Intelligently Routing Underwater Wireless Sensor Networks: A Survey

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Abstract

Current marine scientific research faces a big challenge in accurately and timely collecting marine data due to the highly dynamic underwater environment. Underwater Wireless Sensor Networking (UWSN) systems with intelligent routing approaches are a way to rise to this challenge as the rapid development of Artificial Intelligence (AI) technologies. Unlike traditional routing approaches driven by mathematical-models, the ones underwater are intelligent and data driven, which better adapt to the dynamic underwater environment and are able to optimize various performance indicators. This paper reviews the state of arts of applying AI technologies in routing UWSN systems. It divides the routing approaches for UWSN systems into non-cross-layer and cross-layer based. Cross-layer based approaches can be further grouped into traditional cross-layer and intelligent cross-layer approaches, as AI technologies can help data sharing among layers in UWSN systems. This paper focuses on the intelligent cross-layer routing approaches and discusses them according to the type of machine learning algorithms applied. Challenges and some open issues in intelligently routing UWSN systems are also provided. To the best of our knowledge, this work is the first effort on summarizing the challenges, algorithms, and issues in routing UWSN systems intelligently.

Keywords: Routing algorithms, Evolutionary algorithms, Supervised learning, Reinforcement learning, Underwater wireless sensor networks

1 Introduction

Oceans cover 71% of the Earth surface and store 97% of the global water resources. Although oceans are one of the major components of the global climate system and human sustainable development, more than 95% of marine resources remain underexplored and unexplored. Underwater wireless sensor networks (UWSNs) are networking systems including components such as vehicles and sensors that are deployed in a specific sea area to perform collaborative monitoring and data collection tasks. UWSNs have been the dominant technologies for better exploration and exploitation of marine resources [1-3].

UWSNs typically use sound waves for underwater communication. Figure 1 shows a schematic diagram of a two-dimensional underwater sensor network. Sensor nodes are anchored on the seabed. They connect to underwater convergent nodes via wireless acoustic links. The sink node acts as a relay and is responsible for collecting the data from underwater sensor nodes and communicating with stations on the water. To realize the entire data transmission process, the sink node is equipped with two acoustic transceiver devices: a vertical transceiver and a horizontal transceiver. While the horizontal transceiver is used by the sink node to send instructions and configuration signals to underwater sensor nodes, the vertical transceiver is used by underwater sensor nodes to forward data collected to the surface site. In addition to the hydroacoustic transceiver that can handle multiple parallel communications among the deployed sink nodes, the surface station is also equipped with transmitting equipment that communicates with shore receivers, satellite systems, and other surface receivers. In general, UWSNs deploy sensor nodes with low energy consumption, communication bandwidth, and computation capabilities to monitor a water area. UWSNs form an underwater monitoring networking system in a self-organizing manner, and the collected data are finally reach end users through the surface base stations or ships via acoustic communication.

Wireless sensor networks have been developed on land for decades [4-5]. However, the mature communication technologies of wireless sensor networks on land, such as power control technology, MAC protocols, and routing protocols, cannot be directly applied in underwater networks, because

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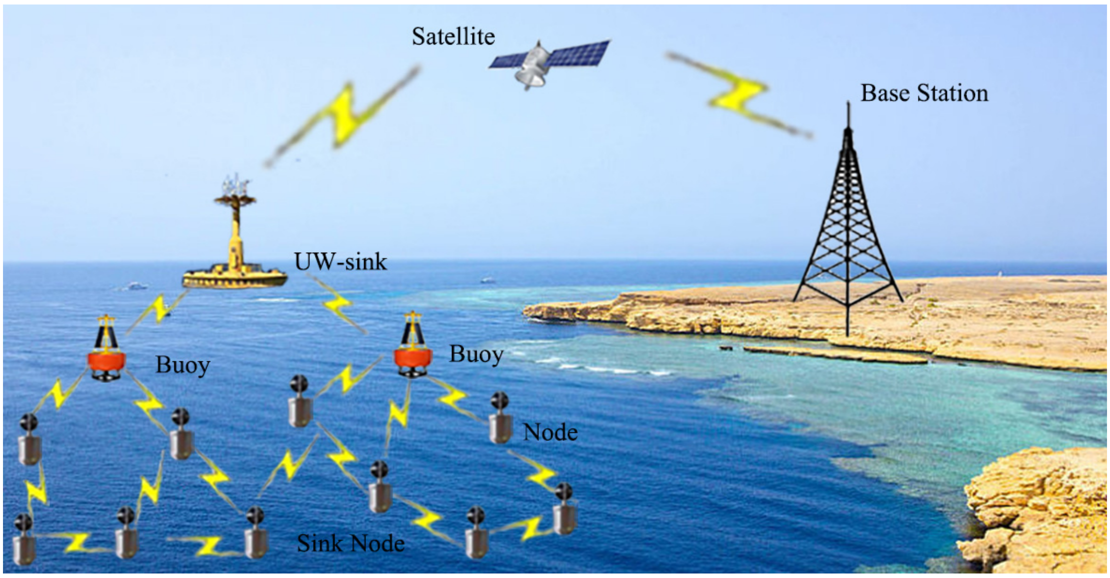

Figure 1. Schematic diagram of a two-dimensional underwater wireless sensor network

UWSNs highly rely on underwater acoustic communication technology and underwater acoustic data has very different features from land data. The inherent ocean current movement in the underwater acoustic environment and the time-space-frequency variation of the underwater acoustic channel characteristics make UWSNs face many challenges, such as long propagation delay, poor robustness, and high energy consumption that do not exist in land-based sensor networks.

