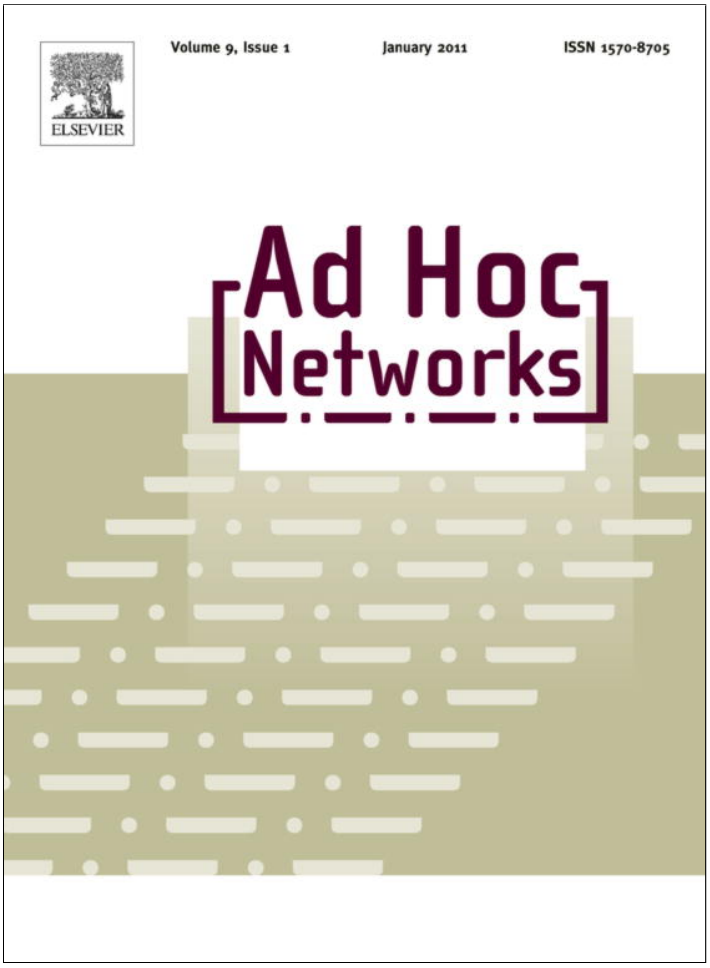
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Performance evaluation of distributed localization techniques for mobile underwater acoustic sensor networks

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ABSTRACT

Underwater sensor networks (USN) are used for tough oceanographic missions where human operation is dangerous or impossible. In the common mobile USN architecture, sensor nodes freely float several meters below the surface and move with the force of currents. One of the significant challenges of the mobile USN is localization. In this paper, we compare the performance of three localization techniques; Dive and Rise Localization (DNRL), Proxy Localization (PL) and Large-Scale Localization (LSL). DNRL, PL and LSL are distributed, range-based localization schemes and they are suitable for large-scale, three dimensional, mobile USNs. Our simulations show that, DNRL and LSL can localize more than 90% of the underwater nodes with high accuracy while LSL has higher energy consumption and higher overhead than DNRL. The localization success and accuracy of PL is lower than the other techniques however it can localize underwater nodes faster when small number of beacons are employed.

1. Introduction

Underwater sensor networks (USNs) can be used in various fields such as; naval defense, earthquake or tsunami forewarning, water pollution detection, and ocean life monitoring systems. In naval defence, USNs can provide instant deployment capability and increased coverage in surveillance applications of coastal regions. For earthquake or tsunami forewarning systems, USNs with underwater sensor nodes mounted on the ocean bottom can detect earthquakes and tsunami formations before they reach inhabited regions. For water pollution detection systems, mobile USNs can follow polluted waters as they propagate from their source to clean waters and warn authorities to take action. Last but not least, USNs can be used in monitoring sea animals and coral reefs where human operation would provide limited information.

USN architectures may vary depending on the specific target application, yet two general categorizes can be defined which are stationary and mobile USN architectures. In stationary USNs, underwater sensor nodes are attached to fixed anchors. They are ideal for securing or monitoring a fixed target region, e.g. monitoring oil drilling platforms, harbor entrances or seismic activity. On the other hand, mobile (untethered)[1] USNs employ freely floating underwater sensor nodes. They are more convenient for short term exploration of moving targets, for instance, tracking a chemical spill or a pollutant that may be dangerous for human health or sea life.

In a sensor network, sensor nodes sample several properties from their surroundings, according to their deployment purpose and sensors they carry on board. Temperature, pressure, salinity and acceleration are typical

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[1] Hereafter we will use "mobile" and "untethered" interchangeably to mention the sensor network with nodes that are not anchored and can drift with the force of the currents. In this study, we do not consider propelled equipments.

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sensors for USNs. When a sensor node attains the measured values, it generally tags these with time and location information because applications associate the sampled values with when and where they were collected. In USN applications, sensors can be scattered through the wide and deep oceanographic region and they need to know their location for data tagging. Location is also required for target detection and node tracking. For example, surveillance applications may require submarine detection and tracking. In addition, localization is essential for position-based routing algorithms which are alternatives to classical routing approaches for Mobile Ad Hoc Networks (MANET).

Localization is a well studied topic in terrestrial sensor networks. Nevertheless, for USNs, localization is still challenging due to several reasons: (i) unavailability of GPS; (ii) low bandwidth, long delay and high bit error rate of the acoustic links; (iii) necessity of large amount of sensor nodes to cover wide and deep (three dimensional) oceanographic regions [1–3]. GPS uses high frequency radio signals and they are quickly absorbed in water. Hence the use of GPS is limited to surface nodes. GPS-less (GPS-free) positioning schemes, which are proposed for terrestrial sensor networks, could be used for localizing underwater nodes however these techniques usually involve intensive messaging, and hence they have high overhead. This may not significantly affect the performance of terrestrial sensor networks however USNs communicate via the low bandwidth and low data rate acoustic links and their performance is drastically affected by protocol overhead. Data rates of underwater acoustic links w.r.t. various ranges are given in Table 1 [4]. Besides low data rates, acoustic communications have high propagation delay. The high delay is due to the slow speed of sound in water which is approximately equal to 1500 m/s, i.e. five orders of magnitude slower than radio signals. Moreover, due to ocean bottom and surface reflections, and temperature variations, underwater communications have multipath propagation property which increases the bit error rate. Therefore, in USN, localization protocols are expected to avoid excessive overhead and establish localization with least possible messages. This is also enforced by the limited battery life of the underwater sensor nodes and the difficulty of recharging or replacing the batteries in an underwater application. As seen in Table 1, the data rate of the acoustic link increases for shorter distances. This implies, an USN with short-range nodes, requires a large number of nodes to cover the three dimensional oceanographic zone. In a large-scale USN, the messaging intensity of localization protocols may increase. In addition, for a mobile USN, localization should be repeated periodically which also increases the overhead. Considering all these challenges related with USN communication medium, architecture and applications, it is essential to develop novel localization protocols tailored for the mobile USNs.

