Variable Rate Image Compression based Adaptive Data Transfer Algorithm for Underwater Wireless Sensor Networks

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Keywords: Underwater Wireless Sensor Networks, Underwater Image, Routing Algorithm, Reinforcement Learning (RL), Haar Wavelet Transform Algorithm.

Abstract: Underwater image, as a kind of important data in underwater wireless sensor networks, can more comprehensively and intuitively reflect the state of underwater environment, but the traffic demand of which is greater than the demand of the numerical data. However, the underwater acoustic channel has the characteristics of high bit error rate, high delay, low bandwidth and so on, and the energy of communication nodes is limited, and the position is time-varying, which makes the transmission of underwater image data extremely difficult. Aiming at this problem, this paper proposes an adaptive image transfer algorithm for underwater wireless sensor networks. The algorithm is based on HAAR wavelet transform algorithm to provide multi-resolution image lossless compression, and can adapt to different image transmission bit rates according to the changes of underwater transmission conditions. It can intelligently select the transmission routes based on reinforcement learning algorithm to achieve reliable and efficient underwater image transfer. Experiments show that the algorithm can effectively improve the packet delivery rate of underwater image, reduce the transmission delay and energy consumption, and can distinguish the transmission of image feature data and detail data, and balance the distribution of communication energy consumption among underwater communication nodes.

1 INTRODUCTION

Underwater wireless sensor networks are generally composed of data centers, water surface sink nodes, underwater communication nodes and underwater sensor nodes (Qiu, 2020), which rely on the self-organizing communication ability between nodes to achieve the data transfer. Underwater wireless sensor networks are widely used in many fields such as accident warning, ecological monitoring, hydrological data collection, marine resource exploration, auxiliary navigation and so on (Qiu T, Jiang S.). At present, underwater long-distance wireless communication is still dominated by underwater sound. Compared with the terrestrial wireless sensor network based on the radio, the underwater transmission channel has the characteristics of small capacity, large delay, more noise and interference factors, and the communication node has the characteristics of limited energy, difficult supply, and high spatiotemporal dynamics (Fattah and Haque), which makes it extremely difficult to achieve the reliable underwater communication.

Underwater images can truly, accurately, and continuously reflect the real-time situation of the monitoring area. They are widely used in the monitoring of marine perimeter, important underwater facilities, and marine biodiversity. They are also an important basis for underwater target positioning and recognition (Gupta and Boukerche). The quality of underwater images and the transmission efficiency from underwater to water surface greatly affect the effect of follow-up monitoring and research work. Compared with the numerical data, the underwater image data is larger, and the underwater image data transfer is more difficult. However, there is some redundancy in the underwater image data. The image compression algorithm based on HAAR wavelet transform can realize the lossless compression of the underwater image data. And it can not only reduce the data transfer demand, but also adjust the transmission data type and the transmission code rate according to the change of transmission conditions and optimize the output underwater image quality (Menon and Kanagaraj).

Wang, B. and Ben, K.
Variable Rate Image Compression Based Adaptive Data Transfer Algorithm for Underwater Wireless Sensor Networks.
DOI: 10.5220/0012273900003807

In *Proceedings of the 2nd International Seminar on Artificial Intelligence, Networking and Information Technology (ANIT 2023)*, pages 61-69
ISBN: 978-989-758-677-4

Reinforcement learning (RL) refers to the process in which agents learn a mapping relationship from environmental state to behavior by continuously interacting with the environment and using the reward of environmental feedback [Guo W, Chen Y]. Nodes in underwater wireless sensor networks can update the status of the transmission environment based on the information interaction between neighbor nodes, and then determine the current reward and cumulative reward after each action. By calculating the status value obtained, the strategy for performing the next action is determined (Zhou Y-Su Y). The transmission route of underwater network needs to be dynamically selected according to the change of transmission conditions. After reinforcement learning algorithm is applied to underwater wireless sensor networks, it can provide decision-making basis for underwater image data when selecting the next hop node according to underwater transmission conditions and historical data forwarding.

