run from time to time. However, for one localization process, if it is much faster than the network's moving speed, which is usually true considering that the underwater nodes usually move with a speed less than 3 m/s and the acoustic signal propagate with a speed of about 1500 m/s, the needed localization message is still constrained by our convergence analysis.

4. Performance evaluation

In this section, we evaluate the performance of our proposed localization scheme through simulation.

4.1. Simulation settings

In our simulation experiments, 500 sensor nodes are randomly distributed in a 100 m $\times$ 100 m $\times$ 100 m region. We define node density as the expected number of nodes in a node's neighborhood, hence node density is equivalent to node degree. We control the node density by changing the communication range of each node while keeping the area of deployment the same. Range (i.e., distance) measurements between nodes are assumed to follow normal distributions, with real distances as mean values and standard deviations to be one percent of real distances. This is a reasonable assumptions and can be easily satisfied by existing underwater distance measurement technologies [46,26]. 5%, 10% and 20% anchor nodes are considered in our simulations. Besides our scheme, we also simulate a Euclidean scheme and a recursive scheme for comparison. The recursive scheme here is the same as in [36]. As for the Euclidean scheme, we use the three dimensional Euclidean distance estimation as the distance propagation method and then use the triangulation method to estimate an ordinary node's position if it gets to know four or more reference nodes. It works almost the same as the Euclidean scheme for two-dimensional networks [19].

We consider three performance metrics: *localization coverage*, *localization error* and *average communication cost*. *Localization coverage* is defined as the ratio of the localizable nodes to the total nodes. *Localization error* is the average distance between the estimated positions and the real positions of all nodes. As in [19,37], for our simulations, we normalize this absolute localization error to the node communication range *R*. *Average communication cost* is defined as the overall messages (including beacon messages and localization messages) exchanged in the network divided by the number of localized nodes which is normalized to the size of the beacon message(16 bytes in our simulations).

4.2. Performance in static networks

In this set of simulations, nodes in the network are fixed. The confidence threshold λ is set to 0.98, and the localization message threshold N is set to 5. We change the range of the nodes from 17 m to 21 m with step 0.5 m, which result in the average node density changes from 8 to 16. We compare our scheme with the Euclidean scheme and the recursive scheme and the results are plotted in Figs. 6–8.

4.2.1. Localization coverage

Fig. 6 shows that our scheme outperforms both Euclidean scheme and recursive scheme in terms of localization coverage. This is reasonable since any node which can be

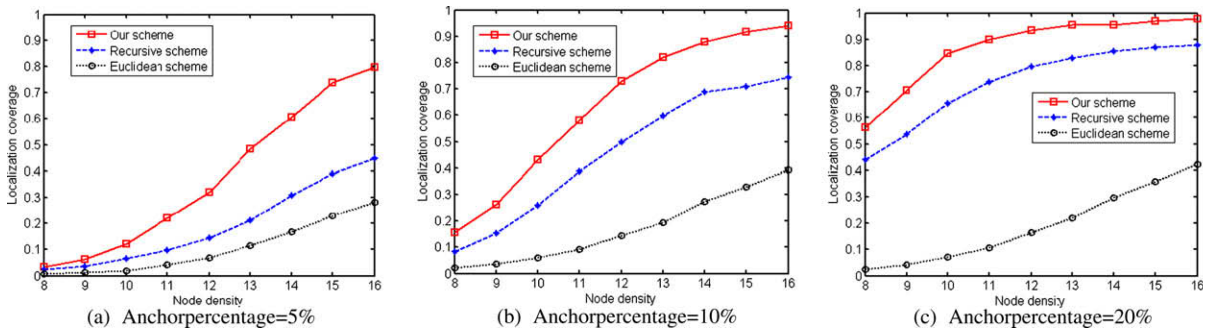


Fig. 6. Localization coverage.

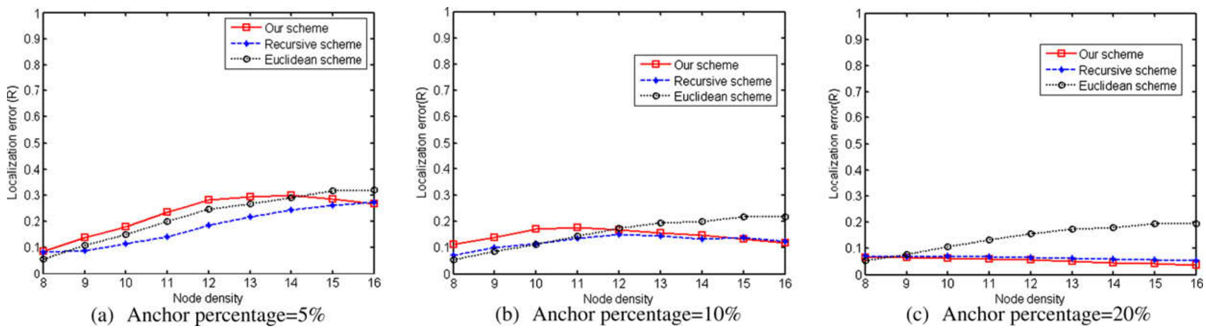


Fig. 7. Localization error.

