A Channel-Aware Routing Protocol With Nearest Neighbor Regression For Underwater Sensor Networks

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ABSTRACT The underwater acoustic channel is one of the most challenging communication channels. Due to periodical tidal and daily climatic variation, underwater noise is periodically fluctuating, which result in the periodical changing of acoustic channel quality in long-term. Also, time-variant channel quality leads to routing failure. Routing protocols with acoustic channel estimation, namely underwater channel-aware routing protocols are recently proposed to maintain the routing performance. However, channel estimation algorithms for these routing protocols are mostly linear and rarely consider periodicity of acoustic channels. In this paper, we introduce acoustic channel estimation based on nearest neighbor regression for underwater acoustic networks. We extend nearest neighbor regression for SNR (Signal-to-Noise Ratio) time series prediction, providing an outstanding prediction accuracy for intricately periodical and fluctuating received SNR time series. Moreover, we propose a quick search algorithm and use statistical storage compression to optimize the time and space complexity of the algorithm. In contrast with linear methods, this algorithm significantly improves channel prediction accuracy (over three times at most) on both simulation and sea trial data sets. With this channel estimation method, we then propose a Depth-Based Channel-Aware Routing protocol (DBCAR). Taking advantage of depth-greedy forwarding and channel-aware reliable communication, DBCAR has an outstanding network performance on packet delivery ratio, average energy consumption and average transmission delay which is validated through extensive simulations.

INDEX TERMS Channel Estimation, Depth, Nearest Neighbor, Routing, Underwater Sensor Networks.

I. INTRODUCTION

During the past decade, there has been a significant development in underwater acoustic communication, thus inspiring extensive research on underwater sensor networks (UWSNs). At the same time, marine applications on underwater sensor networks, including ocean exploration, submarine tracking, and marine rescue [1]–[3] have gradually matured. Long-term and reliable data transmission is the primary research object for UWSNs which faces many challenges: long transmission delay as the propagation speed of acoustic waves in water is approximately 1500 m/s, which is five orders of magnitude lower than that of radio frequency [4]; limited-bandwidth as it is difficult for the bit rate of acoustic channels to exceed 100 kbps in a long-range system [5]; time variable channel as underwater acoustic channel affected by ambient noise, leading to severe bit error [1].
tistical analysis, exponential moving average (EMA) and auto-regression (AR) were adopted for underwater channel quality series analysis. However, these algorithms are linear and rarely consider periodicity of acoustic channels. With periodical tidal and daily climatic variation, underwater noise is changing periodically in long-term [10]. Meanwhile, the fluctuations of SNR values exist intrinsic periodicity in long-term underwater communication.

In this paper, we consider intrinsic periodicity in long-term underwater acoustic channels and propose the nearest neighbor regression (NNR) based channel estimation algorithm. Moreover, we propose a depth-based channel-aware routing (DBCAR) protocol with NNR channel estimation algorithm. Depth-based routing protocols [11]–[13] are location-free and stateless which have unstable packet delivery ratios in sparse networks but low transmission delay. On the contrary, channel-aware routing protocols have better packet delivery rates but high transmission delay. DBCAR with NNR channel estimation provides a more powerful solution with excellent packet delivery ratios while keeping a reasonable transmission delay. In summary, we make two significant contributions for underwater acoustic channel estimation and channel-aware routing protocols: 1) We introduce NNR for underwater channel quality estimation, and extend NNR for time series analysis, thus providing a better prediction precise for intrinsically periodic and fluctuating received SNR time series. In addition, we use hash table and statistical storage compression to optimize the time and space complexity of NNR quality estimation algorithm. 2) Based on the NNR quality estimation algorithm, we propose a depth-based channel-aware routing protocol, DBCAR. Besides residual energy, we take historical statistical parameters, current SNR gradient, and depth into consideration to explore the best forwarder hop by hop. The accuracy of NNR quality estimation algorithm has been evaluated through simulations on different SNR fluctuation scenarios and sea trials data sets, including ideal periodic fluctuation, periodic fluctuation with stochastic noises and random periodic fluctuation, and underwater experiment data, KW14 and KAM11. The performance of DBCAR has been evaluated through extensive simulations using Bellhop [14] and Aqua-sim [15].

The rest of the paper is organized as follows. Selected works on acoustic channel estimation methods and channel-aware routing protocols are summarized in Section II. Proposed channel estimation algorithm and a channel-aware routing protocol are presented in Section III including NNR channel quality estimation algorithm, time and space complexity optimization and DBCAR, a depth-based channel-aware routing protocol with NNR. Extensive evaluations and results are analyzed in Section IV. Section V concludes this paper.