For the underwater target recognition applications, this paper presents an adaptive data transfer algorithm for underwater wireless sensor networks based on variable bit rate image compression and reinforcement learning (VRC-ADTA). In this algorithm, HAAR wavelet transform is used as variable rate image compression algorithm, and Q-learning is used as reinforcement learning algorithm. The reward function is designed based on the position of underwater communication nodes, residual energy, and transmission delay. The variable transmission code rate adjustment and dynamic routing of underwater image data are realized. The simulations show that VRC-ADTA can satisfy the accuracy requirements of underwater target recognition, improve the efficiency of underwater image data transfer, reduce the transmission delay, the energy consumption, and improve the packet delivery rate.

2 RELATED WORKS

To overcome the unfavorable conditions of underwater network, researchers have studied and implemented efficient and reliable data transfer routing algorithms for underwater wireless sensor networks from different perspectives. Table 1 lists several typical routing algorithms and their characteristics, among which communication efficiency mainly requires routing algorithms to control transmission delay and reduce communication energy consumption.

Table 1: Several typical data transfer algorithms for underwater wireless sensor networks.

Algorithm	Establishment Method	Application	Efficiency
VBF [Xie P]	Routing based on node location.	No distinction	Low
QELAR [Hu T]	Routing based on the node location and residual energy.	No distinction	Low
RCAR [Jin Z]	Routing based on the delay and residual energy.	Business flow	Middle
EP-ADTA [Wang B]	Routing based on the node location, the delay, and the residual energy.	Content prediction	High
VRC-ADTA	Routing based on the node location, the delay, and the residual energy.	Adjustable code rate	High

The VBF proposed by Xie et al. belongs to the geographical routing protocol. According to the position vector between the sending node and the target node, the node is selected as the next hop, but it cannot balance the energy consumption between the neighbor nodes, making the nodes closer to the position vector consume more energy due to excessive forwarding. QELAR proposed by Hu et al. builds the transmission routes based on reinforcement learning, and adaptively selects the best route to reduce the transmission hops and balance the energy consumption. Both VBF and QELAR can find a suitable underwater route to realize data transfer without distinguishing between the carried applications. However, it is necessary to adjust the transmission route reasonably according to the priority of applications and the queue length of nodes.

The RCAR proposed by Jin et al. focuses more on the congestion avoidance method in the case of large traffic. Through the reinforcement learning algorithm, it optimizes the distribution of the delay and energy consumption on the transmission route, and can well adjust the traffic distribution in case of heavy traffic. Although RCAR optimizes the traffic layout in time-varying underwater networks and can provide a good QoS, it is not enough to only consider improving the unfavorable underwater transmission conditions. It is also necessary to consider how to better integrate the business applications to improve the efficiency of underwater communication.

The EP-ADTA proposed by Wang et al. is designed for the transmission of the time series monitoring data. While selecting the transmission route, it adaptively adjusts the transmission accuracy of the monitoring data according to the transmission conditions. When the underwater environment is good and the transmission route can provide enough transmission bandwidth, high-precision monitoring data can be transmitted. When the transmission environment is bad and the transmission route cannot provide enough bandwidth, the transmission accuracy of monitoring data shall be appropriately reduced to ensure that the characteristic data is transmitted to the surface sink node in priority. Therefore, EP-ADTA considers the reliability and efficiency of transmission. However, EP-ADTA can only be applied to the time series data acquisition, and is not applicable to the underwater image data.

Therefore, based on the above research, aiming at the fixed 3D underwater wireless sensor network, in order to improve the efficiency of underwater image data transfer, the research of adaptive data transfer algorithm based on variable bit rate image compression technology (VRC-ADTA) is carried out.

3 ALGORITHM DESIGN

VRC-ADTA consists of two parts. One is the image compression algorithm based on the HAAR wavelet transform, which realizes lossless compression of image data and converts the image data into the average feature data and the detail coefficient data. The image compression algorithm is implemented in underwater sensor nodes. The second is the routing algorithm based on the reinforcement learning, which realizes the optimal underwater transmission route selection. The routing algorithm is implemented between the underwater sensor node and the communication node.

3.1 Image Compression Algorithm Based on HAAR Wavelet Transform

The image, especially the static continuous tone image, has great redundancy between adjacent pixels. The change of image sample values between adjacent pixels is smooth and generally does not change suddenly, even if there is a mutation, it is only at the edge of the object in the image, which makes it possible to compress images. In order to compress the image effectively, we must focus on the redundancy contained in the signal and reduce its redundancy. In the usual image, most of the signals are concentrated in the lowest frequency component. The higher the frequency, the more the signal strength decays.