Table 1
Data rates for underwater acoustic links with various ranges.

Span	Range (km)	Data rate
Short range	<1	∼20 kbps
Medium range	1–10	∼10 kbps
Long range	10–100	∼1 kbps
Basin scale	3000	∼10 bps

In this paper, we compare three distributed, range-based localization schemes which are proposed for large-scale, three dimensional USNs. These schemes are Dive and Rise Localization (DNRL), Proxy Localization (PL) and Large-Scale Localization (LSL). Distributed localization protocols are more convenient than centralized protocols for large-scale USNs and for applications that require instant information. Moreover, DNRL, PL and LSL are range-based localization techniques. In literature, there are range-free localization algorithms, as well however their high overhead impacts their scalability where DNRL, PL and LSL are scalable. DNRL [5] uses mobile beacons to distribute the location of the anchor nodes, PL is an extended version of [6] and employs iterative localization. LSL [7] uses an hierarchical architecture where anchor nodes are scattered in the three dimensional USN. We use Qualnet Network Simulator [8] for our simulations. Our performance metrics are localization success, accuracy, overhead, energy consumption and delay.

When comparing the performance of the localization techniques for a mobile USN, a realistic underwater mobility model is essential. Recently, the works of [6,9] have applied the real ocean current behavior to USNs. We use their mobility model to compare the performance of three localization schemes.

The main contribution of this paper is presenting and comparing localization schemes for mobile USNs. We select three localization methods that are range-based and developed for distributed localization in large-scale, three dimensional USNs. In literature, generally, the results of the localization protocols omit MAC layer contentions and hence, do not include performance degradation due to contention. We use a realistic acoustic physical layer and a MAC layer in Qualnet where we also implement the localization schemes. Moreover, mobility is usually modeled with random waypoint mobility however this model is not convenient for the underwater environment. To the best of our knowledge, our paper is the first to compare these localization schemes considering MAC layer contentions and using a realistic underwater mobility model.

This paper is organized as follows: In Section 2, we summarize the state-of-the-art in localization for underwater sensor networks. In Section 3, we introduce the DNRL, PL and LSL methods. We discuss the simulation results in Section 4. Section 5 concludes the paper by giving future directions.

2. Related work

Basically, localization means estimating the location of a node. Localization has been widely studied in terrestrial sensor networks literature. However, the USN uses acoustic communication and due to its challenges, new solutions are required [10].

Current localization techniques in oceanography are Short Base-Line (SBL) and Long Base-Line (LBL) systems [11]. In SBL and LBL, equipment locations are determined with acoustic communications, using a set of receivers. In the SBL system, a ship follows the underwater equipments and uses a short-range emitter to enable localization. In the LBL system, acoustic transponders are deployed either on the seafloor or under the surface moorings around the area of operation. The devices that are in the transmission ranges of several sound sources are able to estimate their location. These systems are not suitable for USNs. SBL has high cost and is not feasible since a ship may not be able to follow sensors. LBL uses high power signals sent by the moorings that are kilometers apart. For an USN, these signals will create interference and disable the communication among sensor nodes. Alternative solutions have been recently investigated for underwater sensor networks.

In [12], authors propose an anchor-free, cooperative localization method for USNs. Localization starts with a node discovery phase where a seed node, which knows self location, selects other seeds iteratively. Nodes estimate their positions by the help of seeds. The node discovery phase requires high number of messaging. [12] may be used for stationary USNs where localization only runs at the set up of the network. For mobile sensor networks, repeating the node discovery each time the topology changes, is unaffordable.

Area-based Localization Scheme (ALS) is proposed in [13]. ALS is a range-free, centralized, course-grained localization technique for underwater sensor networks. In ALS, anchors partition the region into non-overlapping areas by changing their power levels. An underwater sensor keeps a list of anchors and corresponding power levels. The sensor node sends this information to the sink and the sink determines the area in which the sensor resides in. ALS gives course-grained location estimates and it is centralized. Hence, it is not suitable for large-scale USNs and for the applications that require accurate, instant location estimates.

In [14], authors aim to solve the localization problem for mobile USNs with a centralized localization technique. Nodes collect distance measurements to their neighbors during the localization epoch. The distance measurements are processed offline to establish localization. This scheme is targeted for applications where the location information is needed once the mission has finished, i.e. data is tagged at the post processing stage. However, for USNs that need to do online monitoring or for underwater networks with actuators, real-time location information is necessary.

In [15], localization for a hybrid network architecture is proposed. Underwater sensor nodes are stationary and a mobile Autonomous Underwater Vehicle (AUV) patrols the network region to localize the sensor nodes. AUV broadcasts its coordinates from different locations. The underwater nodes estimate their location by lateration when they hear from more than three non-collinear AUV positions. This method has high localization delay due to the slow speed of AUV, therefore it is convenient for stationary USNs.

Localization with Directional Beacons (LDB) [16,17] also uses an AUV for localization of a USN. In LDB, AUV uses a directional acoustic transceiver to broadcast self coordinates and the angle of transceiver's beam. An underwater sensor node records the coordinates of the AUV when the AUV first gets into its communication range and when AUV exits the range. Then, it estimates its x-coordinate as the average of the x-coordinates of two AUV positions which are the first and last heard positions of AUV. y-coordinate is estimated by using the range and the x-coordinate in the euclidean relation. The drawback of LDB is that its accuracy depends on the frequency of AUV messages and the slow speed of AUV increases the localization delay.

In [18], a prediction-based localization scheme is proposed for mobile underwater sensor networks. The same hierarchical architecture of LSL, with buoys, anchors and ordinary sensors, is employed here. Buoys float on the surface and receive GPS coordinates. Anchor nodes periodically predict their locations, and confirm the accuracy of their predictions via distance measurements to the surface buoys. If their prediction is inaccurate, they update their mobility pattern and send message to ordinary sensor nodes. Ordinary sensors predict their location with their mobility model which is updated when anchor nodes announce an update message. The performance of prediction-based schemes depend on the structure of the mobility pattern. When the motion is uncorrelated, the performance of these schemes may degrade. In this paper, we consider estimation-based localization protocols.

Another prediction-based scheme, Collaborative Localization (CL), is proposed in [19] for "fleets of underwater drifters". The architecture of "fleets of underwater drifters" uses "profilers" which can be considered as the pioneering nodes that move before the others and provide an estimate of future locations to the "follower" nodes. A follower node predicts its location by using its previous location and the displacement of the profiler. The drawback of CL is its architectural dependence; for a sparse or non-homogenous network, the performance of CL could be affected significantly.

In [20–22], authors propose a projection technique for USNs. Projection transforms 3D localization problem to 2D localization, which enables the use of a large number of localization algorithms proposed in literature.

