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Data Collection in Underwater Sensor Networks based on Mobile Edge Computing

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ABSTRACT With the rapid developments in edge devices and wireless technologies, the underwater wireless sensor networks (UWSNs) are in the process of vigorous development. In UWSNs, the traditional multi-hop data collection methods have some disadvantages such as high power consumption, severe unbalance in power consumption, and so on. In recent years, mobile edge elements (such as an autonomous underwater vehicle, AUV) are widely used in underwater data collection to solve energy consumption imbalance problems. However, the existing methods do not fully consider the efficient mobile edge computing and the real mobility model of AUV in the underwater environment. In this paper, we propose a data collection scheme based on a mobility model of mobile edge elements under water. In this model, the mobility direction and velocity are fully considered, which are close to the mobility characteristic of AUVs in the stable 3D environment. By using computing, storage, and mobility abilities of AUVs, a target selection algorithm is designed to calculate the mobility path of data collection for AUV. The theoretical analysis and experimental results show that the proposed method improves the efficiency of data collection, reduces the power consumption of nodes, and extends the network lifetime.

INDEX TERMS Underwater sensor network, mobile edge computing, data collection, mobile elements.

I. INTRODUCTION

In recent years, the IoT (Internet of Things) has been increasingly applied in various fields, such as smart home, smart city, intelligent transportation, environmental monitoring, security systems, and advanced manufacturing [1] [2] [3]. The IoT is composed of technologies such as network edge devices (mobile devices) and wireless technologies [4] [5]. With rapid developments in mobile devices and wireless technologies, mobile devices and mobile applications play an increasingly important role in daily life, and provide great potential developments for Mobile Edge Computing (MEC) [6] [7]. Mobile edge computing is a computing paradigm to implement the cloud computing services on network edges, using mobile edge devices, such as gateways, routers, micro servers. Mobile edge devices have advantages in storage, mobility and computing, which are close to the edge of the network [8]. Therefore, MEC can provide faster service responses and reduce the network congestion in the IoT [9].

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Similarly, with developments of the underwater IoT and mobile devices, such as acoustic sensors, and AUV. UWSNs are widely used in ocean resource detection, underwater environment monitoring, and auxiliary navigation. The UWSNs is an underwater monitoring network system, which are composed of many sensor nodes with communication, data collection and computing capabilities [10]. Data collection is a very important research field in the UWSNs, and can be treated as a mobile edge application. Modern underwater applications generate massive data, such as high-definition video, audio, and pictures. For long distance transmission by wireless signal in UWSNs, the collected data is easy to lose. The data collected by sensor nodes needs to be transmitted to the receiving node, and it forwards through multi-hop routing, which consumes a lot of energy [11]. Moreover, it is difficult to charge the battery of the underwater mobile edge elements. Hence, how to reduce the energy consumption of nodes has become an urgent problem. Currently, the main challenges of data collection in UWSNs are as follows.

First, most AUV-aided data collection methods are based on the assumption that the movement velocity of the AUV is constant [12]. However, in the underwater environment, movement velocity of the AUV is influenced by many factors, such as water flow, water pressure and obstacles. Moreover, actual motion status of AUV includes rising, sinking and turning when AUV moves to different target nodes, so the velocities of AUV are different [13]. Therefore, setting the same velocity make the AUV miss some target nodes.

Second, most data collection algorithms are run on the cloud. The cloud is far away from the data source nodes, transmitting the collected data to the cloud would increase energy consumption of nodes [14]. In addition, some key nodes die firstly and make the network die.

Two typical methods are used to collect underwater data: multi-hop data collection methods and AUV-aided data collection methods. The former would cause unbalanced energy consumption. If the relay node is closer to the receiving node, it consumes the more energy. The latter have serious data collection delay, because the AUV needs to visit all nodes and to collects data each cycle. However, the movement velocity of AUV is slow.

In order to tackle these constraints, this paper proposes a data collection scheme based on mobile edge model. In the mobility model, the underwater vehicle is influenced by its own gravity and buoyancy, which together produces the heave speed, making the maneuver ability of the underwater vehicle close to the real world. The AUV has advantages in computing, storage and mobility in UWSNs. Therefore, it is used as the MEC layer, providing the MEC service and data collection service. Meanwhile, a target node selection method is deployed on the AUV. In the proposed method, the residual energy of nodes and the distance between nodes are selected as criterion to select target nodes. The node with large residual energy is selected as the target node, and the target node is updated dynamically each cycle. The proposed target node selection method enables the AUV to access all target nodes in the shortest time and balance the energy consumption of the whole network. Furthermore, most work on UWSNs considered acoustic communications until recently. We combine magnetic induction (MI) communications with acoustic communications in this paper. The communication range of MI is less than 10m. The data rate of MI is up to a few Mbps(up to 10 Mbps) and more than acoustic communication ($\leq$ 100bps). The propagation path loss of MI is very small [15] [16]. When the AUV accesses the target node, the distance between the AUV and target nodes is less than 10 m, so the target nodes can transmit data to the AUV directly by using MI communication. This reduces the data transmission time efficiently. Other nodes transmit data to the target nodes by using acoustic communication.

The main contributions of this paper are as follows:

(1) We combine magnetic induction (MI) communications with acoustic communications to transmit data, which can reduce the data transmission time effectively.

