Scalable Localization with Mobility Prediction for Underwater Sensor Networks

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Abstract—Due to harsh aqueous environments, non-negligible node mobility and large network scale, localization for large-scale mobile underwater sensor networks is very challenging. In this paper, by utilizing the predictable mobility patterns of underwater objects, we propose a scheme, called Scalable Localization scheme with Mobility Prediction (SLMP), for underwater sensor networks. In SLMP, localization is performed in a hierarchical way, and the whole localization process is divided into two parts: anchor node localization and ordinary node localization. During the localization process, every node predicts its future mobility pattern according to its past known location information, and it can estimate its future location based on the predicted mobility pattern. Anchor nodes with known locations in the network will control the localization process in order to balance the trade-off between localization accuracy, localization coverage, and communication cost. We conduct extensive simulations, and our results show that SLMP can greatly reduce localization communication cost while maintaining relatively high localization coverage and localization accuracy.

Index Terms—Network architecture and design, network communications, network protocols, applications, miscellaneous, localization, underwater sensor networks.

1 INTRODUCTION

LAST several years have overseen a rapidly growing interest in underwater sensor networks [1], [2], [3], [4], [5], [6], [7]. One important reason is that they can offer significant advantages and benefits in a wide spectrum of aquatic applications: underwater environmental observation for scientific exploration, commercial exploitation, coastline protection, and target detection in military or terrorist events. On the other hand, underwater sensor networks represent one of the hardest networking scenarios we have ever encountered. They drastically differ from terrestrial sensor networks because: 1) electromagnetic waves cannot propagate over a long distance in water. Thus, underwater sensor networks must rely on acoustic signals that feature large latency, low bandwidth, and long end-to-end delay; and 2) sensor nodes move with water currents and dispersion, which results in dynamic network configurations that need to be monitored. All these unique features cause grand challenges to the networking issues at almost every layer of the protocol stack [8], [9], [10], [11], [12], [13], [14], [15], [16], [17], [18], [19], [20].

Localization of mobile sensor nodes is indispensable for underwater sensor networks. For example, in aquatic environment monitoring applications, localization is an essential task in order to get useful location-aware data. Location information is also required for geo-routing, which is proved to be more scalable and efficient in mobile underwater sensor networks [16]. So far, only a limited number of schemes have been proposed for the localization service in underwater acoustic networks [21], [22], [23], [24]. These solutions are mainly designed for small-scale static networks (usually with tens of nodes or even less). However, many aquatic applications, such as marine surveillance, require a localization solution that can scale to a large number (hundreds to thousands) of nodes. In this paper, we focus on the localization service for large-scale mobile underwater sensor networks.

Due to harsh aqueous environments, non-negligible node mobility and large network scale, localization for large-scale mobile underwater sensor networks is very challenging. Since radio does not work in water, acoustic communications have to be employed. The unique features of acoustic channels (high error rate, low bandwidth, and long propagation delay) cause many constraints on the localization schemes for underwater sensor networks. Traditional multihop localization schemes for terrestrial sensor networks are inefficient because of their huge communication overheads [25], [26]. Meanwhile, underwater sensor networks are mobile networks and node locations change continuously. In such environments, most localization schemes designed for static sensor networks need to run periodically to update the location results, as will dramatically increase the communication overhead. Further, distributed localization schemes designed for small-scale underwater acoustic networks [23], [24] cannot work well in large-scale underwater sensor networks due to their slow convergence speed and high communication overhead. Last, high localization coverage and low localization error are always desired for a localization scheme, while these performance requirements are specially challenging for underwater sensor networks with stringent resource limitation. In this paper, *we aim to design a scalable localization scheme with low communication*

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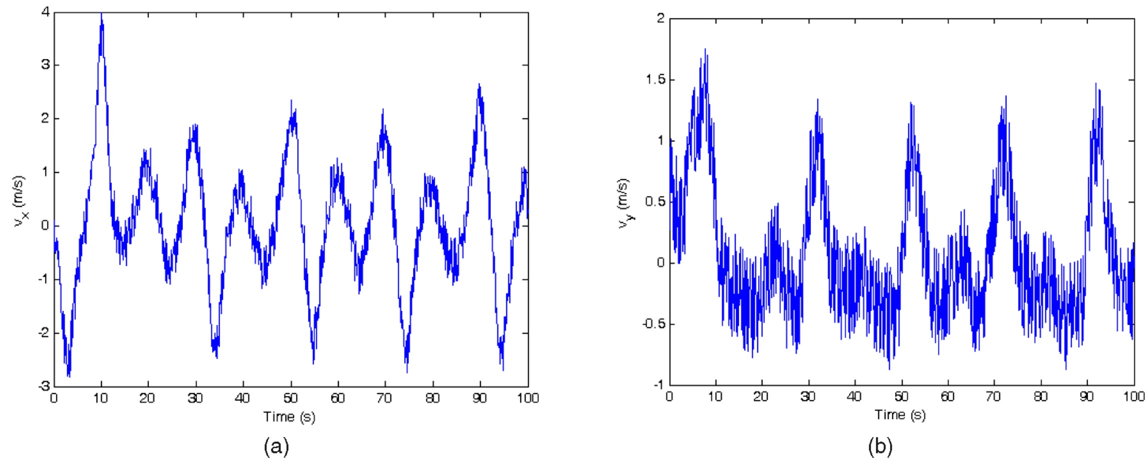

Fig. 1. Mobility patterns of underwater objects in a seashore environment. (a) Velocity in x-axis. (b) Velocity in y-axis.

overhead yet good localization performance for large-scale underwater water sensor networks.

Although the network conditions in underwater environments are extremely tough for localization (as we discussed above), some unique properties can be indeed effectively exploited. A very useful property we find is that underwater objects move with predictable patterns, though these patterns are in a large part determined by environmental factors [27], [28]. This mobility property can actually provide us an efficient way for high performance localization. In this paper, we propose a scheme, called **S***calable* **L***ocalization scheme with* **M***obility* **P***rediction* (**SLMP**), for underwater sensor networks. In SLMP, localization is performed in a hierarchical way, and the whole localization process is divided into two parts: anchor node localization and ordinary node localization. During the localization process, every node predicts its future mobility pattern according to its past known location information, and it can estimate its future location based on its predicted mobility pattern. Anchor nodes with known locations in the network will control the whole localization process in order to balance the trade-off between localization accuracy, localization coverage, and communication cost. Simulation results show that SLMP can greatly reduce localization communication cost while maintaining relatively high localization coverage and localization accuracy.

Our contributions are threefold. First, we propose a novel localization scheme, SLMP. This scheme is scalable and can achieve a good balance between localization accuracy, localization coverage, and communication cost. Second, as a case study, we analyze the mobility pattern in seashore environments and propose a simple yet effective mobility prediction algorithm. Third, we investigate the performance of SLMP through extensive simulations. Our results show that some useful technologies such as linear prediction algorithms in signal processing can be imported for network localization. We hope that our work can shed some light on this new research direction.