II. RELATED WORK

Acoustic channel quality is time-variant [16] while most underwater network protocols assumed acoustic channel quality is static [11], [17], [18], leading to unsatisfying network performance, including low packet delivery ratio, low throughput, and redundant re-transmissions in real underwater environments. Channel estimation algorithms considering time variability of acoustic propagation results in a better channel estimation accuracy. Besides, considering time-variant channel quality provides a practical performance evaluation for network protocols [19]. Underwater routing protocols with channel quality estimation, namely channel-aware routing protocols [6]–[9] can investigate a reliable communication path from sources to sinks hop by hop, maintaining a remarkable network performance in time-variant underwater acoustic channel states.

Acoustic channel quality estimation is the core process for channel-aware routing protocols. Historical and current packet success ratio [6], [7] and received signal-to-noise ratio [8], [9] were taken into account as the primary channel quality indicator for estimation and prediction. Packet success ratio (PSR) is the ratio of successful delivery packets and total transmitted packets counted hop-by-hop between each node and its neighbors. Received signal-to-noise ratio (SNR) is computed as Equation 1 where \( P \) is the transmission power, \( A(r, f) \) is the attenuation over a distance of \( r \) with a signal of frequency \( f \). \( N(f) \) is the noise power spectral density and \( \Delta f \) is the receiver noise bandwidth [20]. Packet success ratio and received signal-to-noise ratio have an equivalence relation from Equation 2 [21]. Besides packet success ratio and received signal-to-noise, hops away from sinks, residual energy, and other auxiliary parameters were also considered for channel quality estimation and best forwarder selection.

\[
SNR = \frac{P}{A(r, f)} \frac{1}{N(f)\Delta f}
\]  
(1)

\[
PSR = 1 - \left(1 - \frac{1}{2}erfc(\sqrt{SNR})\right)^L
\]  
(2)

Channel quality estimation can be modeled as a time series analysis process. Simple mean statistical analysis [9], exponential moving average (EMA) [6], [7], [22] and auto-regression (AR) [23] were adopted for underwater channel quality time series analysis. The EMA for a series \( Y \) may be calculated recursively as Equation [3] For AR, the notation AR\( (p) \) indicates an auto-regressive model of order \( p \) defined in Equation [4]. However, linear time series analysis methods are not precise for underwater link quality estimation as SNR intricately fluctuating with ambient noise. Also, SNR fluctuation exists intrinsic periodicity in long-term underwater communication [10]. Also, these conclusions can be drawn from real ocean experiments, including KW14 (Fig 1) and KAM11 (Fig 2). KW14 sea trials took place August 2014 in Keweenaw Waterway near Michigan Tech. Received SNR time series in decibels are presented in Fig. 1, the receiver is 312m away from the transmitter. Kauai Acomms MURI 2011 (KAM11) Experiment took place from June to July 2011 in waters around the coast of Martha’s Vineyard (MA, USA), Pianosa (Italy), and Kauai (HI, USA) islands, respectively.
SNR measurements taken on July 8 were shown in Fig. 2 [19], [24].

\[ S_t = \begin{cases} Y_1, & t = 1 \\ \alpha \cdot Y_t + (1 - \alpha) \cdot S_{t-1}, & t > 1 \end{cases} \]

\[ X_t = c + \sum_{i=1}^{p} \phi_i X_{t-i} + \epsilon_t \]

With acoustic channel quality estimation, some channel-aware routing protocols were proposed [6], [7], [9], [22], [25]. In [22], a cross-layer routing protocol for UWSN was proposed which exploited link quality information for cross-layer relay determination. In addition, simple network topology parameters, including hop count, were considered to improve routing performance. EMA was selected as the major channel estimation method. [6], [7] extended ideas in [22] to sea trials and multi-modal communications. In [9] an energy efficiency channel-aware and depth-based routing protocol was proposed with autonomous underwater vehicles. Besides channel quality, this paper considered node energy, hop count and propagation delay to improve routing performance. Average peak signal-to-noise vectors (PSNR) [26] were used to estimate channel quality. In [25], a channel-aware, depth-adaptive routing protocol was proposed, taking sound speed and underwater noises into account to relief the rate of transmission error. On relay selection, three factors were taken into consideration: successful transmission probability, the distance between candidate nodes and the destination, and the distance between candidate nodes and the ideal path. The successful transmission probability was computed between a source node and its neighbors respectively.