(2) We propose a new data collection scheme based on a mobility model of mobile edge elements under the underwater sensor networks.

TABLE 1. Different types of data collection methods.

Data collection methods	Algorithms
Muti-hop data collection	VBF [17], HH-VBF [18]
AUV-aided data collection	Mobicast [19], PNCS-GHA [20]
Muti-hop transmission+AUV	AEERP [21], DGS [22]

(3) We use AUV as the mobile edge computing layer, providing the mobile edge computing and data collection service.

(4) We propose a target nodes selection algorithm based on the mobile edge model, which enables the AUV to visit all nodes in the shortest time and balance energy consumption of the whole network.

The rest of this paper is organized as follows. Section II reviews the related works. The scenario is set and the relevant model is given in Section III. Section IV proposes the relevant algorithms. The simulation results and performance analysis are discussed in Section V. Section VI concludes the paper.

II. RELATED WORK

In UWSNs, three common schemes are used to collect data. At the early stage, most data collection methods are based on the multi-hop collection scheme, because the computing performance of mobile edge devices is limited. With the development of mobile edge devices, many researchers used AUV-aided data collection scheme. Recently, data collection adopts a scheme that combines multi-hop scheme with AUV-aided data collection scheme. Table 1 shows some typical algorithms.

In the multi-hop data collection scheme, source node collects data and selects the relay node to forward the data to the sink node. Xie et al. [17] proposed a vector based on forwarding (VBF) protocol. In the VBF, packets are forwarded in a fixed virtual pipeline between each pair of sources and targets. In the sparse network, the performance of VBF decreases and the candidate nodes in the pipeline could hardly be found. To increase the possibility of finding a node in the pipeline, Nicolaou et al. [18] proposed the forwarding protocol based on hop-by-hop vector (HH-VBF). HH-VBF needs to initiate a different pipe from each intermediate (relay) node on each hop.

The multi-hop data collection scheme is unable to solve the energy consumption unbalance problem in UWSNs, the AUV-aided data collection scheme was proposed. Chen et al. [19] proposed the Mobicast protocol. They assumed that all possible sensor nodes form a 3D geographic region are near the AUV, called 3D reference region (3D ZOR). The AUV follows user-defined paths and continuously collects data from a series of sensor nodes in 3D ZOR to adapt to different time spans. The Mobicast protocol relies on two phases. In the first phase, the AUV collects data in 3D ZOR. In the second phase, the nodes in the next 3D ZOR would be awakened and topology vulnerabilities would be avoided. This method could avoid the low efficiency of direct traversal nodes and reduce energy consumption of nodes.

Han et al. [20] proposed the PNCS-GHA method. These are two AUV data collection algorithms are based on probabilistic neighborhoods. The AUV follows the designed path to collect data from the adjacent area. For three-dimensional UWSN with known deployment information, The AUV only needs to construct a minimum probability neighborhood coverage set for the aim access several selected locations to reduce data latency.

The serious data delay in AUV data collection scheme, many researchers combined the multi-hop data collection scheme with AUV-aided data collection scheme. In the combination scheme, the AUV does not traverse all nodes or monitoring areas. Assuming that the network is clustered with some cluster heads or gateway nodes and other nodes would forward the data to the cluster heads or gateway nodes through multiple hops. Hence, the AUV only needs to visit the cluster heads or gateway nodes to collect data. Ahmadet al. [21] proposed the AEERP method. In AEERP, the AUV moves with predetermined elliptical trajectory in each cycle. However, in a wide network, there is no restriction about the hop distance between the member and the gateway nodes, causing a lot of energy consumption. Cheng and Li [22] proposed that the important data could be forwarded to the corresponding layer by multi-hop, and other data is collected from the bottom to the top by AUV. It could reduce the latency of important data.

Meanwhile, path selection methods of AUV have a crucial impact on the efficiency of data collection. Basagni et al. [23] set a value based on the importance of the data, which decreases the total time. The goal is to determine the collection path for the AUV to maximize the value of data. Researchers proposed a heuristic algorithm for AUV routing (GAAP), which drives AUV to collect data from nodes to maximize data transmission. This algorithm could quickly collect data with large important values to a large extent, but most of the data with small relative values have serious delay and low efficiency. Researchers [21] proposed a pre-fixed elliptical trajectory of the AUV to collect data from the nodes. Although this method could reduce the moving path, it extends the distance from the member nodes to the gateway or cluster heads. Moreover, it could not cover all nodes. The researchers [24] selected the cluster heads and then used the AUV to collect data from the cluster heads. The shortest path algorithm (TSP) is used to calculate the AUV mobility path of data collection.

With the development of the IoT, there is great potential in the computing service of the IoT [25] [26], such as the IoT applications in smart cities, the scheduling of emergency data [27], and the security service [28]. The underwater sensor network is a product of the IoT technology and edge devices. MEC has become a new paradigm to solve the needs of IoT and provide localized computing service [29]. In addition, it is a method to alleviate resource congestion and upgrade in the mobile networks. Firstly, a number of computing nodes distributed across the network could off load the computational stress away from the centralized data center. Secondly, compared with traditional cloud services, distributed architecture could balance network traffic and reduce the response time of real-time IoT devices. In addition, the system could extend the network lifetime and transfer the computing and communication overhead of a node with less energy to a node with higher energy.