3. Distributed localization protocols for large-scale USNS

3.1. Dive and Rise Localization (DNRL)

In long-term ocean missions, the common approach for localization has been the LBL technique. In those missions, usually equipments are placed kilometers apart and they collect data individually. They transfer collected data to a central station via satellite links. They do not communicate with each other, i.e., they do not form a network. However, the current oceanographic applications demand networking capability of sensor nodes. In this case, in order to achieve higher data rates, range between sensors has to be decreased. For localization in such an underwater sensor network, the long range pingers should be replaced with short range alternatives. Therefore location information needs to be forwarded iteratively to nodes that are not in the transmission range of the surface buoys or some mobile nodes need to deliver the GPS driven coordinates by moving to the vicinity of underwater nodes. To extend the global location information of the GPS service to the underwater environment, we proposed the DNRL technique in [5].

DNRL uses mobile beacons to distribute the GPS driven coordinates to the underwater sensor nodes. DNR beacons learn their coordinates when they float on the surface of the ocean. Then, they periodically descend to the deepest level of the network and ascend to surface, in order to receive their current location. While descending and ascending, DNR beacons broadcast localization messages. The underwater nodes passively listen to these messages and establish localization. Underwater nodes do not spend energy for the localization process.

A DNRL localization message includes a timestamp field and coordinates of the DNR beacon. The timestamp field is used to calculate the distance between the beacon and the node, by using the Time of Arrival (ToA) technique. Since the acoustic signals propagate slower than the radio signals it is appropriate to multiply the difference between the arrival time and the timestamp with the speed of sound to get the distance between two nodes. We assume that the nodes are synchronized and the speed of sound is constant around the network region. The nodes may be assumed to be synchronized for several weeks after initial deployment. However if the USN is used for a long-term mission it is clear that an additional synchronization protocol needs to be executed before localization. In DNRL, when the underwater node receives messages from three or more beacons it calculates self coordinates via lateration.

Lateration can be used to estimate n coordinates if there are $n + 1$ or more beacon messages. The method is based on the idea of intersecting circles. It is a widely used technique which is also employed by the GPS system. Basically, the estimated coordinates should satisfy a set of equations:

$$(x - x_i)^2 + (y - y_i)^2 + (z - z_i)^2 = d_i^2, \tag{1}$$

where i denotes the beacon id, (x_i, y_i, z_i) are the coordinates of the beacon and d_i is the measured distance between the beacon and the node. Note that three independent equations are sufficient for solving this nonlinear equation system for (x, y). Since the sensor nodes have pressure sensors on board, the depth, i.e. the z-coordinate is already known. The equation system is linearized by subtracting the $(n + 1)$th equation from the first n equations. Then, the coordinates are estimated with a least squares estimator, by solving $A\varphi = b$ where,

$$A = \begin{bmatrix} 2(x_1 - x_n) & 2(y_1 - y_n) \\ \cdot & \cdot \\ \cdot & \cdot \\ \cdot & \cdot \\ 2(x_{n-1} - x_n) & 2(y_{n-1} - x_n) \end{bmatrix},$$

$$b = \begin{bmatrix} x_1^2 - x_n^2 + y_1^2 - y_n^2 + z_1^2 - z_n^2 - 2z(z_1 - z_n) + d_n^2 - d_1^2 \\ \cdot \\ \cdot \\ \cdot \\ x_{n-1}^2 - x_n^2 + y_{n-1}^2 - y_n^2 + z_{n-1}^2 - z_n^2 - 2z(z_{n-1} - z_n) + d_n^2 - d_{n-1}^2 \end{bmatrix}.$$

The coordinates $\hat{\varphi} = [\hat{x}\hat{y}]^T$ are estimated by using a least-squares approach: $\hat{\varphi} = (A^TA)^{-1}A^Tb$.

In DNRL, a node is considered as a localized node if the estimation error is less than the communication range, R. The error, ϵ, is defined as the difference between the estimated distance and the measured distance [23]. Estimated distance is the distance between the estimated coordinates of the node and the beacon coordinates. Measured distance is calculated via ToA.

$$\epsilon = \frac{1}{n}\sum_{i=1}^{n} \sqrt{(x_i - \hat{x})^2 + (y_i - \hat{y})^2 + (z_i - z)^2} - d_i. \tag{2}$$

If $\epsilon > R$ then the node is marked as non-localized. Note that, the localization is done periodically and a non-localized node may become localized later and the localized nodes may refine their estimates. Since we consider a mobile network, in DNRL, nodes periodically refresh their localization tables. Each localized node flushes its table after a period of T_r.

3.2. Proxy Localization (PL)

A preliminary version of Proxy Localization is proposed in [6] where the localized underwater nodes are allowed to aid localization. Similar recursive approaches have been proposed for terrestrial sensor networks [24] and PL tailors this idea to underwater environment.

PL uses the DNRL technique to localize the upper portion of the network. The DNR beacons descend until the mid-depth of the three dimensional USN. Then, localized nodes become location proxies for the nodes floating at deeper levels. In PL, location proxies announce self coordinates. Non-localized underwater nodes may use the coordinates of the proxies in lateration and localize themselves. A non-localized underwater node uses the hop count metric to choose the "reliable" proxies among candidates. Hop count is the hop distance between a proxy node and a beacon. In iterative localization techniques, error accumulates at the proxy nodes that are distant from the beacons. Therefore, proxy nodes with least hop distance to the beacons can be preferred in lateration equations to increase accuracy.

The packet format for PL is given in Fig. 1. Coordinates are used in lateration. Distance is measured by ToA of the messages by using the timestamp field. The Maximum Dive Depth (MDD) field limits the number of proxy beacons. Localized sensors may become proxy nodes only if they lie below the maximum dive depth of the DNR beacons. This controls the protocol overhead. The Hop Count (HC) is the cumulative hop distance between the beacons and the node as explained above. In PL, a proxy node may help localizing its neighbors and later, a localized neighbor may send an update to the proxy node. To prevent the ping-pong effect on message propagation, messages with higher timestamp and lower hop count are used in lateration. Localization tables are refreshed at a period of T_r.

3.3. Large-Scale Localization (LSL)

In [7], authors consider a hierarchical localization scheme for large-scale USNs. They use surface buoys and

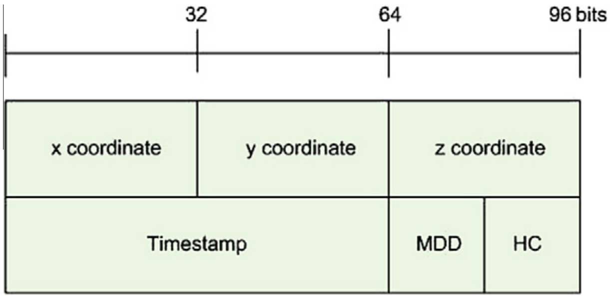

Fig. 1. Localization packet format for Proxy Localization.

two types of underwater nodes: anchor nodes and ordinary sensor nodes. Surface buoys attain their coordinates through GPS. Anchor nodes are spread among the whole sensor network. In [7], authors consider only the localization of ordinary sensor nodes and omit anchor localization. Following their work, we also omit anchor localization for comparison purposes.

