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A Hierarchical Information Acquisition System for AUV Assisted Internet of Underwater Things

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ABSTRACT As an extension and novel category of the Internet of Things (IoT), the Internet of Underwater Things (IoUT) attracts growing interest in sensing and exploiting ocean. Underwater Sensor Networks (UWSNs) are the existing application to support the concept of IoUT but faced with many challenges in information acquisition as well. To tackle these issues, this paper proposes an autonomous underwater vehicle (AUV) assisted hierarchical information acquisition system composed of a marine stationary sensor layer and an AUV motion layer. Different from the most existing data-gathering schemes that ignored the energy management of underwater sensor nodes and the angle control in AUV operation, this work designs an energy-aware clustering protocol based on the improved K-Means algorithm (ECBIK) to achieve energy efficiency of sensor nodes and proposes a novel Ant Colony (ACO) algorithm integrating with Markov Reward Process (R-ACO) to optimize the distance and angle in AUV path planning. Specifically, in the sensor layer, we first calculate the accurate number of clusters according to the Elbow method, and then introduce a cluster head dynamic conversion mechanism by considering energy load and node survival rate. In the AUV motion layer, we establish a reliable AUV trajectory model to quantify the angle change during its operation. Meanwhile, we apply far-sighted feature of MRP to path optimization. Finally, simulation results validate the performance of our designed algorithms. Compared with the traditional clustering methods of K-Means and LEACH-L, the node survival rates of the proposed ECBIK are increased by 26% and 129.1% respectively. And in the aspect of path planning, the distance and angle under R-ACO are reduced by 4% and 18% respectively compared with ACO.

INDEX TERMS Internet of Underwater Things (IoUT), Underwater Sensor Networks (UWSNs), autonomous underwater vehicle (AUV), hierarchical information acquisition, clustering, AUV path planning.

I. INTRODUCTION

In the last few decades, the Internet of Things (IoT) plays an increasingly important role in many fields [1]–[3]. More and more physical objects are interconnected with the Internet to satisfy the wide-ranging applications in our daily lives. Nowadays, with the skyrocketing demands for marine detection and exploitation, the researchers set out to explore the possibility of applying the IoT technology underwater. As response, the concept of the Internet of Underwater Things (IoUT) was first discussed in 2010s [4] and defined as an extension and novel category of the IoT, which promises to establish intelligent interconnection of underwater objects [5], [6] and realize the smart ocean [7], [8]. Due to the unique characteristics of the ocean, the Land-based IoT technology cannot be applied directly. Additionally, the low transmission quality of underwater acoustic communication in the vast ocean area has posed considerable challenges to reliable information acquisition for IoUT [9]. In fact, Underwater Sensor Networks(UWSNs) have been verified as promising paradigm for the application of IoUT. As the primary component of UWSNs, the cable-connected sensor networks are still frequently-used in underwater communication due to its easy operation [10]. However, the wired communications have been criticized for its costly deployment. Furthermore, multi-hop relaying transmission technique has been

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proposed as an optimized alternative for underwater data collection by using buoy floating at the specific depth [11]. Although this method achieves long-range underwater acoustic communication from the seabed to the surface, the unstable communication links and weak robustness still exist obviously. Thus, the demand for applying a mobile sink appears [12]. As a typical model, an autonomous underwater vehicle (AUV) sails to visit anchored sensor nodes and establishes a short-range stable communication link, finally offloads the retrieved information back to the designated location [13].

Currently, AUV is expected to build a bridge between the sea surface and the seabed for sensing the ocean [14]. Especially in AUV assisted IoUT, AUV and underwater sensor nodes construct a hierarchical architecture and use variety technologies to transmit the gathered information to the surface for data mining. In such case, sensor nodes are clustered according to certain properties, and a part of them are chosen as cluster heads (CHs), which are mainly engaged in aggregating and fusing data originating from the common nodes (CNs). As a dynamic node, AUV only needs to visit these few CHs rather than all the nodes to save the traversal time and energy overhead. However, there remains two challenges: Firstly, the energy management of sensor nodes is essential in such model, since the energy storage of node is seriously restricted and batteries cannot be readily recharged due to bottleneck of ocean pressure and erosion [15], [16]. Considering the selected CHs undertake more tasks, they have more energy consumption than other nodes. Hence, the efficient energy management must be adopted for such hierarchical information acquisition especially for CHs. Secondly, AUV cruise path selection imposes directly influence on the performance and efficiency of the system. The common practice is to formulate the path length as a primary indicator when tackling such problem. Actually, under the influence of various underwater forces, the movement of AUV is complicated and consists of at least six actions including traverse, heel, heave, turn, trim as well as advance and retreat. For these actions, angle control is crucial [17]. In [18], it is mentioned that the US Naval Research Institute found that AUV in motion has huge moments of inertia and requires much energy to change its direction of movement, which verifies the significance of angle control. Accordingly, considering the impact of heading angle is also essential in AUV path planning. In addition, we should fully consider the obstacle avoidance during AUV movement in the complex and varied underwater environment.

In summary, the wired communications are too expensive to be widely used, and the underwater acoustic multi-hop transmission is subject to link instability and large delays in long distances communication. A promising solution to address these issues is to use a highly mobile AUV as dynamic node to transmit with certain CHs anchored on the seafloor. However, most AUV assisted schemes not only neglect the energy management of underwater sensor nodes, but also omit the angle control during AUV movement. Therefore, we designed an energy-aware clustering protocol based on the improved K-Means algorithm (ECBIK) for UWSNs, which achieves energy balance by adding CH Dynamic Conversion (CHDC) mechanism. Meanwhile, to solve the Traveling Salesman Problem (TSP) with obstacles, we introduce MRP in the ACO algorithm to optimize the patrol distance and angle in AUV path planning. We summarize the main contributions of our work as follows:

- We design an autonomous underwater information acquisition for AUV assisted IoUT based on hierarchical framework. To be specific, we construct a realizable scene for portraying the characteristics of the sensor nodes and AUV, as well as the unique communication conditions with obstacles.
- For the problem of energy management of underwater sensor nodes, we propose an energy awareness clustering protocol based on improved K-Means algorithm for UWSNs. Specifically, we design the CHDC mechanism by considering the node location and its residual energy, which can balance the energy load effectively to extend the life of the network.
- We utilize the kinematic equations to indicate the AUV trajectory for executing trackable analysis of the path planning problem, which is the first time that the AUV control theory is applied in the information acquisition. Additionally, the rotation-angle of AUV and its influence has been quantified based on its dynamic characteristics.
- For AUV path planning, we propose a novel ACO algorithm based on MRP, namely R-ACO algorithm, which aims at optimizing the patrol distance and angle with faster convergence speed in TSP scenario.