Due to the scalable resolution of the discrete wavelet transform, the image compression algorithm based on wavelet transform can transform the resolution repeatedly in space, and reduce the redundancy of the image and compress the image. HAAR wavelet transform is a typical wavelet transform, which takes the average value of two adjacent values as the low-frequency coefficient and the difference between two adjacent values as the high-frequency coefficient [Xiang W, 20]. When the adjacent values are equal or the change rate is very gentle, the low-frequency coefficient can be used as the approximation of the sample value, while the high-frequency coefficient is a value close to 0. In this way, in some cases, the high-frequency coefficient can be discarded and the low-frequency coefficient can be directly used to restore the image. The restored image cannot reach the quality of the original image. In many cases, this loss of image quality can fully meet the needs of practical applications (Bagmanov V H, Porwik P).

Suppose a one-dimensional image with a resolution of only 4 pixels, and the corresponding pixel values are respectively: [9 7 3 5], calculate its HAAR wavelet transform coefficients.

Step 1: calculate the average value. Calculate the average value of adjacent pixel pairs to get a new image with relatively low resolution, whose number of pixels has become 2. That is, the resolution of the new image is 1/2 of the original, and the corresponding pixel value is [8 4], where 8= (9+7)/2, 4= (3+5)/2.

Step 2: calculate the difference value. When this image is represented by 2 pixels, the image information has been partially lost. To reconstruct the original image composed of 4 pixels from the image composed of 2 pixels, it is necessary to store the image detail coefficients for retrieving the missing information during reconstruction. The method is to subtract the average value of the pixel pair from the first pixel value of the pixel pair. The first detail coefficient is (9-8) =1, because the calculated average value is 8, which is 1 smaller than 9 and 1 larger than 7. Storing this detail coefficient can restore the first two-pixel values of the original image. Using the same method, the second detail coefficient is (3-4) =-1, and the last two-pixel values can be restored by storing this detail coefficient. Therefore, the original image can be expressed as [8 4 1 -1] with the following two average values and two detail coefficients.

Step 3: repeat steps 1 and 2 to further decompose the image obtained from the step 1 into the images with lower resolution and the detail coefficients. At last, the whole image is represented by the average value of one pixel 6 and three detail coefficients 2, 1 and -1. The decomposition process is shown in Table 2.

Table 2: Schematic diagram of HAAR wavelet transform.

Resolving power	Average value	Detail factor
4	[9 7 3 5]	
2	[8 4]	[1 -1]
1	[6]	[2]

It can be seen from Table 2 that the image composed of four pixels is represented by one average pixel value, one first-order detail coefficient and two second-order detail coefficients through the above decomposition.

After the underwater image data is compressed based on HAAR wavelet transform, the pixel data of the image is transformed into a combination of the average feature value and the detail coefficient values. And the data combination of the average value and the detail coefficient values of the transmitted image can restore the image of the previous level of resolution. Only transmitting the average value can retain the feature of the image and reduce the demand for data transfer. After the detail coefficient data arrives at the later stage, the underwater image quality can be further improved.

3.2 Routing Algorithm Based on Reinforcement Learning

Reinforcement learning is a machine learning algorithm aimed at finding the optimal mapping strategy from state to action, typically used to solve problems related to Markov decision processes (MDP) (Dugaev, 2020). The process of reinforcement learning is usually represented by five tuples (S, A, P, R, γ) (Jin Z, Shen Z), where S is the environment, A is the action, P is the transition probability, R is the reward, and γ is the discount rate.

Assuming that the underwater wireless sensor network is composed of m nodes, the nodes can be expressed as:

$$\mathrm{N} = \{n_1, n_2, \cdots, n_m\} \tag{1}$$

Where, n_i represents underwater wireless sensor network nodes, and m represents the number of nodes. Each the node of the underwater network can obtain its own coordinate. Then, the candidate relay node set of the current node n_i can be expressed as:

$$N_r(i) = \{n_j | [N | d(n_j) - d(n_i) \le 0] \cap nei(n_i)\} \tag{2}$$

Where, $N_r(i)$ is the set of candidate relay nodes, $nei(n_i)$ is the neighbor nodes set covered by one hop, $\{N | d(n_j) - d(n_i) \le 0\}$ represents the node set which is shallower than the depth of the current node.