III. PRELIMINARIES

In this section, we firstly set up the data collection scenario and describe the data collection process. Then, we introduce the evaluation mechanism. Finally, we illuminate the underwater edge network architecture.

A. SCENARIO AND NOTATION

A set of n sensors $[s_1, \ldots, s_i, \ldots, s_n]$ are randomly deployed on different monitoring areas in the underwater 3D ($L \times W \times H$) environment. The nodes collect data and then transmit the collected data to relay nodes or AUV. When the nodes consume all energy, the nodes would die automatically. When m (m/n <some constant) nodes die, the network would fail. An AUV is deployed to visit all target nodes and collect data. In each cycle T, the AUV floats up to the surface and forwards data to the sink node, and then the sink node sends data to the cloud.

Assumptions:

(1) Underwater environment is basically stable. Nodes and AUV are not affected by water flow [30] [31].
(2) As shown in Fig.2 (AUV 3D underwater mobility model). The initial position and target node position of AUV are given. The initial velocity is v_{AUV} of AUV, and the heave velocity is v_f.
(3) The location of the n sensor nodes $[s_1, \ldots, s_i, \ldots, s_n]$ and each node s_i is given [32] [33].
(4) The underwater environment is relatively stable, the nodes do not move in a certain period of time, the end-to-end communication path between nodes is not affected [34] [35], which can't lead to the formation of underwater delay tolerant networks [36] [37].
(5) The remaining power R of the node s_i is given.
(6) Energy of AUV and sink node is unlimited.
(7) AUV proactively moves around and collects data, which is unaffected by network partitioning.

Goal: Maximizing the entire network lifetime.

As shown in Fig.1, we use the AUV to collect data. The whole process is described as follows. In a given monitoring area, sensor nodes are divided into several clusters. In a cluster, we select a target node, and is also named the cluster head, which is the node that AUV visits and collects data. Other nodes in the cluster are called member nodes. The member nodes are responsible for collecting data and forwarding data to target nodes by acoustic communication. Finally, the AUV visits all target nodes and collects data by MI communication. Target nodes usually consume a lot of energy, so the network energy consumption is balanced by periodically updating target nodes. In the mobile edge computing platform, the AUV

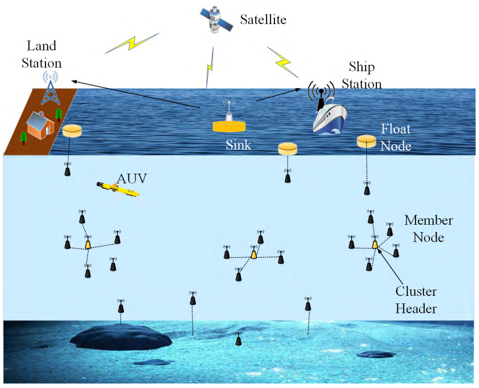

FIGURE 1. Underwater sensor network and AUV based data collection.

processes and stores a large amount of data that will be used in the next cycle.

B. EVALUATION MECHANISM

The evaluation mechanism is a key to measure the performance of data acquisition methods. This paper evaluates the performance of data acquisition methods by using network energy consumption and data delay.

In this paper, the energy consumption is divided into two parts: the data collection energy consumption $E_{collection}$ and the data transmission energy consumption E_{send}. The total energy consumption can be defined as:

$$E_{total} = E_{collection} + E_{send} \tag{1}$$

where $E_{collection} = xP_cT_c$ is the energy consumption of data collection, P_c is the energy consumption of data collection, and T_c is the time of collection of collection of x bits data.

The data transmission energy consumption is mainly influenced by transmission bandwidth, transmission delay and transmission loss. The data transmission energy consumption is composed of two parts: transmission energy consumption and noise loss. The energy consumption of data transmission could be defined as [38] [39]:

$$E_{send} = P_s \cdot T_s \cdot A(d) \tag{2}$$

where P_s is the energy of data transmission by the node, T_s is the time of data transmission, $A(d)$ is the energy loss of the distance, and d is the distance between the sender and the receiver.

In this paper, the AUV visits the target nodes to collect data through magnetic induction and transmits data to sink node by radio. The radio speed is very fast, so data transmission time between the AUV and the sink node is ignored. Therefore, three different delays lead to data collection delays: computing delay $T_{computation}$, the time T_{AUV} taken by the AUV visit target nodes during data collection, and the waiting time T_d that AUV waits target nodes to transmit data to the AUV.

$$T_{total} = T_{computation} + T_{AUV} + T_d \tag{3}$$

$$T_{AUV} = \sum_{i \in TNs} \frac{L_{AUV \to i}}{v_{AUV \to i}} \tag{4}$$

where $L_{AUV \to i}$ is the distance between AUV and target nodes TN_i, TN_i is the cluster head, it is also the target node for AUV to collect data, and $v_{AUV \to i}$ is the average moving speed of AUV from the current position to the target head TN_i.

C. UNDERWATER EDGE NETWORK ARCHITECTURE

In the underwater edge network architecture, the AUV as a mobile edge element can provide data collection, storage and computing services. Hence, UWSNs can be divided into three layers: data acquisition layer, data processing layer and application service layer.

