Cross-layer Design for Software-defined Underwater Acoustic Networking

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***Abstract*—In this paper, a network relying on software-defined underwater acoustic nodes is proposed: by receiving a periodic beacon signal from the sink node, each node in a cluster obtains a prediction about the communication quality of the potential links to its one-hop neighbors as well as to the available relay nodes within the cluster. The hidden Markov process is used to predict the next state of the channels, using the probability distribution of random gain and delay spread from previous observations. Each transmitting node evaluates the quality of links to its one-hop neighbor relay nodes. Accordingly, a normalized weight representing the channel quality assigns to each link. The channel gain and its delay spread are the two metrics that are used to define the channel quality. To evaluate the network in realistic conditions, the output of a statistical model combined with Bellhop is compared to experimental data. Using the channel quality, each transmitter node in the network will select its next hop optimum relay node. This scheme minimizes the number of transmitted control packets and also reduces the re-transmission of data packets, by predicting the channel status rather than exchanging an excessive number of control packets which typically convey expired channel state information. Minimizing the overhead and selecting the optimum channel saves on the energy per bit consumption while maintaining high packet delivery ratio and low latency.**

***Index Terms*—Underwater acoustic sensor network, multi-hop relaying, underwater acoustic channel quality, large-scale channel estimation, hidden Markov process.**

I. Introduction

Establishing a reliable and low latency end-to-end link from the underwater acoustic node to the surface sink nodes is still a bottleneck in the development of remote underwater sensing and monitoring technologies including the Internet of Underwater Thing (IoUT). Despite all the efforts in recent years to design underwater networking protocols, the inherent characteristics of the underwater acoustic channel, including its time-varying and long propagation delay introduces important challenges. To provide the optimum physical layer configuration as well as energy efficient routing and media access control (MAC) at the higher network layers, it is necessary to have a dynamically adaptable communication stack which can be optimized with the time varying characteristics of the channel [1]. Multi-hop relaying [2] is considered as the preferred network topology to cover large areas underwater, but the efficiency and practicality of the provided solutions are questionable. Flooding-based routing protocols have attracted a lot of attention as a reliable solution for multi-hop underwater acoustic sensor networks (UWASN) due to their low latency and high packet delivery ratio (PDR) [3]. However, the multicast relaying mechanism required for flooding, significantly raises the energy demand. Also, excessive packet broadcasting increases the probability of collisions. The channel-aware routing protocol (CARP) [4] is another promising routing scheme that exploits channel quality information for data forwarding. Using CARP, nodes which exhibit recent history of successful transmissions to their neighbors are selected as relays. It is assumed that robust modulation schemes, such as Frequency Hopping Binary Frequency Shift Keying (FH-BFSK) [5], can mitigate small-scale channel variations, particularly when using channel aware detection algorithms. Nonetheless, the channel can be subject to large variations over time, which makes the packet delivery reliability variable. Moreover, periodically sharing the packet delivery history among nodes imposes large overhead on the network. Due to the variant nature of the underwater acoustic channel, it is important to redefine an underwater communication stack with dynamically adaptable lower layers including the physical layer, the routing layer and the MAC layer, such that they adjust to the varying channel and topology conditions. For this purpose, an adaptable software-defined acoustic network relies on predicting the quality of the available channels to acquire the optimum link [6].

In [7] the large-scale temporal variation in the underwater acoustic channel is predicted and the channel signal-to-noise ratio (SNR) is selected as a figure of merit. A Markov latent process accounts for the modelling of the channel SNR process as a summation of an environment process. The SNR is an important parameter in underwater networks, however it is not the only decisive parameter to determine the channel quality. Indeed, the acoustic channel delay spread and Doppler spread also play significant roles in channel quality. Further, statistical models should be used to predict future channel parameters, since historical channel SNR measurements solely, cannot describe a real-time acoustic channel behavior.

In this paper a statistical model of acoustic channel is used to predict the future state of the channel. Accordingly, a figure of merit based on the channel's estimated posterior gain and delay spread is assigned to each link between the transmitter node and its one-hop neighbors. Using this figure of merit, each transmitter node can decide on selecting between available channels and adapt its lower communication stack layers using predicted channel conditions.

