AUV-Aided Isolated Sub-Network Prevention for Underwater Wireless Sensor Networks

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***Abstract*—This short paper presents an AUV-aided isolated sub-networks (ISNs) prevention protocol for underwater wireless sensor networks (UWSNs). In a multi-hop UWSN, the death of a special node, namely the cut-vertex (CV), divides the network into the main network and an ISN. This results in a loss of data generated by the ISN. To overcome this problem, in the proposed protocol, the AUV first determines a CV by utilizing the information collected from the sensor nodes. Then, using the Chapman–Kolmogorov equation, the AUV predicts the residual energy of the CV in future time-slots and guarantees that it reaches the CV before the CV's energy is depleted and an ISN is formed. The AUV then collects data from the sensor nodes instead of the CV. During the time-slots in which the AUV performs data collection, the CV harvests energy from ambient underwater sources and rejoins the network after it has sufficiently recharged its energy. Our preliminary simulation results show that the proposed protocol outperforms the stratification-based data collection scheme and Q-learning-based topology-aware routing protocol in terms of network lifetime and delay.**

***Index Terms*—AUV, Chapman–Kolmogorov, data-collection, energy harvesting, cut-vertex, Markov chain, underwater wireless sensor networks.**

I. INTRODUCTION

Underwater wireless sensor networks (UWSNs) have gained popularity for underwater data collection, monitoring, navigation, and disaster prediction. However, the adverse conditions of the underwater acoustic channel and the energy limitations of underwater sensor nodes present challenges to the performance of UWSNs [1]. For power, underwater sensor nodes rely on batteries that are difficult and costly to replace. Usually, the sensor nodes far from the sink have to relay data through other nodes in a multi-hop fashion. However, the death of a single next-hop forwarder node, called cut-vertex (CV), can divide a network into a main network and isolated sub-network (ISN) [2]. Understanding the significance of a CV, a study in [3] developed a protocol to identify the CV by considering the network topology in order to achieve balanced and reduced energy consumption. Thus, the lower-level nodes (nodes far from the sink) of the CV become aware of their isolation once the CV dies and save energy by entering sleep mode. Nonetheless, the death of the CV leads to a shorter network lifetime (the time when the first node in the network dies). Due to the loss of connectivity to the main network, the data collected by the ISNs cannot be relayed to the sink, decreasing the network's reliability.

Many studies have demonstrated that autonomous underwater vehicles (AUVs) can be used for a variety of purposes to extend network lifetime and reduce energy consumption. Based on water velocity, a protocol in [4] divides the network into two layers. Multi-hop transmission is employed in the upper layer, where nodes experience high water velocity. AUV-aided data collection is employed in the lower layer, where nodes are relatively static. However, there may be a significant delay since the gateway nodes in the upper layer must wait for the AUV to collect and relay the data to the sink. Moreover, the lower layer network is not available once the AUVs fail in reality. In [5], [6], the AUVs carry the replacement sensor node and replace them in the areas where there is no communication possible due to the absence of a next-hop forwarder on the routing path. According to [7], underwater sensor nodes equipped with acoustic communication interfaces could last for two weeks, even if the node activity is very low. Thus, sensor nodes need to be replaced repeatedly, which is an expensive operation. Some other studies explored energy harvesting as a solution to extend the network lifetime by collecting energy and storing it in an energy buffer from sources in the aquatic environment such as flows/tides, solar, and electrochemical [8]. The authors of [8], [9] consider the predicted harvestable energy and residual energy of sensor nodes while making routing decisions. However, these solutions are associated with high deployment costs.

Motivated by the issues presented above, this paper employs the AUV to explore the network and identify the CV, predict the future residual energy of the CV using Chapman-Kolmogorov (C-K) equation, ensure arrival before the CV dies, and collect data instead of the CV until the CV rejoins the network after sufficiently recharging its energy. The proposed protocol not only reduces the network deployment cost but also prolongs the network lifetime and reduces the delay of UWSNs.