In the proposed architecture, the MEC layer lies between the bottom nodes and the cloud. The mobile edge layer is close to data source, which can process and transmit data faster and reduce the delay [8]. In this paper, the AUV is close to the underwater nodes, and it is taken as the edge computing layer. The AUV has the ability to store and process data. Mobile edge devices can attain the aim of collecting data, providing computing services and reducing data latency and the computation of nodes compared to cloud computing [40] [41]. The data collection method proposed based on edge devices is implemented in the mobile edge computing layer.

IV. DATA COLLECTION PROTOCL BASE ON MOBILITY MODEL (DCRTM)

In this section, we firstly present the detailed analysis of the mobility model. Secondly, we introduce the target nodes selection method. Finally, we give the detailed analysis of DCRTM.

A. THREE-DIMENSIONAL MOBILITY MODEL OF AUV

In this paper, the AUV is used as the edge computing layer. Therefore, it is vital to determine the performance of the realistic mobility model. In the three-dimensional underwater space, two angles are required to determine direction of AUV.

Considering AUV is affected by its own gravity and buoyancy, we propose a speed synthesis algorithm, as shown in Fig.2. Therefore, the synthesis speed can be defined as follows:

$$v_s = v_f + v_{AUV} \tag{5}$$

$$\beta = arccos(\frac{L \cdot v_f}{|L| \cdot |v_f|}) \tag{6}$$

$$v_s = |cos(\beta + arccos(\frac{v_f}{v_{AUV}} \cdot cos\beta)) \cdot v_{AUV}/cos\beta| \tag{7}$$

where, L is the vector from AUV to the target node, v_{AUV} is the initial velocity of AUV, and v_f is the heave velocity of AUV. The vector from AUV to the target node is the synthesis speed v_s. The angle between the position of the target node and the heave velocity vector is β.

The realistic speed and direction of AUV could be obtained through the above formula (5) - (7). In this paper, the

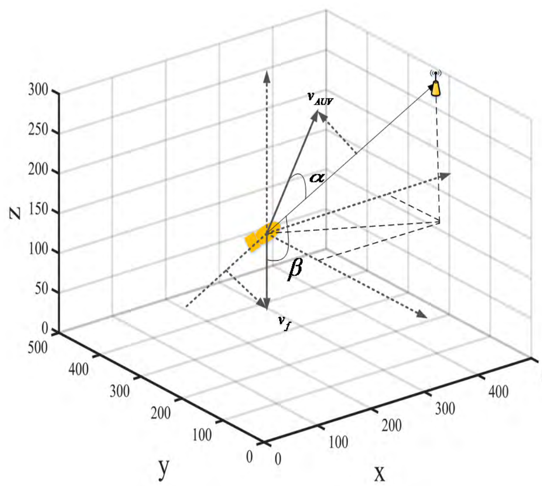

FIGURE 2. AUV 3D mobility model.

implementation of AUV mobility model is based on AUV controllable.

B. CLUSTER FORMATION BASED ON K-MEANS

The selection and clustering of target nodes are of great significance to reduce the network energy consumption. The target node is the cluster head, which is the node that AUV visits and collects data. Clustering is based on cluster heads. In this paper, target nodes selection method is proposed based on residual energy and distance of nodes. The target nodes selection method directly affects the performance of the overall network. Furthermore, the target nodes selection method is designed to run on the AUV and the collected data information includes residual energy of each node and distance between two nodes.

For clustering algorithm, K-means clustering algorithm is used for clustering, which is a typical distance-based clustering algorithm. It believes that clusters are made up of objects that are close to each other. It takes compact and independent clusters as target.

Bipartite K-means clustering algorithm is a special form of k-means, which can be applied in the node partition and then to form a sub-group structure in the underwater sensor networks. Bipartite K-means clustering algorithm is insensitive to the selection of initial clustering centers and easy to converge to the global optimal clustering. Hence, Bipartite K-means clustering algorithm is used in this paper. The method is described as follows:

(1) Two nodes are randomly selected as initial clustering centers, and K-means algorithm is used to obtain clustering results. Two subgroups are formed and their objective functions are calculated:

$$T = \frac{\sum_{i=1}^{k} \sum_{s \in X_i} \frac{\|s-c_i\|}{n}}{\|c_1 - c_2\|} \tag{8}$$

where, k is the number of clusters, here the number of clusters is 2; X_i is the NO. i ($i = 1, 2$) clustering subset; s is the sample point in X_i (sensor node); C_i is the center of NO. i cluster subset. The numerator of the objective function is used to compute the average distance between all sample points on their respective class centers. The denominator of the objective function represents the distance between two class centers. Obviously, the smaller the T value is, the better the effect of node partition is.

(2) Reselect randomly selected initial clustering centers and complete the clustering calculation N times, retaining the clustering results with the minimum T value as the subgroup structure of network partition.

The aim of this paper is to use clustering theory to divide the n sensor nodes in the underwater sensor network into several subgroups according to their space positions, as shown in Fig.5.

Definition 1: Subgroup, that is dividing n nodes into K node sets by clustering method, in which each node set becomes a sub-group.

In order to get the appropriate size subgroup structure for AUV to collect the data of nodes, it is necessary to continue clustering and node partitioning within sub-clusters by using bipartite K-means network until the size constraints satisfy the conditions. This process is called sub-cluster-based network partitioning.

