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Dynamic mobile anchor path planning for underwater wireless sensor networks

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ABSTRACT

In an underwater wireless sensor network (UWSN), the location of the sensor nodes plays a significant role in the localization process. The location information is obtained by using the known positions of anchor nodes. For underwater environments, instead of using various static anchor nodes, mobile anchor nodes are more efficient and cost-effective to cover the monitoring area. Nevertheless, the utilization of these mobile anchors requires adequate path planning strategy. Mzost of the path planning algorithms do not consider irregular deployment, caused by the effects of water currents. Consequently, this leads towards the inefficient energy consumption by mobile anchors due to unnecessary transmission of beacon messages at unnecessary areas. Therefore, an efficient dynamic mobile path planning (EDMPP) algorithm to tackle the irregular deployment and non-collinear virtual beacon point placement, targeting the underwater environment settings is presented in this paper. In addition, EDMPP controls the redundant beacon message deployment and overlapping, for beacon message distribution in mobile assistant localization. The simulation results show that the performance of the EDMPP is improved by increasing the localization accuracy and decreasing the energy consumption with optimum path length.

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1. INTRODUCTION

In the past few years, the interest of the wireless sensor network (WSN), particularly for the underwater wsn (UWSN) has increased exponentially [1], [2] mainly to monitor the underwater environment. In contrast to the standard environment setting, several aspects need to be considered in the implementation of UWSN, particularly, vast deployment areas, irregular deployment patterns, and unique water characteristics such as temperature, salinity and depth. In order to monitor the area, utilization of the mobile anchor is an ideal option because it can serve as a reference node for the sensor nodes to determine their locations. Mobile anchors enhance the accuracy of the localization as the sensor nodes receive beacon messages directly from the mobile anchor at a single-hop distance.

The deployment of the sensor nodes will become irregular due to the influence of the effects of water currents [3], [4]. Due to this irregularity, the placement of underwater sensors at an exact location is a challenge [5], hence requiring a mobile anchor path planning algorithm to assist the localization process. The localization process can aid to identify and determine the location of the sensor node, which is an essential aspect of UWSN due to the ability to pinpoint the location of any occurrence of reported events to address the events timely and assist location-based applications. A strategic mobile path planning can avoid the placement of beacons using random movement that can cause a large location error due to the usage of beacons with high estimation error. Besides, the possibility of a mobile anchor visiting the same area beyond what it should or should not visit in some areas is high.

However, existing localization schemes exclusively focus on selecting the nearest sensed node and following the nearest neighbour until it covers all sensor nodes without relying on any discovery strategy. Unfortunately, such a solution may cause the mobile node to reach a dead-end before covering the entire area, which requires the mobile beacon to revisit the previous trajectory to turn back in the attempt to cover the uncovered node. As a result, the mobile beacon travelling distance is increased, which consumes more energy and may lead to redundant beacon deployment.

Therefore, the mobile anchor path planning is required to improve the localization accuracy for localization schemes. There are two types of mobile path planning, namely, static and dynamic path planning [6], [7]. Each type has different characteristics based on the sequence of the executions and changeability. Most of the existing path planning algorithms for mobile assistant localization schemes focus exclusively on localization coverage and trajectory length in the uniform deployment using static path planning. These static path planning algorithms, namely, 3D-HILBERT [8], SCAN [9], CIRCLES [10], [11], S-CURVE [12], LMAT [13], SLMAT [14], Z-Curve [15], trilateration-based movement [16-19] and swarm-based optimization [20-23] are identical in a sense that they are unsuitable for the application in irregular deployment areas [24]. Any brute implementation only causes significant localization delay, low localization ratio, and high localization error, mainly due to the beacon message transmission waste. Several attempts have been made in utilizing dynamic path planning algorithms to solve the irregular deployment area application [24-30]. The dynamic path planning provides the ability to modify changing paths depending on the demand or sensor nodes deployment area. For example, the number of mobile beacons is increased to create a dynamic formation [24]. Apart from adding the number of hardware, a depth-first traversal algorithm based on received signal strength (RSS)-based distance information is proposed [25]. This software-based improvement idea is also being adopted by [26] and [28], which relies on heuristic-based calculation and perpendicular bisector strategy (PBS) approaches, respectively.