Different from above algorithms and protocols, we introduce NNR for underwater channel quality estimation in this paper, extending NNR for time series analysis and providing a better prediction precise for intricately periodical and fluctuating received SNR time series. However, NNR based channel estimation algorithm is non-linear, thus increasing time and space complexity than linear algorithms. Therefore, we use hash table and statistical storage compression to optimize the time and space complexity of NNR quality estimation algorithm, getting an approximate linear performance. Based on the NNR quality estimation algorithm, we proposed a depth-based channel-aware routing protocol (DBCAR). Besides residual energy, we take historical statistical arguments, current SNR gradient, and depth into consideration to explore the best forwarder hop-by-hop. We will present proposed algorithm and protocol in the next section.

III. ALGORITHM AND PROTOCOL DESCRIPTION

In this section, we start by describing the network model before defining the initialization process. Then, we present NNR channel quality estimation algorithm together with time and space complexity optimization methods. Finally, we present a depth-based channel-aware routing protocol.

A. NETWORK MODEL

We constitute the network within a cube area. N underwater sensor nodes are vertically deployed in the area and slowly moving with water currents. As shown in Fig. 3, sensor nodes are uniformly deployed. Besides, there is one or multiple sinks on the surface. Each sensor node has a unique identi-
fication number and the same transmission power. Channel attenuation function is defined in Equation 5

\[ A(l, f) = l^p a(f)^l \]  

(5)

\[ 10 \log A(l, f) = p \cdot 10 \log l + l \cdot 10 \log a(f) \]  

(6)

where \( l \) is transmission distance, \( f \) is carrier frequency. \( A(l, f) \) is acoustic channel attenuation function in units of \( dB \) given by Equation 6, \( p \in [1, 2] \), \( a(f) \) is the absorption coefficient.

Once an underwater node deployed into the water and switched on, it will broadcast a handshake packet to explore neighbors and initialize a vector of SNR vectors, noted as \( M_{SNR} \) based on ACK packets from neighbors given by Equation 7, where \( X^{ID} \) is the received SNR vector of neighbor \( ID \). For the NNR channel quality estimation algorithm, the input vector is an element of \( M_{SNR} \), noted as Equation 8, where \( x_t \) notates SNR values is X from a neighbor with \( ID_t \) at \( t \) moment.

\[ M_{SNR} = \left[ X^{ID_1} \; X^{ID_2} \; \ldots \; X^{ID_i} \; \ldots \; X^{ID_n} \right] \]  

(7)

\[ X^{ID_i} = (x_{t_1} \; x_{t_2} \; x_{t_3} \; \ldots \; x_{t_n}) \]  

(8)

B. NNR CHANNEL ESTIMATION ALGORITHM

In this section, we extend NNR to the time series prediction problem. In the primal NNR algorithm, the training set contains a group of vectors taking values in \( \mathbb{R}^4 \) and \( y \) is the output label of each vector given in Equation 9.

\[
\begin{align*}
(x_1^1 & , x_2^1, \ldots x_n^1) \sim y_1 \\
(x_1^2 & , x_2^2, \ldots x_n^2) \sim y_2 \\
(x_1^3 & , x_2^3, \ldots x_n^3) \sim y_3 \\
& \vdots \\
(x_1^n & , x_2^n, \ldots x_n^n) \sim y_n
\end{align*}
\]  

(9)

We want to predict the output label \( y_{n+1} \) of \( (x_1^{n+1}, x_2^{n+1}, \ldots, x_n^{n+1}) \) based on the training set. \( k \) nearest neighbor vectors are taken from the training set by distance function (e.g., Euclidean distance function given by Equation 10).

\[ D(X^1, X^2) = \sum_{i=1}^{n} (x_i^1 - x_i^2)^2 \]  

(10)

Then, output label \( y \) of the input vector is determined by Equation 11 with inverse distance weighting of the \( k \) nearest neighbors where \( q \) is a negative integer, and \( d_i \) is the distance. Inverse distance weighing is a weighted average method that weight decreases as distance increases when computing weighted average.

\[ y = \sum_{i}^{k} \omega_i y_i \; \omega_i = \frac{d_i^q}{\sum_{i}^{k} d_i^q} \]  

(11)

However, in a time series prediction problem, there is no direct output label \( y \) but a vector of values with the same property and constantly accumulate with time, like the time series in Expression 12.