Definition 2: Subgroup threshold, the maximum Euclidean distance between any two nodes in subgroup X, that is,

$$max\left(\|s_i, s_j\|\right), \quad s_i, s_j \in X \tag{9}$$

Definition 3: Size threshold, setting the communication radius R_{sen} of underwater sensor nodes.

Therefore, the clustering condition for underwater sensor networks is that the boundaries of all subgroup which are less than the size threshold. At this time, all nodes in the cluster can send data to the cluster head node.

The partitioning algorithm of underwater sensor network based on K-means is given in Algorithm 1.

Algorithm 1 Cluster Formation Based on K-Means

1: Setting all sensor nodes as initial subgroup X and setting size threshold R as input of the algorithm;
2: The initial sub-group X is clustered into two sub-groups by dichotomous K-means clustering, which divides the underwater sensor network into two sub-groups. This step includes the process of repeating clustering N times and retaining the clustering result with the minimum objective function value;
3: Determining whether the bounds of subgroups obtained in step (2) are less than the size threshold. If there are subgroups that do not satisfy the conditions, then the K-means clustering is continued;
4: When all subgroups satisfy the above conditions, the execution of the algorithm ends and the resulting subgroups are saved as output results.

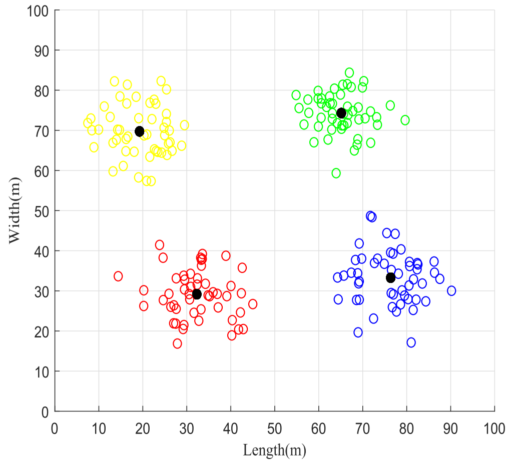

FIGURE 3. Example of clustering.

The most important thing in clustering method is to determine the number of clusters. Assuming that there are n nodes in the network and the number of initial clusters is k. In general, there are n/k nodes in each cluster. Cluster head nodes transmit data to AUV. The size of the network is $L * L * L$. According to [42], the optimal number of clusters is:

$$k = \sqrt{\frac{\wedge L}{\pi d}} \tag{10}$$

where d is the distance between nodes and the AUV.

After clustering, all member nodes send data to cluster heads. So the cluster heads consume the most energy, and we choose the node with the most residual energy as the cluster head in a cluster. In this way, the energy consumption of network nodes can be balanced. According to formula (2), the energy consumption of data transmission is positively correlated with distance. Through the above process, the member nodes send data to the cluster head and reduce the data transmission distance, so the total energy consumption of all nodes is the minimum. It can be expressed as follows:

$$argmin \sum_{s_i \in S} E_{send} \Rightarrow argmin \sum_{s_i \in S} (E_{collection} + E_{send}) \tag{11}$$

C. PATH SELECTION BASED ON AUV MOBILITY MODEL

After clustering, AUV collects data of target nodes through a mobility path. Most methods treat selection path as a traveling salesman problem (TSP), a class of NP hard problem [43] [44]. According to the mobility model, we use a greedy algorithm to collect data over a short period of time. We can figure out the distance between any two points in three dimensions by using Euclid's formula for distance [45]:

$$d(i-1, i) = \sqrt{(x_{i-1} - x_i)^2 + (y_{i-1} - y_i)^2 + (z_{i-1} - z_i)^2} \tag{12}$$

In this paper, the goal is not to find the shortest distance path. Instead, it is to find the path that takes the shortest time of data collection from AUV, as show in Fig.4. The AUV travels to target nodes in different positions, so the velocities

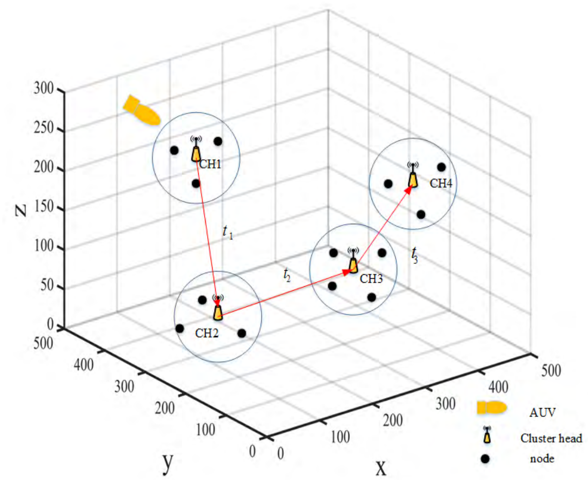

FIGURE 4. Example of path selection based on AUV mobility model.

of AUV are different. Therefore, the velocity of AUV could be calculated by combining the realistic mobility model. The velocity $v_{i-1 \to i}$ of AUV from position of node $i-1$ to position of node i could be obtain by using the realistic mobility model. t_i is the time when AUV accesses node i from node $i-1$ that could be obtained:

$$t_i = \frac{d(i-1, i)}{v_{i-1 \to i}} \tag{13}$$

Greedy algorithm is used to calculate the time cost between nodes, find out all possible data acquisition paths, and calculate the path that needs the shortest data acquisition time. The process is described as Algorithm 2.