Nevertheless, most of these dynamic algorithms suffer from the increase in communication and deployment costs, irregularity and coverage overlapping. Additionally, these algorithms still ignore the unique underwater environment characteristics; hence they are not directly applicable. Theoretically, the mobile trajectory should provide each unknown node with at least four non-collinear beacon points to achieve a unique estimation of unknown nodes position, which leads to an excellent mobile beacon localization scheme. However, existing path planning algorithms proposed for the underwater environment attempt to either reduce the path length of the mobile beacon with irregular deployment or increase localization accuracy [27].

An enhanced path planning algorithm, known as efficient dynamic mobile path planning (EDMPP) to improve the localization accuracy of the localization scheme, specifically targeted for the underwater environment is proposed in this paper. The rest of this paper is organized as follows; a detailed description of the proposed method with several enhancements in terms of underwater properties and wide-area parameters to the dynamic path planning algorithm is presented in section 2. The purpose is to tackle the irregular mobile nodes deployment and to provide optimum non-collinear beacon messages while reducing the communication overhead. Next, the simulation process to evaluate the performance of the EDMPP and analyze the simulation results is described in section 3. Finally, the proposed work is concluded in section 4.

2. RESEARCH METHOD

In this work, the proposed mobile beacon path planning algorithm is divided into three main execution stages, namely, as area partitioning, sensor discovery, and location determination. Figure 1 illustrates the relations between each stage, which is implemented as a pipeline execution to produce the optimum path planning. The algorithm is split into three stages to ensure coverage of the monitoring area without compromising the accuracy and shortest path. Generally, in a mobile-assistant localization scheme for a WSN, the mobile anchor/beacon has gathered the localization information based on the movement of the global positioning systems (GPS) across the surveillance region where the localization is carried out. Additionally, in UWSN, after receiving the GPS locations, the mobile anchor node will dive into the specified depth to obtain information regarding the absolute position. Along the way, across this area, the mobile anchor will stop and distribute beacon messages containing current location information of other mobile beacons across nearby sensors. These points are called virtual anchor nodes. The recipient of the beacon messages depends on the communication radius for mobile anchor nodes and sensor nodes.

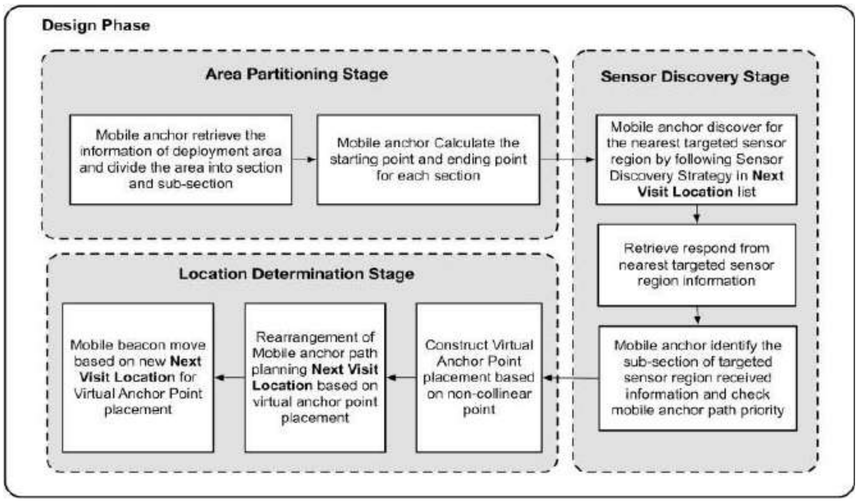


Figure 1. Generic overview of the proposed EDMPP algorithm

2.1. Area partitioning

This stage is structured to reduce the signal transmission of the mobile anchor nodes by preventing these nodes from the problems of revisiting and redundancy. In this stage, the specific area for the sensor deployment is divided into a virtual grid, composed of sectors and sub-sectors, which are the locations for the corresponding mobile sensors. A mobile anchor will position these sensors that traverse through the sub-sectors, using a grid division strategy. As stated in Algorithm 1, the mobile anchor node determines the starting and ending point of each sector based on the sector travel sequences. When the mobile anchor node arrives at the endpoint of each sector, the current position of the mobile anchor node is set as a new starting point of the next sector, iteratively. Furthermore, in this current study, the symmetric square-grid formation for the transformation of these sectors is utilized to avoid mobile anchors nodes from revisiting problems, which can reduce signal transmission.