\[ x_{t_1} \; x_{t_2} \; x_{t_3} \; \ldots \; x_{t_{n-m}} \; x_{t_{n-m+1}} \; x_{t_{n-m+2}} \ldots x_{t_{m}} \]  

(12)

To predict \( y_{t+1} \), we define a time window with a length of \( m \). We use the latest \( m \) SNR values as an input vector of NNR, then sliding the time window from the beginning of the SNR vector, setting \( m + 1 \) SNR value as corresponding output \( y \), thus getting a training set noted in Expression 13: \( (m = 3) \). With the training set, we can calculate distances step by step, getting \( k \) nearest vectors in \( m \) dimension. With \( k \) nearest vectors, we get \( k \) prediction values, constituting the prediction vector. For example, we assume \( k = 2, m = 3, n = 10 \), and we want to predict \( x_{t_1} \). Therefore, the input vector of NNR is \( (x_8, x_9, x_{10}) \). Then, we assume the 2 nearest neighbor is \((x_1, x_2, x_3)\) and \((x_4, x_5, x_6)\) with distances \( d_1 \) and \( d_4 \) away from the input vector. Thus, we get the prediction vector \((x_4, x_7)\). With inverse distance weighting function given by Expression 14, we get prediction value of time \( x_{t_1} = \frac{d_1^q x_4 + d_4^q x_7}{d_1^q + d_4^q} \) eventually, where \( p \) is generally set to be 2.

\[
\begin{align*}
(x_1 & , x_2, x_3) \sim x_4 \\
(x_2 & , x_3, x_4) \sim x_5 \\
(x_3 & , x_4, x_5) \sim x_6 \\
& \vdots \\
(x_{n-3} & , x_{n-2}, x_{n-1}) \sim x_n
\end{align*}
\]  

(13)

The time complexity of this algorithm is \( O(nm) \) and space complexity is \( O(n) \) where \( n \) is the length of an SNR vector, and \( m \) is the length of sliding window. However, it is not an efficient solution so that we will optimize the time and space complexity of this algorithm in the next section.

C. ALGORITHM OPTIMIZATION

Time Complexity Optimization: We adopt a hash table to store SNR records. Multiplying each SNR by \( 10^3 \) and keeping the integral part to form a new SNR vector. Using an arbitrary hash function to compute an index. We get hash keys from SNR values and hash values are the corresponding time stamps of SNR values, then turning SNR values into an array of buckets, from which the time stamp of an expected SNR value can be directly found. When finding \( k \) nearest neighbors, we shorten searching range after the \( min \) values upgraded. In general, we usually initial the \( k \) \( min \) values with a big number, e.g. 65535. Therefore, the initial searching interval is the whole SNR vector. During the calculation, we update the \( k \) \( min \) values while we get a distance smaller than the max value of \( k \) \( min \) values. Once the \( k \) \( min \) values updated, we shorten the search range with recently updated \( min \) value. The searching interval is given in Expression 15, where \( x_{t_{n-m+1}} \) is defined in Expression 8.
\[ x_{t_{n-m+1} - \sqrt{\min}}, x_{t_{n-m+1} + \sqrt{\min}} \]  

**Space Complexity Optimization:** Length of an SNR vector is continuously increasing with time, consuming lots of hard disk space. SNR values far from now have little significance for current prediction. So we employ time inverse distance weighting like Equation 15 to compress prior SNR values. We set a storage limit \( L \) and a period \( T \). When the length of SNR vector reaches \( L \) or the sensor node operates for \( T \) hours, the compression process will be triggered. The first \( \alpha L \) SNR values will be compressed into an inverse distance weighting average, then the length of SNR vector is \((1-\alpha)L\), where factor \( \alpha \in [0, 0.5] \).

\[
y = \sum_{i}^{\alpha L} \omega_i x_i \quad \omega_i = \frac{d_i^p}{\sum_i d_i^p} \quad (15)
\]

Then we will prove that the time complexity of the optimized algorithm will be reduced by orders of magnitude. Underwater channel quality is mainly affected by marine environmental parameters such as hydro-meteorology. The statistical law of general meteorological data conforms to the normal distribution. Therefore, we assume that the channel quality satisfies the discrete normal distribution in the proof of algorithm complexity [27]. According to the conclusions of Szabolowski [28], while the variance \( \sigma^2 > 0.73 \), the probability density of discrete normal distribution can be approximated by Equation 16 where \( \alpha \) is the mean and \( \sigma \) is the variance.

\[
P(X = i) = \frac{1}{\sigma \sqrt{2\pi}} e^{-\frac{(i-\alpha)^2}{2\sigma^2}} \quad (16)
\]

Setting the channel quality values fluctuate within \( r = |v_{\text{max}} - v_{\text{min}}| \), keeping the channel quality two decimal before hashing, that is the same with multiplying all channel quality values by 100 and retain the integer part. And now the values fluctuate within 100\( r \), so the total number of keys in the hash table in Fig. 4 is at least 100\( r \).