Algorithm 2 Path Selection of AUV Alogorim

Require: The set of target nodes TN_s; the time t_i of from TN_{i-1} to TN_i
Ensure: Mintime
1: Initialization: mintime=0; the set T of total time
2: Define function(TN_s)
3: // Represents lines 3 to 13 of the algorithm
4: **while** $TN_i \in TN_s$ and $TN_s \neq \phi$ **do**
5: visit TN_i
6: mintime = mintime+t_i
7: // Visit to a target node, add the time spent visiting that node a to sum of time
8: remove TN_i from TN_s
9: **if** $TN_s \neq \phi$ **then**
10: function(TN_s)
11: // A recursive call to the function itself
12: add mintime to set T
13: // Add minimum time to time set T
14: **end if**
15: **end while**
16: **return** *argmintime*

In Algorithm 2, the shortest time is initialized and the time set of all paths is spent on the first line; in the second line, a function for paths selection is defined; in the fourth and fifth line, the AUV visits a target node TN_i, $TN_i \in TN_s$; in the sixth line, the time spent on visiting the node is accumulated; in the seventh line, the visited node is removed from the current target node set TN_s; in the eighth and ninth lines, the function of paths selection is executed iteratively, and the total time spent is added to the time set T. When all paths are traversed, the minimum time in the time set T is returned. The path that takes the shortest time is the best one.

Through the above process, we can find the path that takes the shortest time and collect data on this path. The shortest time for data collection to move could be expressed by the following formula:

$$\begin{aligned} T_{AUV} &= argmin \sum_{t_i \in T} t_i \Rightarrow \\ T_{total} &= argmin(T_{computation} + T_{AUV} + T_d) \end{aligned} \tag{14}$$

After each round of data collection, target nodes are updated.

D. ANALYSIS OF DCRTM

In this paper, clustering is based on mobile edge devices (AUV). Traditional algorithm is carried out in the cloud, because the cloud is far away from the edge devices. thus,

$$T_{edge} < T_{cloud} \tag{15}$$

where T_{edge}, and T_{cloud} denote the delay of the mobile edge computing, and the delay of cloud computing respectively. According to formula (5), we reduce the calculation delay, thus reducing data delay. In algorithm 1, the complexity of algorithm is related to the number of nodes. Assuming that there are k target nodes, the time complexity is $O(k * n)$ in the worst case. The time complexity is $O(n!)$ of traditional path planning TSP based on the greedy algorithm. In this paper, based on the mobile model of path planning, the time complexity of using greedy algorithm is $O(n!)$.

V. SIMULATION AND PERFORMANCE EVALUATION

A. SIMULATION SETTING

Simulation experiments are implemented on the MATLAB 2018a software. Some parameters utilization are given as follows. 150-550 sensor nodes are randomly distributed in the 400m*400m*400m monitoring area under the water. The acoustic transmission rate is set up 4kbps. Other environment Settings are shown in Table 2.

The simulation results are evaluated by analyzing the following indicators: PDR, the collection delay, the unit energy consumption and the network lifetime. Unit energy consumption is defined as the average energy consumption per node in each round when forwarding packets once. Network lifetime is defined as the elapsed time when the first node dies in the network. PDR denotes the ratio of packets successfully received by the AUV to the packets sent by all nodes.

TABLE 2. Simulation parameters.

Parameter	value
Network Size(L*W*H)	400m*400m*400m
Number of Nodes(|S|)	150-550
Sensed Range(R_{k-1})	50m-60m
Speed of AUV(V_{AUV})	2m/s
Packet Size(L)	1024bit
Data Rate(DR)	4kbps,6kbps,8kbps
Data Packets Generation Rate	100p/r per sensor
Node Initial Energy((E_0)	100J
Reception Power Consumption	$0.8*10^{-3}$ W
Transmission Power Consumption	$1.6*10^{-3}$ W
Power Consumption(idle)	$0.1*10^{-3}$ W

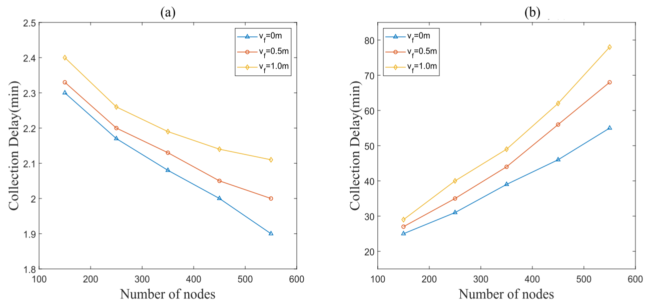

FIGURE 5. Simulation results with different heave velocities. (a) Unit Energy Consumption(J). (b) Collection Delay(J).

B. RESULT AND ANALYSIS

1) THE EFFECT OF AUV HEAVE VELOCITY

The AUV is influenced by its own gravity and buoyancy in the underwater environment, producing the heave velocity in vertical. In the simulation, we set three heave velocities to 0m/s, 0.5m/s, and 1m/s respectively, as shown in Fig.5(a). The relationship between unit energy consumption and the number of nodes is negative. When the heave velocities are different, the initial speeds and directions of AUV are different. This results in that the AUV will not move along the desired trajectory and consume unnecessary energy. The results show that the faster the heave velocity, the more energy the AUV consumes. Fig.5(b) shows the relationship between the data collection delay and the number of nodes is positive, and it also demonstrates that the greater the heave velocity is, more serious the data collection delay is.