The rest of this paper is organized as follows: In Section 2, we will give some background knowledge on underwater object mobility and briefly review some related work on localization. Then, in Section 3, we will describe SLMP in detail using seashore environments as an example. Following that, we present simulation results in Section 4. Finally, we conclude the paper in Section 5.

2 Background and Related Work

2.1 Mobility Characteristics of Underwater Objects

Underwater objects are moving continuously with water currents and dispersion. Research in hydrodynamics shows that the movement of underwater objects is closely related to many environment factors, such as the water current and water temperature [27], [28]. In different environments, the mobility characteristics of underwater objects are different. For example, the mobility patterns of objects near the seashore demonstrate a certain semiperiodic property because of tides; but for objects in rivers, their moving behaviors have no such a property. While it is almost impossible to devise a generic mobility model for underwater objects in all environment conditions, some mobility models for underwater objects in specific environments based on hydrodynamics have been devised [27], [28]. This indicates that the movement of underwater objects is not a totally random process. Temporal and spatial correlation are inherent in such movement, which make their mobility patterns predictable in nature.

As a case study, in this paper, we will investigate the mobility characteristics of objects in shallow seashore areas (referred to as *seashore environments* in this paper). Tidal areas are characterized by their shallowness and their strong tidal currents. The nonlinear interaction of tidal currents and bottom topography produces currents, which give nonzero contributions to the tidally averaged currents. These so-called residual currents are important for the transport and mixing properties of the tidal flow.

Fig. 1 shows the velocity of an underwater object with time in a typical seashore environment. We can clearly see that the moving speed of the object changes continuously and shows certain semiperiodic property. This is mainly due to the tides and bathymetry. The exhibited strong time-domain correlations tell us that it is possible to estimate future values based on measured past values with high accuracy.[1]

Further, [27] and [28] show that spatial correlations exist in underwater environments, which means that the

1. In this paper, we assume that objects keep constant in z (depth) axis, and the mobility pattern of objects is only related to the (x, y) axis. Thus, objects with the same (x, y) but different z move with the same mobility pattern. This is a common assumption in hydrodynamics [27], [28].

movement of one object is closely related to its nearby objects. In other words, underwater objects possess certain group movement properties.

2.2 Related Work on Localization

Localization for terrestrial sensor networks has been widely explored, and a significant number of schemes have been proposed [29], [30], [31], [32], [33], [34], [35], [36], [37], [38], [39], [40], [41], [42], [43], [44]. 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 estimates (i.e., range) or angle estimates to calculate locations while the latter makes no assumptions about the availability or validity of such range information. 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 this paper, we are more interested in accurate localization. Moreover, in underwater sensor networks, acoustic channels are naturally employed and range measurement using acoustic signals is much more accurate and cheaper, compared with that in terrestrial sensor networks using radio [2], [16]. Thus, range-based schemes are potentially good choices for underwater sensor networks. However, due to the unique characteristics (such as low communication bandwidth, node mobility, and three dimensional node deployment) of underwater sensor networks, the applicability of these existing range-based schemes is unknown.

Localization for terrestrial mobile sensor networks has also been explored recently [45], [46]. In [45], Hu and Evans propose a range-free localization scheme based on a sequential Monte Carlo localization method and show that their scheme can exploit mobility to improve the localization accuracy. In [46], a predictive protocol which can control the frequency of localization based on sensor mobility behavior to reduce the energy requirements while bounding the localization error has been proposed. Both of these two studies assume that sensor nodes are moving randomly and the inherent properties of object mobility patterns are not explored.

As mentioned in Section 1, there are a couple of studies on *localization for underwater acoustic networks* [21], [22], [23], [24]. These proposals are mainly designed for small-scale static networks. For example, underwater "GPS" systems (GIB (GPS Intelligent Buoys) [21] and PARADIGM [22]) have been proposed based on surface buoys and one-hop communication. Localization for sensor nodes is centrally performed at surface buoys. In [23], a distributed protocol is proposed for multihop underwater robot networks. This protocol is based on the iterative multilateration methods and is suitable for small-scale static underwater networks. For large-scale mobile underwater sensor networks, this protocol is inefficient because of the high communication cost and low convergence speed.

Last several years have overseen the active research in the *localization for underwater sensor networks*. In [25], the authors survey different localization algorithms that are relevant to underwater sensor networks, and discuss the challenges in meeting the requirements posed by emerging applications. In [47], Cheng et al. proposes a silent positioning scheme for one-hop underwater networks. This scheme is quite effective and does not need synchronization. An efficient scheme has also been proposed in [48] by the same research group for multihop 3D underwater networks. This scheme transforms the 3D underwater positioning problem into its 2D counterpart via a projection technique, which greatly simplifies the localization process and reduces the connectivity requirement for the localization purpose.

Mobile beacon nodes, such as AUV, have also been used to aid the localization process. In [49], Erol et al. propose to use an AUV to aid the localization process. In this scheme, the AUV works as a mobile satellite and can localize the nodes within its communication range. A follow-up work is presented in [50]. 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. A bio-inspired localization scheme has been proposed in [51], where location information is stored in a 2D upper hull of a sensor equipped aquatic swarm, and a mobile sink uses its trajectory projected to the 2D hull to maintain location information.

Localization for mobile underwater networks has also been investigated recently. In [52], Mirza et al. propose a low-overhead scheme which is able to trade accuracy for energy savings by cleverly selecting the specific links that are required for the self-localization algorithm. This scheme is adaptive to the on-demand change in accuracy requirements and reduces the position estimation costs by 40 percent or more under various underwater environments. In [53], an energy-aware, distributed localization solution based on inter-node range measurements for mobile underwater networks has been proposed. This scheme can achieve high localization accuracy with low communication overhead. And its location estimation is performed after the mission is over.

However, none of the above works takes the inherent mobility pattern of underwater objects into consideration.

3 Description of SLMP

In this section, we present SLMP, a scalable localization scheme with mobility prediction for underwater sensor networks. We will first describe the network architecture and give an overview of SLMP. We then show how SLMP works in detail using the mobility patterns in seashore environments.

3.1 Network Architecture

To accomplish the localization task for large-scale underwater sensor networks, we propose a network architecture that comprises of three different types of nodes, as shown in Fig. 2.

- *Surface Buoys*. Surface buoys are equipped with GPS to obtain their location estimates. They serve as the "satellite nodes" in underwater localization schemes.
- *Anchor Nodes*. Anchor nodes are powerful nodes which can make direct contact with the surface

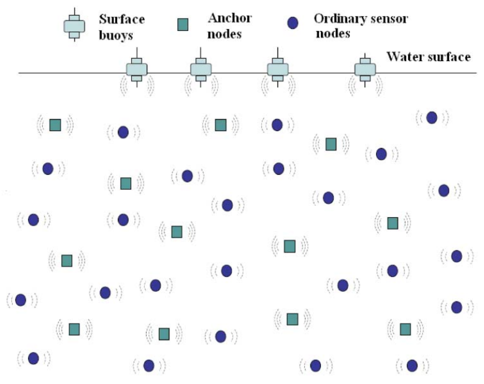

Fig. 2. Underwater sensor network architecture.

buoys and are capable of self-localization based on such contacts by using existing underwater GPS approaches. Interested readers can refer to [21], [22] for details.