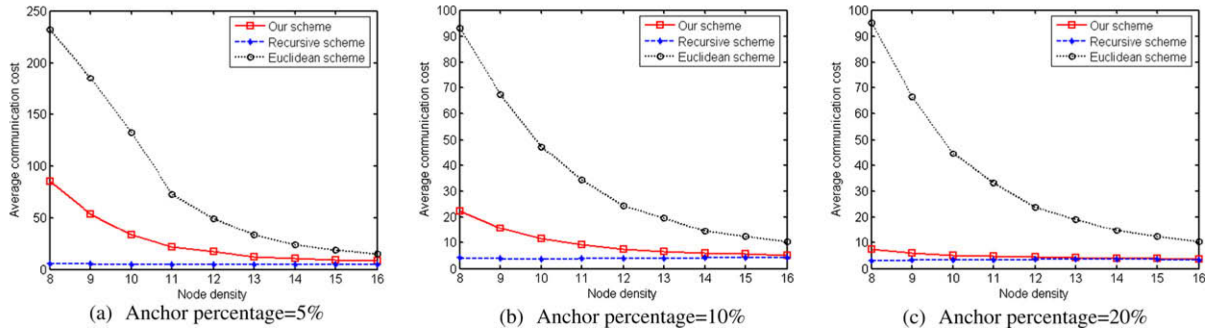


Fig. 8. Average communication cost.

located by either Euclidean scheme or recursive scheme can also be located by our scheme. The localization coverage of our scheme increases monotonically with the node density. But when the node density is relatively large, the coverage reaches a relatively high value and will not change much after that. For example, when the anchor percentage is 20%, the localization coverage reaches 94% at node density 12 and does not increase much with the node degree lifted. And we can also see that the more the anchors, the higher the localization coverage. For example, if the anchor percentage is 5%, the localization coverage can only reach 0.4 when the node density is 13, but if the anchor percentage is 10%, the localization coverage can reach 0.8 when the node density is 13. This suggests us that in sparse networks, we can increase the number of anchor nodes to achieve higher localization coverage. It should be noted that the localization coverage of both the Euclidean method and the recursive method also increase with the anchor percentage. For example, when the node density is 12, if the anchor percentage change from 5% to 10%, for the Euclidean scheme, the localization coverage increases from 0.07 to 0.13.

For a given localization coverage, the 3-D underwater environment puts a higher requirement on the node density than the 2-D terrestrial networks. In our scheme, by combining the recursive method and the 3-D Euclidean method, the localization coverage of the network can be improved much, especially in the low node density region. For example, as shown in Fig. 6, when the anchor node is 5% and the average node density is 12, the localization coverage of our scheme is about 0.31, which is much higher than that of the recursive scheme 0.14 and that of the Euclidean scheme 0.07. However, it also comes with the cost of a moderate increase in the average communication costs, which is shown in Section 4.2.3.

4.2.2. Localization error

Fig. 7 plots the relationship between the localization error and the node density. We can observe that when the node density is relatively small, the localization error of our scheme is almost the same as that of the other two schemes. With the increase of the node density, the localization error of our scheme will increase and become a little larger than recursive scheme but much smaller than Euclidean scheme. This is because with the increase of the node density, the localization coverage of our scheme increases much faster than the other two schemes, as leads the growth of the localization error. But this growth is much slower rate than that of the localization coverage. As the node density continues to increase beyond some point, the localization error of our scheme will decrease slowly. This can be explained as follows. When the node density reaches a certain point, most sensor nodes can localize themselves. If we continue to increase the node density, ordinary nodes will get to know more anchor nodes and have more choices to calculate their locations. Thus, the localization error will decrease. But, as shown in Fig. 7, this decrease is very limited. For example, when the anchor percentage is 5%, if we increase the node density from 13 to 16, the localization error only decreases from 0.3R to 0.27R. Thus, in practice, we cannot expect to reduce the localization error by simply lifting the node density. Fig. 7 also shows us that the localization error will decrease observably with the anchor percentage. For example, at node density 13, when the anchor percentage is 5%, the localization error is 0.3F. But when the anchor percentage is enlarged to 20%, it reduces to 0.05R. Thus, more anchor nodes can translate into smaller localization errors.[2]