II. SYSTEM MODEL

The 3D network deployment model is presented in Fig. 1, which consists of a static sink on the water surface, randomly distributed underwater sensor nodes, and an AUV. The sink has no prior knowledge about the location of sensor nodes. Sensor nodes determine their hierarchical level (HLV) through network initialization, which is defined as the number of hops from the sink denoted by an integer starting from level-0 (highest-level), as it is incrementally assigned to each level. The information about the neighboring nodes' ID and HLV are stored by each sensor node in a list called the neighbors' list. Sensor nodes generally consume energy in three different states: listening, receiving, and transmitting. We divide the time into time-slots, and sensor nodes stay in one of those states during a time-slot. We assume the sensor nodes are equipped with rechargeable batteries capable of energy harvesting. We suppose the AUV has higher energy and storage capacities than sensor nodes and is also capable of establishing a communication link with a range much longer than the sensor nodes. When the AUV energy falls below a specific energy threshold, it returns to the sink for a recharge. We suppose that the required number of sea current turbines are installed that are sufficient for the sensor nodes to harvest the energy.

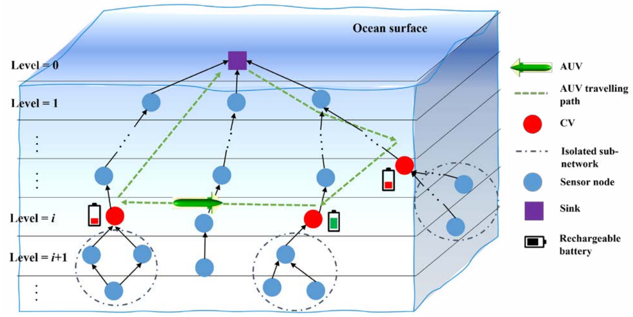

Fig. 1: Network model.

III. Proposed Protocol

The proposed protocol consists of two phases: 1) Knowledge-gathering phase and 2) Data-gathering phase. The knowledge-gathering phase is further divided into two sub-phases: a) Network exploration and CV detection phase; and b) CV residual energy prediction phase. In the network exploration and CV detection phase, the AUV moves around in a lawn-mower pattern to collect information such as sender ID, HLV, location, and neighbors' list of the sensor nodes. The AUV then identifies the CVs as follows: If a sensor node has only one higher-level neighbor (nodes closer to the sink) in its neighbors' list, then the neighbor is classified as a CV. Then, AUV creates a list of the CVs.

The proposed protocol then enters the CV residual energy prediction phase. Since the speed of the AUV is slow, it takes a certain amount of time to reach the CV to collect data from its lower-level nodes. The AUV should arrive at the CV before the CV has drained its energy; otherwise, the data collected by the CVs and its lower-level nodes is lost. Thus, we propose a prediction model based on the C-K equation [10] to estimate the residual energy of the CVs in future time-slots. This model enables the AUV to plan its route ahead of time and visit each CV before the energy depletes. To predict the residual energy of the CVs in the future time slots, AUV first collects information about the CV's state and one-slot transition probability matrix (discussed in the below paragraph) by visiting each CV in the list. The AUV visits each CV, starting with the one closest to its current location and moving to the next closest one until all listed CVs are visited. After collecting this information, the AUV uses the C-K equation to predict the CV's future residual energy.