The remainder of this paper is organized as follows. Section II reviews some typical works in this field, Section III establishes the system model and problem formulation. The energy aware clustering algorithm and the AUV path planning scheme are detailed in Section IV. The simulation verification on the proposed algorithms has been carried out in Section V, and all the conclusions are presented in Section VI.

II. RELATED WORKS

In recent years, more and more researches focus on stable underwater data collection and reasonable path planning of AUV in UWSNs [19]. Current mainly researches have generally been divided into two categories. The first type is that the trajectory of AUV is fixed. Such as in [20]–[22], the authors assumed that the trajectory was ellipse. In [20], the fixed Gate Nodes (GNs) were used to collect data from member nodes (MNs), while transmitting data to the moving AUV to strengthen the network performance, especially in data delivery ratio and energy consumption. However, the rapid energy exhaustion of GNs leaded to a shortened network life. In [21], a new clustering protocol was designed based on the Received Signal Strength Indicator (RSSI) value. Meanwhile, the Shortest Path Tree (SPT) was established to assign MNs to GNs. Moreover, the role of the gateways was varied according to the residual energy for balancing the energy consumption. However, this approach did not constrain the number of MNs communicated with GNs, resulting in data flooding and excessive energy consumption. As an improvement of [21], [22] proposed a GN selection scheme based on dynamic data acquisition time, and a MILP model was formulated to restrict the assignment of MNs. Authors in [23] regarded the magnetic-induction as a significant standard for reduction of energy consumption in the AUV data collection and designed a distributed algorithm to select sink sensor sets in information collection. However, due to the fixed trajectory of AUV motion, the nodes for data transmission with AUV remained unchanging, leading to increasing their burden and shortening the network life. On the other hand, from the perspective of practice, the dynamic advantages of AUV were not fully exploited.

AUV path planning is another hot topic in UWSNs. Generally, most works take distance as the object of optimization. In [24], the authors utilized the classical Dijkstra algorithm to solve the single-source shortest path problem. Furthermore, as an essential metric of Quality of Information (QoI), the transmission delay was taken into account in [25]–[27]. The authors solved the possible delay problem during AUV traversal through different schemes to achieve the target of path optimization. Apart from the above, the Value of Information(VoI) in [28]–[30] has been used as a significant indicator to measure QoI from the perspective of event importance. Usually, the approaches were to treat this question as ILP problems and sought a heuristic answer, such as in [28]. Under different scenarios, the authors considered the timeliness of VoI in the AUV data collection process. Especially in [29], the event significance and promptness were treated as a linear combination for VoI while solving the AUV path optimization problem through a dynamic programming protocol. In [30], Duan et. al, enriched the definition of VoI and proposed an effective information collection system for UWSNs based on the importance, timeliness, and their relationships of the event. But these works did not take into account the angle control in the AUV movement. Moreover, the authors in [31] paid attention to this issue by qualitatively demonstrating the importance of angle for the AUV path selection. Nevertheless, this work did not clarify how to calculate the angle, so this problem has not been fully solved.

In order to efficiently complete the energy management of sensor nodes to extend the life of the network, and give full play to the dynamic characteristics of AUV to achieve the goal of path optimization in the underwater obstacle environment, this work designs an energy-awareness clustering algorithm by introducing CHDC mechanism. Meanwhile, a novel heuristic algorithm with considering the traversal distance, angle and obstacles is proposed based on MRP.

III. SYSTEM MODEL

We first illustrate the proposed system, including the overall architecture and network energy consumption. For the sake of clarity, we make the following hypotheses:

- The AUV has infinite resources, such as energy, storage space, and computational ability. Moreover, its velocity is constant.
- The anchored sensor nodes are randomly distributed on the seabed, and their positions can be known. Furthermore, they have the same initial energy and data processing capabilities.

A. NETWORKS STRUCTURE

As shown in Fig. 1, we depict the system framework and operational mode. We establish an information acquisition system which consists of a sensor layer anchored on flat seafloor and an AUV motion layer above the seafloor. The sensor layer is comprised of multiple sensor nodes anchored on the seabed, and the sensor nodes are divided into several clusters to collect underwater information. Each cluster contains a CH and a set of CNs. CNs are responsible to collect underwater information and transmit the collected data to the CH. Meanwhile, the CH is in charge of aggregating the data and forwarding them to the AUV. In AUV motion layer, an AUV moving in uniform motion periodically communicates with CHs to retrieve the collected information on the plane which is h meters above the seabed. AUV starts from the base station and returns to discharge the collected data after traversing all the CHs, and then by way of maritime wireless transmission or satellite transmission, the base station sends the data to the shore-based processing center. The algorithms for the clustering sensor nodes and the AUV path planning scheme will be introduced in detail in Part IV.

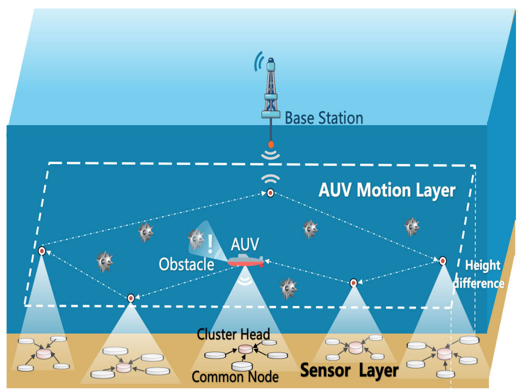


FIGURE 1. A paradigm of the hierarchical information acquisition for AUV assisted IoUT. Sensor nodes anchored on the seafloor are clustered for collecting underwater information. The white nodes are MNs, and the red nodes are CHs. On a plane which is *h* meters above the seabed, an AUV moving in uniform motion communicates with CHs, and finally retrieves the collected information back to the base station.