- *Ordinary Nodes*. Ordinary sensor nodes are low-complexity sensor nodes that cannot directly communicate with surface buoys—they are cheap, and they do not wish to be wasteful with their energy. Typically, the ordinary sensor nodes can only connect to its local (usually one-hop) neighbors. Through local message passing among themselves and with nearby anchor nodes, the ordinary sensor nodes desire to self-localize so that they can effectively participate in the network operation.

In short, anchor nodes localize themselves via direct communication with several surface buoys, while ordinary nodes perform self-localization through neighboring anchor nodes and/or ordinary nodes.

In the target network, we assume that every sensor node needs to get its location periodically. We define T_1 as the period in which each node needs to get its location, and we call T_1 *localization period*. This is a reasonable assumption since in many applications such as environment monitoring, sensor nodes only need to report their observed data periodically to the sink. For these applications, location information is only useful at these discrete time points.

It should be noted that when the localization period T_1 is small, a relatively high communication cost will be introduced for the localization service. This will put a high burden on the network because of the limited bandwidth of its acoustic channels. But if we can take full advantages of the inherent predictable nature of underwater objects' mobility, it is possible to get needed location information with low communication cost and high localization accuracy. Our "SLMP" is exactly based on this motivation.

3.2 Overview of SLMP

SLMP adopts a hierarchical localization approach. In SLMP, the whole localization process is divided into two subprocesses: anchor node localization and ordinary node localization.

At the beginning, only several 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. Since anchor nodes are more powerful and can measure their locations directly from the surface buoys in every localization period, some complex mobility prediction algorithms can also be implemented on them.

For the ordinary node localization, we propose a distributed recursive range-based scheme which will be described in detail in Section 3.4. Since ordinary nodes are limited in computation power and memory, it is hard to implement complicated prediction algorithms on them. Fortunately, due to the group movement properties of underwater objects, an ordinary node can deduce its mobility pattern from the mobility patterns of nearby nodes.

In every localization period, an anchor node estimates its current location according to its previous location estimations and its predicted mobility pattern. It compares this estimated location with its measured location.[2] If the euclidean distance between its measured location and its estimated location is larger than the stipulated threshold s_t, this anchor node will determine that its current mobility pattern is not so accurate and needs to be updated. Then, it runs its mobility prediction algorithm (which will be described in Section 3.3) to get a new mobility pattern. After that, it will broadcast a new localization message which contains its current location and new mobility pattern to the network. It is clear that a new localization process is initiated by anchor nodes, and it is the anchor nodes who can control the frequency of the localization message flooding.

For an ordinary node, it tries to receive any localization messages it can get in the network. If it has not received any localization message for a long period (longer than some predefined threshold), it will judge that it is out of range with other nodes and will label itself as unlocalized. On the other hand, when it receives some localization messages from others, it will run its localization and mobility prediction algorithm to estimate its own location and mobility pattern (the prediction algorithm will be described later in Section 3.4).

3.2.1 The Design Philosophy

The guideline behind SLMP is to achieve a good balance between localization error and communication cost. With mobility prediction mechanisms, anchor nodes need not broadcast localization message in every localization period and every localized node can predict its location in the future localization period. Thus, communication cost and energy consumption can be reduced. However, accompanied with the benefits of the mobility prediction mechanisms, another problem arises: how to control the localization error throughout the network. With mobility prediction, ordinary nodes can no longer estimate the accuracy of their predicted locations. Fortunately, anchor nodes can measure their locations at any time, which makes it possible to estimate their prediction accuracy. Because anchor nodes are assumed to be dispersed randomly in the network, their measurements can be viewed as samples of the prediction

2. It should be noted that an anchor node can communicate with surface buoys directly and can measure its current location at its will.

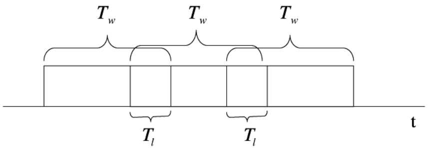

Fig. 3. Overlapped prediction windows.

error of the whole network. In SLMP, we use anchor nodes to measure and control the prediction error of the whole network. Simulation results in Section 4 will show that SLMP can achieve a good balance between communication cost and localization error.

3.3 Anchor Node Mobility Prediction

Anchor nodes can easily measure their locations directly at any localization period since they can directly communicate with the surface buoys, and they could also predict their future mobility patterns based on their past measurements.

From Fig. 1, we can observe that the moving speed of the underwater object in seashore environments changes continuously and demonstrates certain semiperiodical properties. We also notice that its waveform is very similar to that of the voice signal. It is well known that the voice signal can be closely approximated by an all-pole model and thus can be predicted with linear prediction algorithms [54], [55], [56]. Inspired by this, we adopt the linear prediction method [57] in our system for anchor node mobility prediction. It works as follows.

First, as shown in Fig. 3, we divide time into multiple *prediction windows* with length set to T_w. One window is one prediction unit. We assume that the mobility behaviors of the nodes will not change during adjacent prediction windows, which means that the coefficients for the underlying all-pole mobility model do not change (node speed might change a lot in adjacent prediction windows). This is a reasonable assumption considering the continuity and the semiperiodicity of the underlying mobility behavior. Thus, we can use measured values in the previous window to predict the mobility behavior of the next window. Window length T_w should be an integer multiple of the localization period T_1, which is the period every node needs to get its location, as defined in section 3.1. We denote this as

$$T_w = k \times T_1. \tag{1}$$

The length of prediction window T_w is important to the performance of our prediction algorithm. If T_w is too small, the known data from the previous prediction window are not enough to capture the characteristics of the underlying mobility model, and thus, the prediction results are not so accurate. But if T_w is too large, it will increase the computational complexity. Further, a large T_w will not be always helpful to improve the prediction accuracy. This is because the underlying mobility model changes over one window period if T_w is too large, which will degrade the prediction performance [54], [55], [57]. In practice, we can choose T_w according to the application requirements and system environments.

To further improve the accuracy of our prediction, neighboring windows should be overlapped to some extent

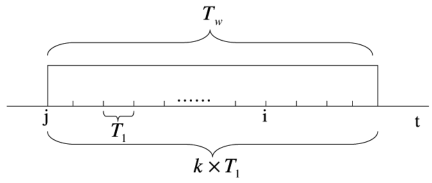

Fig. 4. Structure of a prediction window.

to avoid the edge effects of the windowing operation [55], [56]. In Fig. 3, T_l is used to denote the length of this overlapped window area. We set $\varsigma = \frac{T_l}{T_w}$, and it is self-evident that $0 < \varsigma < 1$. The typical value for ς is from 0.1 to 0.5 [55], [56]. In our simulations, we choose ς to be 0.2 and we find out that this value is good enough to filter out the edge effects in our applications.