In the ordinary sensor localization, the anchor node broadcasts a localization message that includes its coordinates. In addition to these localization messages, all the nodes exchange beacons periodically to measure the distances to their neighbors. If an ordinary node gathers enough localization messages (e.g. three for localization in 3D where the depth information is obtained from pressure sensor) it does lateration to estimate self coordinates. Later, the localized node calculates its confidence value, σ, using:

$$\sigma = \begin{cases} 1, & \text{for anchor nodes,} \\ 1 - \frac{\sum_i |(\hat{x}-x_i)^2+(\hat{y}-y_i)^2+(z-z_i)^2-d_i^2|}{\sum_i (\hat{x}-x_i)^2+(\hat{y}-y_i)^2+(z-z_i)^2}, & \text{otherwise,} \end{cases} \tag{3}$$

where $(\hat{x}, \hat{y})$ are the estimates for (x,y) coordinates, (x_i, y_i, z_i) are the coordinates of the anchor nodes and d_i is the measured distance between the node and the anchor. If the confidence value is above a certain threshold then the node becomes a "reference node".

If the number of localization messages are insufficient to localize the ordinary node, it broadcasts the received localization messages along with distance measurements to its neighbors and distance measurements to anchors. A non-localized node can use these messages in Euclidean distance estimation algorithm. The two dimensional Euclidean algorithm of [25] is extended for the three dimensional case in [7]. In the Euclidean distance estimation, the key idea is to estimate the distance between two nodes that are two-hops away by using one-hop distance measurements. The details of the method is described in [7]. The Euclidean distance estimation method requires nodes to store and exchange the distance estimates to neighbors and anchors.

4. Simulation results

We use the Qualnet simulator [8] to compare the performance of DNRL, PL and LSL. Existing protocol stack of the Qualnet simulator is modified in order to make the simulation environment suitable for underwater sensor networks. The underwater acoustic channel is implemented as follows. The attenuation over a distance d for a signal of frequency f can be modeled by:

$$A(d,f) = d^k \times a(f)^d, \tag{4}$$

where k is the spreading factor and $a(f)$ denotes the absorption loss. The geometry of propagation is described using the spreading factor $(1 < k < 2)$, and we use $k = 1.5$ (corresponding to most practical scenarios). The absorption loss $a(f)$ is described by the Thorp's formula [26]. In our physical layer implementation, the receiver node successfully receives a packet if the Signal-to-Noise Ratio (SNR) is above a threshold, where noise is assumed to be a function of the noise factor, bandwidth and temperature. We set the data rate of the acoustic channel to 50 kbps with a channel frequency of 100 kHz. The speed of sound is set as 1500 m/s.

Nodes are placed in a $(1000, 1000, 600)$ volume. The transmission range is set to 180 m. There are 250 nodes and the average node degree is 9. To calculate the average node degree, for each topology (generated with a different seed), we run an application protocol to count the average number of neighbors of each node. We analyze the performance of the protocols for varying beacon percentage as 10, 15, 20, 25, 30 and 35. Here, we define the beacon percentage as the percentage of the beacons at the initial deployment phase. For PL and LSL methods, beacon percentage increases as the underwater nodes become proxies and contribute to localization.

In the mobile USN, nodes are allowed to drift in a 20 km $\times$ 20 km domain. Simulations last 6000 s and the domain is large enough to contain all the mobile nodes during the simulation time. In DNRL and PL techniques, mobile beacons ascend and descend using a mechanical technique, i.e. volume expansion, they are not propelled. Therefore they have a slow vertical velocity of $v_d = 1$ m/s. For the first set of simulations, we set the frequency of localization messages to $T_d = 100$ s intervals. In PL, proxy nodes send messages with the same period $T_p = 100$ s. We assume the nodes are synchronized and distance can be measured by ToA. Each underwater node keeps a limited number of beacon message entries, i.e. $M = 4$. In LSL, localization messages which include coordinates of anchor nodes are sent at $T_l = 100$ s intervals. Beacon exchange messages that are used in distance estimation are also sent at $T_b = 100$ s intervals. Location tables and neighbor tables are exchanged at $T_{lt} = 100$ s and $T_{nt} = 200$ s intervals, respectively. The neighbor tables contain largest amount information exchanged between the nodes therefore its frequency is kept low. The confidence threshold for LSL is set to 0.98. For all methods the refreshment period is selected as $T_r = 500$ s.

We give the average of 50 simulation runs. We present 95% confidence intervals in the figures. Performance of the three localization techniques is analyzed in terms of localization success, communication cost, accuracy, overhead, energy consumption and delay. In the next section, we give details of the mobility model used in our simulations.

4.1. Mobility model

Mobility of the untethered sensors are determined by the ocean currents. Accurate modeling of ocean currents can be as complex as weather forecast however, in oceanography literature, a computationally efficient kinematic approach has been proposed in [27]. The model has been proven to successfully capture the dynamics of the ocean movement when the underwater equipments are calibrated to follow an isopycnal surface. An isopycnal surface has a constant density and can be assumed to be horizontal [28].

The subsurface current model was first introduced in [27] and the model parameters were clearly defined in [29]. In [9], the authors apply this model to USNs. The current flowing in the subsurface layer is defined by a non-dimensional streamfunction [27,30]:

$$\psi(x,y,t) = -\tanh\left[\frac{y - B(t)\sin(k(x-ct))}{\sqrt{1+k^2B^2(t)\cos^2(k(x-ct))}}\right]. \quad (5)$$

The streamfunction in Eq. (5) represents a jet-like current meandering between recirculating vortices. The amplitude of the meanders is modulated by the time-dependent function $B(t) = A + \epsilon\cos(\omega t)$, and their phase shifts with a speed of c. For a wide range of parameters, this flow induces a net mass transport along the current and at the same time, a vigorous chaotic mixing across the current. Following [9], we use $A = 1.2$, $c = 0.12$, $k = 2\pi/7.5$, $\omega = 0.4$, $\epsilon = 0.3$. With these scalings, the streamfunction (5) is representative of a typical coastal current. The meanders is 7.5 km, the typical current speed inside the jet is about 0.3 m/s, and the modulation period is about half a day. From ψ, the two components (u, v) of a divergenceless, horizontal velocity field are calculated as:

$$u = -\frac{\partial\psi}{\partial y}; \quad v = \frac{\partial\psi}{\partial x}. \quad (6)$$