Algorithm 1. Area partitioning

```
Input DeploymentAreaInformation
Output MobileBeaconPathDirection
INITIATE Start_Position = XStart = , YStart = 0, and ZStart  = 100;
INITIATE Target_Position = XEnd = 1000, YEnd  = 1000, and ZEnd  = 100;
SET Curr_Position = Start_Position
DIVIDE discovery area into 4 sections
DEFINE Movement_Priority ⟶ Path_Data
DEFINE Next Visit Location(NVL) list =[]
SET Curr_Section = 1;
while Curr_Position != Target_Position do
   CHECK Number of Curr_Section
     SET Curr_Section(Starting_Point) ⟵ Curr_Position
     CALCULATE Curr_Section(End_Point)
     RETRIEVE Path_Data(Curr_Section)
     UPDATE Next Visit Location (NVL) list ⟵
[Path_Data(Curr_Section),Curr_Section(End_Point)]
     CALL SensorDiscovery(NVL, Curr_Section(End_Point))
   SET Curr_Section= Curr_Section + 1;
end while
```

2.2. Sensor discovery

In this stage, the mobile anchor is required to cross each sector in turn, within the specified movement dimensions, until it receives feedback from its targeted sensor. Next, this information is processed to determine their location. The movement dimension of the mobile anchor is within the virtual grid sub-sectors, guided by a generic localization process and an optimal number of virtual anchor points, which help the sensor node determine their positions more accurately. During the discovery process, the GPS navigation system is utilized to obtain the actual location of the mobile anchor nodes positioned on the water surface through the radio wave transmission. While underwater, the mobile anchor node moves to a certain depth vertically to obtain a reasonably precise position. It then calculates the ongoing location information using GPS as reference while surfing. When the mobile anchor node reaches the position of the predetermined starting point, it starts to broadcast the information consisting of the location and timestamp to the surrounding area. It then coordinates the direction to move the mobile anchor to the next visit location (NVL) based on the previous process.

As shown in Algorithm 2, throughout the coordination process, the mobile anchor node is in a listening mode and does not broadcast any additional information. The targeted node will send acknowledgement information and timestamp as feedback to the received information. Once the mobile anchor node receives the feedback information, the mobile anchor node calculates the signal reception angle to determine the location of the targeted node in the virtual grid of sub-sectors. The mobile anchor should ensure that movement during the discovery stage covers the entire deployment area. However, it is essential to reduce the energy consumed by the mobile anchor. To achieve this objective, a discovery process to minimize the overlap area of the virtual anchor point coverage is introduced, which can reduce the energy consumption by mobile anchors.

Algorithm 2. Sensor discovery

```
Input List(NextVisitLocation(NVL)), Curr_Section
Output DiscoveryMessage
   GET NVL, Curr_Section(End_Point)
   while Curr_Position != Curr_Section(End_Point) do
   MOVE Next direction point [NVL]
   BROADCAST Discovery message
   LISTEN Sensor node response
     if Rec_Response >0
                 ESTIMATE non-collinear position of Sensor Response
       CALL VirtualAnchorPlacement function
       MOVE Next direction point [NVL]
           else
     MOVE Next direction point [NVL]
     BROADCAST Discovery message
            end if
   end while
```

2.3. Location determination

The localization scheme calculates the location of the targeted sensor nodes. By dividing the area into virtual grids, the effective deployment strategy is possible for implementation. Based on the received information, the mobile anchor node determines the location of the virtual anchor point placement based on the virtual sub-sector location. Once determined, the mobile anchor node enters this location information into the network variables list (NVL). This list implementation is according to the path priority. As visualized in Figure 2, the movement of the mobile anchor will refer to the NVL list to identify the coverage status, with the consideration of the number of virtual anchor nodes and collinearity problems. To determine the location of the targeted node, a coordinate calculation technique i.e. trilateration is utilized. Hence, the acceptance of at least three reference nodes is required to enable the location determination calculation process of the targeted node.