For every node, we use speed vector $V = [v(1), v(2), \ldots v(i), \ldots, v(k)]$ to represent its mobility behavior in every prediction window, where $v(i)$ denotes the average speed in the ith localization period. In order to predict $v(i)$, we use a linear prediction algorithm as follows:

$$v(i) = \sum_{m=1}^{l} a_m v(i-m), \tag{2}$$

where l is the length of prediction steps, and a_m is the linear prediction model coefficient of $v(i-m)$ where $1 \leq m \leq l$. Further, a_ms can be estimated by using measured location data from previous windows. In our work, we use the well known Durbin algorithm [54], [55], [57] to estimate them. We choose Durbin algorithm mainly because of its simplicity and low-computation complexity $O(l^2)$, where l is the length of prediction steps.

In localization period i, an anchor node can measure its actual location $Loc_a(i)$, and at the same time, it will calculate its estimated location $Loc_e(i)$ as follows:

$$Loc_e(i) = Loc_a(j) + \sum_{m=j}^{i} T_1 \times v(m), \tag{3}$$

where $Loc_a(j)$ is the measured location in localization period j. As shown in Fig. 4, j is the last localization period when this node runs its prediction algorithm and broadcasts a localization message. And j is also the starting point of the current prediction window.

If the error between the estimated location $Loc_e(i)$ and the measured location $Loc_a(i)$ is smaller than the stipulated threshold s_t, this indicates that the predicted speed vector V works well and there is no need for further action. Otherwise, the current active speed vector V is not so accurate. Then, this anchor node needs to rerun the mobility prediction algorithm to update its speed vector V and broadcast its current location and predicted speed vector V in one localization message to inform the network.

The structure of a localization message is shown in Fig. 5, with each field explained as follows:

- *Node id*: The unique identification number of the message sender.
- *Time stamp*: The time when this message is sent. It is needed for some range measurement methods

Node-id	Time-stamp	Location	Speed vector	Confidence value

Fig. 5. Localization message structure.

such as TOA (Time of Arrival) and TDOA (Time Difference of Arrival).

- *Location*: The current location of the message sender.
- *Speed vector*: The predicted speed vector for the next window.
- *Confidence value*: The confidence value of the message sender. It is used to denote the location estimation accuracy. For original anchor nodes, they are set to be 1. We will discuss how to calculate this value for ordinary nodes later in Section 3.4.

Localization messages could be sent by both anchor nodes and localized ordinary nodes. The latter case will be discussed in Section 3.4.

3.4 Ordinary Node Mobility Prediction & Localization

As for ordinary nodes, because of their limited memory and computing capacity, they cannot perform complicated temporal prediction algorithms. In SLMP, we take full advantages of the spatial correlation that underwater objects possess to facilitate mobility prediction.

3.4.1 Mobility Prediction

Assume we want to get the velocity $[v_x(j), v_y(j)]$ of node j, where $v_x(j)/v_y(j)$ denotes the current speed of node j in the x/y axis. If we get to know the velocities of its neighboring nodes, then we can estimate the velocity of j as follows [27], [28]:

$$\begin{cases} v_x(j) = \sum_{i=1}^{m} \zeta_{ij} v_x(i) \\ v_y(j) = \sum_{i=1}^{m} \zeta_{ij} v_y(i), \end{cases} \tag{4}$$

where m is number of neighbors. The interpolation coefficient ζ_{ij} is calculated as

$$\zeta_{ij} = \frac{\frac{1}{r_{ij}}}{\sum_{i=1}^{m} \frac{1}{r_{ij}}}, \tag{5}$$

where r_{ij} denotes the euclidean distance between node i and node j.

3.4.2 Localization Process

For ordinary nodes, we adopt a recursive localization method. We smoothly incorporate mobility prediction into the localization process.

First, we define *reference nodes* as nodes with known locations and confidence values higher than the confidence threshold.

In the *initialization phase*, all anchor nodes label themselves as reference nodes and set their confidence values to 1. All the ordinary nodes are nonlocalized nodes. With the advance of the localization process, more and more ordinary nodes are localized and become reference nodes. Each ordinary node maintains a reference list to record all its known reference nodes. Each reference node entry in the list includes the following information: the reference node ID; the arrival time of the latest localization message from this reference node; the reference node's location and speed vector, the distance to this reference node; and the confidence value of the reference node.

In each localization period, every node updates its known reference list. This updating process includes the following operations:

- Check the arrival time of the latest localization message from every known reference node. If the distance between the current time and the last arrival time is larger than k localization periods, this reference node is too old to be useful and should be deleted from the list.
- For every known reference node, update its location as follows:

$$Loc(i) = Loc(i-1) + T_1 \times v(i), \tag{6}$$

where $Loc(i)$ denotes the estimated location of this reference node in localization period i and $v(i)$ is the estimated speed of this reference node in localization period i.
- Update the confidence value of every known reference node. To well reflect the network conditions, the confidence value of a known reference node should decrease with time if no new localization message has been received from that reference node. In our simulations, we update the confidence value for a reference node as follows:[3]

$$\eta = \frac{k - \frac{(t_c - t_{rev})}{T_1}}{k} \times \eta_0, \tag{7}$$

where t_c denotes the current time, t_{rev} denotes the arrival time of the latest localization message from this reference node, and η_0 is the old confidence value obtained from the last localization message.

In a localization period, if a nonlocalized ordinary node does not receive any localization message, it will update its current location estimation using its previous location estimation and its predicted speed vector. If it receives a localization message from a reference node, it will update its reference list and perform new location estimations. This process includes the following operations:

- If this reference node is unknown before, a new entry will be inserted into the known reference list. Otherwise, the corresponding entry is updated.
- If the number of its known reference nodes is equal to or larger than 4, then it selects four reference nodes with largest confidence values to do location estimation. It also performs mobility prediction according to (4), labels itself as localized and

3. In this formula, the confidence value of a reference node decreases linearly with time. At the beginning of every localization period, it is set to its initial value η_0. With time goes, it decreases linearly with time. We choose this linear formula mainly because of its simplicity. More efficient yet complicated schemes warrant for future research.

calculates its own confidence value η. The confidence value of this node is not only related to itself, but also related to the confidence value of the chosen reference nodes. In our simulations, we calculate the confidence value as follows:

$$\eta = \frac{\sum_{i=1}^{4}\eta_i}{4} \times \left(1 - \frac{\delta}{\sum_{i=1}^{4}\sqrt{\left[(u-x_i)^2+(v-y_i)^2+(w-z_i)^2\right]}}\right), \tag{8}$$

where (u, v, w) are the estimated coordinates of this node; (x_i, y_i, z_i) is the location of reference node i; η_i is the confidence value of reference node i; and δ is defined as follows:

$$\delta = \sum_{i=1}^{4}\sqrt{\left|(u-x_i)^2+(v-y_i)^2+(w-z_i)^2-l_i^2\right|}, \tag{9}$$

where l_i is the measured distance between this node and reference node i. The basic idea of (8) comes from the fact that the accuracy of one ordinary node's location estimation is determined by its reference nodes and its range measurements. The first item of (8) averages the confidence values of its reference nodes, thus taking the effects of its reference nodes into consideration, while its second item is closely related to the error of the range measurements. Equation (8) is simple and is shown to be quite effective in the simulations.