2) THE EFFECT OF DATA RATE

The target nodes transmit the collected data to AUV, and the data transmission rate directly affects the data collection time of the AUV, because the data transmission rate of electromagnetic wave signal is 10Mpbs in the underwater environment. We set the data transmission rate to 10k, 20k and 40k respectively in the simulation. As shown in Fig.6(a), the relationship between the energy consumption of each node and the data transmission rate is negative. The higher data transmission rate is, the higher PDR is. The higher the transmission success rate is, the lower the energy consumes. Fig.6(b) shows that relationship between data collection delay and data transmission rate is positive. higher the data transmission rate is, the shorter the transmission time of packets is.

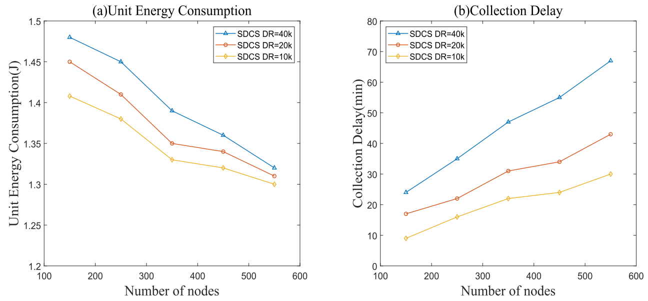

FIGURE 6. Simulation results with different DRs. (a) Unit Energy Consumption. (b) Collection Delay.

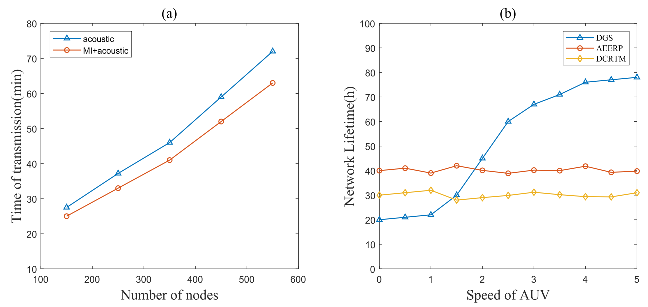

FIGURE 7. (a) Simulation results with different transmissions. (b) Simulation results with different speeds of AUV.

3) COMPARISON OF DIFFERENT DATA TRANSMISSION METHODS

Nodes range from 150 to 500, each node transmits data at 100p/r (packets per round), the data transmission rate of acoustic communication is 100bps, and the data transmission rate of magnetic induction (MI) is 10Mbps. The first data transmission method is acoustic communication. Both the member nodes transmit data to the target nodes and the target nodes transmit data to the AUV by acoustic communication. The second data transmission method is the combination of acoustic communication and MI. The member nodes transmit data to the target nodes by acoustic communication while the target nodes transmit data to the AUV by MI. According to Fig.7(a), it can be inferred that combination of acoustic communication and MI require less data transmission time than single acoustic communication method. As the number of nodes increases, the combined transmission mode reduces more transmission time than the single transmission mode. It's for the reason that the number of target nodes increases with the number of nodes increasing, the data transmission time between the target nodes and the AUV increases.

4) THE EFFECT OF SPEED OF AUV

Fig.7(b) shows the comparison of network lifetime among the DGS, AEERP, DCRTM by setting different speed of AUV. From Fig.7(b), when the speed of AUV is less than 1m/s, the network lifetime is unchanged in the DCRTM. After the AUV traverses the target nodes each round, the target nodes update dynamically. When the AUV speed is very small, the target node updates very slowly, and the network lifetime changes little. However, when the speed of AUV is greater than 1m/s, as the speed of AUV increases, the network time would increase until the speed of AUV is at approximately 4m/s. Then the network lifetime would remain unchanged in general. For the reason that when the speed of AUV is over 4m/s, updating target nodes are unable to increase network lifetime. According to Fig.7(b), we also could conclude that the network lifetime is still unchanged in the DGS and the AEERP, when the speed of the AUV changes, because gateway nodes consume more energy in both the DGS and the AEERP, and there is no relationship between updating gateway nodes and the speed of AUV.

5) COMPARISON OF DIFFERENT ALGORITHMS

We compare the proposed method with three common methods (CARP, Mobilcast, AEERP). All methods work in the same simulation environment. Fig.8(a) presents that the unit energy consumption changes with the number of nodes. The results show that the unit energy consumption of the proposed algorithm is less than CARP and AEERP but greater than Mobilcast. In addition, the unit energy consumption decreases when the node density increases.

Fig.8(b) shows relationship between the network lifetime and the number of nodes. The network lifetime of the proposed algorithm is longer than the other three algorithms at the same number of nodes. The proposed algorithm updates the target nodes each cycle, selecting the nodes with the higher energy as the target nodes. Hence, the proposed algorithm reduces the energy consumption when forwarding data to the target nodes and balancing the energy consumption of the network. The CARP consumes the most energy due to the multi-hop data collection scheme. The Mobilcast uses the AUV to collect data from each node, and could balance the energy consumption too. In the AEERP, member nodes send data to the gateway nodes, and AUV collects data of the gateway nodes. In the AEERP, AUV trajectory is fixed, and the gateway nodes change little, which increases the energy consumption of the gateway node greatly.