The rest of this paper is organized as follows: in Section II, the network model and a discovery beacon to acquire a $priori$ information will be described; in Section III time varying channel's statistical model is presented and results from sea trials are shown to verify consistency of probability distribution function (PDF) of both statistical and experimental models; in Section IV, the hidden Markov model is applied on observations vector to predict channels posterior state and then future channel's quality is determined accordingly. Finally in Section V conclusions will be discussed.

II. Network Model

In this section, a communication architecture for collaborative underwater acoustic network (UWAN) is described. The conventional clustered topology in which acoustic nodes are interconnected to a sink node is the most common UWAN architecture [8, 9, 10]. Instead, in this work, within each cluster a distributed multi-hop network topology is assumed to extend the network coverage range which includes multiple fixed and mobile acoustic nodes. Similarly, each cluster of nodes is supported by a sink node.

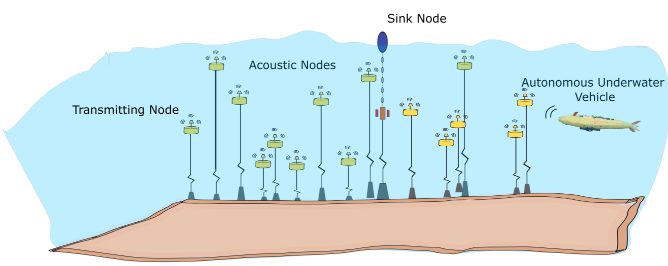

Fig. 1: illustration of a typical underwater network geometry

In the proposed network, it is assumed that each node knows its depth, as well as the sea bottom bathymetry. Also, the local sound speed profile (SSP) is available at each node. Figure 1 depicts a network of self-configured software-defined underwater acoustic nodes (SUANs) in which a mobile and fixed SUANs are deployed in a relatively large area, e.g. 100 square kilometers. The network coverage is extended using multi-hop relaying between the SUANs. The SUANs are equipped with an out-of-band beacon generator to send discovery messages and busy tone signals.

If a transmitter node has packets to send after a collision detection backoff time T_L [11], it reserves the channel using a silence request to its neighbors and forwards its packets by sending it to its optimum neighbor relay node.

The proposed communication system structure requires two phases for communication. First, an initial network control phase that provides a $priori$ knowledge about the topology and potential routes to the nodes in the cluster. The network control phase is initiated by a beacon signal from the sink node. Second, a data transmission phase in which multi-hop relaying forwards data packets from the transmitter node to the sink node. Figure 2 illustrates the two network communication phases.

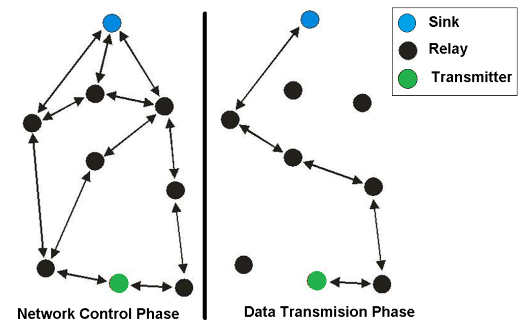

Fig. 2: Illustration of control and data transmission phases

In the network control phase, each SUAN acquires $priori$ knowledge about the network using periodic beacon signals. These beacons are discovery messages and are initiated to broadcast from the sink node to train a channel prediction model at each receiving node. Using a beacon forwarding strategy described in [12], each receiving relay node piggy-backs its ID on the received beacon and broadcasts it again. The network discovery beacons are short messages which are broadcast using the flooding routing protocol [3].