Therefore, UWSNs have been a hot research area in current research. The U.S. Navy has conducted SeaWeb's submarine wireless communication network test many times since 1998. The test has been a major part of the U.S. Navy's experimental long-range sonar and ocean network plan [6-7]. Led by Woods Hole with the participation of multiple universities and institutes in the U. S., a global coastal ocean observation network was established to provide the ocean physics, ocean chemistry, ocean geology and seabed information platforms such as biology. At present, the seabed observation network, including Canada's Neptune Observation System, Europe's ESONET Observation Network, and Japan's DONET Project, has been established internationally [8]. Many universities and institutes in China have also developed their underwater wireless sensor network networks since 1980. For instance, a three-dimensional monitoring demonstration network for the Taiwan Strait and adjacent seas, including 5 sets of buoys, 14 sets of ecological buoys, and 1 set of seabed bases, was established in 2012; and the National Seabed Long-term Scientific Observation System[1], led by Tongji University and jointly built by the Institute of Acoustics of the Chinese Academy of Sciences, was formally approved in 2017. The construction period is 5 years, and the total investment exceeds 2.1 billion.

UWSNs are very complex systems including the technologies of routing protocols, Media Access Control (MAC) protocols, localization protocols, energy consumption, and security. Although some researchers have made surveys on the related requirements, protocols, and applications, this paper focuses on the intelligent routing algorithms of UWSNs. Particularly, we review the state of arts of intelligent routing algorithms in UWSNs, as Artificial Intelligence (AI) technologies have been widely applied in various fields such as the atmosphere, medical treatment, climate change, radio communication, and marine information technology [9]. The main contributions of this paper are three folds:

- We classify underwater routing protocols into two types: cross-layer and non-cross-layer routing protocols. We further categorize the former into traditional routing protocols and intelligent routing protocols.
- We categorize the intelligent routing algorithms, based on the machine learning algorithms applied, into three types: supervised learning based, combination of evolution algorithms and supervised learning based, and Reinforcement Learning (RL) based, and introduce the typical routing systems for each category.
- We discuss the challenges and open issues in designing and deploying intelligent routing algorithms for UWSNs.

The rest of is paper is organized as follows. Section 2 summarizes the related surveys, and section 3 introduces the major challenges in designing and developing routing protocols in UWSNs. While routing algorithms and intelligent routing algorithms for UWSNs are reviewed in sections 4 and 5, respectively, the challenges and open issues in designing, developing, and deploying intelligent routing algorithms for UWSNs

[1] https://mgg.tongji.edu.cn/mggen/e6/50/c10531a124496/page.htm

are introduced in section 6 followed by the conclusion in section 7.

2 Related Surveys

Many researchers have reviewed the related technologies, algorithms, and applications in various UWSN user scenarios. While Fattah et al. [10] summarized the requirements, taxonomy, recent advances, and open research issues of UWSNs, Jouhari et al. [11] discussed the enabling technologies, localization protocols, and internet of underwater things for UWSNs. Although Faiza et al. [12] focused on the localization schemes in UWSNs, Gupta and Goyal [13] put their efforts on the evolution of data gathering static and mobility models in UWSNs. Although Luo et al. in [14] and Khalid et al. in [15] did similar study on reviewing the routing protocols and related issues for UWSNs, Luo et al. focused on the optimization objectives of routing algorithms and categorized the routing algorithms into three types: energy-based, data-based, and geographic information-based; and Khalid et al. paid their attention to the localization issues in routing UWSNs, and further categorized the routing algorithms into localization-based and non-localization-based algorithms. In this paper, we review the intelligent routing algorithms as well as the general routing algorithms for UWSNs. To the best of our knowledge, this work is the first effort that summarizes the state of arts of AI technologies applied in routing UWSNs.

3 Routing Approaches in UWSNs

3.1 Challenges in Routing UWSNs

Routing algorithms for UWSNs are responsible for the selection of a path from a source node to a sink node. Routing algorithms typically consist of two functions: finding the optimal path between a source node and a sink node and grouping the data along the optimal path, and forwarding them correctly. Unlike wireless sensor networks on land supported by mature communication technologies such as power control technology, MAC protocols, and routing protocols, UWSNs highly rely on underwater acoustic communication technology. Since underwater acoustic data has very different features from land data, as listed in Table 1, UWSNs face the following four challenges in the routing process:

- **Long communication propagation delay.** Routing in terrestrial wireless networks can be realized through multiple polls and repeated confirmations, and the delay caused by these operations is negligible due to the propagation speed of the radio. However, routing in underwater wireless networks suffers a long time delay, since the propagation of acoustic signals is only approximately 1500 m/s, and the repeated confirmation and poll causes a long waiting time delay, leading to a reduced communication efficiency over the entire network.
- **Mobility of nodes**. Different from sensor nodes fixed on the ground in terrestrial wireless networks, the ones in underwater wireless networks are typically randomly placed, or semifixed through cables and anchors. Therefore, the locations of sensor nodes are not fixed during a routing process. In dynamic environment, an existing route may be broken if the time efficiency and robustness in updating and maintaining the route become more demanding. As positioning signals such as Global Position Signal (GPS) are difficult to be received in underwater, it is hard to obtain real-time and accurate position information of nodes underwater, leading to locality issues that generate certain difficulties in the design of routing algorithms.
- **Higher packet loss rate of the channel**. Due to the absorption of sound waves by seawater, the sparse distribution of the network caused by expensive sensor nodes, and the influence of ocean noise, underwater channels generally cannot maintain an ideal transmission performance. Therefore, data packet loss in routing is inevitable. Therefore, the reliability must be considered in underwater routing.
- **Energy saving**. As the life time of each underwater node is limited due to the high transmission power, the low battery carried, and the difficulty in battery replacement, energy savings must be considered.

Table 1. Comparison of characteristics between land data and ocean data

Characteristics of land data	Characteristics of ocean data
Easy access to large amounts of data	Hard to obtain ocean data Difficult for channel data to accurately reflect channel characteristics
Diversity of data sources	Ocean data is mainly marine data Underwater acoustic channels in different sea areas/sea conditions are very different.
Low-value density	Sparsity of the impulse response of the underwater acoustic channel
Authenticity	Accurately restoring the sound field characteristics is difficult

3.2 Underwater Routing Algorithms

In a real marine environment, the problems of UWSNs are mainly reflected in the battery energy, processing data, storage capacity, and communication bandwidth. Routing algorithms are typically designed for such purposes. Although there are many methods to categorize routing algorithms for UWSNs in current research, no method has been widely recognized. In this paper, we categorize the underwater routing algorithms according to the layered structure of UWSNs and the interaction between such layers.

Particularly, we divide the underwater routing protocols into non-cross-layer and cross-layer. As introduced by Li et al. in [16], the non-cross-layer protocol mainly divides the entire network into five layers. Although each layer is designed and optimized independently, the communication is only enabled between adjacent layers. The cross-layer routing protocols break the strict concept of levels, and enable information to be shared among multiple levels to achieve joint optimization, as shown in Figure 2.

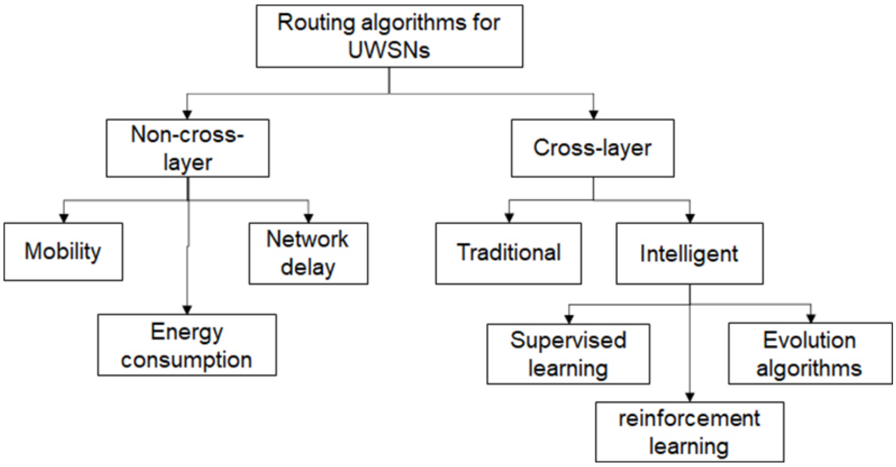

Figure 2. Classification of routing algorithms for UWSNs

Cross-layer routing protocols can be subdivided into traditional routing protocols and intelligent routing algorithms. Traditional ones are often assisted by geographic location information. Routing based on geographic information as proposed by reference [17] used the link quality of neighboring nodes to study a channel-aware routing protocol for multi-node transmission. It ensured the simple topology information successfully bypassing the cavity region. Reference [18] proposed a routing approach based on reliable pressure. It solved the problem of packet loss caused by the harsh underwater environment and increased the data packet transfer rate. In order to solve the mobility problem of nodes. The reference [19] proposed a routing protocol based on hop-by-hop dynamic addressing. It did not require any location information or maintenance of complex routing tables.

Non-cross-layer routing protocols are typically refined into routing protocols that optimize node mobility, energy consumption, and network delay. Routing based on energy consumption as proposed in [20] presented a routing protocol for vector forwarding. It relied on the location information, the remaining energy, and the number of retransmissions in the previous cycle to determine the data forwarding. It achieved a uniform energy consumption and reliable data transmission. As reference [21] proposed an adaptive and life-cycle-aware routing protocol to find the most suitable and economic data transmission route to improve the life cycle of the underwater acoustic network; reference [22] introduced an energy-saving collaborative opportunistic routing protocol, in which the source node first determined the forwarding relay based on the local depth information and then used a fuzzy logic-based relay selection scheme to select the best relay to solve the energy consumption problem. While a delay-sensitive deep routing algorithm was proposed by [23], a delay-sensitive energy-saving deep routing algorithm was provided by [24], and a delay-sensitive adaptive depth routing approach was carried out in [25]. To simultaneously improve the end-to-end delay and transmission loss, reference [25] also introduced three other routing schemes, and developed a delay-effective priority factor and the delay-sensitive holding time, by slightly reducing the network throughput to minimize the end-to-end delay to a large extent. It met the strict time requirements of the underwater acoustic networking scenarios such as earthquake monitoring.