B. UNDERWATER ACOUSTIC CHANNEL MODEL

In this paper, we adopt the underwater acoustic channel model based on [32]. Assuming that the power required by a node to receive a single message is at least p_0, to ensure the node at a distance of x can receive the data, the transmission power should be at least $p_0 A(x, f)$, where $A(x, f)$ is an attenuation. Therefore, we can deduce when sending T bits of data to the destination, the power consumption is at least $E_t(T, x)$, which can be expressed by:

$$E_t(T, x) = Tp_oA(x, f). \tag{1}$$

The attenuation $A(x, f)$ is given by [33]:

$$A(x, f) = x^k a^x, \tag{2}$$

where k is the energy propagation coefficient associated with underwater acoustic propagation ($k = 1.5$ represents the actual underwater acoustic propagation model), and $a = 10^{a(f)/10}$ is the term associated with frequency and derived from the absorption coefficient $a(f)$. According to Thorp's expression [34], $a(f)$ is calculated by:

$$10\log(a(f)) = 0.11\frac{f^2}{1+f^2} + 44\frac{f^2}{4100+f^2} + 2.75\times10^{-4}f^2 + 0.003. \tag{3}$$

The ambient noise in underwater acoustic channel can be modeled by four basic sources as follows:

$$N(f) = N_t(f) + N_s(f) + N_w(f) + N_{th}(f), \tag{4}$$

where $N_t(f)$, $N_s(f)$, $N_w(f)$ and $N_{th}(f)$ represent the main underwater noisy sources: turbulence, shipping, waves, and thermal noise respectively. Besides, these noise in dB re μPa per Hz can be expressed by the following empirical formulae:

$$10\log N_t(f) = 17 - 30\log f, \tag{5a}$$

$$10\log N_s(f) = 40 + 20\left(s - \frac{1}{2}\right) + 20\log f - 40\log(f+0.4), \tag{5b}$$

$$10\log N_w(f) = 50 + 7.5w^{\frac{1}{2}} + 20\log f - 40\log(f+0.4), \tag{5c}$$

$$10\log N_{th}(f) = -15 + 20\log f, \tag{5d}$$

where s is the shipping activity factor in range of [0, 1], and w denotes the wind speed in m/s. Actually, the nominal signal-to-noise ratio (SNR) is affected by the attenuation $A(x, f)$ and the noise $N(f)$, it can be formulated as:

$$\zeta(x, f) = \frac{1}{A(x, f)N(f)}. \tag{6}$$

Note that the underwater transmitter and receiver are narrowband applications, we can use the optimal frequency $f_o(l)$ and the corresponding SNR $\zeta_o(l)$ to donote the definition of the narrow-bandwidth in the underwater acoustic channel. Moreover, we define the frequency range as $[f_L(x), f_U(x)]$, and the corresponding narrow-bandwidth $B = f_U(x) - f_u(x)$. For short distance transmission systems, the transmission distance is less than 1 km, and the practicable 3-dB frequency range is dozens of KHz. Therefore, we calculate the lower bounds function of SNR for underwater acoustic channel as follows:

$$\tilde{\zeta}(x) = \begin{cases} \min\left\{\zeta\left(x, f_c - \frac{B}{2}\right), \zeta\left(x, f_c + \frac{B}{2}\right)\right\} & f \in B \\ 0 & \text{Otherwise,} \end{cases} \tag{7}$$

where $\tilde{\zeta}(x)$ is the replacement of the true SNR function $\zeta(x, f)$ for idealized, and f_c represents the center frequency. Based on additive white Gaussian noise (AWGN) channel, the capacity of the underwater acoustic channel can be formulated by:

$$R(x) = B\log_2\left(1 + \frac{P_{sl}\tilde{\zeta}(x)}{B}\right), \tag{8}$$

where P_{sl} is the transmitted power in dB re μPa. For the sake of translating the electrical power P_t in Watt to the underwater acoustic power P_{sl}, the empirical relations are applied as follows:

$$P_{tr} = \frac{2\pi}{\sigma} \times H \times I_T, \tag{9}$$

$$P_{sl} = 10\frac{I_T}{1\mu\text{Pa}}, \tag{10}$$

where σ denotes the overall efficiency of the electronic circuitry, and H represents the depth of water, $1\mu\text{Pa} = 0.67 \times 10^{-18}$ Watts/m^2 while I_T is the intensity at the reference distance of 1m from the source.

C. SENSOR LAYER

We assume that N nodes are randomly anchored in the designated area to detect underwater environments. During the information gathering process, all nodes are classified into several clusters according to certain properties, which are composed of CHs and CNs. As mentioned above, each node has the equal initial energy denoted by E_0. Besides, it will consume the energy of nodes when transmitting, receiving, and processing data.

In view of the diverse operating modes of CHs and CNs, we can calculate their energy consumption respectively. We take a cluster as an example for illustration. Firstly, we analyze the energy consumption of the single CH, which composed of the following four parts. The first part of energy consumption is caused by CH broadcasting information including its location and ID. As such the nodes adjacent to the CH in the same cluster will take notice of the CH's existence at the initial phase of data collection. The other three parts are the energy consumption of receiving original data, fusing original data, and sending the processed data to AUV during the data transmission phase. We define the above four energy consumption as E_{br}, E_r, E_f, and E_s separately. According to (1) and (2), E_{br} can be given by:

$$E_{br} = l_b p_0 {d_b}^{1.5} a^{d_b}, \tag{11}$$

where l_b is the broadcast packet size of CH, and d_b indicates the broadcast distance. The energy consumption of receiving data E_r can be expressed as:

$$E_r = \sum_{i=1}^{j} T_i \times P_r, \tag{12}$$

where $T_i = R(d_i)t_i$ represents data size received by the CH from the i-th CN in the cluster, and d_i represents the distance from i-th CN to CH. t_i is the transmission time, which can be calculated as:

$$t_i = \frac{V_s}{d_i}, \tag{13}$$

where V_s is the underwater sound velocity, and it is usually equal to 1500 m/s. P_r is a constant depending on the property of the sensor itself.

In most current researches, the energy consumption of sensor data fusion is regarded as a constant or simply ignored, which is quite different from the actual condition. Therefore, this work adopts the weighted-average fusion method mentioned in [35].

Considering that there are j CNs in the cluster collecting information from the underwater environment independently, the size of data they collected is T_i. The CH will aggregate these data and process them to avoid the conflicts of redundant data. We define the size of all data after fusion as T_f, and it can be given by:

$$T_f = \sum_{i=1}^{j} w_i T_i, \tag{14}$$

where T_f represents the size of the fused data by CH, and w_i is the weighted coefficient and meets the following condition:

$$\sum_{i=1}^{j} w_i = 1. \tag{15}$$

We assume that the weights of data collected from each CN are approximately equal, and according to (15), we can find $w_i = \frac{1}{j}$ so that it can be updated by:

$$T_f = \frac{1}{j} \sum_{i=1}^{j} T_i. \tag{16}$$

Therefore, E_s can be calculated by:

$$E_s = T_f p_0 h^{1.5} a^h, \tag{17}$$

where h is the height difference. And the data processing energy consumption E_f can be expressed as:

$$E_f = E_{DA} \times \sum_{i=1}^{j} T_i, \tag{18}$$

where E_{DA} represents the energy consumption of the sensor when processing one single data, it can usually be set as 5 nJ/bit.