As illustrated in Figure 2, during the network control phase a discovery message is forwarded from the sink node to all cluster nodes through multiple relay nodes. The discovery messages provide each node the information about its neighbors. As such each node can learn about the existence of the possible routes to the sink node by reading the sink node's ID in the received beacons. The beacons can also be used to obtain information about the location of the different nodes. It is also assumed that the physical environment parameters are available at each node. Then, each SUAN estimates the channel impulse response to its next one-hop relays using a built-in Bellhop software and stores in memory a channel samples window of the most recent channel impulse impulses, this will be described in III-A. Specifically, each transmitter node i) simulates the channel condition of its one-hop relay nodes, and ii) weighs each link to its one-hop neighbors, as will be explained in Section IV. Then, the transmitter node selects the optimal next hop relay according to the highest channel quality weight to send its data packets.

III. Time varying channel model

To enable underwater acoustic communication, it is important to design the communication stack to be adaptable to time varying channel condition. For this purpose, the channel estimator is an important block of the SUAN. Because of the variations of the channel physical properties in time and spatial domains, it is particularly challenging to predict the the underwater channel behavior. The varying ocean environment as well as differences in temperature, salinity and pressure for different water depth levels cause the acoustic rays to refract, which results changes in their path lengths. Accordingly, a time-varying mutipath fading channel that is accompanied with large delay spread and Doppler spread is formed.

In the following Section III-A, an analytical channel model will be described that captures most of the physical properties of a channel in shallow waters. Then, the overall gain and root mean square (RMS) probability density function for a channel between two nodes will be calculated.

A. Analytical acoustic channel model

In a particular large-scale channel realization time t_n, the time-varying multipath effect can be described by the following transfer function [13]:

$$H(f,t) = \sum_{p=1}^{n} h_p(t_n)\gamma_p(f,t)e^{-j2f\pi\tau_p(t)}, t \in T_n \quad (1)$$

where for each path p at time t, $\gamma_p(f,t)$ are scattering coefficients that contribute to the small-scale channel variations induced by relative motion of transmitter/receiver or any reflection points in the channel. The scattering coefficients follow a complex Gaussian distribution. The Statistical properties of $\gamma_p(f,t)$ (correlation in time and frequency) are determined from the received paths length variance σ^2 and the Doppler spread B_d of the received paths. When there is a strong direct path, the envelop of a signal that has passed through the channel can be represented statistically using a Ricean distribution. In absence of a strong direct path a Rayleigh fading model is assumed for the channel amplitude [14]. Furthermore, the path p delay $\tau_p(t) = \tau_p - \alpha_p t$ is time varying with a Doppler scaling factor $\alpha_p = v_p/c$, where v_p is the speed of relative motion between the transmitter and receiver and c is the sound speed. For example a stationary underwater acoustic system may experience unintentional motion at 0.5 m/s (1 knot), which would account for $\alpha_p = 3 \times 10^{-4}$. Accordingly, $h_p(t_n)$ is the time varying amplitude of each path of p which can be considered as a low-pass filter. In contrast, large-scale variations affect the paths transmission loss where the energy is inversely proportional to the distance squared and is modelled as log-normally distribution [13]. The large-scale and small scale together result in a complex Gaussian distortion. The amplitude of the received signal is modeled as

$$H_p(f) = \frac{\Gamma_p}{\sqrt{A(l_p,f)}} \quad (2)$$

where Γ_p is cumulative reflection coefficient of path p over the water surface and bottom and $A(l_p,f)$ is the absorption factor experienced over the path length of l_p at the frequency of f [13]. Effectively, using the transfer function of each path, the multipath channel transfer function can be expressed as

$$\bar{H}(f) = \sum_{p=1}^{n} H_p(f)e^{-j2f\pi\bar{\tau}_p} \quad (3)$$

where $\bar{\tau}_p$ is the propagation delay of path p with respect to the first tap arrival delay $\bar{\tau}_0$.

The transfer function in (3) is a low pass filter and accounts for all paths where different delays and gains are applied to each path. Specifically, the low-pass filtering accounts for energy absorption which is higher for higher acoustic frequencies.