Total number of nearest neighbor calculations is related to the length of timing sequence vectors \( n \), the length of the time window for calculating the nearest neighbor regression \( m \) and the value of target channel quality \( i \), denoted as \( T(X = i, m, n) \). When there are \( n \) keys, the expected length of the value vector that is randomly selected in the hash table is \( n \frac{1}{\sigma \sqrt{2\pi}} e^{-\frac{(i-\alpha)^2}{2\sigma^2}} \). According to proposed optimized algorithm, \( T(X = i, m, n) \) is the sum of the \( m \) value vector lengths of all the data in the hash table (Equation 17).

\[
T(X = i, m, n) = \frac{n}{\sigma \sqrt{2\pi}} \left( \frac{1}{e^{\frac{(i-\alpha)^2}{2\sigma^2}}} + \frac{1}{e^{\frac{(i-\alpha)^2}{2\sigma^2}}} + \ldots + \frac{1}{e^{\frac{(i-\alpha)^2}{2\sigma^2}}} \right) \\
\leq \frac{nm}{\sigma \sqrt{2\pi}} \left( \frac{1}{e^{\frac{\sigma^2}{2\sigma^2}}} \right) \quad (17)
\]

When \( r \geq 10 \), we have 100\( r \) ≥ 1000. The distance between randomly selected key \( i \) and the expectation key \( \alpha \) is denoted as \( E(i - \alpha) \). Then we have Equation 18.

\[
E(i - \alpha) \geq \frac{\sum_{i=1}^{500} i}{500} \geq \frac{500(500 + 1)}{1000} \geq 250
\]

While \( 1 < \sigma^2 < 12.5 \), we have \( \sigma \sqrt{2\pi} e^{\frac{i - \alpha}{\sigma^2}} \geq \sigma \sqrt{2\pi} e^{10} \geq e^{11} \). Then Equation 17 can be further organized as Equation 19.

\[
T(X = i, m, n) = \frac{n}{\sigma \sqrt{2\pi}} \left( \frac{1}{e^{\frac{(i-\alpha)^2}{2\sigma^2}}} + \frac{1}{e^{\frac{(i-\alpha)^2}{2\sigma^2}}} + \ldots + \frac{1}{e^{\frac{(i-\alpha)^2}{2\sigma^2}}} \right) \\
\leq \frac{nm}{\sigma \sqrt{2\pi}} \left( \frac{1}{e^{\frac{\sigma^2}{2\sigma^2}}} \right) \quad (18)
\]

Finally, we get that, when \( r > 10, 1 < \sigma^2 < 12.5 \), proposed optimized algorithm is able to reduce time complexity by approximately 5 orders of magnitude.

**D. DBCAR: A DEPTH-BASED CHANNEL-AWARE ROUTING PROTOCOL**

In this section, we apply NNR-based channel estimation algorithm to depth-based routing protocols, then propose a depth-based channel-aware routing protocol, DBCAR. Depth-based routing protocols are location-free and stateless.
with unstable packet delivery rates in sparse networks but low transmission delay. On the contrary, channel-aware routing protocols have better packet delivery rates but high transmission delay. DBCAR with NNR channel estimation provides a more powerful solution among depth-based routing protocols and channel-aware routing protocols with outstanding packet delivery rates while keeping a reasonable transmission delay.

In DBCAR, each underwater node has three operation processes, including the initialization process, the listening process, and the forwarding process. Transition relationship between the three processes is described in Fig. 5.

Each underwater node starts initialization process once deployed into the water and switched on. In the initialization process, each node broadcasts a handshake packet containing node ID and initial energy value. Every neighbor node that receives the handshake packet will reply an ACK packet containing node ID and residual energy volume. With ACK packets and the corresponding received SNR values, nodes in initialization process construct the list of SNR vectors described in Section III-A. Besides the list of SNR vectors, we utilize residual energy which can be obtained in a variety of ways [29] [30], historical SNR means, and variances as auxiliary parameters for best forwarder selection. After the initialization process, each underwater node has a list of neighbor nodes information, including received SNR vectors, latest residual energy and historical SNR means and variances, then changes to the listening process.