- If the calculated confidence value η is larger than or equals to the confidence threshold λ, then this node labels itself as a new reference node and sends out a localization message. Otherwise, this node is treated as a localized ordinary node and keeps silent.

The localization process of an ordinary node is illustrated in Fig. 6.

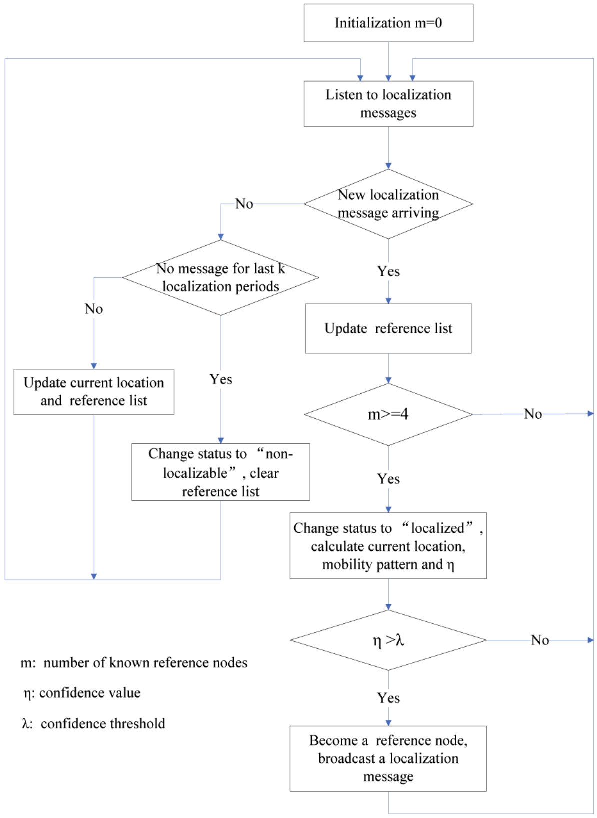

Fig. 6. Localization process of ordinary nodes.

4 Simulation Results

In this section, we evaluate the performance of SLMP using simulations.

4.1 Simulation Settings

In our simulations, 500 sensor nodes are randomly distributed in a $100\ \mathrm{m} \times 100\ \mathrm{m} \times 100\ \mathrm{m}$ 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 every 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 two percent of real distances. This is a reasonable assumption and can be easily satisfied by existing underwater distance measurement technologies [21], [58]. Five percent, 10 percent, and 20 percent anchor nodes are considered in our simulations. Besides SLMP, we also simulate one localization scheme without mobility prediction, which is proposed in [59] for comparison. The localization process of this scheme is almost the same as that of SLMP, except that it does not involve mobility prediction.

As for the node mobility pattern, we consider the kinematic model in [60]. The current field is assumed to be a superposition of a tidal and a residual current field. The tidal field is assumed to be a spatially uniform oscillating current in one direction, and the residual current field is assumed to be an infinite sequence of clockwise and anticlockwise rotating eddies. The dimensionless velocity field in the kinematical model can be approximated as

$$\begin{cases} V_x = k_1\lambda v \sin(k_2 x)\cos(k_3 y) + k_1\lambda\cos(2k_1 t) + k_4 \\ V_y = -\lambda v \cos(k_2 x)\sin(k_3 y) + k_5, \end{cases} \tag{10}$$

where V_x is the speed in the x axis and V_y is the speed in the y axis. Also, k_1, k_2, k_3, λ, and v are variables which are closely related to environment factors, such as tides and bathymetry. These parameters will change with different environments. Further, k_4 and k_5 are random variables. We can see from (10) that a node's speed is not only related to the time t, but also related to its current position coordinates x and y. In our simulations, we assume k_1 and k_2 to be random variables which are subject to the normal distribution with π as the mean and 0.1π as the standard derivation; k_3 is subject to the normal distribution with 2π as the mean and 0.2π as the standard derivation; λ is subject to the normal distribution with 3 as the mean and 0.3 as the standard derivation; v is subject to the normal distribution with 1 as the mean and 0.1 as the standard derivation; and

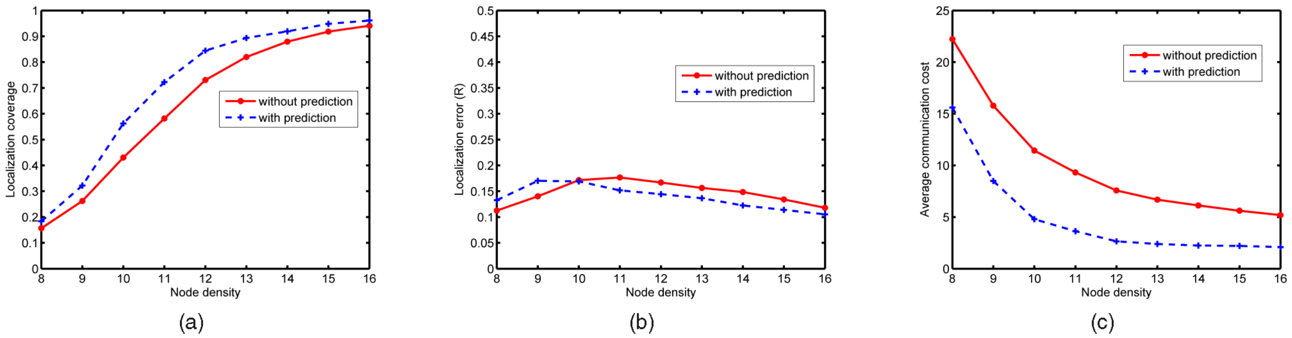

Fig. 7. Performance impact of average node density. (a) Localization coverage. (b) Localization error. (c) Average communication cost.

k_4 and k_5 are random variables which are subject to the normal distribution with 1 as the mean and 0.1 as the standard derivation.

Every simulation lasts for 1,100 s. The first 100 s of every simulation are used for anchor nodes' training. During this training process, anchor nodes measure their locations every T_1 seconds and get their initial mobility patterns. After this training process, anchor nodes will send out their first localization messages which contain their initial locations and mobility patterns, and then start the localization process.

Unless specified otherwise, we have the following parameters. Localization period T_1 is set to be 1 s. The prediction error threshold of anchor s_t is set to be $0.05R$, where R is the node's communication range. The number of prediction l is set to be 15. The prediction window size T_w is set to be 60 s and $\varsigma = 0.2$. The confidence threshold of ordinary node λ is set to be 0.98.

Three performance metrics are considered in our simulations: 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 [35], [39], [61], for our simulations, we normalize this absolute localization error to the node's communication range R. *Average communication cost* is defined as the overall messages exchanged in the network divided by the number of localized sensor nodes.