If the packet is located at the node n_i, the current environment state S can be defined as:

$$\mathrm{S} = \{\mathrm{n_i}\} \cup \mathrm{N_r(i)} \tag{3}$$

The action A can be defined as:

$$\mathrm{A} = \{\mathrm{a_j} | \mathrm{n_j} \in \mathrm{S}\} \tag{4}$$

If the current packet is at the node n_i and n_j is selected as the relay node, the reward function is:

$$R_{n_i n_j}^{a_j} = -R_0 - [\varphi_e \times co(e) + \varphi_t \times co(t)] \tag{5}$$

The reward function R includes fixed cost, residual energy cost of neighbor node and transmission channel delay cost in three parts.

The significance of R_0 is that the fixed cost needs to be increased every time the data forwarding of a hop node is experienced. The existence of R_0 can help the agent to select the route with fewer hops.

The significance of $co(e)$ is that selecting the node with large residual energy as the next hop node is beneficial for extending the service time of the underwater networks. The existence of $co(e)$ can help the agent select the node with greater residual energy as the next-hop node. It can be expressed as:

$$\mathrm{co}(e) = 1 - \frac{E_r^j}{\sum_{k \in N_r(i)} E_r^k} \tag{6}$$

Where, E_r^j represents the residual energy of the next-hop node, and $\sum_{k \in N_r(i)} E_r^k$ represents the total residual energy of the candidate node set, φ_e is the sensitivity coefficient for the $co(e)$.

The significance of $co(t)$ is to select the transmission channel with smaller transmission delay to reach the next-hop node, and the smaller transmission delay shows that the transmission channel is more stable, reliable, has less bit error rate and congestion. It can be expressed as:

$$co(\mathrm{t}) = 1 - \frac{1}{\overline{t_t^{i \to j}} + 1} \tag{7}$$

Where, $\underline{\varphi_t}$ is the sensitivity coefficient of the $co(t)$, $\overline{t_t^{i \to j}}$ is the total transmission delay of the packet.

If the current packet is at the node n_i, the transition probability of the node n_i to the node n_j is defined as:

$$\mathrm{P}_{\mathrm{n_i n_j}}^{\mathrm{a_j}} = \frac{\mathrm{R}_{\mathrm{n_i n_j}}^{\mathrm{a_j}}}{\sum_{\mathrm{n_k} \in \mathrm{S}} \mathrm{R}_{\mathrm{n_i n_k}}^{\mathrm{a_k}}} \tag{8}$$

In order to embody the impact of the next state on the current state, the overall reward is defined as:

$$R_t = r_t + \gamma r_{t+1} + \gamma^2 r_{t+2} + \cdots = \sum_{j=0}^{\infty} \gamma^j r_{t+j} \tag{9}$$

According to the Q-learning, the state action function under the policy π is defined as:

$$Q^{\pi}(s, a) = E_{\pi}\{R_t | s_t = s, a_t = a\} \tag{10}$$

Assuming that sum is the next action a' and the next state s', the optimal solution $Q^*(s, a)$ in the state $Q^{\pi}(s, a)$ can be expressed as the iterative equation:

$$Q^*(s, a) = r_t + \gamma \sum_{s' \in S} P_{ss'}^{a} \left\{ \max_{a'} Q^*(s', a') \right\} \tag{11}$$

The V value function will select the Q value that can obtain the maximum benefit, which is defined as:

$$\mathrm{V}_t^*(s) = \max_a Q^*(s, a) \tag{12}$$

At the initial stage, the Q value table of each agent is initialized according to its neighbor relationship and the position to improve the convergence speed of the Q value. The initial setting of Q value is:

$$Q_{n_i \to n_{\bar{j}}}^{ini} = -10\,, \quad n_i, n_{\bar{j}} \in N, n_{\bar{j}} \notin N_r(i) \tag{13}$$

As the Q values and V values are gradually updated and converged according to formulas (11) and (12), a good data transmission strategy will eventually emerge.