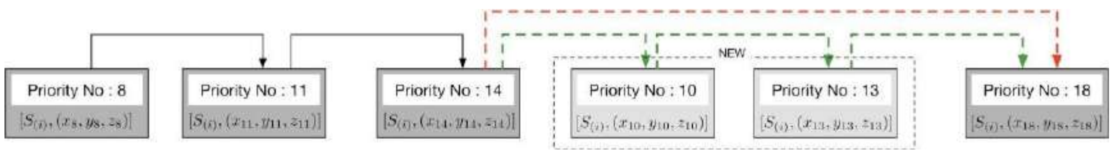


Figure 2. The strategy of next visit location (NVL) list rearrangement

3. RESULTS AND ANALYSIS

This section presents the simulation setup and the outcome results of the proposed EDMPP algorithm. In simulation setup sub section, the technical detail on the simulation setup and the environment use for the simulation is discussed. The performance of proposed EDMPP algorithm is evaluated through several evaluation metrics, consisting of communication cost, localization accuracy, and travelling length. These results are extensively analyzed and discussed in the performance analysis sub section.

3.1. Simulation setup

The proposed EDMPP algorithm is implemented and simulated using the MATLAB 2018, with the configurations of Intel Core i5 processor with 16GB RAM in a Linux Ubuntu operating system platform. To simulate the experiment, MATLAB was utilized with various parameters received from the AquaSim simulator tool to generate the underwater signals. The parameter settings of the simulation process are as tabulated in Table 1. Other existing algorithms such as 3D-HILBERT [8] and 3D-SCAN, which is the new derivation from SCAN [9] in 3D form factor is also implemented and compared with the performance of the proposed algorithm.

These algorithms are run in the setting of three dimensions (3D) environments. It is mainly due to the assumption that the sensors should be floating and roaming inside the underwater, within the boundary of the specified deployment area. The existence of any physical obstacles and external noises within this area are ignored. In this work, the deployment area of the sensor nodes is considered to be 0.2 km^3 with a varying number of sensors ranging from 100 to 1000 nodes. These sensor nodes are randomly deployed within the defined range with various parameters defined in Table 2. The performance of the proposed algorithm is measured with the variation of 20 iterations. The value of each underwater environment parameter is fixed for each iteration, which includes the temperature, salinity and the acoustic speed. All of these parameters' values are obtained using specified equations, as expressed in (1), (2), and (3), respectively. Water temperature as shown in (1) is manipulated by the depth values. Hence, the temperature, *T*, can be measured as:

$$T = 7.5 + \frac{8.5}{700} \times (700 - depth) \tag{1}$$

where depth is the relative length between the node and sea level. Next, the salinity of the seawater, *S*, scaled in practical salinity scale (PSU) is also considered the depth as one of the variables to determine the level of saltiness of the seawater, which can affect the density and surrounding temperature. Salinity value is calculated using (2) as follows:

$$S = 34.2 + \frac{1.3}{1000} \times (1000 - depth) \tag{2}$$

Table 1. Deployment configurations

Parameters	Value(s)
Deployment Area (m^3)	(1000,1000,200) $m3$
Number of Sensor Nodes	100 − 1000nodes
Mobile Anchor Speed (*m/s*)	5
d_{max}, Mobile Anchor (*m*)	200 m
d_{max}, Sensor Node (*m*)	100 m

Table 2. Underwater environment parameters

Parameters	Value(s)
SNR (*dB*)	20
Acoustic Speed (*m/s*)	1508.1
Acoustic Signal Error (*m*)	0.07
Depth (*m*)	100
Temperature (*°C*)	14.1785
Salinity (*psu*)	35.37