4.2.3. Communication cost

Fig. 8 shows the average communication cost with the changing node density. In the recursive localization scheme, only nodes with known locations broadcast messages and other nodes keep silent. Therefore, the average communication cost of this scheme is very small. For our scheme, when the node density is small, it introduces larger communication cost than the recursive scheme. This is because in our scheme, when the network is sparse, although many nodes exchange beacon messages, they cannot finally localize themselves. In other words, these beacon messages are actually "wasted" in the localization process. But with the increase of the node density, this waste becomes smaller and smaller, and the average communication cost of our scheme becomes closer and closer to the recursive scheme. From the figure, we can also ob-

[2] This conclusion still holds for the Euclidean scheme and the recursive scheme. For example, As shown in Fig. 7, when the node density is 12, if the anchor percentage increases from 5% to 10%, for the Euclidean scheme, the localization error decreases from 0.22R to 0.16R.

serve that the average communication cost of our scheme decrease with the increase of anchor percentage.

Compared with the Euclidean localization scheme, our scheme can always achieve much lower communication cost. This is due to the fact that the recursive component in our scheme helps to find more reference nodes in the localization process. Thus, many nodes which cannot get localized in the Euclidean method can be localized in our scheme. Correspondingly, the localization coverage increases, which decreases the average communication costs.

4.2.4. Discussions

It is shown in [37] that range-based ad hoc localization schemes have high requirements on the node density of the networks. The paper also shows that in a two-dimensional network, the node density needs to be at least 11 in order to localize 95% nodes with less than 5% localization error when 20% anchor nodes are present in the network.

From Fig. 7c, we can observe that when there are 20% anchors, our scheme can localize more than 95% nodes with less than 5% localization error if the node density is 12 in a 3-dimensional UWSN. Compared with the results in [37] for two-dimensional networks, our scheme can achieve the same performance in 3-dimensional networks, with the connectivity requirement increased from 11 to 12. This indicates the good performance of our proposed scheme.

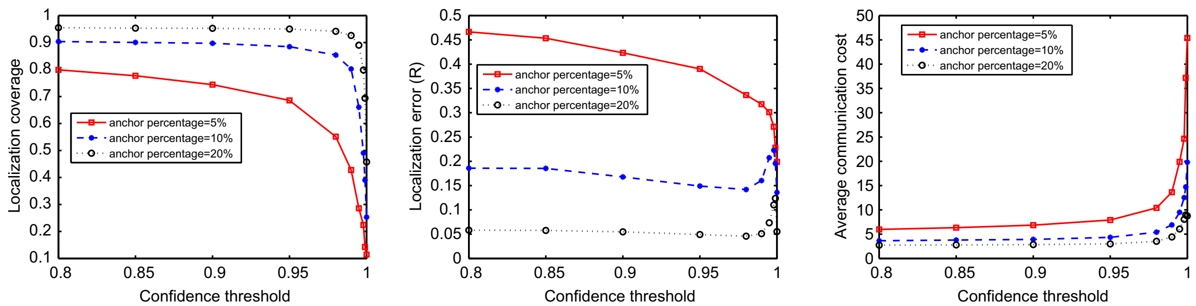
4.3. Impact of confidence threshold

Here, we set the node density to 13 and change the confidence threshold from 0.8 to 1. The localization message threshold is set to be 5. Fig. 9a shows that with the increase of confidence threshold, the average localization coverage will decrease correspondingly. There exists some critical values. Below these values, the localization coverage will not decrease much, but above these values, the localization coverage will drop abruptly. For example, as show in Fig. 9a, when the anchor percentage is 10%, this critical value is 0.98.