Given the above assumptions, the energy consumption of the CH in a cluster can be calculated as:

$$E_{ch} = E_{br} + E_r + E_f + E_s. \tag{19}$$

Regarding to the energy consumption of a CN, it is mainly consumed while transmitting the collected data to CH and receiving the broadcast beacon from CH in the cluster. We define it as E_{cn}, which can be expressed as:

$$E_{cn} = T_i p_0 d_i^{1.5} a^{d_i} + l_b P_r. \tag{20}$$

Consequently, the energy consumption of all CNs in a cluster can be expressed as E_{cn}^t, and it can be calculated by:

$$E_{cn}^t = \sum_{i=1}^{j} T_i p_0 {d_i}^{1.5} a^{d_i} + j l_b P_r. \tag{21}$$

D. AUV MOTION LAYER

As a dynamic relay node, the AUV travels from a base station, patrols all CHs to retrieve, transport, and offload the collected data. When the AUV reaches and hovers over one CH in a corresponding position, an underwater acoustic communication link is immediately established to receive information from the CH. After the assignment, the AUV will navigate to the next CH and implement the information gathering process recurrently. Meanwhile, we also need to tackle the obstacle avoidance issue of AUV in traversal. Therefore, we first denote the environment with obstacles based on a grid map, as shown in Fig. 2. The black object indicates that the position cannot be traversed directly by AUV, and the red dot indicates the corresponding position where the AUV and CHs communicate with each other. Specifically, we employ E to depict the environment. When E_{ij} is equal to 1, it means there is an obstacle between position i and position j. Conversely, 0 means no obstacles.

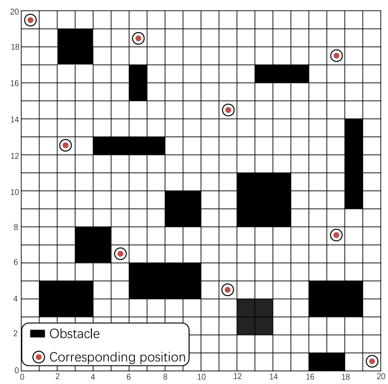


FIGURE 2. Map of the AUV environment. The black object indicates the obstacle, and the red dot indicates the corresponding position where the AUV and CHs communicate with each other.

In such AUV motion layer, we consider the AUV path planning in the horizontal direction and establish a kinematic model to indicate the movement of AUV, as shown in Fig. 3.

The position vector η and velocity vector υ are utilized to denote the trajectory of the AUV:

$$\begin{cases} \eta = [x, y, \varphi]^T, \\ \upsilon = [u, v, \omega]^T, \end{cases} \tag{22}$$

where x and y are coordinates of the AUV position, φ is its direction of travel. While u, v, and ω represent the surge velocity, sway velocity, and yaw velocity, respectively. We define θ to be the angle between the vector $\overrightarrow{ij}$ and the horizontal direction. Additionally, we call the angle between φ and θ as the rotation-angle of AUV in position i to position j,

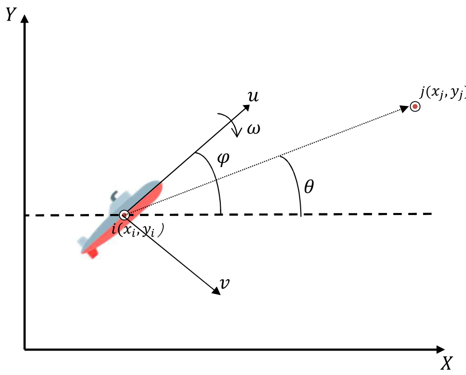


FIGURE 3. The motion of AUV in the horizontal direction.

which indicates the degree of the changed corner in AUV motion, and it can be expressed as:

$$r_{ij} = \varphi - \theta = \varphi - \arctan \frac{(y_j - y_i)}{(x_j - x_i)}. \tag{23}$$

The trajectory of AUV can be calculated by [36]:

$$\eta_{t+1} = J(\eta)\upsilon, \tag{24}$$

where η_{t+1} is the location of the next moment, and $J(\eta)$ is the kinematic transformation matrix related to φ, it can be expressed as:

$$J(\eta) = \begin{pmatrix} \cos\varphi & -\sin\varphi & 0 \\ \sin\varphi & \cos\varphi & 0 \\ 0 & 0 & 1 \end{pmatrix}. \tag{25}$$

Since we have assumed that the value of AUV velocity is constant, we can easily calculate the position of AUV at the next moment based on its speed and current location. Hence, the path planning problem can be formulated as:

$$\min \sum_{i,j \in route} d_{ij} + \xi \sum_{i,j \in route} \left(\varphi - \arctan \frac{(y_j - y_i)}{(x_j - x_i)} \right), \tag{26}$$

where ξ is a constraint factor to represent the weight of the rotation-angle, d_{ij} indicates the distance between position i and position j, and *route* is the path of AUV travel.

IV. ALGORITHM DESIGN

In our model, CHs are not only responsible for aggregating and fusing underwater information, but also need to communicate with the AUV. At the same time, the selected CHs are still the inevitable position in the subsequent AUV cruise. The key steps of our proposed technique are explained as Fig. 4.

A. CLUSTERING ALGORITHM

K-Means algorithm is a compelling clustering technique and widely used in practical applications [37], [38] and the K is a hyper-parameter that usually needs to be optimized to get the best results and performance for learning [39]. Usually, K-Means algorithm chooses the number of clusters randomly. However, in our model, the number of clusters is crucial.

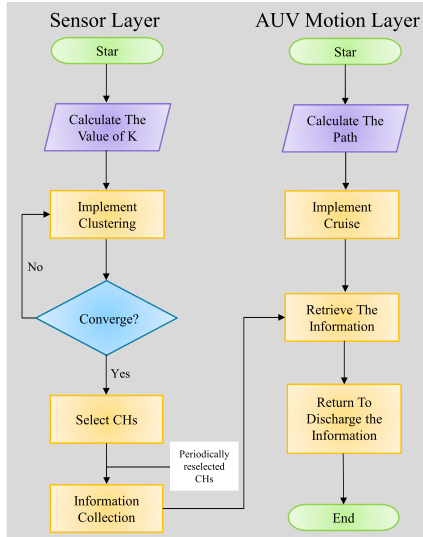


FIGURE 4. The flowchart of AUV assisted IoUT technique.