4.2 Results and Analysis

4.2.1 Performance with Changing Node Density

In this set of simulations, we set the anchor percentage to be 10 percent and change the average node density from 8 to 16 by changing the node transmission range R. We compare our SLMP (denoted as "with prediction" in Fig. 7) with a localization scheme without mobility prediction (denoted as "without prediction" in Fig. 7), which was proposed in [59]. The results for localization coverage, localization error, and communication cost are plotted in Figs. 7a, 7b, and 7c, respectively.

Without surprise, Fig. 7a shows us that the localization coverage increases monotonically with node density. Further, the localization coverage of our scheme with prediction (i.e., SLMP) is higher than that of the scheme without prediction. This is because with mobility prediction, some nodes which cannot get localized with the previous scheme can be localized with the prediction scheme. Thus, compared to the scheme without mobility prediction which needs to redo one complete localization process in every localization period independently, our scheme can achieve even higher localization coverage.

It is shown in [37], [39], [40], [61], [62] that range-based distributed localization schemes have relatively high requirements on the node density of the network. For example, in [39], it is shown that for distributed ad hoc localization protocols, the average node density needs to be at least 10 in order to localize 85 percent nodes when 20 percent anchor nodes are present in a 2D terrestrial sensor network. The 3D underwater network puts a higher requirement on the node density for the distributed localization protocols since one more dimension needs to be calculated. From Fig. 7a, we can observe that our SLMP can achieve 85 percent localization coverage with 10 percent anchor nodes when the node density equals to 12. Compared with the results for 2D networks, our scheme can achieve almost the same performance in 3D networks with a little higher node density, which indicates the high performance of our protocol.

Fig. 7b shows us that with the increase of node density, the average localization error of our scheme will first increase a little and then it will decrease monotonically. The increase in the lower node density region comes from the rapid increase of the corresponding localization coverage. However, when the node density reaches a certain point, most localizable nodes get localized. With the further increase of node density, un-localized nodes will get to know more reference nodes and have more choices to calculate their locations. Thus, the localization error reduces.

Compared to the scheme without mobility prediction, the localization error of our scheme is slightly higher in the low node density region. While when the node density is relatively high (in this simulation setting, more than 10), our scheme can achieve lower localization errors. This can be explained as follows: In the low node density region, the localization coverage is low and most localizable nodes are localized with high accuracy. Mobility prediction will introduce prediction errors to the network, thus increasing the localization error a little. But with the increase of node density, more and more nodes get localized. Because of the mobility prediction, our scheme will introduce more reference nodes into the network, which will contribute to the

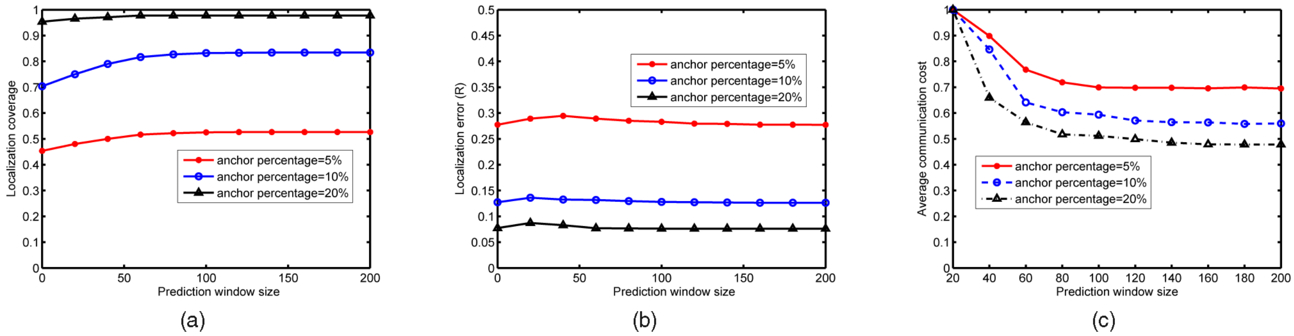

Fig. 8. Performance impact of the size of prediction window. (a) Localization coverage. (b) Localization error. (c) Normalized average communication cost.

reduction of the localization error. With the increase of node density, this reduction finally outweighs the effects of prediction errors. Thus, our scheme achieves smaller localization error than the scheme without mobility prediction.

Fig. 7c clearly shows us that with the increase of node density, the average communication cost decreases rapidly in the first. This is because with the increase of node density, the localization coverage increases drastically. Further, we can observe that when the node density increases to some points, for example, in Fig. 7c, when it increases to 12, the average communication cost will stabilize at some small values. Fig. 7c also shows us that our mobility prediction scheme can greatly reduce the communication cost. This is because in our scheme, anchor nodes need not send localization messages in every localization period and thus limit the frequency of localization message flooding. Correspondingly, the overall communication cost is reduced. This is quite important for underwater sensor networks with limited bandwidth and energy.

4.2.2 Performance with Changing Prediction Window T_w

In this set of simulations, node range R is fixed to be 20 m and thus the average node degree is about 12. We change the prediction window T_w from 20 s to 200 s. Here, in order to show the advantages of mobility prediction, we normalize the average communication cost to that of localization scheme without mobility prediction.

Fig. 8 shows that with the increase of prediction window, the localization coverage increases slightly. At the same time, the localization error decreases a little. This is because the larger the window size, the more accurate the prediction results for anchor nodes, which causes more ordinary nodes to become reference nodes. Thus, the localization coverage of the whole network will increase and the localization error will decrease slightly.

As shown in Fig. 8, the normalized average communication cost decreases monotonically with the prediction window. This is because more accurate prediction results mean less traffic that anchor nodes send out. But when the prediction window reaches some large value, for example, 100 s for the case of 10 percent of anchor nodes, increasing prediction window will not contribute much to the reduction of communication cost. This is because in such situations, the communication cost of the localization process is dominated by the localization messages among ordinary nodes as well as the beacon messages which are used to measure distance among nodes periodically.

4.2.3 Performance with the Length of Prediction Step l

In this set of simulations, node communication range R is fixed to be 20 m and thus the average node degree is about 12. We change the length of prediction step l from 0 (without prediction) to 30. Here, to show the advantages of mobility prediction, we normalize average communication cost to that of localization scheme without mobility prediction.