![FIGURE 5: Transition Relationship between Operation Processes](image)

In the listening processes, each node keeps listening and analyzing every received packets. When parsing received packet, the node obtains received SNR, residual energy, forwarder ID and other information of the source node. We assume a node A in the listening process receives a packet from node B. Then node A will update received SNR vectors and other parameters corresponding to node B in \( M_{SNR} \) (defined in Equation 3). If the forwarder ID is the same with node A, this node will change to forwarding process. Because node B has chosen node A as the best forwarder. Otherwise, node A maintains in the listening process. To calculating mean and variance of received SNR values based on time series, we introduce a recursive algorithm utilizing only the latest arrived value, latest mean and variance. This algorithm has a time complexity of \( O(n) \) in contrary to the naive calculation of mean and variance using all historical data with the time complexity of \( O(n^2) \). The mean and variance calculation methods are expressed in the form of recursion formula as Equations 20, 21 and 22.

\[
M_i = \frac{i-1}{i} M_{k-1} + \frac{1}{i} x_i \quad (20)
\]

\[
S_i = S_{i-1} + (x_i - M_i)(x_i - M_{i-1}) \quad (21)
\]

\[
V = \frac{S_i}{i-1} \quad (22)
\]

where \( i \) is the number of total SNR values, \( x_i \) is the latest arrived SNR value, \( M_{i-1} \) is latest mean and \( \frac{S_i}{i-1} \) is latest variance. \( M_i \) and \( V \) are updated mean and variance of all historical SNR values.

A brief demonstration of Equation 20 is given in Equation 23. In addition, a brief demonstration of Equation 21 is given in Equation 24.

\[
M_i = \frac{x_i + x_{i-1} + \ldots + x_1}{i} \quad (23)
\]

\[
M_{i-1} = \frac{x_{i-1} + \ldots + x_1}{k-1} \quad (24)
\]

\[
kM_i - (i-1)M_{i-1} = x_n \quad (25)
\]

\[
S_i = \sum_{j=1}^{i} (x_j - M_i)^2
\]

\[
= \sum_{j=1}^{i-1} (x_j - M_{i-1} - \frac{x_i - M_{i-1}}{i})^2 + \frac{(i-1)(x_i - M_{i-1})^2}{i}
\]

\[
= \sum_{j=1}^{i-1} (x_j - M_{i-1})^2 + \left[ \frac{i-1}{i^2} + \frac{(i-1)^2}{i^2} \right] (x_i - M_{i-1})^2
\]

\[
= S_{i-1} + \frac{(i-1)}{i} (x_i - M_{i-1})^2
\]

\[
= S_{i-1} + (x_i - M_{i-1})(x_i - M_i) \quad (26)
\]

As mentioned in the listening process that once a node receives a packet with the same ID with its own, it will change to the forwarding process. Nodes in the forwarding process take responsibility to explore the best forwarder for the next hop. In DBCAR, nodes in forwarding process (the source node) will broadcast a handshake packet to determine communicable neighbors. Each neighbor node receives this handshake packet will reply an ACK packet containing ID, residual energy, and current depth. Then the source node will consider current received SNR values, current depth, residual energy and current SNR fluctuation trends and substitute each value into Equation 28 thus obtaining the calculating...
result of each neighbor node. The neighbor node with the highest calculation result will be chosen as the forwarder for the next-hop. Node ID of the next-hop forwarder will be encoded into the packet transmitted by the source node. The primal parameter of Equation 28 is \( s \) and \( \Delta d \). We use NNR-based channel estimation algorithm in Section III-B to compute \( s \). We traverse \( M_{SNR} \) and put each SNR vector into the channel estimation algorithm. Then we get a vector of \( s \) corresponding to each neighbor of the source node.

\[
SNR(s, g) = s + \alpha \cdot \text{sgn}(g)s
\]  

(27)

\[
f(SNR(s, g), \Delta d, m, v, E) = \frac{mE}{v} \Delta d \cdot SNR(s, g)
\]  

(28)

In addition, we add a coefficient considering channel stability, residual energy and SNR prediction value. \( m \) and \( v \) indicate channel stability where \( m \) and \( v \) are the mean and variance of SNR vectors. The neighbor with a higher mean and lower variance will improve the final calculation result. Besides, \( E \) is ratio of the residual energy and initial energy \( \frac{E_{init}}{E_{max}} \) in percentage. Even a node has a good channel quality but is running out of energy, the node might not be chosen as the best forwarder. It is an efficient strategy to balance energy so as to extend network lifetime. \( SNR(s, g) \) is given in Equation 27 where \( g \) is the gradient between \( t \) and \( t - 1 \) moments and \( \text{sgn} \) is the sign function. \( \alpha \in [0, 0.3] \) is an impact factor of gradient.