If the number is too small, excessive underwater nodes will be divided into a cluster, resulting in a large amount of redundant information and increasing the burden of CH. If the number is too large, it means that the mobile node needs to perform data transmission with more CHs, resulting in more energy overhead and system latency. In view of the above, we determine the number of cluster k based on the Elbow method [40]. For a set of n objects, we add the number of clusters from 1 to n one by one, and record the corresponding Sum Squares Error (SSE) value simultaneously, which is the sum of the Euclidean Distances from each object to its corresponding cluster centroid. It can be calculated by:

$$SSE = \sum_{i=1}^{k} \sum_{x \in C_i} \|x - \overline{x_i}\|_2^2, \tag{27}$$

where C_i indicates the set of all objects in the cluster, x and $\overline{x_i}$ are the coordinate vectors of an object and the centroid, k is the amount of clusters. In addition, we define ΔS as the difference of SSE produced by two adjacent k. When the difference value between two adjacent ΔS changes drastically and forms an obvious corner, then the inflection point is exactly k. This process can be given by:

$$k = \underset{k}{\text{argmax}}\ \Delta S(k) - \Delta S(k+1). \tag{28}$$

After determining the number of clusters, we use the value of SSE as the standard measure function, and constantly update the centroid to achieve clustering the nodes until satisfying the convergence condition. The centroid update function can be given by:

$$\overline{x_i} = \frac{1}{|C_i|} \sum_{x \in C_i} x, \tag{29}$$

and the convergence condition can be expressed as:

$$|SSE_1 - SSE_2| < \varepsilon, \tag{30}$$

where ε is a minimal value, SSE_1 and SSE_2 indicate the current measure function value and the preceding measure function value respectively. After that, we select the node closest to the centroid as the initial CH, which is responsible for information collection and transmission to AUV. To avoid CHs becoming invalid rapidly, we introduce the CHDC mechanism. After the first round of data collection, we reselect the new CHs for clusters at the initial phase of each subsequent round. We define the probability of node s becoming the CH as $T(s)$, whose range is (0, 1), and it can be calculated by:

$$T(s) = \begin{cases} \dfrac{1}{1+e^{-(w_1 d_s + w_2 E_j + \lambda)}}, & \text{if } s \in G, \\ 0, & \text{otherwise.} \end{cases} \tag{31}$$

G represents the set of nodes which are not selected as CH in the previous round, w_1 and w_2 are the weighted coefficients, d_s is the reciprocal of the distance between the node and the centroid, E_j indicates the ratio of the residual energy to the initial energy of the node, and λ is the bias constant. As we can see, when d_s and E_j approach infinity, $T(s)$ is approximate to 1, that is, the node which is closer to the centroid with more residual energy will be selected as the new CH. Therefore, it manifests that the proposed clustering protocol has energy-awareness. The above clustering process is performed periodically.

The clustering algorithm is detailed in Algorithm 1.

Algorithm 1 Energy Aware Clustering Protocol Based On the Improved K-Means Algorithm

Initialize the $maxround$, n, D, l_d, l_f, E_0, E_f, T_i, p_r, p_0, w_1, w_2, f, w and s.
for each $k \in [1, n]$ **do**
  Calculate K-Means SSE slop S by (27) then
  Record S list $[S_1, S_2, \cdots, S_n]$.
  for each $k \in [1, n-1]$ **do**
    Calculate $\Delta S_k = S(k) - S(k+1)$ then
    Record ΔS list $[\Delta S_1, \Delta S_2, \cdots, \Delta S_{n-1}]$.
    Calculate the value of k by (28).
    Use k as the cluster number.
  end for
end for
Cluster nodes by (27), (29), and (30), then find the node closest to centroid as CH.
for each round $\in [1, maxround]$ **do**
  Calculate each alive CNs energy consumption by (21).
  Calculate CH energy consumption by (19).
  Refresh CH candidate list.
  for each node in head candidate list **do**
    Calculate head reselect threshold $T(s)$ by (31).
    if random number $\leq T(s)$ **then**
      Set node as CH.
      Remove node from CH candidates.
    end if
  end for
end for
End.

B. PATH PLANNING ALGORITHM

The ACO algorithm is a heuristic algorithm inspired by the actual foraging behavior of ant colony [41], and it is often used to tackle path planning problems in TSP model because of its strong robustness, easy implementation, and convenient combination with other algorithms to improve performance [42]. However, the traditional ACO algorithm only considers the pheromone in the current state and neglects the influence of pheromones in subsequent states. Therefore, the ACO algorithm has the drawback of low solving efficiency and is prone to a local optimum. Moreover, conventional path planning problems usually overlook importance of angle optimization. To address the above issues, we propose a novel ACO algorithm based on the MRP, namely R-ACO algorithm, which owns far-sighted evaluation compared with traditional ACO.

The MRP is introduced by Howard [43], which is a Markov chain with values [44]. Specifically, when the system transforms from a state s to another state s', it can obtain a timely expected reward and the discounted value of the subsequent states. This process aims to maximize the expected cumulative reward to guide the system in making optimal decisions, and it can be expressed as:

$$v(s) = R_s + \gamma \sum_{s' \in S} P_{ss'} \upsilon\left(s'\right). \tag{32}$$

The tuple of (S, υ, R, P) is utilized to depict the properties of MRP, where S, υ, R, P are the set of states, the value, the reward, and the state transition probability respectively. γ is a discount factor in range of [0, 1), which determines the importance of future rewards. When γ closes to 0, it leads to myopic evaluation, namely the result may only be local optimum rather than the global optimum. When γ closes to 1, it leads to far-sighted evaluation. However, the future rewards cannot be estimated accurately. Therefore, the typical value of γ is within [0.5, 0.99] [45]. In this paper, we set it to 0.6.

Afterwards, we assume that there are n patrol locations and N_{ant} ants. Let $\tau_{ij}(t)$ denote the remaining intensity of pheromone between position i and position j at time t. Therefore, at time t, the transfer probability of ant k can be calculated by:

$$p_{ij}^k(t) = \begin{cases} \dfrac{\left[\tau_{ij}(t)\right]^\alpha \left[\eta_{ij}(t)\right]^\beta}{\sum\limits_{s \in n(i)} \left[\tau_{is}(t)\right]^\alpha \left[\eta_{is}(t)\right]^\beta}, & j \in n(i) \\ 0, & \text{others.} \end{cases} \tag{33}$$

$n(i)$ is the set of neighbors at position i, α denotes the weight of pheromone, and β denotes the weight of heuristic factors which can be formulated as:

$$\eta_{ij}(t) = \frac{1}{d_{ij}} + \frac{1}{r_{ij}}. \tag{34}$$

Algorithm 2 ACO Based On Markov Reward Process Algorithm

Initialize the *maxround*, τ_{ij}, *ant_count*, α, β, ρ, γ, Q_1, Q_2.
for each generations $\in [1, maxround]$ **do**
  for ant$k \in [1, ant_count]$ **do**
    Set the ban set C as the position node of ant k, and set it to null.
    while C is not full **do**
      Calculate the probability of ant k moving to position j by (33).
      Add location j to C and move the next location.
    end while
    Revise the pheromone table pursuant to (35), (36), and (37).
  end for
end for
End.