The last important parameter for underwater is the speed of the acoustic. It is important to know this characteristic since it can exploit the movement of the mobile anchor due the waves within the underwater current. Hence, the calculation of the speed of the acoustic is performed based on (3). The temperature values for the conversions were utilized, with the application of several constant values as the representation of standard values of liquid according to the relative water area.

$$C = 1448.96 + 4.591 \times T - 5.304 \times 10^{-2} \times T^2 + 2.374 \times 10^{-4} \times T^3 + 1.34. \tag{3}$$

For sensor node deployment, two types of deployment pattern were employed. The first pattern is the Square-shape pattern, illustrated in Figure 3 (a). This pattern can cover the deployment area based on a regular shape cell, which is a non-random grid pattern. Another deployment pattern the C-shape, which is shown in Figure 3 (b). This C-shape deployment pattern is categorized as a random pattern since it does not cater any symmetrical geometric form. For each deployment, the number varies within the range of 100 to 1000 nodes.

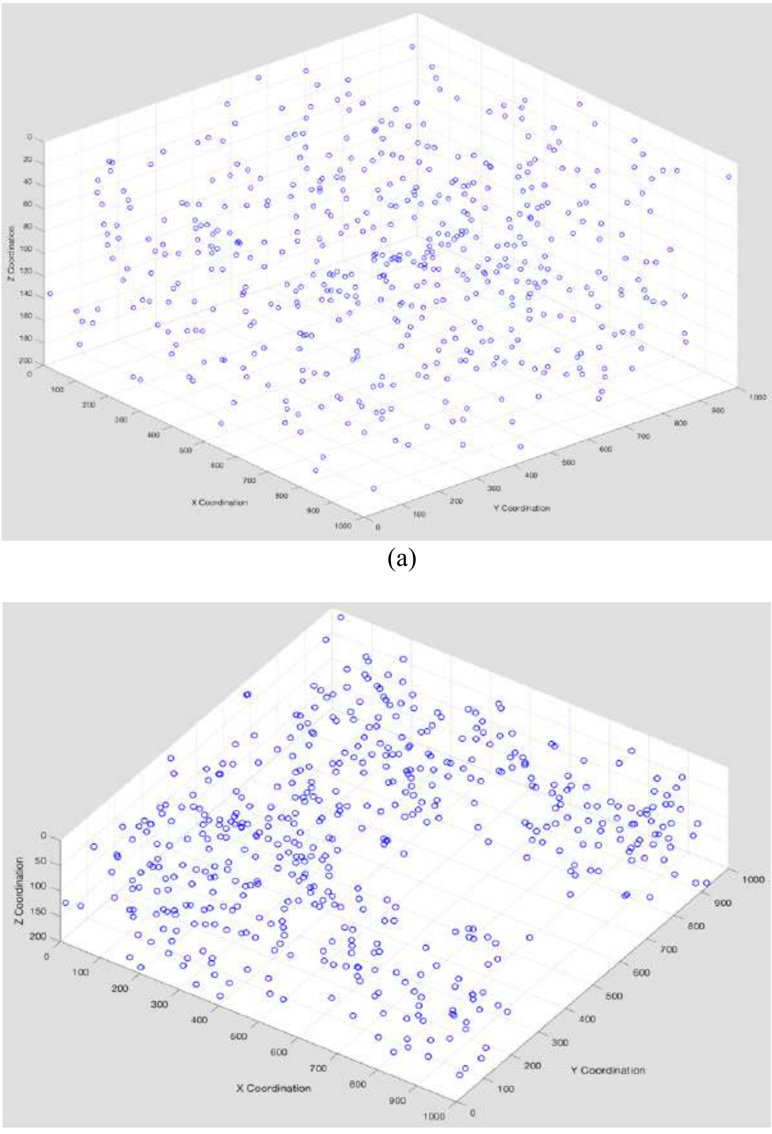
3.2. Performance analysis

The performance of the proposed EDMPP algorithm is evaluated using three metrics, namely, communication cost, localization accuracy, and travelling length. Each evalution metrics use to evaluate the performance plays its own role in assessing the level of efficiency. The efficiency of the EDMPP is analyzed against two existing algorithms such as 3D-HILBERT [8] and 3D-SCAN [9].