Fig. 9b shows the relationship between the localization error and the confidence threshold. When the anchor percentage is 5%, the localization error will decrease monotonously with the confidence threshold. But when the anchor percentage is 10% and 20%, when the confidence threshold is small, the localization error will decrease slowly with it. But after some critical points, the localization error will increase abruptly and then decrease again. This can be explained as follows. On the one hand, with the increase of the confidence threshold, only nodes with higher localization accuracy will become reference nodes in the future, which will contribute to the reduction of the localization error. On the other hand, if the confidence threshold is set too high, the available reference nodes in the network will decrease significantly. More nodes have to rely on the three dimensional Euclidean distance estimation method to estimate their distances to the reference nodes, which are not accurate as the results of direct range measurement in noise environment. This will contribute to the increase of the localization errors. At the beginning, the first factor dominate the second, thus, the localization error decrease. With the further increase of the confidence value, the second factor play a major part, which leads to the increase of the localization error. However, if the confidence value is too high, the available reference nodes in the network will be greatly reduced, which leads to a dramatic decrease of the localization coverage. In this situation, only nodes with high accuracy can be localized, which again leads to the decrease of the average localization errors

Fig. 9c shows the average communication cost with the confidence threshold. We can observe that when the confidence threshold is small, the average communication cost increase slowly with the that of the confidence threshold. But after some critical values, the average communication cost will increase much faster. This is reasonable since the higher the confidence value, the lower the localization coverage.

Fig. 9 also suggests us that by changing the confidence threshold, we can control the tradeoff between the localization error, the localization coverage and the average communication cost. For example, with the increase of the confidence threshold, the localization coverage and the localization error will decrease, but the average communication costs will increase to some extent. For UWSNs where location information is only used for geo-routing, high localization accuracy is not required [24], but a high localization coverage is desired. For this type of networks,



(a) Localization coverage (b) Localization error (c) Average communication cost

Fig. 9. Impact of confidence threshold.

the confidence threshold can be set to a relatively small value. While for UWSNs which require high precise location information, the confidence value should be set to a relatively large value. Some adaptive algorithms can be used to control this parameter to provide some performance guarantees. This is an interesting topic but it is beyond the scope of this paper.

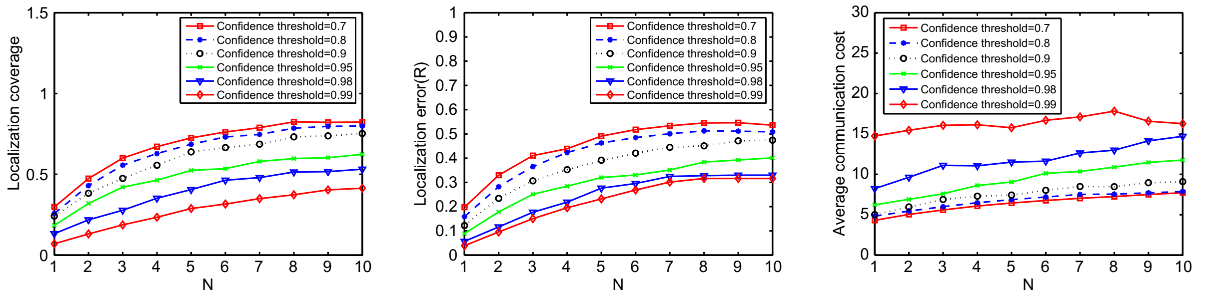
4.4. Impact of localization message threshold

In this subsection, we study the impact of the localization threshold. In this set of simulation experiments, we set the anchor percentage to be 10%, the node density to be 13. We change localization message threshold N from 1 to 10 and the confidence threshold from 0.7 to 0.99. The results are plotted in Fig. 10. From this figure, we can see that with the increase of N, the localization coverage will increase correspondingly. But at the same time, the localization error as well as the average communication cost will also increase. In addition, we can also observe that there exist critical values (the convergence point) (e.g., it is 5 in Fig. 10). If N is smaller than this value, the localization coverage, the localization error and the average communication cost will increase rapidly. When N is larger than this value, the localization coverage and the localization error will not change much. But the communication cost will continue to increase. This means that after this critical value, increasing N can only increase the communication cost and will not bring any benefits.

Our previous analysis on the convergence property in Section 3.3 give us a theoretical upper bound on the convergence point. In this network setting, this upper bound is $\frac{100\sqrt{3}}{20} \approx 9$. Here, we can see that this is a relatively loose bound. In practice, we need to carefully choose N according to different network environments. But it should be smaller than the theoretical upper bound. In the next, we will show that in some network conditions, for example, in the grid network with high density, the theoretical upper bound is tight.