3.3 Summary

In summary, hydroacoustic networking routing protocols can be categorized into non-cross-layer and cross-layer routing protocols, according to the layered structure of UWSNs and the interaction among the layers. While non-cross-layer routing protocols can be further divided into three types based on the mobility, energy consumption, and delay of senser nodes, cross-layer routing protocols can be clustered into AI-based and traditional. AI-based routing protocols can be further grouped based on the AI algorithms applied, while traditional routing protocols can be separated based on the objectives the routing protocol aimed to optimize. Such objectives may be to reduce end-to-end delay, system energy consumption, and system distribution loss. However, the highly differentiated marine hydroacoustic communication channel makes such routing algorithms unable to meet the needs of large-scale underwater systems for robust and reliable networking applications. One of the important reasons is the complicated time-space-frequency characteristics of the underwater acoustic channel. Also, the traditional routing theories and technologies still have difficulty in carrying out a good adaptive matching design in a timely, reasonable, and effective manner.

4 Intelligent Routing Algorithms in UWSNs

In recent years, with the rapid development and deployment of AI technologies [26] in various fields such as the atmosphere, medical treatment, climate change, and radio communication, relevant methods of AI have been applied in marine information technology such as ocean big data and smart oceans. AI technologies bring new ideas to break through the traditional routing technology bottleneck in UWSNs, such as to select optimal underwater routing nodes reasonably and rapidly, to automatically learn the dynamic changes of the underwater acoustic channel amplitude-time-space-frequency, to adapt to the dynamic changes of underwater acoustic channel, and to constitute feedback to the signal transmitter.

AI technologies have been widely applied in the routing algorithms on land. As early as 1994, Boyan et al. [27] proposed an intelligent routing algorithm based on Q-learning in communication networks. Experiments showed the proposed routing algorithm, comparing with the traditional shortest path routing, could effectively avoid network congestion and reduce the transmission delay of data packets. In 2010, Hu et al. [28] proposed the QELAR that applied the Q-learning to optimize the energy consumption and lifespan of wireless sensor in wireless sensor networks. Basagni et al. [17] further applied the Q-learning to enable reliable transmission and accelerate the forwarding of wireless sensor networks.

5 Data-driven Underwater Intelligent Routing Algorithms

Intelligent routing algorithms can be driven by mathematical models or data. Although many AI algorithms have been proposed in current research, most of them are based on mathematical models, intelligent routing algorithms driven by underwater acoustic data are still in their infancy. Mathematical model driven routing algorithms usually make some assumptions for application scenarios to simplify the problems. However, it is difficult to fully meet such assumptions in the real underwater network environment, making the routing algorithms based on mathematical model unable to ensure its performance in the real scene. AI algorithms driven by data can address this issue by training intelligent models based on massive data. They have demonstrated a strong learning, generalization, and expression abilities in solving routing optimization problems and giving intelligence to UWSNs.

Data-driven aritificial intelligent routing algorithms can be clustered by the types of AI algorithms applied. AI algorithms can be categorized into supervised learning, semi-supervised learning, unsupervised learning, and RL according to the number of labeled samples used to train the models. Supervised learning approaches uses samples with labels to train models, semi-supervised learning uses a small volume of labeled samples together with a big volume of unlabeled samples due to the difficulty in obtaining labeled samples. Unsupervised learning does not need labeled samples to train models. However, unsupervised learning approaches typically do not have time efficiency. Accordingly, unsupervised learning is hardly used in routing algorithms. RL is a type of environment-friendly AI approaches that can adapt to the change of environment. Evolutionary algorithms are a type of optimization technology. Since they simulate the behavior of animals in natural evolution, they are also AI approaches.

In the rest of this subsection, we categorize the data-driven routing approaches into supervised learning based, evolutionary algorithms based, and RL based, and discuss the typical routing systems for each category. We list all the related references in Table 2.

5.1 Intelligent Routing Algorithm Based on Supervised Learning

Supervised learning refers to the use of known input and output samples to train the model so that the model can accurately complete a type of machine learning task of input to output mapping [29]. In recent years, intelligent underwater routing methods based on supervised learning have mainly included decision trees (DT) [30], artifical Neuron Networks (NN) [31], and support vector machine (SVM) [32]. The purpose is to learn more complex strategies through labeled data.