3.2.1. Communication cost

First, the performance of the proposed algorithm is evaluated based on the energy consumption, used by the mobile anchor. To measure this energy usage, the amount of beacon transmitter is quantified as a benchmark for energy consumption measurement. This measurement is known as communication cost. To enable a sensor node to be localized, at least three reference anchor points or known as beacon messages are required. As shown in Figures 4 and 5, the statistics of beacon messages are deployed as Square-shape and C-shape deployment patterns, respectively. Based on Figures 4 (a) and 5 (a), the EDMPP reduces approximately 40% to 52.5% of the number of beacon messages transmitted during the localization process, as compared to 3D-HILBERT and 3D-SCAN. As the node density increases, the number of beacon messages also increases and stabilizes when the number of nodes reaches 300 nodes or more.

Subsequently, the average beacon message received by the sensor nodes is measured using both deployment patterns, Square-shape and C-shape as illustrated in Figures 4 (b) and 5 (b). From these figures, it can be seen that EDMPP obtained a less average number of beacon messages transmitted compared to two other algorithms, which ranged approximately 45.5% to 54%. The reduction in the communication cost indicates that the EDMPP algorithm has successfully lessen the energy consumption of mobile anchors during the localization process. Based on these results, it can be concluded that the enhancement strategy used in the proposed algorithm helps mobile anchors transmit an optimum number of beacon messages for sensor node localization.



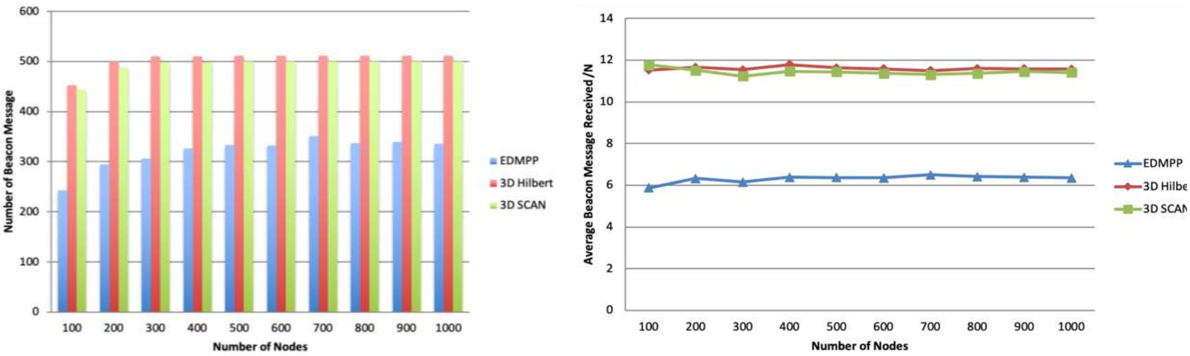
(a)

(b)