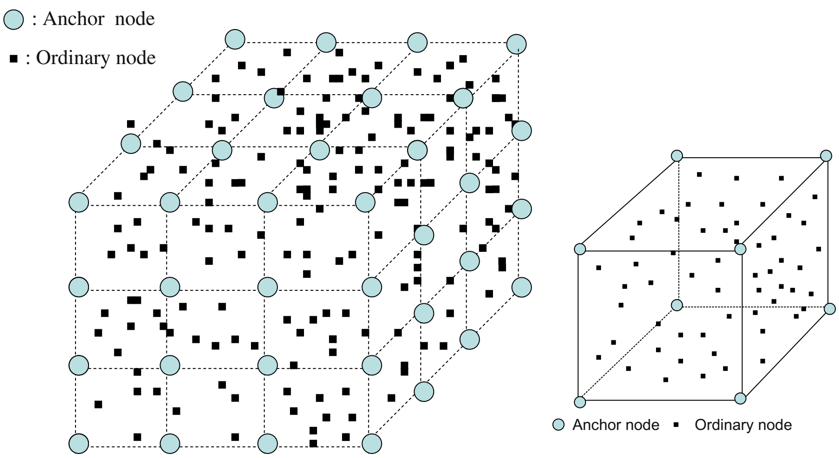
4.5. Convergence property

To verify our analysis on the convergence property, we simulate an underwater *grid-random* network. The network topology is shown in Fig. 11a. Sixty-four anchor nodes are placed as a grid in a 100 m × 100 m × 100 m re-



(a) Localization coverage (b) Localization error (c) Average communication cost

Fig. 10. Impact of localization message threshold.



(a) three dimensional grid networks (b) one grid unit

Fig. 11. Simulated network settings.

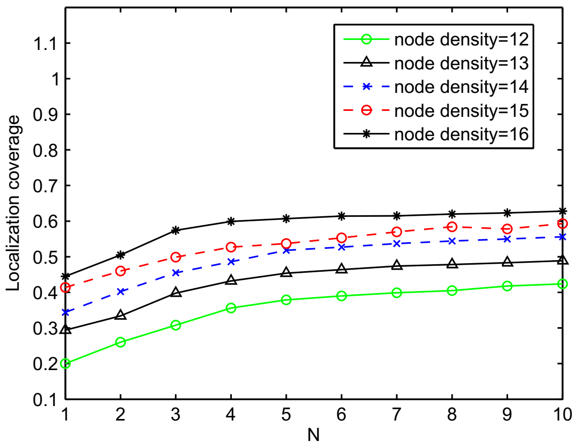


Fig. 12. Convergence property in a grid network.

gion. The distance between any two anchor nodes is about 33 m. Five hundred ordinary sensor nodes are randomly distributed in this network.

In this grid-random network, the whole localization process can be approximately divided into multiple parallel localization processes in every grid units. This is because for any node in the network, its nearest anchor nodes will be the anchor nodes in the same grid unit. In dense networks, each node can do localization with high probability just based on the information of the anchor nodes in the same grid unit.

For one grid unit in the network, as shown in Fig. 11b, the possible longest distance between an anchor node and an ordinary node is $\sqrt{(3 \times 33^2)} = 57$ m. The one-hop transmission distance here is about 20 m. According to our analysis on convergence before, we know that its convergence time will be $57/20 \approx 3$. In Fig. 12, it is clearly shown that when node density is high, the localization coverage will arrive at its maximal value and get stabilized when $N \geqslant 3$, this also verify our previous analysis on the convergence property for the high node density region.

From Fig. 12, we also observe that with the decrease of the node density, the convergence point is lifted a little. In our simulated settings, this is because of the following two reasons: (1) Because of the relatively low node density and the random nature of the network, the maximal hop count from one node to the anchor nodes in the same grid unit will be larger than 3, which is only the maximal hop count for line-of-sight distance within a grid unit; (2) some nodes can be localized using the information of the anchor nodes in the neighboring grid units. On the other hand, we can also see that the increase after 3 is minor. For example, with node density at 13, when N changes from 3 to 10, the localization coverage increases no more than 7%.

4.6. Performance in mobile networks

In underwater sensor networks, most nodes can move passively with water currents or tides [3]. In the mobile network case, localization procedure has to be executed periodically. In this set of simulation experiments, we apply our scheme into a random mobile network and investigate the impact of node mobility on the localization performance. We set the anchor node percentage to 10% and the localization message threshold N to 5. Confidence threshold λ takes a value of 0.98. The node mobility model is assumed as follows. For every specified period (5 s in our simulations), all nodes randomly choose one direction, and all of them move in this direction with random speeds distributed uniformly in $\{0.5V_{ave}, 1.5V_{ave}\}$, where V_{ave} is the average moving speed which is closely related to some environment factors such as tides and water currents. We do not choose traditional random waypoint model or other mobility models because in underwater sensor networks, most nodes are moving passively and their mobility behaviors are determined by the environment. Our mobility is a little like the random group movement model, which can approximate underwater environments such as river and seashore. More appropriate mobility models will be investigated in our future work.