Let $\{X_n : n = 0, 1, 2, \ldots\}$ be a Markov chain, where X_n represents the state at the time-slot n . The state space S is given by $S = 1, 2, \ldots, N$, where N is the total number of states in the Markov chain. The transition probability matrix of the Markov chain is denoted by $\mathbf{P}$, which is an $N \times N$ matrix and has an element $= p_{ij}, \{i, j\} \in S$, representing the probability of transitioning from state i to state j in one time-slot, i.e., $P(X_n = j \mid X_{n-1} = i)$. It implies the probability of being in state X_n only depends on the previous state X_{n-1}. Accordingly, the probability of transitioning from state i in the n-th time-slot to state j after m time-slots, is denoted by $P(X_{n+m} = j \mid X_n = i) = p_{ij}^{(m)}, m = 0, 1, 2, \ldots$. According to the C-K equation, m-slot transition probabilities are related to each other, and it provides a way to determine the m-slot transition probability matrix of a Markov chain from the one-slot transition probability matrix of a Markov chain. The C-K equation to calculate the probability of being in state j from state i in m time-slots is given as

$$p_{ij}^{(m)} = \sum_{k \in S} p_{ik}^{(r)} p_{kj}^{(m-r)}, \ 0 \le r < m, \ \forall i, k, j, \tag{1}$$

where k is an intermediate state between state i and state j. Then, the energy consumption of the CV in ϕ time-slots at state i, $E_i^{(\phi)}$, is calculated as

$$E_i^{(\phi)} \triangleq \sum_{\tau=1}^{\phi} \sum_{j \in N} p_{ij}^{(\tau)} \cdot E_j, \tag{2}$$

where E_j represents the energy consumption by the CV in any state j per time-slot. Then, the expected energy consumption value of the CV in ϕ time-slots is determined as

$$E^{(\phi)} = \sum_{i=1}^{N} E_i^{(\phi)} \cdot p_i, \tag{3}$$

where p_i is the probability that the CV is in state i. Given the initial energy of the CV in state i, E_{ini}, we can then calculate the future residual energy of the CV at ϕ time-slot, E_{res}, as

$$E_{\text{res}} = E_{\text{ini}} - E^{(\phi)}. \tag{4}$$

The AUV creates a CV priority list to prioritize the visits to CVs. Let ϕ_{thr} be the time-slot in which E_{res} falls below the CV threshold energy (E_{thr}). The CVs are ranked in ascending order of their ϕ_{thr} values, with those having the least ϕ_{thr} value assigned the highest priority. The AUV then calculates the time required to reach the CV with the highest priority from the current location, denoted as ϕ_{AUV} as

$$\phi_{\text{AUV}} = \frac{\sqrt{(A_x - CV_x)^2 + (A_y - CV_y)^2 + (A_z - CV_z)^2}}{L \cdot v_{\text{AUV}}}, \tag{5}$$

where L denotes the length of a time-slot, (A_x, A_y, A_z) represents the current coordinates of the AUV, (CV_x, CV_y, CV_z) represents the coordinates of the CV with the highest priority, and v_{AUV} represents the speed of the AUV. Before entering into the data-gathering phase, the AUV goes back to the sink and recharges its battery before going to the CV if the following condition is true: $\phi_{\text{thr}} \ge \phi_{\text{sink}} + \phi_{\text{AUV}}$, where ϕ_{sink} is the number of time-slots AUV takes to travel back to the sink from the current location. Otherwise, AUV sleeps to save energy until the $\phi_{\text{go}} (= \phi_{\text{thr}} - \phi_{\text{AUV}})$ time-slot arrives, at which AUV wakes up and travel to that CV.

In the data-gathering phase, the AUV visits the CV according to the priority listed in the CV priority list to collect data in place of the CV. Upon the AUV's arrival at the CV, the AUV starts its data collection instead of the CV, and the CV transitions to sleep mode to begin energy harvesting. Simultaneously, AUV calculates the ϕ_{AUV} to the next highest priority CV from the current location. The data collection process by the AUV continues until the E_{res} reaches the E_{thr} and re-joins the network. Then the AUV starts moving on to the next CV in the CV priority list. Notably, the energy harvesting process is only possible when the sensor node is in sleep mode, and it is assumed that the energy consumption during sleep mode is negligible. However, the data collection by the AUV instead of the CV and CV energy harvesting process continues until the ϕ_{go} of the next highest priority CV. The E_{res} can be updated as $E_{\text{res}} = E_{\text{res}} + E_h$, where