After all ants traverse for once, the pheromone on each path can be updated as follow:

$$\tau_{ij}(t+1) = (1-\rho)\,\tau_{ij}(t) + \Delta\tau_{ij}, \tag{35}$$

where ρ is the volatilization coefficient in the range of (0, 1), which determines the amount of reduction in pheromone concentration over time, $\Delta\tau_{ij}$ represents the amount of pheromone increase after once iteration, which can be calculated by:

$$\Delta\tau_{ij} = \sum_{k=1}^{m} \Delta\tau_{ij}^{k}, \tag{36}$$

where $\Delta\tau_{ij}^{k}$ is the contribution of an ant k to $\Delta\tau_{ij}$. Then, we consider both distance and angle in the pheromone update equation and combine the properties of MRP. As such, the $\Delta\tau_{ij}^{k}$ can be expressed as:

$$\Delta\tau_{ij}^{k} = \frac{Q_1}{d_{ij}} + \frac{Q_2}{r_{ij}} + \gamma \sum_{\substack{s\in n(j)\\ s\neq i}} P_{js}\Delta\tau_{js}^{k}, \tag{37}$$

where Q_1 and Q_2 are the constants, and the state transition probability P_{js} is equal to the probability that ant k moves at next time, γ is the discount factor in range of [0, 1), which depicts the importance of pheromone concentration in the future state. The detailed algorithm is shown in Algorithm 2.

V. SIMULATIONS AND ANALYSIS

This part presents the numerical results to validate the performance of our algorithms.

First, we set the parameters of the experimental scenario. We assume that a total of 120 nodes are distributed in a square area of 500m × 500m under shallow water. The base station is located above the area. The height difference between the sensor layer and the AUV motion layer is 20m. The underwater transmission frequency $f = 25$kHz. The remaining parameters are detailed in Table 1.

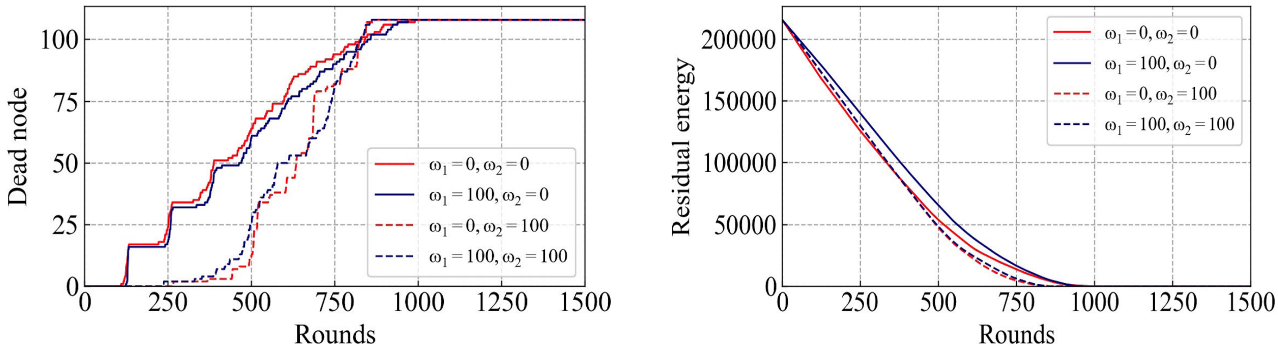
TABLE 1. Detailed System Parameters.

Parameters	Value	Parameters	Value
Minimum transmitted energy p_0	0.001	Weighted coefficients w_1, w_2	10^3, 10
Broadcast packet size l_b	50 bit	Heuristic factor α, β	1, 5
Broadcast distance d_b	100m	Volatilization coefficient	0.1
The constant P_r	0.002	Pheromone constants Q_1, Q_2	50, 25
Data processing energy consumption E_{DA}	5 nJ/bit	Maximum iterations	200
Height difference h	30m	Patrol locations n	10
Number of ants N_{ant}	10	Discount factor γ	0.6
Shipping activity factor s	0.5	Wind speed w	0

To proceed, We evaluate the impact of different weighted coefficients on the performance of the algorithm. Specifically, for each group, (w_1, w_2) = (0,0), (100,0), (0,100), (100,100) correspond to cases that the node, which is considered neither the position nor residual energy, which is only considered the position, which is only considered the residual energy, which is considered both the position and residual energy, is selected as CH respectively. The node survival rate is shown in Fig. 5 (a). As we can see, at the initial stage, the number of dead nodes in the first and second cases are obviously higher than that in the two other cases. This is because the node's own energy is not taken into account for the first and second cases. But in the final stage, the position prioritized cases actually have fewer dead nodes than the energy prioritized cases, which proves that the CH selection ignored position leads to more energy consumption and node failure. Therefore, the survival rate of node is affected by its own energy and also related to its position.

The energy consumption is shown as Fig. 5 (b), in which we observe that the second case achieves the best performance in terms of energy consumption. Additionally, the first case has the lowest residual energy at the beginning, but in the later period, the residual energy of the first case is more than the third and fourth cases. This is because the node with a good position has been preferentially selected as CH while its energy is quickly consumed, and then the node with poor position and high residual energy is selected as the new CH, so that the subsequent energy consumption increases rapidly. Therefore, the energy consumption of a node is only determined by the position and not affected by its own energy. In view of the above, we need to set a balanced combination of weighted coefficients to ensure the performance, and we set it to (10^3, 10).