At the subsurface layer, the current is determined by the large-scale, internal dynamics of the ocean, however, at the surface layer, the motion of the water is directly affected by the local winds. Their interaction and modeling is an active research topic for oceanographers. A simplified surface model is added to the subsurface model in [6]. Surface model assumes that a node floating on the surface has a velocity which is a random perturbation of the subsurface velocity, that is,

$$(u, v)_{\text{node}} = (u, v)_\psi + (u_s, v_s). \quad (7)$$

(u_s, v_s) is modeled by the Ornstein–Uhlenbeck process that is described by the Langevin equation:

$$du = -\lambda u\,dt + \sqrt{2\lambda U^2}\,dw, \quad (8)$$

where $w(t)$ is a Wiener process, the positive constants λ and U are the inverse of the decorrelation time and the root-mean-squared speed of the wind [31,32], respectively. The v component of the velocity is described by the same Langevin equation, with an independent Wiener process. In practice, velocities are computed at discrete time intervals, so we use the following discrete expression of (8)

$$\begin{aligned} u_s(t+\Delta t) &= u_s(t)e^{-\lambda\Delta t} + U\sqrt{1-e^{-2\lambda\Delta t}}\zeta_i, \\ v_s(t+\Delta t) &= v_s(t)e^{-\lambda\Delta t} + U\sqrt{1-e^{-2\lambda\Delta t}}\xi_i, \end{aligned} \quad (9)$$

where ζ_i and ξ_i are independent pseudo-random numbers from a zero-mean, unit-variance gaussian distribution. The parameters are chosen as: $\lambda^{-1} = 2$ days, $U = 0.5$ m/s, following [6], in order to represent a typical coastal current.

4.2. Localization success

Localization success is the ratio of localized nodes to total number of nodes. The localization success of DNRL, PL and LSL, for a mobile USN is given in Fig. 2. For beacon percentage above 15%, DNRL and LSL are able to localize more than 90% of the nodes. PL has lower localization success than DNRL and LSL; it can localize 85% of the nodes. In Fig. 2, DNRL and LSL seem to have identical performance. However, when we zoom in, we observe that for beacon percentages over 20%, DNRL has slightly better localization success. For beacon percentage of 10%, all three methods are able to localize 80% of the nodes.

4.3. Localization accuracy

Localization accuracy is defined by the mean error ratio. Mean error is the average of the difference between the estimated and the true location of a node for location estimations. Mean error is divided by communication range (180 m) to get the mean error ratio. In Fig. 3, we present the mean error ratio of DNRL, PL and LSL. The mean error of DNRL is lower than 40 m for all beacon percentages

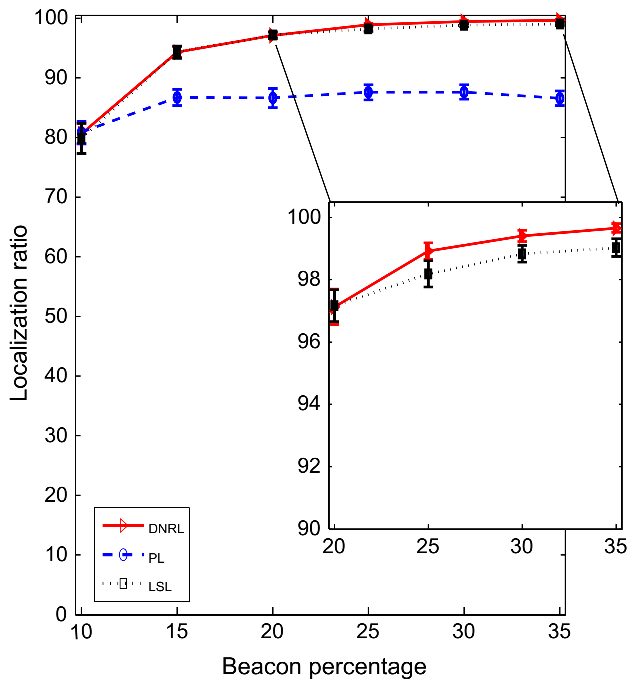

Fig. 2. Localization success for the DNRL, PL and LSL schemes for a mobile USN.

and it decreases at higher beacon percentage. DNRL has the highest accuracy among other methods. LSL has higher mean error ratio than DNRL. The mean error ratio of LSL is 0.4 for low beacon percentage and it decreases below 0.2 for higher beacon percentages. On the other hand, PL has higher mean error than DNRL and LSL. Its mean error is above 90 m for all beacon percentages. This error value is high when compared to an ordinary sensor network however, USN applications may be tolerant to less accuracy considering the scale of the ocean.

4.4. Energy consumption

In Fig. 4, we give the energy consumption of DNRL, PL and LSL. In sensor networks, energy consumption is related with several parameters. Here, we assume that a significant portion of energy is spent during packet transmission. Therefore, energy consumption is related with the number of transmitted bits. Since we assume an acoustic network, the underwater nodes use acoustic modems. Most of the off-the-shelf acoustic modems have large range values because they are designed to work in applications where the distance between nodes are in kilometers. However short range modems are preferred in USNs to achieve higher data rates. Aquacomm modem developed by [33] is a short-range acoustic modem with range 200 m. Here, following [34], we take the energy required to transmit one bit for the short-range acoustic modem as 4.5 mJ. To calculate the energy consumption, we use the average number of transmitted bits and energy per bit values of Aquacomm modem. In Fig. 4, we show that DNRL consumes the least amount of energy among three methods. DNRL is a passive localization technique where only beacons send localization messages and underwater nodes do not spend energy for localization. PL has slightly higher energy consumption since it includes iterative localization where a limited number of nodes are allowed to become proxies. Proxy nodes send messages and contribute to energy consumption. The energy consumption of LSL is significantly higher than PL and DNRL. For low beacon percentages, LSL spends 300 times more energy than PL and DNRL. For high beacon percentages, LSL consumes 10 times more energy. In addition, in LSL, the localization of the anchor nodes requires communication between buoys and the anchor nodes. Although we omit this process, following the original work of [7], this will also increase the energy consumption.

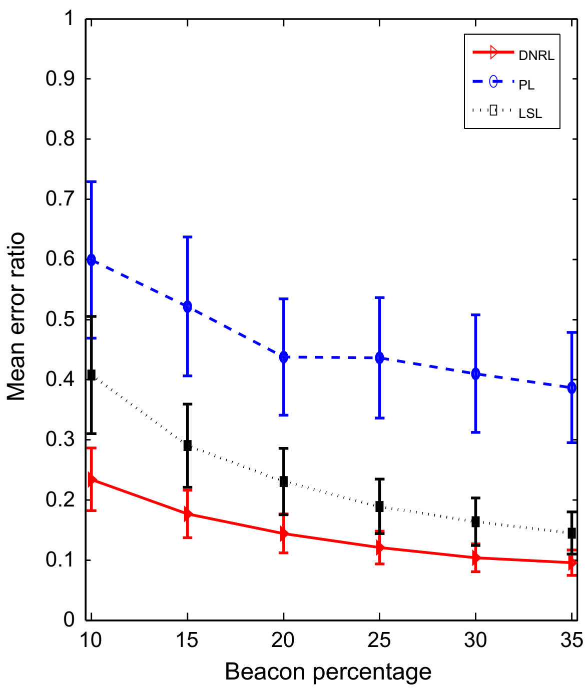

Fig. 3. Mean error ratio for the DNRL, PL and LSL schemes for a mobile USN.