Figure 3. Sensor node deployment pattern: (a) Square shape, (b) C-shape

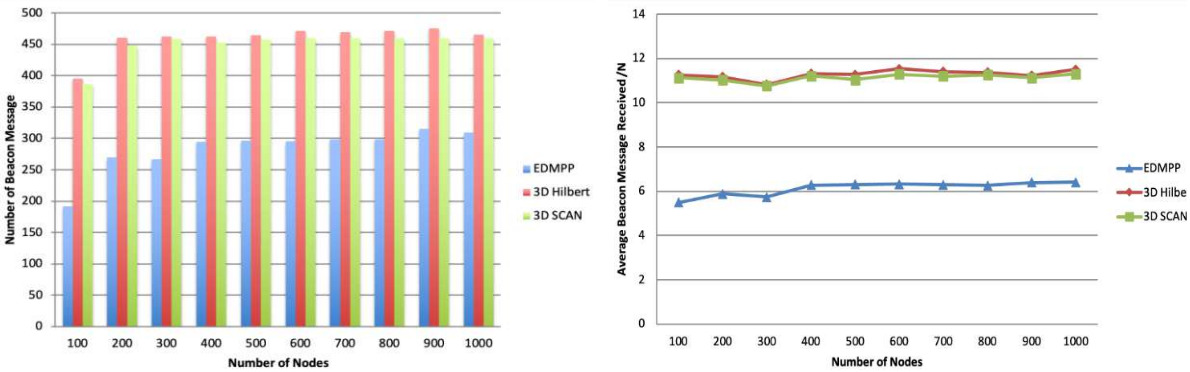
3.2.2. Localization accuracy

The accuracy of the localization is measured using the trends of beacon messages, based on the mean of the localization error against the number of sensor nodes deployed. Figures 6 (a) and (b) show the results of localization accuracy in Square-shape and C-shape deployment patterns, respectively. The localization error inversely implies the degree of localization accuracy. In both deployment patterns, it clearly showed that the EDMPP significantly improved the localization accuracy, with lower localization error, as compared to 3D-HILBERT and 3D-SCAN. As illustrated in Figure 6 (a), the EDMPP portrayed approximately 18.78% improvement against 3D-HILBERT, and 38.66% compared to 3D-SCAN in Square-shape deployment pattern. As for the C-shape deployment pattern, Figure 6 (b) shows the performance of its localization accuracy. From the result, in the C-shape deployment pattern, the localization accuracy of EDMPP outruns 3D-HILBERT and 3D-SCAN by nearly 28.36% and 48.87%, respectively.



(a) (b)

Figure 4. Statistic of beacon message in Square-shape deployment pattern: (a) the number of beacon messages deployed, (b) the average beacon message received by the sensor nodes

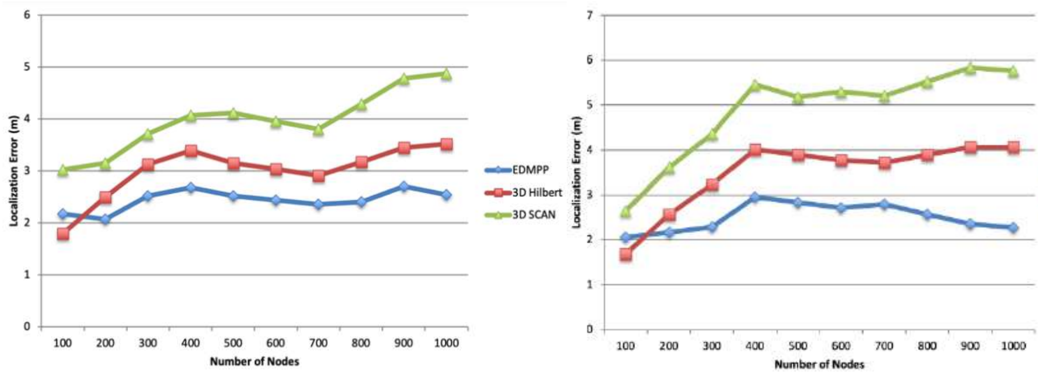


(a) (b)

Figure 5. Statistic of beacon message in C-shape deployment pattern: (a) the number of beacon messages deployed, (b) the average beacon message received by the sensor nodes

Moreover, from the observation, two major factors exist; the number of beacon nodes received, and the location of beacon messages received. In order for a node to be localized, a node must receive at least three beacon messages that are in a non-collinear position. In exception, during the initial phase in Square-shape deployment pattern, EDMPP showed quite significant error in the node density of 100 nodes compared to 3D-HILBERT but had better localization accuracy compared to 3D-SCAN. Consequently, the localization accuracy of the proposed algorithm yields more stable results in the next node density, iteratively. Overall, all path planning algorithms showed approximately the same pattern for different nodes density between 100 to 1000 nodes. Additionally, 3D-HILBERT and 3D-SCAN showed an increase in localization error when node density is at 400 nodes and above in the C-shape deployment area compared to Square-shape deployment. Based on the result, it is demonstrated that EDMPP could maintain localization accuracy stability even in the

C-shape deployment area. Furthermore, it proves that the proposed algorithm improved the performance of localization accuracy by reducing the number of beacon messages from the mobile anchor even if it is in an irregular deployment setting.