Fig.8(c) presents the data collection delay time of different methods. It is obvious that the delay time of the CARP is much lower than the other methods. The Mobilcast has the maximum data collection delay time, because it needs to visit all nodes and data is transmitted by single-hop or multi-hop acoustic signals. In the AEERP, the AUV has a fixed elliptical trajectory. Hence, the movement distance of the AUV is the shortest, which makes the data collection delay of AEERP less than that of Mobilcast and the proposed algorithm. The proposed algorithm enables the AUV to visit target nodes in the shortest time and reduces partial data collection delay. Furthermore, as the number of nodes and the amount of collected data increases, the data collection delay of all algorithms increases correspondingly.

Fig.8(d) shows the performance of different algorithms on the PDR. It is obvious that with more nodes, the network would be denser and the PDR would be higher. The PDR of the proposed method is higher than the VBF, the Mobilcast and the AEERP, because the data transmission method of all

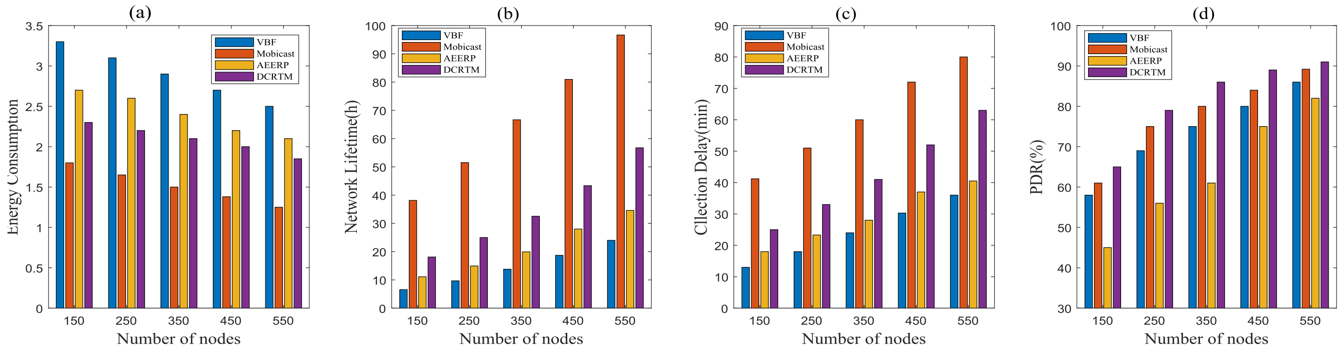

FIGURE 8. **Simulation results with different algorithms. (a) Unit Energy Consumption. (b) Network Lifetime. (c) Cllection Delay. (d) PDR.**

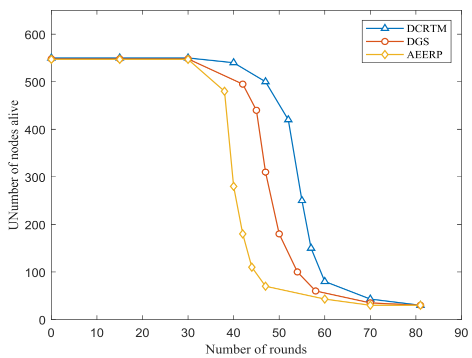

FIGURE 9. **The number of sensor nodes that are alive in the three algorithms.**

member nodes uses single-hop. The VBF uses the multi-hop to forward data, which undoubtedly increases the probability of packet loss through the higher number of hops. In the Mobilcast, the AUV visits all monitoring areas, but part of nodes still forward the data by multi-hop, which increases packet loss. In the AEERP, the AUV has a fixed movement trajectory, and nodes forward the data to gateway nodes by multi-hop or single-hop.

6) THE NETWORK LIFETIME OF DIFFERENT ALGORITHMS

Fig.9 shows the comparison of network lifetime among the DGS, AEERP, and DCRTM. According to Fig.9, we conclude that death time of the first node in the DCRTM is later than the DGS and AEERP. Therefore, the network lifetime of the DCRTM is higher than the DGS and AEERP, because the proposed method selects target nodes based on residual energy of nodes and distance among nodes. We need to select appropriate *TNs* with more residual energy relatively, because *TNs* are responsible for collecting data from their member nodes and transmitting them to the AUV. In order to avoid making the *TNs* die early, we update *TNs* at each round, and nodes with more energy would be more possible to become the target nodes.

VI. CONCLUSION

In this paper, we propose a new data collection scheme based on the realistic model of mobile edge elements. In the realistic mobility model, the mobility direction and velocity are fully considered, making the mobility characteristic of AUVs close to the realistic underwater environment. It provides the mobile edge computing service and data collection service by making full use of computing, storage, and mobility abilities. Then a target node selection algorithm is designed for the AUV, enabling the AUV to visit all nodes in the shortest time and balancing energy consumption of the whole network. The simulation results show that the realistic mobility model could reduce the energy consumption, extend the network lifetime and improve the package delivery ratio. Therefore, there is of great potential for mobile edge elements to provide mobile computing services and underwater data collection services in the mobile underwater environment.

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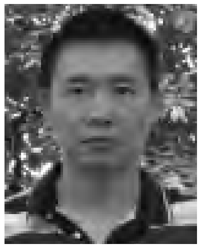

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