Range measurement errors will increase with the node moving speed because of Doppler effects and other environment factors. In our simulations, we use the following formula to capture the effects of node mobility on the range measurement error R_{err}

$$R_{err} = (\beta \times \theta \times V_{ave} + 1) \times 0.01R, \quad (3)$$

where β is a random number between 0 and 1, and it is used to capture the randomness of the range measure-

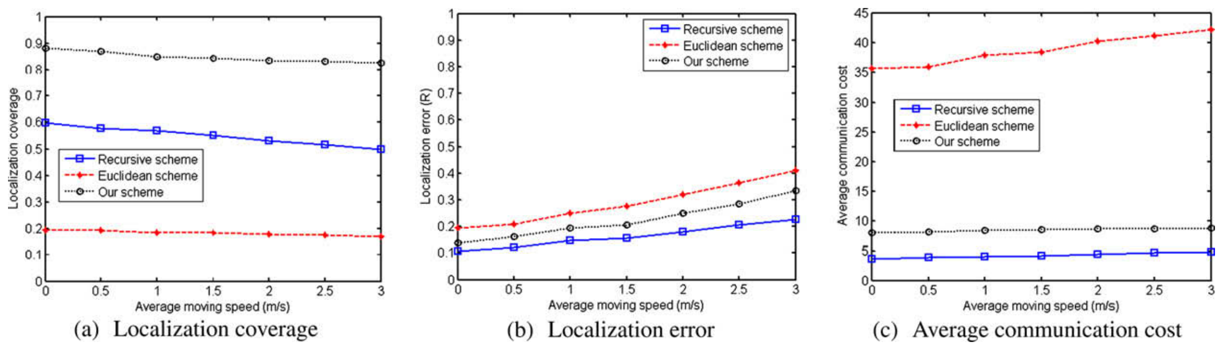


Fig. 13. Performance in mobile networks.

ment, θ is a constant factor which is closely related the impact of node moving speed on the range measurement error. In our simulations, we choose $\theta = 0.2$. More appropriate range measurement error model will be investigated in our future work. Here, since the distance between nodes are small (about 20 m, the signal propagation delay between two neighboring nodes is about 0.015 s), we ignore the impacts of range measurement delay in our simulations.

Fig. 13 clearly shows the effect of the node mobility on the localization performance. We can see that our localization coverage and average communication cost will not be affected much by the node movement, but the localization error will increase with the node moving speed. This is mainly because the average range measurement error increases with the average moving speed. Correspondingly, the final localization error will increase.

In order to further reduce the communication overhead in mobile environments, some movement prediction models can also be imported in the localization process. For example, in [50], a prediction model is used to predict the movement of nodes in order to regulate the inter time of two localization processes. In a UWSN, nodes are often moving along with water currents or tides with some random group mobility properties. A mobility prediction algorithm can be devised based on these properties. And this will be investigated in our future work.

5. Conclusions

In this paper, we presented a hierarchical localization approach for large-scale UWSNs. In this approach, the whole localization process consists of two sub-processes: anchor node localization and ordinary node localization. We focused on the ordinary node localization, for which we proposed a distributed scheme which novelly integrates a 3-dimensional Euclidean distance estimation method and a recursive localization method. Simulation results showed that our scheme can achieve high localization coverage with relatively small localization error and low communication cost. Besides, we also investigated the tradeoffs among the node density, the anchor percentage, the localization error, the localization coverage and the communication cost in our scheme. Different networks may have different requirements for these parameters. By changing the confidence threshold parameter of our scheme, we can well control these tradeoffs.

Future work: (1) Our current simulations assume a collision free Medium Access Control (MAC) protocol. However, for MAC protocols which cannot totally eliminate collisions, localization messages might get lost because of collisions, which will degrade the system performance. In our future work, we want to investigate the impact of MAC protocols on our localization scheme. (2) For mobile networks, the whole localization process of our scheme needs to be run from time to time, which will increase the system overall communication costs. In the future, we want to integrate the mobility pattern of underwater objects and propose some mobility prediction algorithms to further improve the overall system performance.

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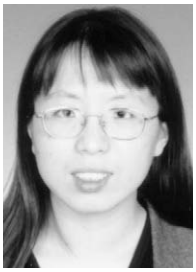

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