IV. PERFORMANCE EVALUATIONS

Performance evaluations consist of three parts: A) Accuracy evaluations of NNR acoustic channel estimation algorithm; B) Time and space complexity optimization evaluation of NNR acoustic channel estimation algorithm; C) Network performance evaluations of DBCAR with NNR.

A. ACCURACY EVALUATIONS OF CHANNEL ESTIMATION ALGORITHMS

We use both simulation and sea trial data-sets to evaluate proposed method. We simulate ideal period SNR samples, fixed period SNR samples with random noises and random period SNR samples with random noise, receptively. Moreover, we used KAM11 and KW14 sea trial data-sets. For acoustic channel estimation methods, we select EMA, AR(2) and AR(5) to compare with the proposed algorithm. We analyze times of best estimation and prediction errors, demonstrating NNR had an outstanding accuracy than other linear methods.

Fig 9-11 present data trends of ideal period data, period data with random noise and random period data with random noise. Fig 9-11 show the times of best estimation of the four channel estimation algorithms concerning ideal period data, period data with random noises and random period data with random noises, respectively. The size of the data sets increases from 1000 to 10000. Best estimation is the channel estimation with minimum error in contrary to real SNR values among the four algorithms. In summary, NNR has an average best estimation rate of 83.9% with ideal period samples while the second best is EMA with an average best estimation rate of 4.6%, demonstrating that NNR has perfect performance on period samples. However, real received SNR samples are not ideal periodicity. Concerning period data with random noises and random period data with random noises, NNR has an average best estimation rate of 54.2% and 43.4% while the second best is EMA with an average best estimation rate of 22.2% and 31.5%. With the size of data sets increasing, the best estimation rate of NNR gradually rises. Fig 12-14 show average channel estimation error of different algorithms on different data-sets. Also, NNR is the best among these channel estimation algorithms. Fig 12-14 show data trends of sea trials, KAM11 and KW14. From Fig 15-16 together, we may conclude that NNR has an average best estimation rate of 47.8% with KW14 and 42.2% with KAM11 while the second best is MA with an average best estimation rate of 15.8% with KW14 and 15.2% with KAM11. Fig 17-18 show average channel estimation error of different methods on sea trial data-sets. We may conclude that NNR is the best among these channel estimation algorithms.

B. COMPLEXITY OPTIMIZATION EVALUATIONS

In this section, we evaluate time and space complexity optimization in Section III-C.

In Fig 19 and Fig 20, we compare time and space efficiency of naive NNR and optimized-NNR. Without loss of generality, we set \( k \) to be 3 and \( \alpha \), then compare the searching time of \( k \) nearest neighbors with the sample size from \( 10^2 \) to \( 10^6 \). Obviously, searching time of optimized-NNR algorithm slightly rises in linear trend while naive NNR in an exponential trend. In addition, we set \( L \) to be \( 10^2 \) and \( \alpha \) to be 0.2 in Equation 15. The result is similar to time complexity comparison. Space consumption of optimized NNR algorithm stopped increasing at \( L \) while naive NNR rises in an exponential trend. Optimized NNR has an approximate linear complexity in time and space. However, time and space optimization results in tiny errors. Fortunately, estimation accuracy of optimized NNR is very close to naive NNR. The estimation error of optimized NNR is less than 1.48% compared with naive NNR in Fig 21.