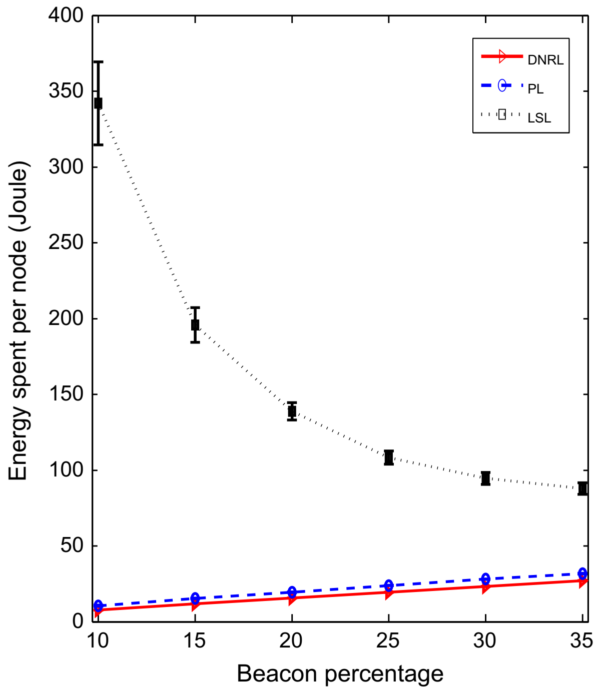

Fig. 4. Energy consumption per node for the DNRL, PL and LSL schemes for the mobile underwater sensor network.

4.5. Communication overhead

Communication overhead is calculated as the average number of localization messages sent per node. In DNRL only the DNR beacons send messages, underwater nodes are passive listeners. In PL and LSL underwater nodes may also act like beacons after they learn their locations. Therefore, in Fig. 5, DNRL has the lowest communication overhead among other techniques. The overhead of PL is higher than the DNRL due to proxy node messages. In the meanwhile, the communication cost of LSL is significantly higher than both of the techniques. In LSL, a localized underwater node announces its location if its location estimate error is under a certain threshold. In addition, non-localized sensor nodes also send messages to announce the coordinates of their neighboring ordinary sensor nodes and anchor nodes. This contributes to the communication overhead of LSL, as well.

4.6. Evolution of localization

Monitoring the evolution of localized nodes is important to understand the required amount of time for locali-

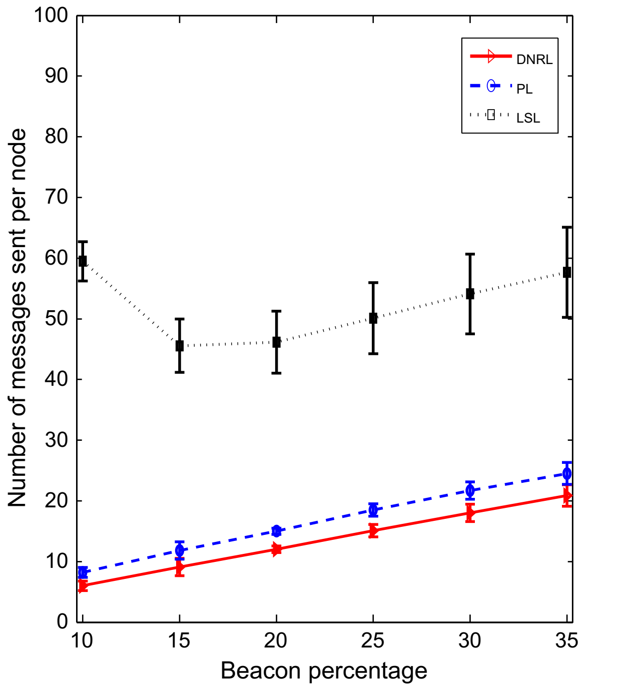

Fig. 5. Total number of sent messages per node for the DNRL, PL and LSL schemes for the mobile underwater sensor network.

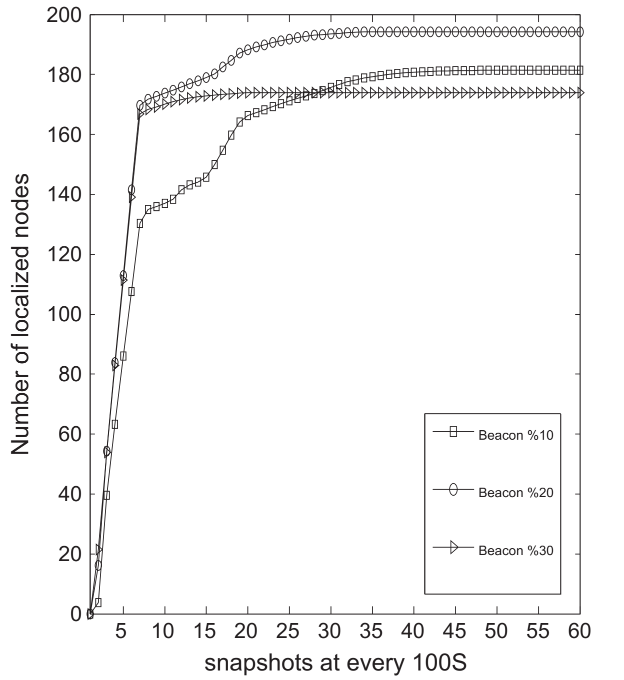

Fig. 6. Number of localized nodes versus time taken in 100 s snapshots for DNRL method under a mobile USN.

zation. Localization is usually not the only task of the sensor network but an essential protocol to make the system function properly. In an application, localization protocol may keep silent for a while so that it does not disturb the ongoing data transmission. To determine the localization period, one needs to know how long it takes to localize a significant portion of the nodes. On the other hand, the delay to localize a significant portion of the underwater nodes also means the delay in starting data tagging and establishing location related tasks. We call the duration between the initial deployment and the time number of localized nodes stabilize, as localization delay.

In Fig. 6, we present the number of localized nodes versus time for DNRL. In DNRL underwater nodes are localized only by the beacon messages which means the nodes at deep levels wait until DNR beacons ascend down and the node is in the communication range of beacons. Therefore, especially for low beacon percentages such as 10%, localization delay is 3500 s. For the beacon percentage of 20%, it is 3000 s. As the beacon percentage increase to 30%, DNRL has lower delay, i.e. 1000 s.

In Fig. 7, we give the evolution of the number of localized nodes with respect to time for the PL method. For the beacon percentage 30%, 1500 s are required to localize 88% of the nodes. For the beacon percentage of 20%, 2000 s are needed to localize 85% of the nodes. For beacon percentage of 10%, 80% of the nodes are localized in 2500 s. Fig. 7 shows that increasing the number of beacons speed up PL method.