Regarding routing application in UWSNs, it is possible to provide an intelligent routing method in an underwater dynamic link in changing network environment. References [33-35] applied DT to route for UWSNs. Although reference [33] relied on DT to select the best message sending path to improve network coverage preservation, reference [34] applied DT and dynamic programming to solve the problem that determined the visiting time and a deadline respect

Table 2. Intelligent routing algorithms for UWSNs

Type	AI algorithms	Reference	Optimization
Supervised learning based	DT	[33]	network coverage preservation
		[34-35]	data transmission delay
	NN	[36]	data fusion
		[37]	DDoS attacking detection
	SVM	[38]	node selection
Evolutionary algorithms & supervised learning	ACO	[43-45]	routing path
	GA	[46]	network topology
		[47-49]	distance and energy
		[50]	Security data transmission
	SA	[53]	Localization of nodes
		[52, 54-55]	Cluster head selection, Lifetime and energy
	WOA	[57-58]	network life time and energy usage
		[59]	solve multi-objective optimization problem
		[60]	Work with ANN
Reinforcement learning based	Classical RL	[56, 63, 67]	energy saving and improve life time
		[65]	congestion avoidance
		[66]	message deliveries
	Q-learning	[61-62]	adaptive to energy consumption and delay
		[17, 64]	packet forwarding

to the amount of captured data and the type of event in routing UWSNs, and reference [35] applied DT-based classifier to classify the application specific events in UWSNs. It enabled an energy-efficient transmission by suppressing the duplicate packet transmission and reducing the transmission of control packets for delay-sensitive routing.

Other supervised learning algorithms are also applied to routing approaches for UWSNs. As reference [36] applied back propagation NN for data fusion to reduce engergy consumption through decreasing the amount of transferred data, reference [37] applied NN to detect distributed denial of service (DDoS) attacking over UWSNs, and reference [38] applied fuzzy logic interence and SVM to determine the appropriate sensors to forward packets to the destination in routing UWSNs.

5.2 Intelligent Routing Algorithms Combining Evolutionary Algorithms and Supervised Learning

At present, the combination of evolutionary algorithms and supervised learning algorithms is used more frequently. Taking the network state and traffic matrix as input, the corresponding routing strategy is calculated through an evolutionary algorithm as output to obtain a training model. When a new flow arrives, the appropriate routing path is output through the training model. Evolutionary algorithms[39], including ant colony optimization (ACO) algorithms [40], simulated annealing (SA) algorithms [41], genetic algorithms (GA) [42], etc., combined with supervised learning algorithms, have been applied in communication network routing and communication quality evaluation.

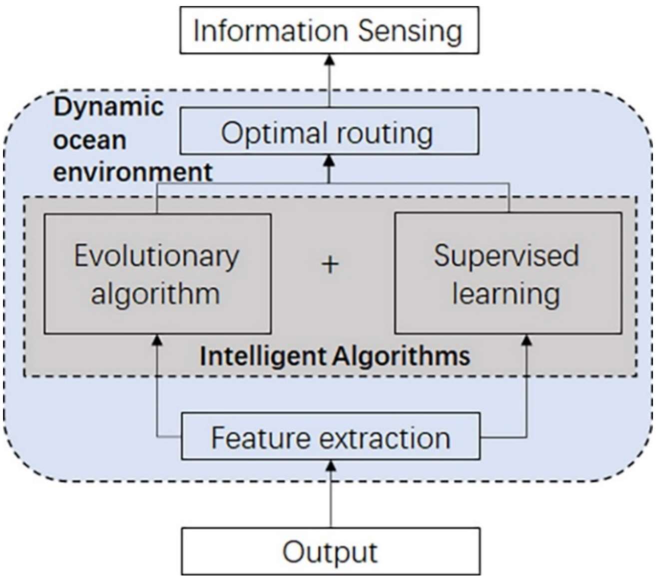

Figure 3. Intelligent routing model combining evolutionary algorithms and supervised learning

Applying intelligent routing protocols that combine supervised learning and evolutionary algorithms are often dynamic, and the goal is to obtain the optimal path that meets the quality of service requirement in UWSNs. The idea of such approach is shown in Figure 3. The input of the evolutionary algorithm layer (global network state) and output (optimal path) are used as datasets for supervised learning, and then in the dynamic routing process, the supervised learning model can quickly calculate the optimal path according to the input network state. The running time is much shorter than the ones only applying evolutionary routing algorithms, but the network delay and jitter is similar.

5.2.1 Ant Colony Optimization Model

The ACO algorithm is an optimization algorithm that simulates the foraging behavior of ants [40]. The ACO algorithm periodically selects a forward ant from each network node, and its task is to find a path to the destination. The identifier of each access node is saved in the memory carried by the ant. The rules for forward ants to select relay nodes are as follows:

$$p_k(r,s)=\begin{cases}\dfrac{\left[T(r,s)\right]^{\alpha}\left[C(s)\right]^{\beta}}{\sum_{u\notin M_k}\left[T(r,s)\right]^{\alpha}\left[C(s)\right]^{\beta}} & if \quad s\notin M_k\\ 0 & otherwise\end{cases} \quad \textbf{(1)}$$

In (1), $p_k(r,s)$ is the probability that ant k chooses to move from node r to node s; T is the routing table on each node, which is used to store the pheromone concentration on each connection; C represents the visibility function. $(1/E_0 - P_{jn}gn)$ is the initial energy of the node level, $P_{jn}gn$ is the energy consumption of node j after n round data collection, and α and β are the parameters that control the relative importance of pheromones and visibility, respectively. The selection probability is a compromise between visibility (the higher the energy of the node, the more likely it is to be selected) and the pheromone concentration (that is, the more traffic on connection (r,s), the more likely this connection is to be selected). The path loss $L_{CH}(i)$ and average throughput C_{ave} of each cluster head are defined by (2) and (3), respectively. After n round of data collection, the remaining energy is computed by (4).