The reinforcement learning adjusts the degree of "exploration" and "utilization" by exploring probability ε to ensure that the best strategy can be used without missing the global best strategy (El-Banna A A A, 2021). When the exploration probability ε is small, the reinforcement learning algorithm will choose more random strategies to explore new transmission route. When the exploration probability ε is large, the reinforcement learning will use more existing optimal strategies to achieve more efficient and reliable data transfer. When transmitting the average value data, because it contains the core features of the image, we choose a larger probability of exploration ε, use the existing optimal strategy for transmission, and increase the data retransmission threshold $times_{thred}$ to improve the reliability of the image feature data transfer. When transmitting the detailed data, choose a smaller exploration probability ε, and try more random strategies to reduce the energy consumption of the optimal path. At the same time, try to obtain the global optimal path and reduce the data retransmission threshold $times_{thred}$. The corresponding relationship between the explore probability ε , the retransmission threshold $times_{thred}$ and the image data type, which is defined as:

$$\varepsilon = \begin{cases} \varepsilon_{max} & when\ the\ \text{average}\ values\ are\ forwarded \\ \varepsilon_{mid}, & when\ the\ first\ detail\ factors\ are\ forwarded \\ \varepsilon_{min}, & when\ the\ second\ detail\ factors\ are\ forwarded \end{cases} \tag{14}$$

$$times_{thred} = \begin{cases} times_{max}, & when\ the\ \text{average}\ values\ are\ forwarded \\ times_{mid}, & when\ the\ first\ detail\ factors\ are\ forwarded \\ times_{min}, & when\ the\ second\ detail\ factors\ are\ forwarde \end{cases} \tag{15}$$

3.3 Simulation and Performance Analysis

The simulation is based on the underwater fish activity monitoring application. The simulation is set as a three-dimensional underwater area. One sensor node is deployed in the underwater area center to collect image data, and several communication nodes are randomly deployed in the water to forward the monitoring data. One sink node is deployed in the surface center to collect the data.

3.4 Simulation and Parameter Setting

In the simulation, the underwater network topology is generated randomly. Each underwater node communicates based on the acoustic channels. Underwater nodes move randomly around their original positions under the influence of water flow. Each pixel of the image is represented by 1 byte, and each packet encapsulates 50-pixel data for transmission. The simulation environment and the parameter settings of VRC-ADTA are shown in Table 3.

Table 3: Simulation and the parameter settings.

Parameter	Value
Underwater network	500m×500m×500m
Sound speed	1500 m/s
Sound frequency	10 kHz
Communication distance	150m
Number of nodes	100, 200, 300
Maximum distance of node movement	0, 5, 10
Initial energy	30000 J
Transmission power	10 W
Receiving power	3 W
Channel interruption probability	0, 0.01,0.1
Image Original Size	(300,500), single channel
Resolution ratio of images (Origin:1level:2level)	16:4:1
Packet transmission rate	10,15,20 packets/minute
Origin data packet size	100Bytes
Mac protocol	S-FAMA
R_0	-1
φ_e, φ_t	0.8, 0.2
$\varepsilon_{min}, \varepsilon_{mid}, \varepsilon_{max}$	0.7, 0.8,0.9
$\text{times}_{min}, \text{times}_{\text{mid}}, \text{times}_{\text{max}}$	0,1,3

The environment is built by Python. The basic state of the environment is that the number of nodes in the underwater network is 100, the data transfer rate is 10 packets/min, the transmission channel is uninterrupted, and the node position is unchanged.

3.5 Image Compression Performance Analysis

As shown in Figure 1-(a), the original image is taken by an underwater camera. The main body of the image is fish swimming in the water, and the background is underwater reef. As shown in Figure 1-(b), the size of the image (1level) after one compression based on HAAR wavelet transform is reduced to 1/2 of the size of the original image, and the pixel data to be transmitted becomes 1/4 of the original image, but the fish swimming in the water can still be clearly identified. As shown in Figure 1-(c), the size of the image (2level) after twice compression based on HAAR wavelet transform is reduced to 1/4 of the size of the original image. The pixel data to be transmitted becomes 1/16 of the original image, and the fish swimming in the water can still be recognized. Therefore, image compression based on HAAR wavelet transform retains the characteristic information of the image. When the transmission channel is bad and a large amount of data is not allowed to upload, the image average data generated by HAAR wavelet transform retains the main characteristics of the image and can meet the basic needs of image monitoring. Because the image compression based on HAAR wavelet transform belongs to lossless compression, after the transmission channel is restored, continue to transmit the image detail coefficient data, which can completely restore the resolution of the original image.

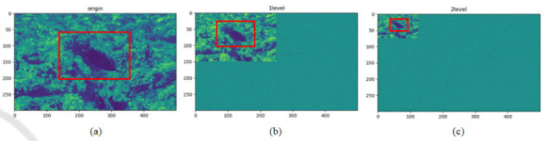

Figure 1: Comparison of image compression effects with different resolutions.