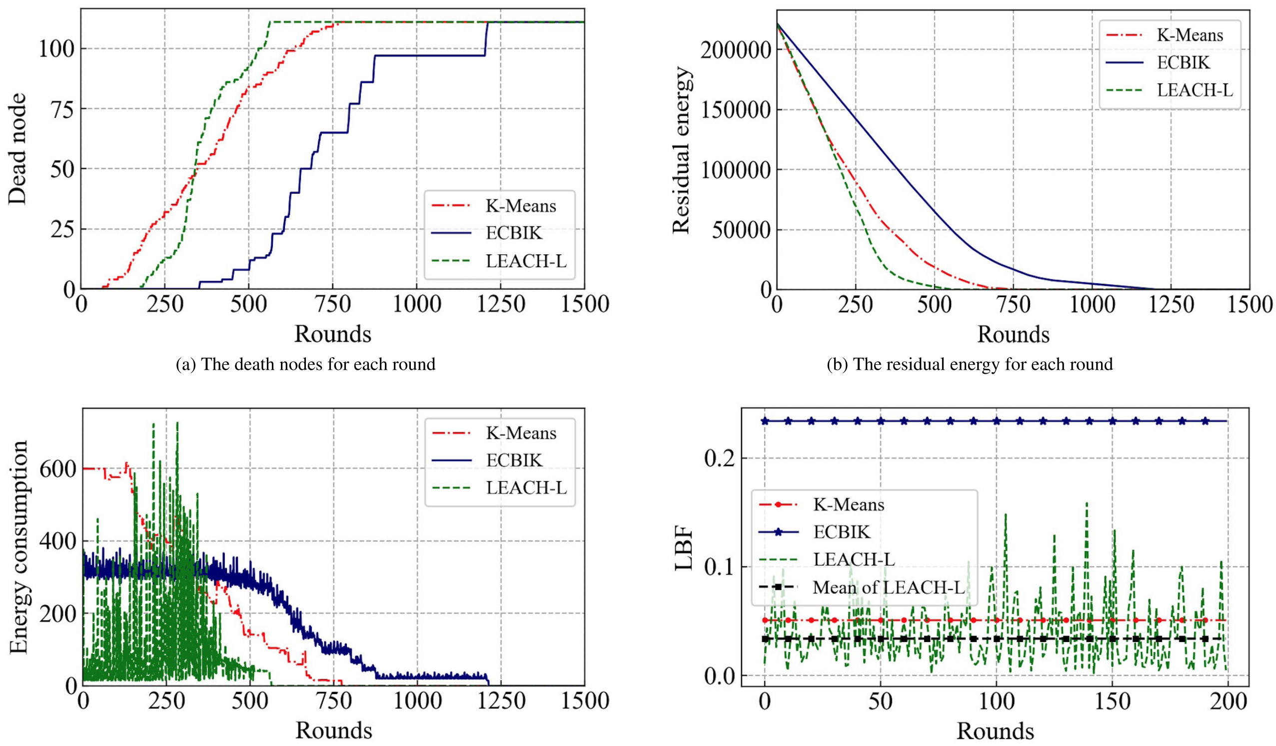
Subsequently, we make a comparison respectively with LEACH-L [46] and K-Means algorithms to evaluate the performance of our proposed ECBIK. The node survival rate of the three protocols is shown as Fig. 6 (a). We can observe that the times of the first dead node appear in 176r, 65r, and 350r, and the times of all nodes died are in 561r, 765r, and 1232r. Compared to LEACH-L and K-Means, ECBIK extends the first node death time by 98.9% and 438.5% respectively. Meanwhile, ECBIK increases the node survival rate by 129.1% and 26% respectively. Since K-Means is not adaptive, it appears the dead node at the earliest. Moreover, LEACH-L randomly selects the CHs without considering the properties of the nodes, so that its node survival rate is



(a) The death nodes for each round

(b) The residual energy for each round

FIGURE 5. **Influence of different weighted coefficients on algorithm performance.**



(a) The death nodes for each round

(b) The residual energy for each round

(c) The energy consumption for each round

(d) The LBF for each round

FIGURE 6. **Performance comparison of different algorithms.**

the lowest among three algorithms. As a result, benefiting from CHDC mechanism, ECBIK has outstanding energy load balancing performance.

Energy consumption is a significant index to measure protocol performance, which is demonstrated in Fig. 6 (c) and (b). As it is shown, the energy consumption of ECBIK is the lowest. Although both ECBIK and LEACH-L are adaptive, the stability of ECBIK is significantly better. This is because the CH selection of LEACH-L only considers the node's energy ignoring the location. Due to the more scientific and comprehensive CH selection methods, ECBIK has excellent energy saving and adaptive abilities.

Load Balance Factor (LBF) is defined as the inverse of MNs number's variance in the cluster, which measures the balance of the CH load. Hence, the larger the LBF is, the better the network load balancing degree is. And it can be calculated as:

$$LBF = \frac{k}{\sum_{n=1}^{k} (x_n - u)^2}, \tag{38}$$

where k is the value of clusters, x_n is the number of nodes in nth cluster, and the average number of neighbor nodes per CH is $u = \frac{N-k}{k}$. The LBF is shown in Fig. 6 (d). We can observe that the LBF of LEACH-L is a floating broken line, and the LBF of ECBIK and K-Means are straight lines, which manifests that the nodes are clustered only once under ECBIK and K-Means, while the nodes are re-clusters each round under LEACH-L. In addition, the LBF of ECBIK and

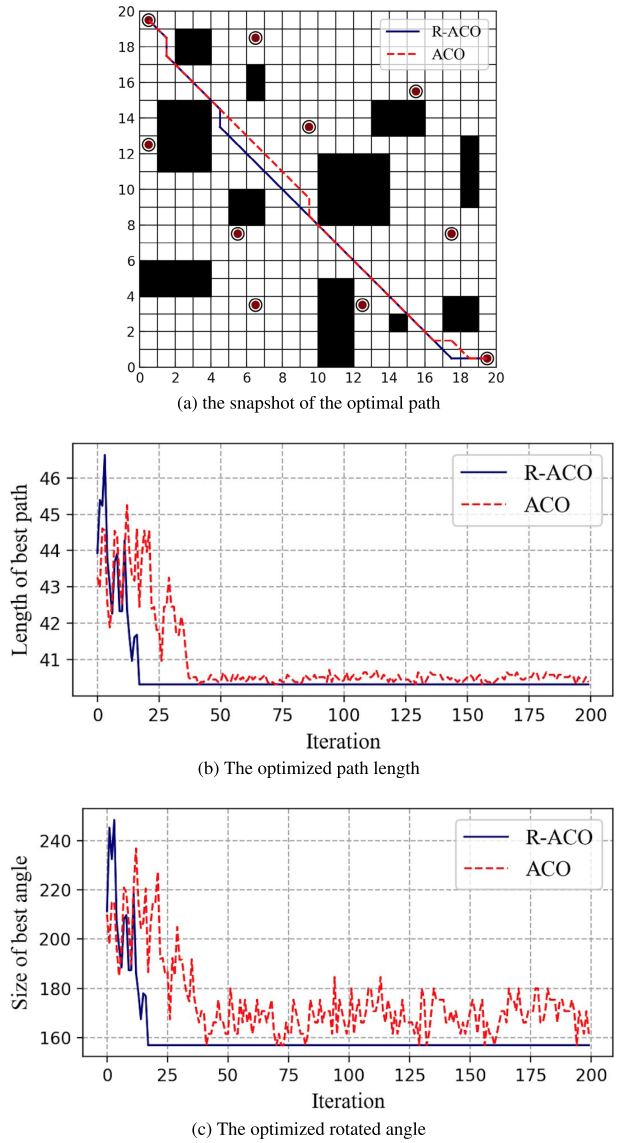


FIGURE 7. Comparison on the performance of two algorithms in P2P model.