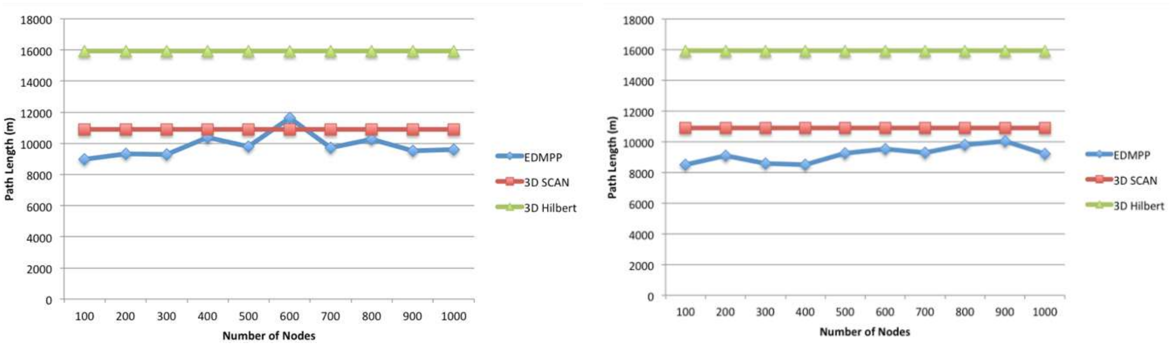


(a) (b)

Figure 6. Localization accuracy: (a) Square shape deployment pattern, (b) C-shape deployment pattern

3.3.2. Travelling length

Finally, the performance of EDMPP is measured based on the travelling length. Figure 7 shows the travelling path length of mobile anchor in both Square-shape and C-shape deployment patterns. As shown in Figure 7 (a), it can be observed that the EDMPP algorithm had reduced almost 36.63% and 31.92% of the overall path length compared to the 3D-HILBERT and 3D-SCAN algorithms in Square-shape deployment pattern, respectively. Similar outcomes were also obtained using the C-shape deployment pattern shown in Figure 7 (b), where EDMPP outruns 3D-HILBERT and 3D-SCAN at approximately 43.33% and 39.24%, respectively, in the overall path length reduction. These results proved the effectiveness of the sensor nodes' discovery strategy. By reducing the mobile anchor path length, it indirectly reduces the mobile anchor energy consumption during the localization process, whereas 3D-HILBERT and 3D SCAN performed the same performance in both deployment patterns due to early predefined path planning without the information of the number of nodes present during the localization process by the mobile anchor.



(a) (b)

Figure 7. Traveling path length: (a) Square-shape deployment pattern, (b) C-shape deployment pattern

4. CONCLUSION

In this paper, the EDMPP has been proposed to mitigate the issue of inefficient energy consumption by mobile anchors due to unnecessary transmission of beacon messages in the irregular deployment. This is mainly caused by the effect of underwater current and environmental properties. Besides, EDMPP prevents the mobile anchors from revisiting previously visited areas and reduces the redundant beacon message transmission. To address this issue, EDMPP transforms the monitoring area into a virtual grid which consists of sector and sub-sectors and constructs the mobile anchor trajectory-based sub-sector discovery in the sensor node discovery stage. After the sensor node is detected, the reconstruction of the mobile anchor trajectory is carried out in the location determination stage to construct the trajectory of non-collinear beacon message deployment. The simulation results verified that EDMPP improved the localization accuracy while reducing the energy consumption in terms of the number of beacon messages transmitted within the shorter path length compared to other mobile path planning algorithms for UWSN. Nevertheless, this research work did not consider any existence of physical obstacles. Signal distractions from external noise like ships, aquatic animals and other unrelated noises were also ignored in our algorithms. Therefore, future studies should consider the obstacles and external noise in order to simulate a more realistic environment and evaluate the efficiency of the proposed algorithm.

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