Where, Figure 1-(a) is the original underwater image; Figure 1-(b) shows the image after one compression based on HAAR wavelet transform; Figure 1-(c) shows the image after twice compression based on HAAR wavelet transform.

3.6 Data Transfer Performance Analysis

VRC-ADTA, QELAR and VBF are used as routing algorithms to forward the image packet in underwater wireless sensor networks, and their transmission performance is compared.

1) Comparison of the packet delivery rate
According to the different conditions, in underwater wireless sensor networks, VRC-ADTA, QELAR and VBF are used to transmit a group of image data (including 1500 packets), and the average packet delivery rate of the image packets transmitted from the underwater sensor nodes to the surface sink nodes is calculated. The comparative results are shown in Figure 2.

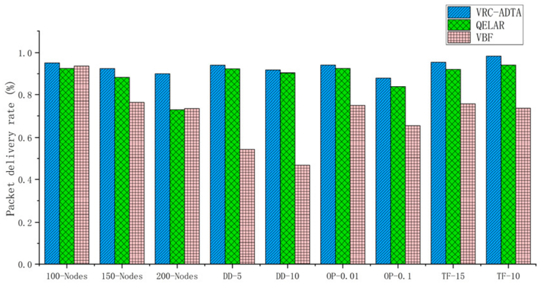

Figure 2: Comparison of the average packet delivery rates.

100-Nodes, 150-Nodes, and 200-Nodes respectively indicate that the network contains 100, 150 or 200 communication nodes; DD-5 and DD-10 indicate that the dynamic range of node position movement in the network per minute is 5 meters or 10 meters; OP-0.01, OP-0.1 indicate that the interruption probability of each data transfer is 0.01 or 0.1; TF-15 and TF-10 indicate that 15 or 10 packets are sent per minute.

Figure 2 shows that under the different conditions, the blue data column representing VRC-ADTA is higher than the green data column representing QELAR and the red data column representing VBF. This shows that the average delivery rate of image data in VRC-ADTA is higher under different conditions. Due to the comprehensive consideration of transmission hops, transmission delay, residual energy, and service type, VRC-ADTA can provide more reliable data transfer with the support of the adaptive improved Q-learning.

2) Comparison of the Transmission Delay

VRC-ADTA, QELAR and VBF are used to forward a group of image data, and the transmission delay of a single image packet from the sensor node to the sink node is calculated. The comparative results are shown in Figure 3.

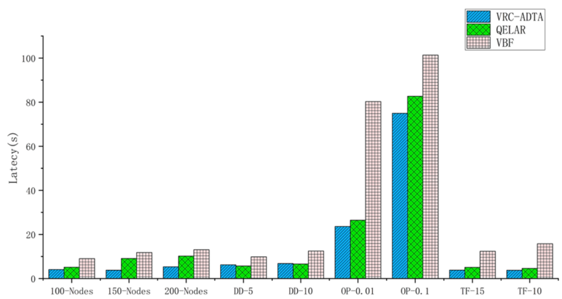

Figure 3: Comparison of the transmission delay of a single packet transmitted.

Figure 3 shows that under different conditions, the blue data column representing VRC-ADTA is lower than the green data column representing QELAR and the red data column representing VBF. This shows that the VRC-ADTA consumes less time to transmit a single packet under different conditions. VRC-ADTA can provide faster data transfer. Figure 3 also shows that the increase of interruption probability has a significant impact on the underwater data transfer. With the increase of interruption probability, the data needs to be retransmitted for many times, resulting in the increase of the transmission delay.

3) Comparison of the Energy Consumption

VRC-ADTA, QELAR and VBF are used to transmit a group of image packet, and the communication consumption required to transmit a single image packet from the sensor node to the sink node is calculated. The comparative results are shown in Figure 4.

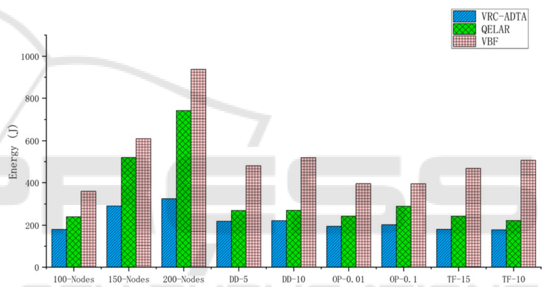

Figure 4: Comparison of the energy consumption of a single packet transmitted.