For a channel with band width B, the overall channel's instantaneous gain $G(t)$ at time t will be

$$G(t) = \frac{1}{B}\int_{f_0}^{f_0+B} |H(f,t)|^2 df \quad (4)$$

The motion of the ocean environment can cause individual Doppler shifts on each independent path. The difference between simultaneously received Doppler shifts is the Doppler spread. Here we assume that the relative motion between the transmitter and receiver is minimal and the Doppler spread is due to channel motion which can be calculated and compensated using the physical layer as will be explained in Section III-C [15].

In the following we evaluate the PDFs of the instantaneous channel gain $G(t)$ and RMS delay spread $\tau_{RMS}(t)$ for a channel between two neighbor nodes in the proposed network scenario, using both statistical model and sea trial measurements.

Several stochastic models have been proposed for time varying underwater acoustic channel (UWAC), which are usually based on collected data from sea trials in a particular location [16]. Here the underwater acoustic channel behavior is investigated using a series of simulations and measurements from sea trials. Figure 3 illustrates the channel geometry and setup for the sea trial as well as for the simulation. The sound speed profile (SSP) was measured throughout the experiments in the south shore of Nova Scotia during the DalComms1 sea trial in July 2017.

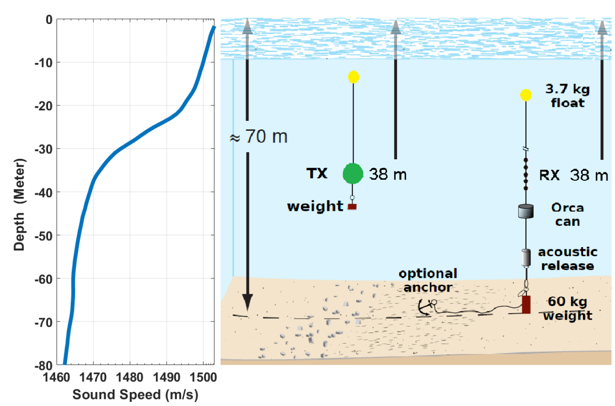

Fig. 3: Channel geometry of two nodes in the depth of 38 meters

The Bellhop ray tracing simulator is utilized to model the acoustic wave propagation physical properties, including attenuation, reverberation and reflection. The output of the ray tracing simulator is applied to a statistical model presented in [13] to provide a time varying channel impulse response which takes into account effects of small-scale and large-scale random water column displacement. The simulation parameters in Table I are defined to represent the deployment area.

TABLE I: Simulation parameters

Parameters and Properties	Environmental file
Frequency (Hz)	2048
Bandwidth (Hz)	240
SSP settings	SVFT
Source depth (m)	38
Receiver center depth (m)	38
Distance between Source and Receiver (km)	4
Bottom Density (g/cm^3)	2.05
Bottom sound speed (m/s)	1800
Bottom Attenuation (dB/m/kHz)	0.5
Ray type (dB/m/kHz)	Gaussian
Resolution (m)	1.0

Figure 4 illustrates the simulated channel impulse response (CIR), as a function of time. In this scenario the delay at approximately 16.5 msec has the highest CIR amplitude. Note that the delay, and amplitude of each path arrival are subject to time variations, as observed during the 510 seconds captured.

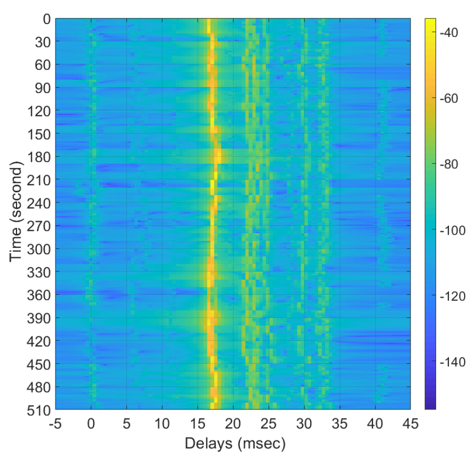

Fig. 4: channel impulse response of two nodes in depth of 38 meters

Once the estimated CIR is obtained, it can be analyzed using multiple channel metrics to get a better understanding of the channel's properties and its impact on the acoustic communication. The instantaneous channel gain and delay spread are two important parameters affecting communication quality. Specifically, the instantaneous channel gain variations in time domain results in instantaneous signal-to-noise ratio (SNR) variations, which effectively affect the bit error rate (BER) and packet error rate (PER). An important characteristic of a multipath channel is the time delay spread it causes to the received signal. This delay spread equals the time delay between the arrival of the first received tap and the last received tap associated with a single transmitted signal tone. If the delay spread is small compared to the inverse of the signal bandwidth, then there is little time spreading in the received signal. However, when the delay spread is relatively large, there is significant time spreading of the received signal which can lead to substantial signal distortion [17].