In Fig. 8, we give the number of localized nodes versus time for LSL. When the beacon percentage is high (30%), a significant portion of the nodes are localized faster than PL and DNRL, i.e. less than 500 s. For the beacon percentage of 20% and 10% the localization delays are 1500 s and 3000 s, respectively.

To summarize, for high beacon percentages, the localization delay of LSL is lower than DNRL and PL. For low beacon percentage, PL has lower delay than LSL and DNRL.

4.7. Impact of localization update interval

In this section, we analyze the effect of the frequency of localization message updates. We employ 20% beacons and

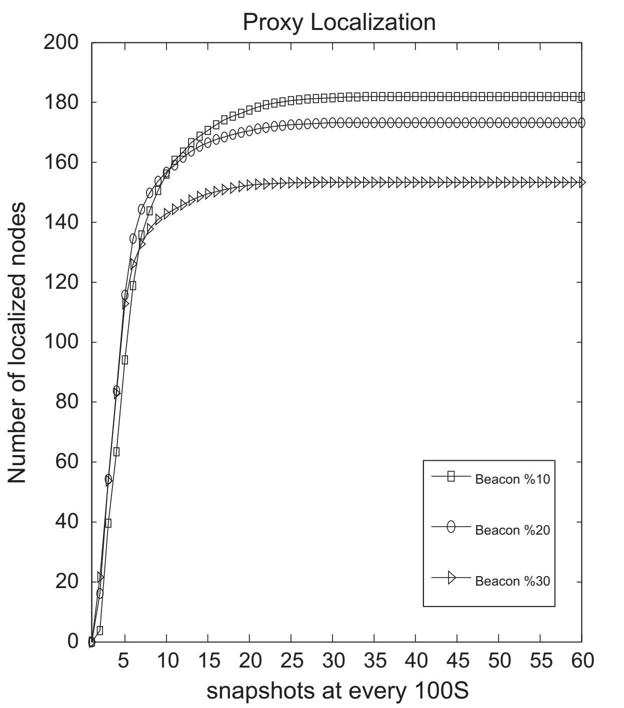

Fig. 7. Number of localized nodes versus time taken in 100 s snapshots for PL method under a mobile USN.

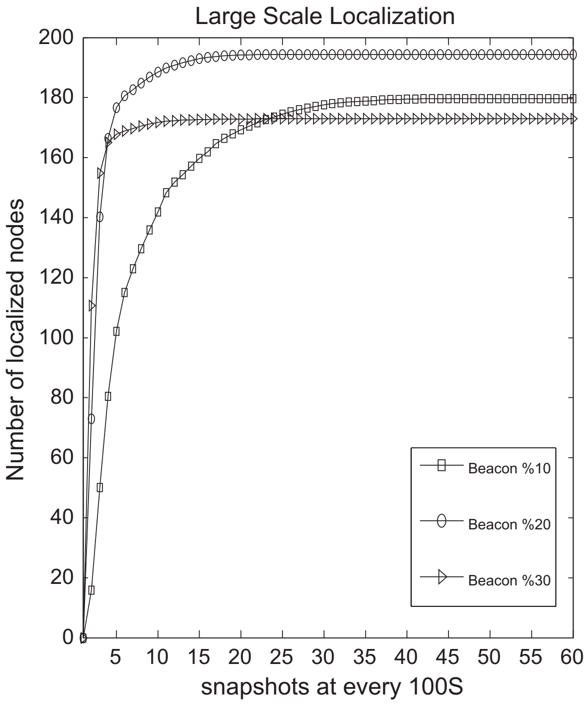

Fig. 8. Number of localized nodes versus time taken in 100 s snapshots for LSL method under a mobile USN.

vary message intervals between 20 s and 80 s. In Fig. 9, we show the localization success of DNRL, PL and LSL for varying intervals. The performance of DNRL is not affected by decreasing the localization message interval however PL and LSL has higher localization ratios for lower intervals, i.e. frequent updates. In Fig. 10, we show the mean error ratio for DNRL, PL and LSL for varying intervals. Accuracy also improves with frequent location updates. Although lower update intervals improve localization success and mean error ratio, they increase the energy consumption significantly as seen in Fig. 11. In Fig. 12, the overhead of the protocols is given. Overhead also increases as the frequency of messages increase, which is expected.

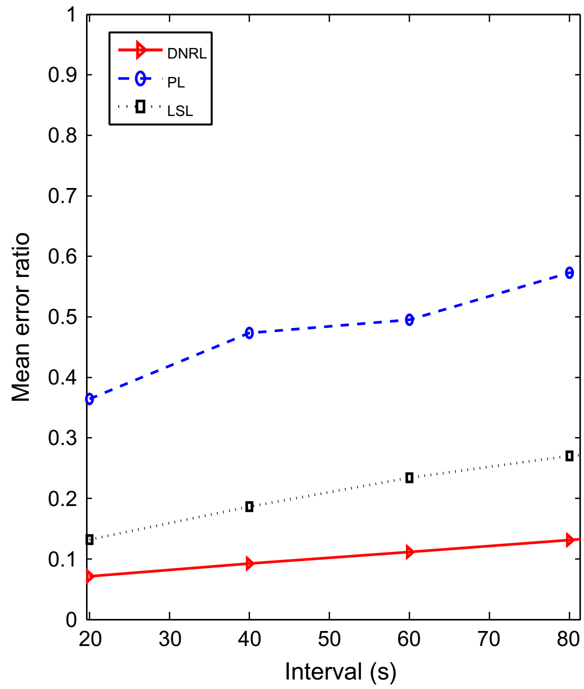

Fig. 10. Mean error for the DNRL, PL and LSL for various location message update intervals.

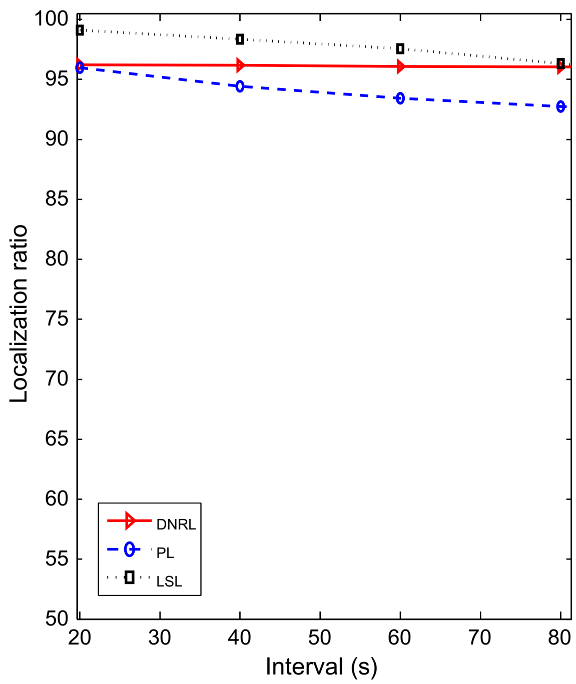

Fig. 9. Localization success for the DNRL, PL and LSL for various location message update intervals.