Figure 4 shows that under different conditions, the blue data column representing VRC-ADTA is lower than the green data column representing QELAR and the red data column representing VBF. It shows that under different conditions, the VRC-ADTA requires the least energy consumption for each node of the underwater network to transmit a single packet. This is mainly because the VRC-ADTA requires less transmission hops, indicating that VRC-ADTA can provide more efficient data transfer. Figure 5 also shows that with the increase of the number of nodes in the network, the energy consumption required to transmit a single image packet increase.

4) Comparison of the Residual Energy Variance

VRC-ADTA, QELAR and VBF are respectively used to transmit a group of image data, collect the residual energy of each communication node, calculate its average and variance of the distribution, and form a comparison result, as shown in Figure 5.

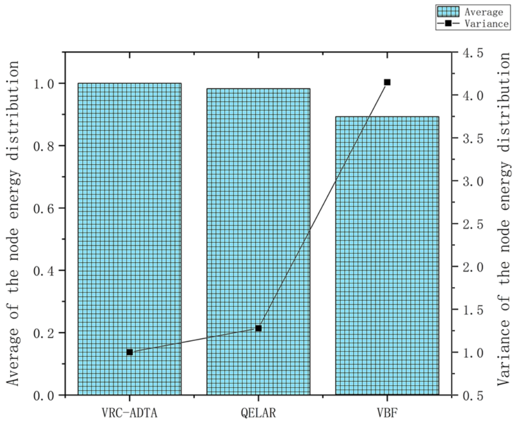

Figure 5: Comparison of the average and variance of residual energy distribution.

Figure 5 shows that VRC-ADTA and QELAR have a larger average of the residual energy than VBF, indicating that the two algorithms are more efficient. The variance of residual energy distribution corresponding to VRC-ADTA is smaller, indicating that VRC-ADTA uses more energy evenly than QELAR and VBF, which is conducive to extending the overall life of underwater network.

4 CONCLUSION

The variable rate image compression based adaptive data transfer algorithm (VRC-ADTA) for underwater wireless sensor networks proposed in this paper contains three innovations. Firstly, it is to introduce the image compression algorithm based on HAAR wavelet transform into underwater image transmission. Because HAAR wavelet transform retains the image features in the process of image compression, even after the image data is greatly compressed, the monitoring object is still clear and recognizable in the image. Because the image compression based on HAAR wavelet transform belongs to lossless compression, whether to transmit the detail coefficient data can be selected according to the change of transmission channel quality. After the detail coefficient data is supplemented, the monitoring image resolution can be restored to the initial state. Secondly, it is to realize underwater network routing based on the reinforcement learning. In the process of the next hop selection, the depth and residual energy of the relay node, the transmission channel delay are comprehensively considered to improve the quality of transmission routing. Thirdly, it based on whether the content of the underwater transmission data is the average value data of the monitoring image or the detail coefficient data, the exploration probability and the retransmission threshold in the routing algorithm are dynamically selected, so that the average value data containing image features can be delivered to the destination by the more efficient and reliable route, while the detail coefficient data that helps to improve the image resolution are delivered by the suboptimal routing, in order to reduce the energy consumption of nodes on the optimal route and optimize the distribution of the residual energy of nodes. Therefore, VRC-ADTA can adaptively select the transmission routes and the resolution of the image data according to the changes of underwater transmission conditions. When the transmission environment is stable, the transmission channel error rate is low, and the delay is small, it can transmit high-resolution high-rate image data. When the transmission environment is unstable and the transmission channel quality is poor, it can transmit low-rate image data containing image features, when feature data and detail data are transmitted at the same time, it can provide more efficient and reliable transmission routes for the image feature data.

Simulation shows that VRC-ADTA can provide efficient and reliable transmission routes under different node densities, dynamic ranges of node locations, interruption probabilities of transmission channels and traffic flows. Compared with QELAR and VBF, the VRC-ADTA can increase the packet delivery rate by 3% -20%, reduce the transmission delay by 10% -50%, reduce the energy consumption by 18% -60%, and reduce the variance of residual energy of nodes by 16% -75%.

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