A channel subject to delay spread introduces inter-symbol interference at the receiver. The RMS delay spread is calculated as

$$\tau_{RMS} = \sqrt{\bar{\tau^2} - (\bar{\tau})^2} \tag{5}$$

where τ is delay and $\bar{\tau}$ is mean excess delay. The mean excess delay is the first moment of the power delay profile whose power level is above some threshold [18]. In this work, only path arrivals whose strength is more than the strength of the direct arrival divided by 20 are considered. This is to account for the noise floor of the probing signature used during measurements. the mean excess delay $\bar{\tau}$ is:

$$\bar{\tau} = \frac{\sum_{p=1}^{n} {h_p}^2 \delta_p}{\sum_{p=1}^{n} {h_p}^2} \tag{6}$$

accordingly, $\bar{\tau^2}$ is:

$$\bar{\tau^2} = \frac{\sum_{p=1}^{n} {h_p}^2 {\delta_p}^2}{\sum_{p=1}^{n} {h_p}^2} \tag{7}$$

The modelling of RMS delay spread is important as this represents the effective value of the time dispersion of a transmitted signal, as caused by the multipath in the channel. For reliable digital communications over the channel, as it is mentioned in [19], the time duration of each transmitted symbol should be longer than the value of RMS delay spread in order to minimize the distortion of the symbol shape observed at the receiver.

The RMS delay spread is inversely proportional to the coherence bandwidth B_c of the channel. For a Rayleigh fading channel $B_c = 1/(2\pi \times \tau_{RMS})$. If the symbol duration is long enough compared to the delay spread, one can expect an ISI-free channel [20]. Figure 5 illustrates the variations of the channel's instantaneous gain and RMS delay spread captured over a period of 510 seconds.

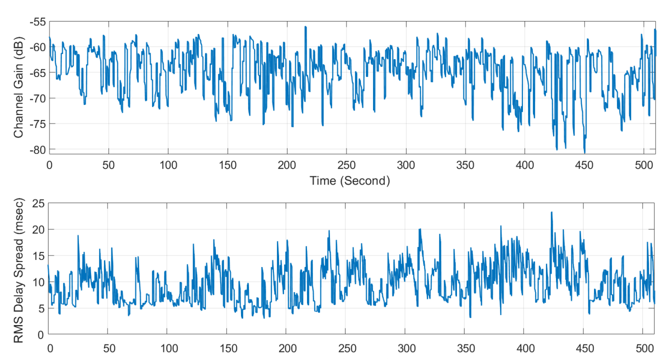

Fig. 5: Illustration of instantaneous variations of channels gain and RMS delay spread resulted from the statistical model

Figure 6 depicts the PDF of channel gain and RMS delay spread. The channel gain PDF in Figure 6 resembles a log-normal distribution and the most probable value for channel gain is 5×10^{-4} or - 66 dB. Accordingly, the most probable value for the RMS delay spread is 14 msec. Typically, when the symbol time period is greater than 10 times the RMS delay spread, no ISI equalizer is needed in the receiver. This suggests that our symbol duration T_{sym} to transmit without the ISI equalizer on this channel should be at least 140 msec.

Next, the probability density function (PDF) of the instantaneous channel gain and PDF of RMS delays spread are validated using real data obtained from sea trials with a configuration similar to the simulation.