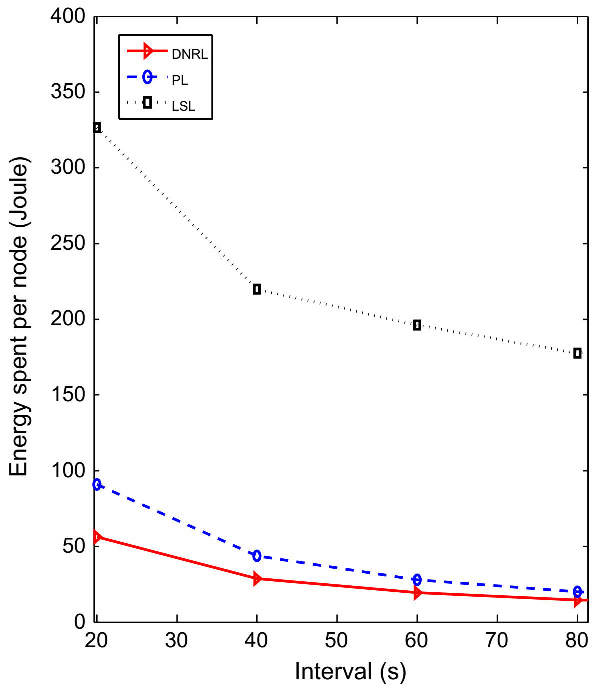

Fig. 11. Energy consumption per node for the DNRL, PL and LSL for various location message update intervals.

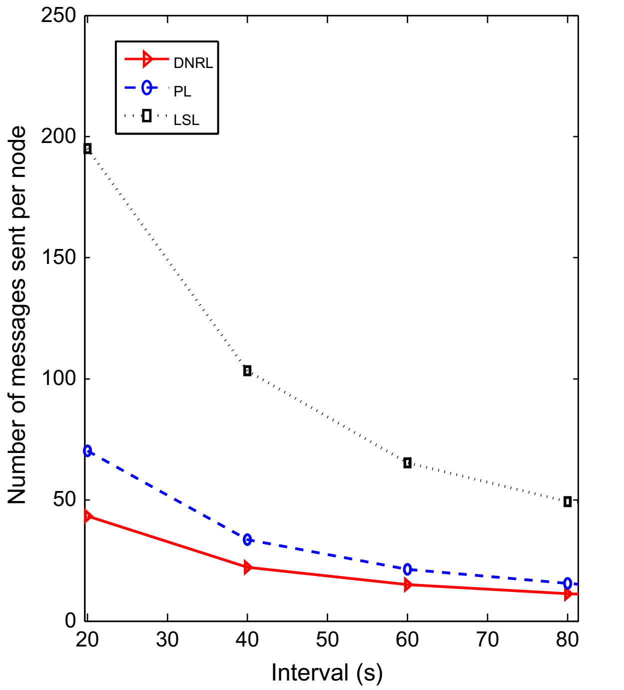

Fig. 12. Total number of sent messages per node for the DNRL, PL and LSL for various location message update intervals.

4.8. Impact of node degree

We analyze the impact of node degree on the performance of DNRL, PL and LSL. In this set of simulations, we set the transmission range to 150 m and the average node degree is 5.7. In this case, the localization success of LSL drops dramatically when the beacon percentage is lower than 30%, as seen from Fig. 13. In LSL, localization is done by the information gathered from anchor nodes and neighbors. Therefore, connectivity plays a key role in the performance. In Fig. 13, when the beacon percentage is 10%, only 20% of the nodes are localized by LSL and only at beacon percentage of 20%, LSL manages to localize a little more than half of the nodes. PL almost has the same localization success as in high connected scenario, likewise DNRL. The overhead and energy consumption performance are similar to the case with average node degree 9.

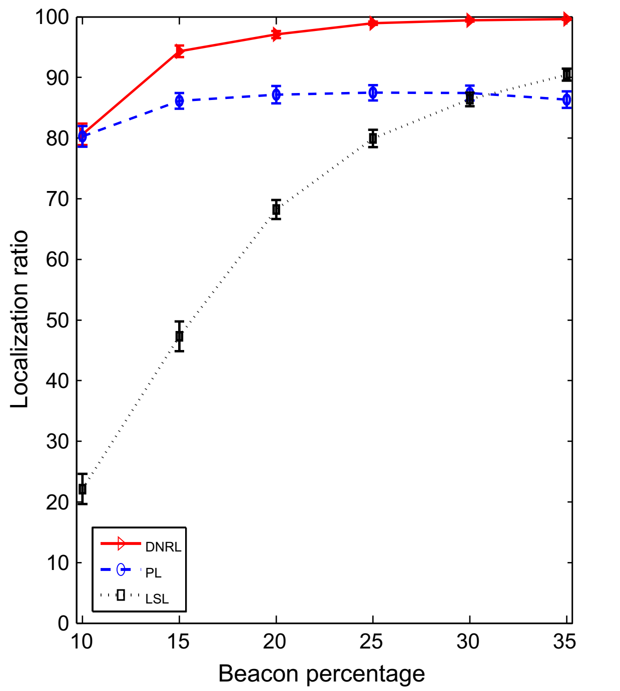

Fig. 13. Localization ratio for the DNRL, PL and LSL schemes for average node degree 5.7.

5. Conclusion

Localization is one of the significant challenges in mobile underwater sensor networks. In this paper, we compare the performance of three distributed, range-based localization schemes, DNRL, PL and LSL. We analyze their localization success, overhead, accuracy, energy consumption and delay for the mobile USN. DNRL has high localization ratio, low mean error ratio, low communication overhead and low energy consumption. PL has moderate localization success, low overhead and low energy consumption. Moreover, PL has lower delay than DNRL and LSL for low beacon percentages. However, its accuracy is less than the other methods. Tolerance to accuracy depends on the application. For example, error values of several tens of meters can be acceptable for underwater applications such as environmental monitoring whereas surveillance applications may require more accurate localization. LSL has high localization ratio and acceptable mean error ratio, however its communication overhead and energy consumption is significantly higher than DNRL and PL. In mobile USNs, localization has to be repeated periodically. Besides, in underwater environment, the bandwidth is limited. Clearly, high communication overhead and energy consumption are handicaps of LSL. Additionally, the performance of LSL is significantly affected by average node degree.

As a future work, we plan to analyze the impact of localization techniques on geo-routing schemes. When localization and routing coexists, the overhead limitations, accuracy requirements and coverage restrictions could affect the performance of the routing protocols.

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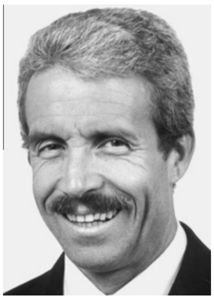

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