From Fig. 9a, we can clearly see that with the increase of prediction step, the localization coverage will increase slowly. This is mainly because with the increase of prediction step, the prediction accuracy will increase

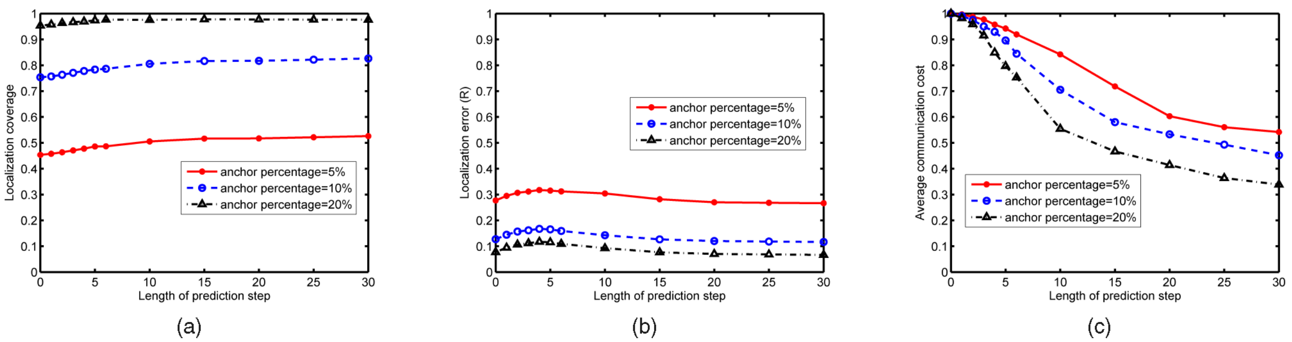

Fig. 9. Performance impact of the length of prediction steps. (a) Localization coverage. (b) Localization error. (c) Normalized average communication cost.

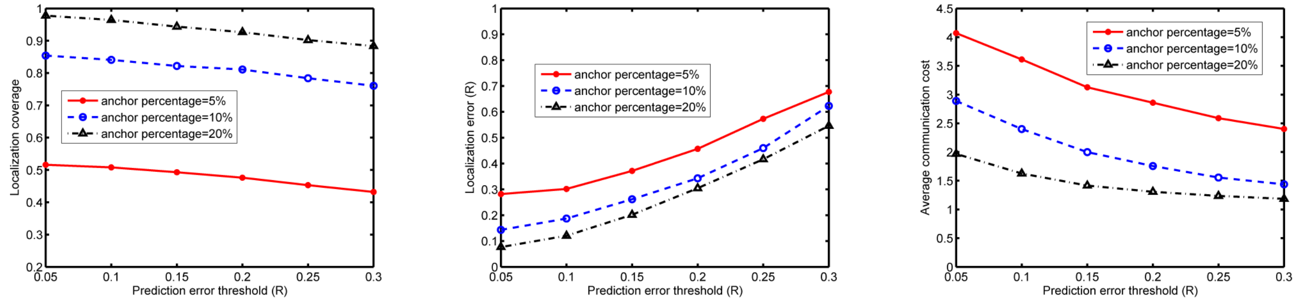

Fig. 10. Performance impact of prediction error threshold. (a) Localization coverage. (b) Localization error. (c) Average communication cost.

correspondingly. As a result, more nodes become reference nodes and thus the localization coverage is increased to some extent.

Fig. 9b shows us the average localization error with prediction step. When prediction step l is small, the localization error will increase slowly. This is because when l is small, although anchor nodes have mobility prediction capacity, the prediction accuracy is limited, which will increase the average location error in the network. But with the increase of l, the average localization error will decrease because of the more accurate mobility prediction of anchor nodes. We can see that when $l > 15$, the average localization error decreases below the the value of localization scheme without mobility prediction (when $l = 0$). This is because when l is relatively large, the mobility prediction is accurate enough and more reference nodes will be introduced to the network in one localization period. Subsequently, every node will get to know more reference nodes which will correspondingly decrease the localization error.

From Fig. 9c, we can see that with the increase of prediction steps, the average communication cost will decrease drastically. This is because the more the prediction step, the more accurate the prediction results of anchor nodes, and thus, the less the localization messages that anchor nodes have to send out. From Fig. 9c, we can also see that when $l \geq 15$, its relative communication cost decreases as low as 0.5, which means that our simple mobility prediction will reduce more than half of traffic load compared with localization scheme with no mobility prediction.

4.2.4 Impact of Prediction Error Threshold s_t

In this set of simulations, the node range R is set to be 20 m. We change anchor node prediction error threshold s_t from $0.05R$ to $0.3R$. The results are plotted in Fig. 10.

From Fig. 10, we can see that with the increase of prediction error threshold, the localization coverage decreases slowly, and the localization error increases correspondingly. This can be explained as follows: With the increase of error threshold, the average prediction error of anchor nodes will increase, as leads to less nodes get high accurate localization results. Correspondingly, this will reduce the available reference nodes in the network (which should be nodes with high localization accuracy), thus resulting in the decrease of the final localization coverage. On the other hand, as we can see from Fig. 10c, the average communication cost decreases dramatically with the increase of prediction error threshold. This is because a large prediction error threshold definitely reduces the number of the localization messages that the anchor nodes send out, which directly contributes to low average communication cost.

4.2.5 Impact of Confidence Threshold λ

In this set of simulations, the node communication range R is set to be 20 m. We change the confidence threshold of ordinary nodes λ from 0.8 to 1.

Fig. 11a shows that with the increase of confidence threshold, the average localization coverage will decrease correspondingly. There exists some critical value. Below this value, the localization coverage will not decrease much, but above this value, the localization coverage will drop

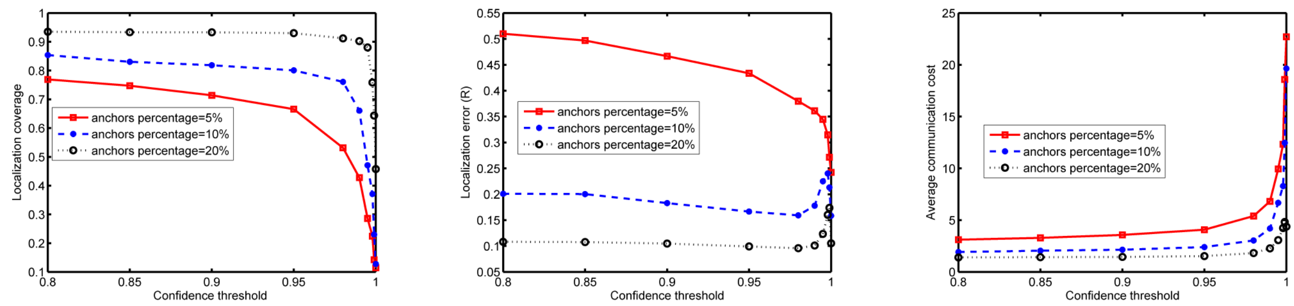

Fig. 11. Performance impact of confidence threshold λ. (a) Localization coverage. (b) Localization error. (c) Average communication cost.