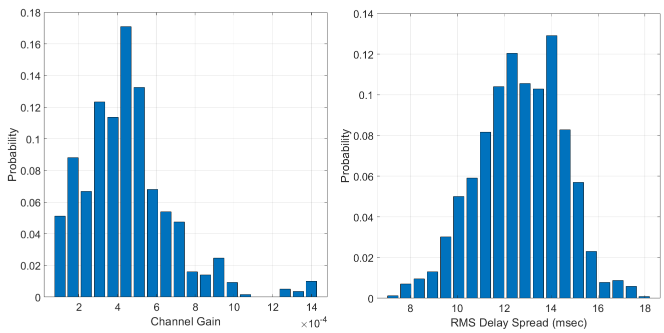

Fig. 6: PDF of channels RMS delay spread and channel gain from statistical model

B. Experimental model of channel

For the experimental model, we use CIR measurements taken 10 km off the south coast of Nova Scotia, near Peggy's Cove, to generate an ensemble of channel responses which was then used to verify the statistical properties of the channel. Several measurements were conducted during the DalComms1 sea trial [16] to validate physical channel characteristics such as the SSP, sea surface roughness, and bathymetry measurements. The data collection took place between July 26^{th} and July 28^{th} 2017 10 km off the coast of Nova Scotia providing in a 80 meter deep communication channel. All operations were completed between 08:00 ADT and 18:00 ADT. While the communication reliability was evaluated for multiple distances between the source and receiver as long as 10 km, in this section, the channel will be analyzed for the 4 km station. Similar conclusions can be extracted for the different ranges. The main receiver, a 5-elements VLA, was deployed mid-depth (38 m) without any surface expression to limit its interaction with the surface layer. A 60-kg anchor and two buoyancy floats were also used to reduce motion at the receiver. The raw acoustic data sampled at 24 kSps was recorded on local hard drives in the receiver pressure case. A total of 7 wave files with duration between 6.5 and 10 mins were transmitted at the 4 km stations. The wave file of interest in this research was a 510 seconds long and was used to transmit a 1024-symbol QPSK modulated pseudo-random noise (PRN) channel sounding sequence that was repeated continuously. Figure 7 shows the instantaneous variations of channels gain and RMS delay spread during a 510 seconds window. The results obtained in Figure 8 for the PDF of channel gain and RMS delay spread during the DalComms1sea sea trial shows statistical properties similar to those obtained using the statistical model; however, an accurate agreement was not observed. This mismatch may be because only partial knowledge of the environmental conditions was used and also some effects of waves' shape and injected bubbles and etc., is not considered in statistical model.

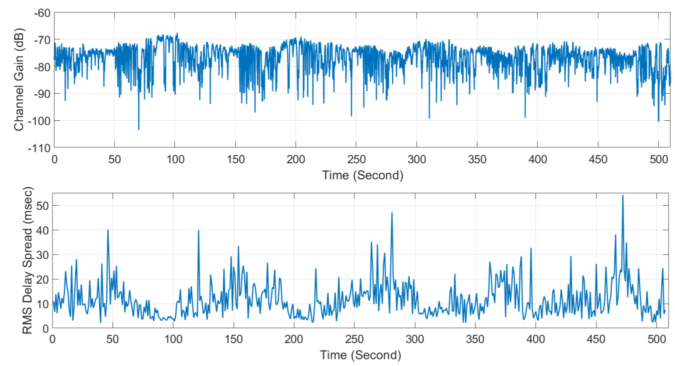

Fig. 7: Illustration of instantaneous variations of channels gain and RMS delay spread during the DalComms1

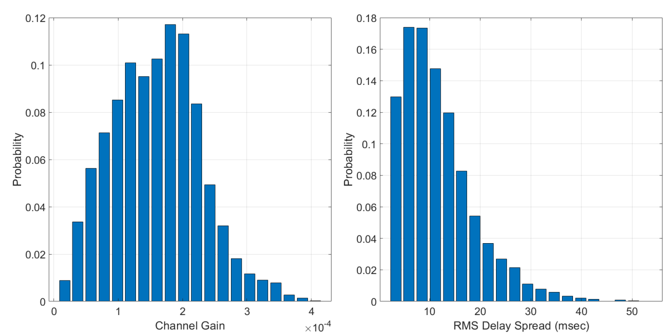

Fig. 8: Illustration of measured channel gain and RMS delay spread PDF during DalComms1