$$L_{CH}(i)=\sum_{j=1}^{N_j}\frac{1}{N_j}L_p(j) \quad \textbf{(2)}$$

$$C_{ave}=\sum_{i=1}^{M}\frac{N_i g C_{packet}}{M g T_i} \quad \textbf{(3)}$$

$$E_{node}(n)=E_0-P_{jn}gn \quad \textbf{(4)}$$

References [43-45] applied ACO algorithms to route UWSNs in a clustered and energy-efficient manner. They divided an UWSN into many clusters, each consisting of one cluster head node (CHN) and several cluster member nodes (CMNs). Although reference [43] proposed HENPC algorithm that applied ACO to select the optimal node by defining the path loss function from each node to the cluster head, the average throughput within the cluster, and the remaining energy of node data collection, reference [44] combined fuzzy c-means and ACO to create and manage the data transmission in UWSNs, and reference [45] selected CHN based on the residual energy of nodes and the distance factor. The selected CHN collects data sent by the CMNs and transmits them to the sink node.

5.2.2 Genetic Algorithm Model

The GA is a computational model that simulates the biological evolution process of natural selection and the genetic mechanism of Darwin's biological evolution theory [42]. It is a method of searching for the optimal solution by simulating the natural evolution process. The selection of the fitness function directly affects the convergence speed of the genetic algorithm and whether the optimal solution can be found. Generally, the fitness function is obtained by transforming the objective function.

Reference [46] reviewed the approaches that applied GA in WSNs for optimizing energy consumption. Regarding UWSNs, GAs could be used to estimate the distance and energy of nodes for node selection in various types of routing approaches to extend the network lifetime [47-48], to improve the localization of nodes in UWSNs to improve the routing approaches indirectly [49], or to partially establish half of the key for the secure underwater communication with less computation and energy consumption [50].

5.2.3 Simulated Annealing Algorithms

SA algorithms are a type optimization approaches simulating the behavior of solids in a heat bath [41]. When we put a solid in a heat bath, the temperature of the solid is firstly raised to a point in which the atoms of the solid can randomly move, and then decreased so that the atoms of the solid can rearrange into a crystallization state, which minimizes the total energy of the system. Carefully selecting the cooling schedule allows a solid to become a crystal that has the lowest energy instead of an amorphous state with higher energy. As we can view the solution of an optimization problem as a solid in a heat bath, the cost of the objective function as the energy of a solid, the optimal solution as the ground energy state of a solid, moving a solution to a neighboring position can be viewed as the rapid quenching, and the search algorithm can be viewed as the cooling schedule. Accordingly, a SA algorithm can be developed to mimic the physical annealing process of physical material.

While reference [51] applied SA to improve the coverage of networks, reference [52] proposed to apply SA to optimize the selection of cluster heads for a cluster routing algorithm with better load balancing. SA was also used to improve the localization of nodes [53], or extend the network lifetime or reduce the energy consumption of nodes [54-55].

5.2.4 Whale Optimization Algorithm Model

The whale optimization algorithm (WOA) [56] is also an evolution algorithm imitating the hunting behavior of humpback whales. In the WOA algorithm, the position of each humpback whale represents a feasible solution. In ocean activities, humpback whales have a special hunting method. This foraging behavior is called the bubble-net predation strategy.

Humpback whales surround their prey when hunting. To describe this behavior, the mathematical model of the whale algorithm is formulated by (5), in which t is the current number of iterations; $X^*(t)$ is the best whale position vector so far, and $X(t)$ is a vector representing the current whale position. A and C are coefficients, and they can be obtained by (7) and (8), respectively. r_1 and r_2 are random numbers ranging in (0,1), a is the value that decreases linearly from 2 to 0, t represents the current number of iterations, and $T_{\max}$ is the maximum number of iterations.

$$D = |CX^*(t) - X(t)| \tag{5}$$

$$X(t+1) = X^*(t) - AD \tag{6}$$

$$A = 2ar_1 - a \tag{7}$$

$$C = 2r_2 \tag{8}$$

$$a = 2 - \frac{2t}{T_{max}} \tag{9}$$

When searching for prey, the mathematical model is formulated by (10) and (11), in which X_{rand} is a randomly selected whale position vector.

$$D = |CX_{rand} - X(t)| \tag{10}$$

$$X(t+1) = X_{rand} - AD \tag{11}$$

The algorithm considers that when A ≥ 1, a X_{rand} is randomly selected, and the positions of other whales are updated according to the X_{rand}. This forces the whale to deviate from the prey and search for a more suitable prey. This strengthens the exploration capabilities of the algorithm so that the WOA algorithm can avoid local optima and perform a global search.

WOA was typically used to optimize the selection of cluster head nodes to enable cluster routing approaches for better energy usage and longer lifetime in UWSNs [57-58]. WOA also had multi-objective versions [59] to balance multiple objectives for routing UWSNs or combined with other algorithms such as NN to further improve the performance of routing approaches for UWSNs [60].

5.3 Intelligent Routing Algorithm Based on Reinforcement Learning

Unlike supervised learning relies on data with labels to train models for routing applications in our case, RL can be typically seen as a process in which a RL agent interacts with the environment in discrete time steps. In the sense that RL may use a small volume of labeled samples together with a large volume of samples without labels to enable routing applications, it also can be seen as a type of semi-supervised learning algorithms.