C. NETWORK PERFORMANCE EVALUATIONS

Network simulations are implemented through Aqua-Sim [13], a widely used UWSN simulation extension package based on NS-2 [31]. Major underwater communication parameters are based on a real-world acoustic modem UWM1000 [32]: bandwidth was 10 kbps; power consumption of sending is 2 watt, receiving is 0.1 watt and idling is 1 \( \times 10^{-2} \) watt. Broadcast MAC protocol is the same as [11]. \( \delta \) in delay function is set to be \( \frac{L}{4} \) in the whole simulation. Sensor nodes are randomly deployed in a 500 \( \times \) 500 m\(^2\) underwater area. Three sinks are uniformly deployed on the surface. The sink nodes are fixed once deployed. For simplicity and without loss of generality, one of the
underwater sensor nodes is set to be the source node. In addition, depth of the source node is set to be the max depth and moving slightly and randomly on this plane. Maximal transmission distance $R$ is 150 m. Length of data packets is 100 bytes and 20 bytes for handshake packets in DBCAR and CARP. We run the simulation for $10^4$ seconds then statistic major network parameters. The number of nodes increases from 100 to 200 with an interval of 10. The source has a packet rate of 0.1 packet/s. Bellhop computes time variable distribution of transmission loss for different locations. Environment data refer to an area in Dickins Seamount located at $54^\circ 30'00''N, 137^\circ 00'00''W$. Sound Speed profiles (SSP) and bathymetry profiles are provided in Acoustic Toolbox [33].

In network performance evaluation, we concern three performance metrics: packet delivery ratio, average end-to-end delay, and average energy cost defined below.

**Packet Delivery Ratio**: the ratio of the number of different packets received at the sink to the number of the total packets transmitted by the source node. This parameter indicates the reliability of a routing protocol.

**Average End-to-End Delay**: the average transmission duration for each packet from the source to the sink. We don’t consider lost packets in this work. This parameter indicates time efficiency of a routing protocol.

**Average Energy Consumption**: the average total consumption for each packet received by the sink. Average energy consumption is the ratio of total energy consumption of the network to the number of packets received by the sink. This parameter indicates energy efficiency of a routing protocol.

Fig. 22 shows packet delivery ratio of DBCAR, CARP, and DBR in terms of different network density. As DBCAR using NNR-based channel quality estimation methods which had an outstanding performance than EMA validated in Section IV-A, DBCAR exceeds DBR without channel quality estimation and CARP with EMA-based channel quality estimation in terms of packet delivery ratio. In contrast with DBR, DBCAR increases packet delivery ratio by 18.2% on average and 39.7% in max. In contrast with CARP, DBCAR increases packet delivery ratio by 15.5% on average and 20.8% in max.

Comparison of average transmission delays of DBCAR, CARP, and DBR is illustrated in Fig. 23. In Fig. 23, DBR has a better time efficiency than DBCAR and CARP because DBR is a depth-greedy routing protocol considering no channel parameters. It can explore the neighbor with max depth difference, then make this neighbor as next forwarder without considering channel quality between senders and receivers. As defined above, we only statistics successfully delivered packets in average end-to-end delay results. Although DBR has a lower packet delivery ratio, packets successfully delivered have a shorter transmission delay. Also, DBCAR exceeds CARP in time efficiency. According to simulation results, DBCAR reduces average end-to-end transmission delay.
delay by 10.3% on average and 11.3% in max in contrast with CARP.

Comparison of Average energy consumption of the three protocols is illustrated in Fig. 2. DBCAR has an outstanding network depth-based channel-aware routing protocol, DBCAR. Taking advantage of depth-greedy routing and channel-aware routing, leading to a better energy efficiency. In contrast with DBCAR, CARP reduces average energy consumption by 26.1% on average and 32.1% in max. In comparison with CARP, DBCAR reduces average energy consumption by 26.2% on average and 34.4% in max.

V. CONCLUSIONS

In this paper, we introduce NNR for underwater channel estimation. We extend NNR for time series analysis and obtain a better prediction precise for intricately fluctuating and periodical SNR time series. Also, we use a hash table and statistical storage compression to optimize the time and space complexity of NNR quality estimation algorithm. In contrast with linear methods, this algorithm significantly improves prediction accuracy on both simulation and sea trial datasets. With this channel estimation algorithm, we then propose a depth-based channel-aware routing protocol, DBCAR. Taking advantage of depth-greedy forwarding and channel-aware reliable communication, DBCAR has an outstanding network performance on packet delivery ratio, average energy consumption and average transmission delay which is validated through extensive simulations.

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FIGURE 15: Optimal Estimation on KW14 sea trial

FIGURE 16: Optimal Estimation on KAM11 sea trial

FIGURE 17: Average Estimation Error on KW14 sea trial

FIGURE 18: Average Estimation Error on KAM11 sea trial
FIGURE 19: Time Complexity Optimization Evaluation

FIGURE 20: Space Complexity Optimization Evaluation

FIGURE 21: Accuracy Evaluation