C. Physical layer

To assess the physical layer reliability, a Janus compatible physical layer presented in [16] was developed and measured in realistic conditions for the 4-km channel. To allow a long transmission range up to 10-km, the sound source is transmitted at a low 2-kHz center frequency in a bandwidth of 240 Hz. A 16-parallel BFSK is implemented to achieve high reliability. Additionally, a convolutional turbo code is demonstrated to increase the robustness of the FSK modulation schemes, particularly in high multipath environments. This physical layer can be utilized to deploy a multiuser network over an area of 100 square kilometers [21]. Due to the limited bandwidth of the sound source, the transmission rate is limited to a few bits per second, at the expense of long-range transmission. Nonetheless, this throughput is sufficient to transfer the intended payload to transmit critical messages reliably between the sensor nodes.

IV. Channel quality prediction Using hidden Markov model

The aim of this section is to develop a scheme to predict channel characteristics that help determining UWA communication quality.

Here we estimate the PDF of the channel gain as well as the RMS delay spread over a relatively large time period sufficient for the transmission of a sensor node data to the sink node. We assume a window of 510 seconds, which allows to transmit continuously 8.6 kilobytes of Janus packets (using 16-Parallel BFSK Signal modulation with R_b= 16 bps) [16].

Following in Section IV-A the hidden Markov process is used to predict the channel characteristics PDF. Then, in Section IV-B, based on the resulted PDFs a channel quality metric is defined to predict the acoustic channel communication quality.

A. Predicting channel characteristics

The hidden Markov model (HMM) is a tool to represent an evolutionary process using probability distributions [22]. The channel gain or RMS delay spread observation at time t is denoted by an observation variable of Y_t, if we can define probability distribution of Y_t and it satisfies the Markov properties we can predict the future state of the process which is the channel gain or RMS delay spread.

There are three important assumptions in a HMM. Firstly, using the HMM it is assumed that the observation at time t was generated by some process whose state S_t is hidden.

It is assumed that observations are sampled at discrete, equally-spaced time intervals, so t can be an integer-valued time index. Secondly, if the value of the state S_{t-1} is given, the current state S_t is independent of all the states prior to $t-1$. In this work the channel's gain level and RMS delay spread are discretized in 20 levels. The output must also satisfy an important property: at the state S_t, the observation Y_t is independent of the state and observation at all other time indices. Thirdly, the hidden state variable is discrete. For this application, it is assumed that S_t can take $K = 20$ states representing the channel gain or RMS delay spread levels. This is denoted by an integer K number of states, in the set $S = \{S^1, .., S^K\}$.

To define the HMM, a matrix of transition probabilities $A_{K\times K} = (a_{ij})$ must be specified, where $a_{ij} = P({S_t}^j | S^i_{t-1})$. Also, the matrix of observation probabilities is $B = P(Y_t \mid S_t)$ and the vector of initial probabilities is defined as $\pi = P(S_i)$.

To define a PDF over sequences of observations the probability distribution should be specified over the initial state $P(S_i)$. Having the matrix of transition probabilities $A_{K\times K} = (a_{ij})$ the output defines $P(Y_t|S_t)$. Accordingly, the resulting probability density for a $D \times 1$ observation vector Y_t is

$$P(Y_t \mid S_t) = \mid R \mid^{-\frac{1}{2}} (2\pi)^{-\frac{D}{2}} \exp\{-\frac{1}{2}(Y_t - \mu_t)^T R^{-1}(Y_t - \mu_t\ )\} \tag{8}$$

where $\mu_t\ = W \times S_t$, W is a $D \times K$ matrix whose columns are the contributions to the means of S_t, and R is a $D \times D$ covariance matrix. Then the model will be represented by $M = (A, B, \pi)$ [23].