RL requires searching between scenarios and appropriate decisions, and rewarding and punishing that search strategy based on feedback, similar to the way humans interact with the environment. The main body of RL is the agent. By interacting with the environment, the behavior is mapped to environmental feedback rewards. The agent continuously learns from environmental feedback and optimizes and corrects its own behavior through environmental rewards to adapt to maximize the return.

At each time point t, the RL agent takes actions according to state s_t and receives a feedback reward r_t. The goal of RL is to find a strategy $\pi(s)$. The strategy function is a mapping from state to action and can maximize decreasing rewards, where $k \in [0,1]$ is the reward discount factor.

Q-learning is one of the main techniques commonly used in RL. Q-learning does not require an environment model and does not need to adjust its own structure. It can handle learning problems through random conversion and reward values. The process of Q-learning can be regarded as a Markov decision process (MDP). The current state of the agent and the selected behavior determine the fixed state transition probability distribution and the agent's next state and instant rewards.

The Q-function, as formulated by (12), is often used to predict the sum of the maximum decreasing rewards corresponding to state t and action s_t observed at time a_t.

$$\begin{aligned} &Q_\pi(s_i, a_i) = \\ &R(s_i, a_i) + \gamma \Sigma_{s_i+1 \in s} P(s_i, a_i, s_{i+1}) Q_*(s_{i+1}, a_{i+1}) \end{aligned} \tag{12}$$

In (12), $R(s_i, a_i)$ represents the reward obtained when the agent takes action a_i in state s_i, $P(s_i, a_i, s_{i+1})$ represents the probability of the agent transitioning to state s_i when it takes action a_i in state s_{i+1}, and $Q_*(s_{i+1}, a_{i+1}) = maxQ_\pi(s_{i+1}, a_{i+1})$ represents the return value obtained when the agent takes action a_{i+1} in the next state s_{i+1}. Based on the above formula, the Q-value is updated by (13).

$$
\begin{aligned}
&Q_{\pi}(s_i, a_i) \leftarrow \\
&Q_{\pi}(s_i, a_i) + a * R(s_i, a_i) \\
&+\gamma \Sigma_{s_{i+1} \in s} P(s_i, a_i, s_{i+1}) Q_{*}(s_{i+1}, a_{i+1}) - Q_{\pi}(s_i, a_i)
\end{aligned} \tag{13}
$$

In the underwater acoustic sensor network, each data packet can become an agent; the current information of the sensor node includes the remaining energy of the node, the depth of the node and the information of neighbor nodes, which constitute the current state of the node. In the current state, a node forwarding a data packet to another node constitutes an act. After a node sends a data packet to one of its neighboring nodes, this node can obtain a return value, and both the sending node and the receiving node will be updated to the latest state. Based on this return value, the agent can make routing decisions in a certain scenario. In such a routing decision algorithm, each node can obtain necessary information such as the Q-value of the node and all its neighboring nodes through periodic broadcasts of the nodes in the network. Therefore, whenever a node needs to send a data packet, the agent can immediately make an optimal path choice while meeting the requirements of reducing energy consumption.

Reference [61] proposed the DQELR, a routing protocol based on a deep Q-network that is adaptive to energy consumption and delay. DQELR used the Q-value as the reward value for decision-making in certain scenarios. It extended the life of the network by selecting forwarding nodes with higher remaining energy, meanwhile reducing energy consumption and strictly limiting the communication delay.

Reference [62] proposed an efficient routing protocol based on Q-learning over 3D underwater wireless sensor networks. In 3D underwater wireless sensor networks, magnetic induction communication is a promising choice due to several unique features, such as a small transmission delay, constant channel behavior and a sufficiently long communication range. The proposed routing protocol apply Q-learning to study resource management in hierarchical networks. By defining the single-hop reward metric of distance and energy, the update formula is derived, and the relationship between energy priority and distance priority is derived. An adjustment factor is set to adjust the ratio between energy savings and low latency, which can meet different needs.

Reference [63] proposed DMARL, an efficient routing protocol based on multiagent RL for underwater optical wireless sensor networks (UOWSNs). UOWSNs have high transmission rate, ultrawideband nature and low latency, but limited energy resources caused by water movement and highly dynamic topology. It is challenging to provide low-consumption and reliable routing in UOWSNs. DMARL addressed this issue by modeling the whole network as a distributed multiagent system, and considering the remaining energy and link quality in the design of the routing protocol. It proposed two optimization strategies to accelerate the convergence of RL algorithms to improve the network adaptability and life time.

Reference [64] proposed a distributed Q-learning game theory to route UWSNs. The proposed approach was based on RL and game theory was designed as a routing game model to provide an effective packet forwarding mechanism. The Q-learning game paradigm captured the dynamics of underwater sensor network systems in a decentralized and distributed manner.

