Poster Abstract: Scalable Localization with Mobility Prediction for Underwater Sensor Networks

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I. Introduction

Localization of mobile sensor nodes is indispensable for underwater sensor networks. For example, in aquatic environment monitoring applications, localization is a must-do 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. So far, only a limited number of schemes have been proposed for the localization service in underwater acoustic networks [1], [3], [6].

Due to adverse 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 (large-latency, low-bandwidth, and long end-to-end delays) cause many constraints on the localization schemes for underwater sensor networks. Traditional multi-hop localization schemes for terrestrial sensor networks are inefficient because of their huge communication overhead. 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 can not work well in large-scale underwater sensor networks due to their slow convergence speed and high communication overhead. In this work, *we aim to design a scalable localization scheme with low communication overhead while good localization performance for large-scale underwater water sensor networks*.

Though 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 objects under water move with predictable patterns, though these patterns are in a large part determined by environmental factors [2], [4]. This mobility property can actually provide us an alternative for high performance localization. In this work, 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 tradeoff between localization accuracy, localization coverage and communication cost. Our simulation results show that SLMP can greatly reduce the communication cost while maintaining a relatively high localization coverage and localization accuracy.

II. Description of SLMP

A. 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.

- *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 buoys, and are capable of self-localization based on such contacts.
- *Ordinary Nodes*. Ordinary sensor nodes are low-complexity sensor nodes which can only communicate with its local (usually one-hop) neighbors for localization.

In the target network, we assume that every sensor node needs to get its location periodically. We define T_1 as the period each node needs to get its location, and we call T_1 *localization period*.

B. SLMP Design

SLMP adopts a hierarchical localization approach. In SLMP, the whole localization process is divided into two sub-processes: 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 complicated mobility prediction algorithms can also be implemented on them.

For the ordinary node localization, we propose a distributed recursive range-based scheme. 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 nodes nearby.

In every localization period, an anchor node estimate its current location, according to its previous location estimations and its predicted mobility pattern. It compares this estimated location with its measured location. If the Euclidean distance between its measured location and its estimated location is larger than the stipulated threshold s_t, this anchor node will judge that its current mobility pattern is not so accurate and needs to be updated. Then, it runs its mobility prediction algorithm 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 in the network. If it has not received any localization message for a long period (larger than some predefined threshold), it will judge that it is out of touch with other nodes and will label itself as un-localized. 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

Anchor Node Mobility Prediction: We divide time into multiple *prediction windows* with length set to T_w. One window is one prediction unit for anchor node mobility prediction and it includes multiple localization periods. We assume that the mobility behaviors of the nodes will not change during adjacent prediction windows. 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:

$$v(i) = \sum\nolimits_{m=0}^{l} a_m v(i-m), \tag{1}$$

where l is the length of prediction steps. In practice, l can be used to control the tradeoff between the computation complexity the prediction accuracy. And a_m is the linear prediction model coefficient between $v(i)$ and $v(i-m)$. a_m's can be estimated by using measured location data from previous windows. In our work, we use the well known Durbin algorithm [5] to estimate them.

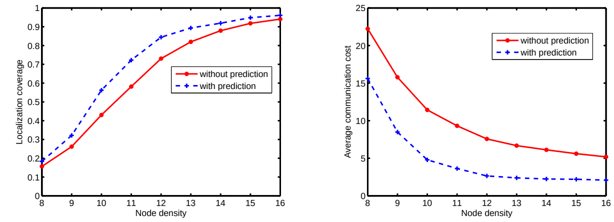
Ordinary Node Mobility Prediction: As for ordinary nodes, because of their limited memory and computing capacity, they can not perform complicated temporal prediction algorithms. In SLMP, we take full advantages of the spatial correlation that underwater objects possess to facilitate mobility prediction.

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 neighbor nodes, then we can estimate the velocity of j as follows [2], [4].

$$\begin{cases} v_x(j) = \sum\limits_{i=1}^{m} \zeta_{ij} v_x(i) \\ v_y(j) = \sum\limits_{i=1}^{m} \zeta_{ij} v_y(i) \end{cases}, \tag{2}$$

where m is number of neighbors. The interpolation coefficient ζ_{ij} is calculated as $\zeta_{ij} = \frac{\frac{1}{r_{ij}}}{\sum_{i=1}^{m} \frac{1}{r_{ij}}}$ where r_{ij} denotes the Euclidean distance between node i and node j.

These two prediction algorithms are integrated in the whole localization process and can greatly improve the localization performance.



(a) Localization coverage (b) Communication cost

Fig. 1. Performance with changing node density

III. Simulation Results

In our simulations, 500 sensor nodes are randomly distributed in a $100m \times 100m \times 100m$ region. We set the anchor percentage to be 10% and change the average node density from 8 to 16 by changing the node range R.

Fig. 1 shows us that the localization coverage of our SLMP is higher than the scheme without mobility prediction. And it can greatly reduce the communication cost. This is reasonable since in our scheme, anchor nodes need not send localization message in every localization period and thus limit the frequency of localization message flooding. Correspondingly, the overall communication cost is reduced. This is quite meaningful for underwater sensor networks with limited bandwidth and energy. Our simulation results also show us that the localization error of our SLMP is low. Interested reader can refer our technical report for more detail [7].

IV. Conclusions

In this work, we have propose 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. While each ordinary sensor node predicts its location by utilizing the spatial correlation of underwater object mobility pattern, weighted-averaging its received mobilities from other nodes. SLMP is scalable and can achieve a good balance between localization accuracy, localization coverage and communication cost

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