TABLE I: Simulation Parameters

Parameter	Value
Network size	6 km × 6 km × 4 km
Data rate	2400 bps
Propagation speed	1500 m/s
Transmission range	1200 m
Transmission mode power	20 W
Receiving mode power	756 mW
Listening mode power	30 mW
Node's initial energy	10 kJ
Speed of AUV	8 m/s
Packet arrival rate	0.001
Energy harvesting rate	4 W [11]
Simulation time	36 000 s
Energy threshold	2000 J

E_h is the energy that the CV harvested. The collected data is then delivered to the sink node for further processing when the AUV returns to the sink for a recharge.

IV. Performance results and future work

We evaluate the performance of the proposed protocol in comparison with the stratification-based data collection scheme (SDCS) and Q-learning-based topology-aware routing protocol (QTAR) in terms of the: 1) **Average lifetime of the CVs**, which is the duration that the CV actively engages in the routing process. 2) **Delay**, which is the average time interval between generating and successfully delivering a data packet to the sink. The simulations are performed in MATLAB software, and the values of the simulation parameters are given in Table I. A total of 100 runs are conducted for each simulation.

In Fig. 2, we present the average lifetime of the CVs. We can observe that the proposed protocol improves the lifetime of the CVs. This is because, in the proposed protocol, the AUV can predict the future residual energy of a CV and prevent it from dying. Furthermore, while the AUV performs the data collection, the CV harvests energy, extending the CV's lifetime. In contrast, QTAR and SDCS are incapable of preventing the death of a CV, shortening the lifetime of the CV. Furthermore, as the number of nodes increases, the average lifetime of the CVs decreases. The reason is that as the number of nodes in the network increases, a CV has to forward more data, resulting in increased energy consumption that leads to faster death of the CV.

In Fig. 3, we present the delay. Compared to SDCS and QTAR, the proposed protocol exhibits a lower delay because the sender selects a next-hop forwarder from higher-level nodes closer to the sink, thus reducing the delay. Additionally, the AUV temporarily collects and delivers data from the CV to the sink in this approach. QTAR may experience more delay than proposed as all isolated group member nodes enter sleep mode if they do not receive an acknowledgment for the successful packet reception from the CV. The isolated member nodes wake up from sleep mode and rejoin the network when a new transmission is overheard. While in SDCS, the AUV alone collects data, causing more delay than QTAR and the proposed protocol. Our future works include analyzing the packet delivery ratio and the lifetime of the network.

V. Acknowledgements

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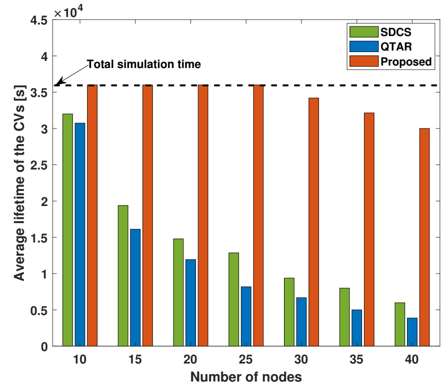

Fig. 2: Average lifetime of the CV's versus the number of nodes.

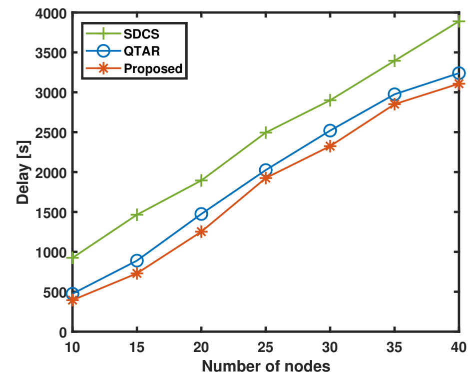

Fig. 3: Average data collection delay versus the number of nodes.

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