Reference [65] proposed a congestion avoidance routing protocol (RCAR) based on RL to avoid congestion meanwhile maintaining energy consumption in underwater acoustic sensor networks (UASNs). Since UASNs face many challenges such as energy saving, large propagation delay, high packet error rate, and low bandwidth, network congestion control, the traditional point-to-point congestion control algorithm cannot guarantee the best end-to-end performance. RCAR applied RL to converge the optimal routing path and explore the surface receiver hop by hop. A reward function was defined, considering both congestion and energy, to make appropriate routing decisions. To accelerate the convergence of the algorithm, a dynamic virtual routing pipe with a variable radius was introduced. Such pipe was related to the average remaining energy of the sending node. RCAR protocol also provided cross-layer information, and the MAC layer handshake was ensured in the information update method for the optimal routing decision.

Reference [66] proposed an efficient protocol called MLProph based on machine learning for routing in opportunistic networks (OppNetS). Various factors such as the predictability value inherited from other routing schemes, node popularity, node power consumption, speed, and location are used to train models. MLProph overperformed PROPHET+, a probability-based OppNet routing protocol, in the number of successful deliveries, discarded messages, overhead, and hop count, but at the cost of a slight increase in buffer time and buffer occupancy.

Reference [67] proposed CARMA, a multipath adaptive routing for UWSNs based on channel-aware RL. Routing solutions for multi-path UWSNs suffered from significant performance degradation due to their inability to adapt to the overwhelming dynamics of underwater environment. CARMA enabled multi-path adaptive routing based on channel-aware RL, and adaptively switched between single-path and multipath routing under the guidance of a distributed RL framework. It jointly optimized routing energy consumption and data packet transmission rate. The simulations and sea experiments demonstrated that CARMA presented higher performance than three other routing solutions.

Reference [28] focused on energy-saving and extending service life of underwater sensor networks. It proposed QELAR, a self-adaptive, energy-saving and life-cycle-aware routing protocol based on RL. OELAR used a general MAC protocol and aimed to extend the remaining energy distribution of sensor nodes more evenly throughout the lifetime of the network. The remaining energy of each node and the energy distribution between a group of nodes were used to calculate the reward function, which helped to select the appropriate transponder for the data packet.

6 Challenges and Open Issues

The methods that train the models driven by data for intelligent routing algorithm can be online or offline. Intelligent routing algorithms based on supervised learning generally adopt offline training methods, while models based on RL can be trained online in real environments or offline in simulation environments. For RL, online training can ensure the trained model to adapt to the changes in the network environment and avoid the difficulties and additional costs caused by the establishment of an offline simulation environment. However, the routing security and reliability problems brought by online training make it difficult to deploy intelligent routing algorithms that require online training in actual deployment. In fact, in the process of online RL, security is a problem that has been widely studied.

Although data-driven intelligent routing approaches have been used in some scenarios of UWSNs, it is often difficult to obtain massive data to enable AI algorithms [68]. The experimental environment is also a big challenge for intelligent routing approaches in UWSNs [69]. Since real and large-scaled underwater environment is hard to establish, many underwater routing protocols are sticked in the simulation stage and never been experimentally verified. However, simulated environment simplifies real environment, some corner situations in real environment may never be verified in simulated environment.

Security attack is also a concern in routing UWSNs [70]. As periodically replacement of sensor nodes is unaffordable in underwater environment, while wireless sensors in UWSNs have various restrictions such as battery and time delay, routing protocols in UWSNs are vulnerable to various attacks. The safety aspects of intelligent routing protocols should be taken account. Energy Consumption has been a hot research topic in sensor networks. As it is hard to replace the battery of sensor nodes in UWSNs, reducing the energy consumption of intelligent routing approach is the key to maintain the network life span. Accordingly, the intelligent routing protocols should consider the residual energy of each individual sensor node as well as the energy balance of the whole network. Time synchronization is also an issue that should be addressed for intelligent routing algorithms in large-scaled UWSNs to improve the routing precision and energy consumption. Time synchronization is also the basis for the sensor nodes working together in UWSNs.

7 Conclusion

This paper has summarized the routing algorithms in UWSNs. Routing algorithms for UWSNs have been divided into two types: cross-layer based and non-cross-layer based. While non-cross-layer based routing algorithms for UWSNs can be further grouped according to the mobility of sensor nodes, the energy efficiency, and the network delay, the cross-layer based can be further separated into two categories: intelligent routing algorithms and traditional cross-layer routing algorithms. While traditional cross-layer routing algorithms are clustered by their optimization objectives, intelligent cross-layer routing algorithms are grouped by the AI algorithms applied.

Intelligent routing algorithms are mainly divided into three types: supervised learning based, the combination of evolutionary algorithms and supervised learning, and RL based. Classical RL and Q-learning are "environmentally friendly" since they enable the collaboration between algorithms and environment. They can automatically adapt to different routing application scenarios and optimize multiple network performance indicators. Intelligent routing algorithms based on supervised learning take the network state and the traffic matrix as the input and output the corresponding routing strategy, and supervised learning is used to obtain a training model. When the new data stream arrives, the appropriate routing path is output through the trained model. Intelligent routing algorithms are typically sensitive to environmental perception and have faster convergence speed. Intelligent routing algorithms based on evolutionary algorithms often combine evolutionary algorithms with supervised/reinforcement learning to search the best route for the optimization of some specific objectives. This paper also analyzed challenges and open issues in designing intelligent routing algorithms.

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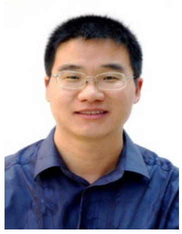
Biographies



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