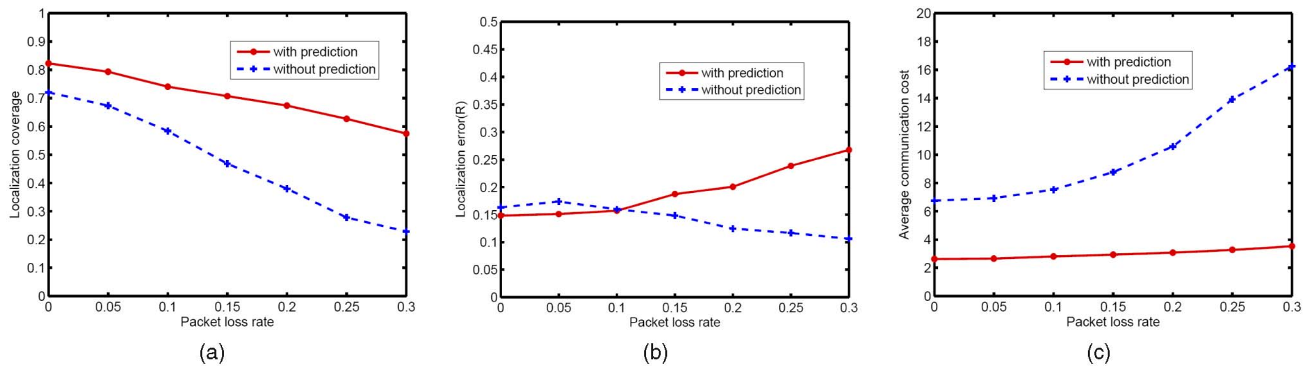

Fig. 12. Performance impact of the packet loss rate. (a) Localization coverage. (b) Localization error. (c) Average communication cost.

abruptly. For example, as shown in Fig. 11a, when the anchor percentage is 10 percent, this critical value is 0.98.

Fig. 11b shows the relationship between the localization error and the confidence threshold. When the anchor percentage is 5 percent, the localization error will decrease monotonously with the confidence threshold, while when the anchor percentage is 10 percent and 20 percent, the localization error will decrease slowly with the confidence threshold at the beginning. But with the further increase of the confidence threshold, the localization error will increase and then decrease again. This can be explained as follows: With the increase of the confidence threshold, nodes with higher localization accuracy will become reference nodes during the localization process. This reduces the localization error at the beginning. However, if the confidence threshold is high, the available reference nodes will decrease significantly, which correspondingly increases the localization errors. Thus, when the confidence threshold is larger than some critical values, localization errors will increase. When the confidence threshold is too high (close to 1), the number of the available reference nodes will be greatly reduced and the corresponding localization coverage will decrease dramatically. In this situation, only nodes with high accuracy can be localized. Therefore, the average localization error will decrease. However, when the anchor percentage is small, for example, 5 percent, the localization coverage is small and changes relatively slow with the confidence threshold. Thus, the average localization error will decrease monotonically with the increase of the confidence threshold.

Fig. 11c shows the average communication cost with different confidence threshold. We can observe that when the confidence threshold is small, the average communication cost increases slowly with the confidence threshold. But after some critical values, the average communication cost will increase much faster. This is because the higher the confidence value, the lower the localization coverage, which contributes to a higher average communication cost.

4.2.6 Impacts of the Loss of Localization Messages

In SLMP, every node needs to broadcast localization messages. However, these localization messages might get lost because of the collisions in the MAC (Medium Access Control) layer or the bad acoustic channel condition, which might degrade the performance of our SLMP. In this set of simulations, the anchor percentage is set to be 10 percent. The node range R is set to be 20 m and thus the average node density is about 12. We change the average packet loss rate from 0 to 0.3 and investigate its impacts.

Fig. 12 clearly shows us with the increase of packet loss rate, the localization coverage of SLMP decreases slowly and its localization error increases. Compared to the localization scheme without mobility prediction, our SLMP can maintain a relatively higher localization coverage with a little larger localization error. From Fig. 12, we can see that even when the average packet loss rate reaches 0.3, our SLMP can still localize about 58 percent of the nodes with an average localization error less than $0.3R$. This is mainly because of the prediction mechanism of our SLMP scheme. With the increase of the packet loss rate, more and more localization messages get lost. In our SLMP, even if a node cannot get localized based on the localization messages it receives in the current localization period, it can take advantages of its mobility prediction mechanism to estimate its location. Thus, the localization coverage of our SLMP will not decrease much with the increase of the packet loss rate. Because the location estimate of SLMP is dependent on the mobility prediction, its accuracy will degrade with time and thus the average localization error increases. However, the story is quite different for the scheme without mobility prediction. In such a scheme, a node cannot get localized if it does not receive enough localization messages from other nodes in the current localization period. Thus, its localization coverage degrades fast with the increase of packet loss rate.

Fig. 12 also shows us that the average communication cost of our SLMP increases slowly with the increase of the packet loss rate. For the scheme without mobility prediction, its average communication cost increases at a much faster rate because of the rapid drop of its localization coverage. In error prone networks, our SLMP is even more efficient in communication cost because of its mobility prediction scheme and its high localization coverage.

4.2.7 Impacts on the Application Data Packet

In this set of simulations, we evaluate the impacts of our localization service on the applications. Every node will generate an application data packet destined to the surface buoys every 10 s. A TDMA MAC protocol is simulated and in every time slot, a node can either transmit an application

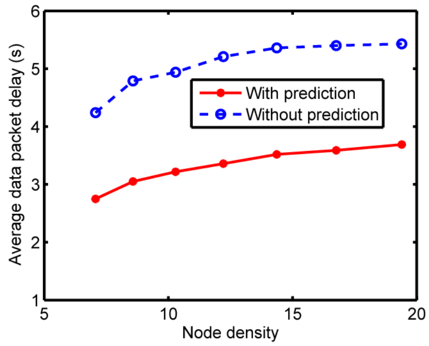

Fig. 13. Average end-to-end delay of the application data packet.

data packet or a localization message. A geographical routing protocol is simulated. And in the routing protocol, every node will forward the application data packet to one of its neighbors with the least depth. We change the average node density from 6 to 18 and measure the average end-to-end delay for the application data packet.

As shown in Fig. 13, the average end-to-end delay for the application data packet under our SLMP is much smaller than that under the localization scheme without mobility prediction. For example, when the node density is 10, the average end-to-end delay for the application data packet under SLMP is about 3.1 s, which is 30 percent less than that under the localization scheme without mobility prediction. This is because the mobility prediction mechanism of our SLMP can effectively reduce the communication costs for the localization purpose, which makes more slots available to the application data and contributes to the reduction of its end-to-end delay.

5 Conclusions

In this paper, we have presented SLMP, a new localization scheme with mobility prediction, for large-scale underwater sensor networks. In SLMP, anchor nodes conduct linear prediction by taking advantages of the inherent temporal correlation of underwater object mobility pattern. Each ordinary sensor node predicts its location by utilizing the spatial correlation of underwater object mobility pattern and weighted-averaging its received mobilities from other nodes. Our simulation results show that SLMP can greatly reduce the communication cost while maintaining a relatively high localization coverage and localization accuracy. With simulations, we also evaluate the impact of various design parameters, such as prediction window, prediction step, prediction error threshold, and confidence threshold, on the localization performance.

In the future, we plan to extend our work in two directions: 1) explore other underwater mobility patterns and examine the applicability of our design, and 2) investigate other prediction algorithms and examine how they affect the localization performance.

Acknowledgments

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