Figure 9 shows the posterior channel's gain and RMS delay spread PDF. Here the HMM is used as a tool for representing the probability distribution over a sequence of observations which resulted from statistical model described in III-A.

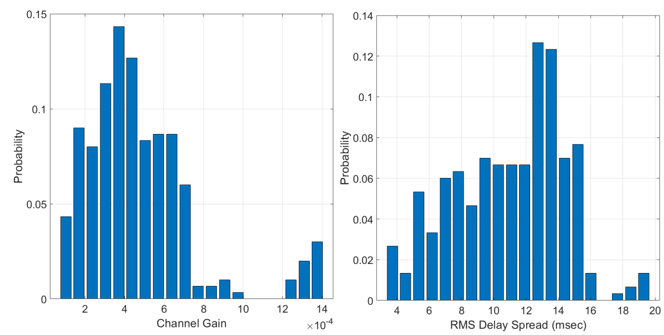

Fig. 9: Posterior PDF of the channel's gain and RMS delay spread

B. Latent channel quality prediction

The communication quality of the acoustic channel varies with time, as a consequence of the large-scale temporal variation in underwater acoustic channels.

These variations makes the end-to-end transmission paths unstable. To define the quality of an acoustic channel for underwater communication we use the channel gain and the RMS delay spread as the figure of merit. By using the HMM, the channel's state between a transmitter and next hop relays can be predicted to obtain channel quality.

In this application, the transmitter node i predicts the channel quality to each of its neighbors according to the posterior channel PDFs computed from the HMM, specifically using the PDF of the channel gain and τ_{RMS} for each link $n \in (1, ..., N)$ where N is the number of its neighbors. Here the channel quality is defined using a weighting factor $W_{i,n}$ that takes into account the most probable channel gain and RMS delay spread values on the x-axis and the probability of its occurrence on the y-axis of the PDF diagrams depicted in Figure 9. The weighting factor is calculated as:

$$W_{i,n} = \frac{G^{max}(i,n) \times P(G^{max}(i,n)}{\tau^{max}_{RMS}(i,n) \times P(\tau^{max}_{RMS}(i,n))} \tag{9}$$

where $G^{Max}(i,n)$ is the maximum normalized channel's gain of the link n for the transmitter node i and $\tau^{max}_{RMS}(i,n)$ is the maximum normalized channel RMS delay spread of the link n for the transmitter node i. Accordingly, the channel weighting factor of the statistical model developed in Section III-A can be calculated to be equal to 1.82, while for the experimental channel shown in Section III-B it will be 1.53, and finally for the predicted channel quality using the HMM presented in Section IV it is equal to 1.69. The proximity between these numbers is because these weighting factors are the metrics to compare the relative quality of the same channel.

Figure 10 illustrates a potential packet route in a 6-node adaptive network, where the transmitting node and relay nodes make local decisions to select the optimum next relay node to forward the data packet based on a local channel quality score as the criterion. The weighing factor of each link is shown and the green path shows the selected route at the relay nodes to forward the packet from the source to the sink node.

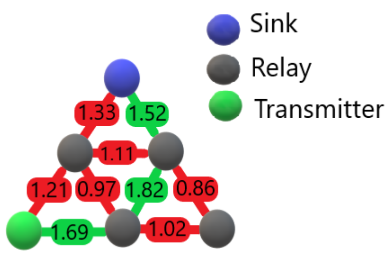

Fig. 10: Illustration of packet routing in network using channel quality

V. Conclusion

To summarize, this paper proposes a new multi-hop relaying method based on hidden Markov model to predict the channel large-scale variations using independent discrete channel observations. The use of a beacon forwarding strategy is described which can minimize the latency in network control phase using the flooding routing protocol [4]. The statistical model for the observations takes into account physical aspects of acoustic propagation. A physical channel model serves to predict the quality of each link, and the simulation model is compared to that of experimental data. Finally, a weighting factor is used to quantify the link quality and select the optimal next hop relay. The contributions of this work are significant because it can be expected that the routing algorithm will improve the PDR and energy consumption without imposing excessive additional traffic on underwater acoustic network.

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