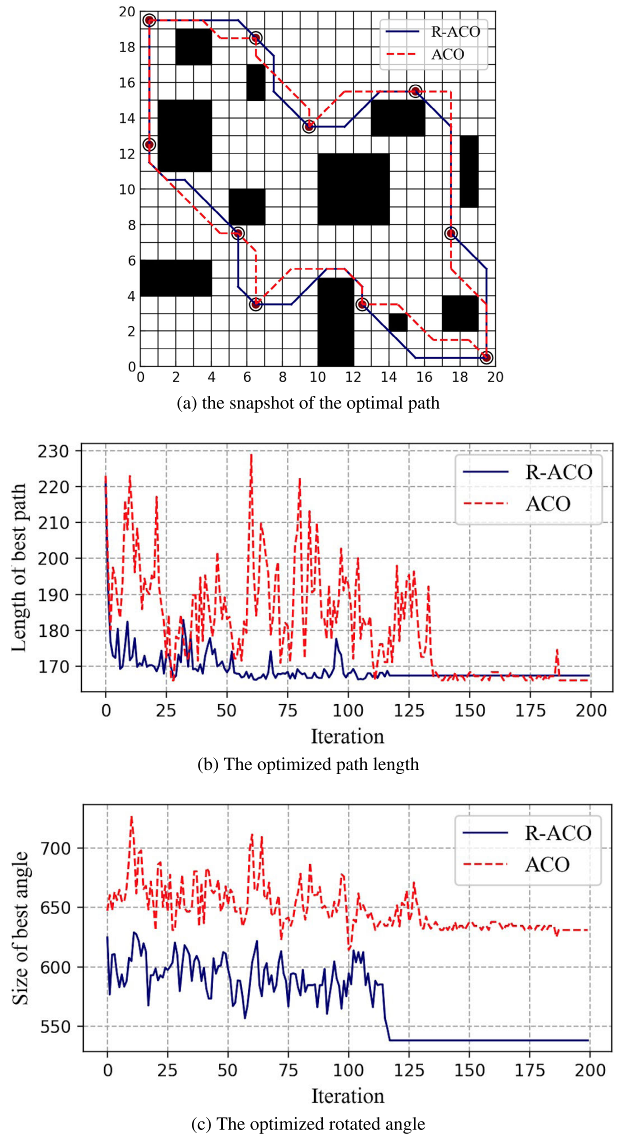


FIGURE 8. Comparison on the performance of two algorithms in TSP model.

K-Means are 0.232, 0.050 respectively, and the mean value of LEACH-L's LBF is 0.032. Obviously, our proposed ECBIK has advantages in balancing the cluster load compared with the other two algorithms.

When there are obstacles in the environment for AUV path planning, the ACO algorithm can usually be utilized to calculate the shortest distance between two points to avoid obstacles, and then this shortest distance can be used to find a global optimal traversal path [47]. Fig. 7 (a) and Fig. 8 (a) depict the snapshots of the optimal paths in the Point to Point (P2P) and TSP models. The specific results in P2P model are shown in Fig. 7 (b) and 7 (c). The lengths of the paths are both approximately equal to 40.3m, and the sum of the rotated angles are equal to 157.3° and 163° respectively, which demonstrate that both algorithms can solve the shortest path problem in P2P experiment. But R-ACO has better stability and faster convergence speed than ACO.

Fig. 8 (b) and 8 (c) portray the results of global optimization. The sum of distances obtaining from the two algorithms are 167.7m, 173.6m, and the sum of angles are 537.7°, 637.9°. Concluded from the above, the distance and angle under R-ACO are reduced by 3.4% and 18% respectively compared with ACO. Therefore, R-ACO can achieve the purpose of reducing the traversal distance and decreasing the rotation angle simultaneously with faster convergence speed.

In summary, our proposed adaptive ECBIK algorithm improves the efficiency of underwater clustering by accurately determining the number of clusters and establishing a CH re-cycle selection mechanism based on location and energy. Subsequently, the selected CHs will be necessary cruise destinations of the AUV to affect the path selection.

Meanwhile, the R-ACO algorithm with a global perspective can select reasonable path based on distance and angle. Therefore, our designed underwater clustering algorithm and the AUV path planning scheme have effectively improved the performance and efficacy of the entire system.

Finally, concluded from Table 2, the time complexity of the proposed algorithms is the same as that of the traditional algorithms. However, the solution time of the proposed algorithms is slightly longer. Actually, we often apply these algorithms in a small scale scenario (i.e., when there are not too many anchored sensor nodes underwater), which means that the solution time is acceptable and tolerable, so our algorithms are practical and feasible.

TABLE 2. Comparison of algorithms time complexity and solution time.

Algorithm Time complexity	K-Means $O(n)$	LEACH-L $O(n^2)$	ECBIK $O(n)$	ACO $O(n^2)$	R-ACO $O(n^2)$
Input size (n)	Solution time (sec)				
10	0.080	0.047	0.232	2.475	1.922
50	0.196	0.406	0.671	17.779	15.728
100	0.348	1.006	0.834	47.251	52.413
500	1.734	26.251	4.281	1756.961	2103.330
1000	2.783	105.672	8.076	9263.211	10710.944

VI. CONCLUSION

In this paper, we proposed a hierarchical information acquisition system for AUV assisted IoUT. Firstly, We designed an adaptive K-Means algorithm with energy awareness to solve the problem of excessive energy consumption for underwater nodes. Then, we utilize the kinetic equations to characterize the motion trajectory of AUV and quantify the rotation-angle. Meanwhile, we put forward a novel ACO algorithm based on MRP in AUV path planning. As a support, simulations and analyses validated the effectiveness of our proposed protocols.

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