Title of Dissertation: Design and Analysis of Underwater Acoustic Networks with Reflected Links

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ABSTRACT

Title of Document: DESIGN AND ANALYSIS OF UNDERWATER ACOUSTIC NETWORKS WITH REFLECTED LINKS
Lloyd Emokpae, Ph.D., 2013

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Underwater acoustic networks (UWANs) have applications in environmental state monitoring, oceanic profile measurements, leak detection in oil fields, distributed surveillance, and navigation. For these applications, sets of nodes are employed to collaboratively monitor an area of interest and track certain events or phenomena. In addition, it is common to find autonomous underwater vehicles (AUVs) acting as mobile sensor nodes that perform search-and-rescue missions, reconnaissance in combat zones, and coastal patrol. These AUVs are to work cooperatively to achieve a desired goal and thus need to be able to, in an ad-hoc manner, establish and sustain communication links in order to ensure some desired level of quality of service. Therefore, each node is required to adapt to environmental changes and be able to overcome broken communication links caused by external noise affecting the communication channel due to node mobility. In addition, since radio waves are quickly absorbed in the water medium, it is common for most underwater applications to rely on acoustic (or sound) rather than radio channels for mid-to-long range communications. However, acoustic channels pose multiple challenging issues, most notably the high transmission delay due to slow signal propagation and the
limited channel bandwidth due to high frequency attenuation. Moreover, the inhomogeneous property of the water medium affects the sound speed profile while the signal surface and bottom reflections leads to multipath effects.

In this dissertation, we address these networking challenges by developing protocols that take into consideration the underwater physical layer dynamics. We begin by introducing a novel surface-based reflection scheme (SBR), which takes advantage of the multipath effects of the acoustic channel. SBR works by using reflections from the water surface, and bottom, to establish non-line-of-sight (NLOS) communication links. SBR makes it possible to incorporate both line-of-sight (LOS) and NLOS links by utilizing directional antennas, which will boost the signal-to-noise ratio (SNR) at the receiver while promoting NLOS usage. In our model, we employ a directional underwater acoustic antenna composed of an array of hydrophones that can be summed up at various phases and amplitudes resulting in a beam-former. We have also adopted a practical multimodal directional transducer concept which generates both directional and omni-directional beam patterns by combining the fundamental vibration modes of a cylindrical acoustic radiator. This allows the transducer to be electrically controlled and steered by simply adjusting the electrical voltage weights. A prototype acoustic modem is then developed to utilize the multimodal directional transducer for both LOS and NLOS communication. The acoustic modem has also been used as a platform for empirically validating our SBR communication model in a tank and with empirical data.

Networking protocols have been developed to exploit the SBR communication model. These protocols include node discovery and localization, directional medium
access control (D-MAC) and geographical routing. In node discovery and localization, each node will utilize SBR-based range measurements to its neighbors to determine their relative position. The D-MAC protocol utilizes directional antennas to increase the network throughput due to the spatial efficiency of the antenna model. In the proposed reflection-enabled directional MAC protocol (RED-MAC), each source node will be able to determine if an obstacle is blocking the LOS link to the destination and switch to the best NLOS link by utilizing surface/bottom reflections. Finally, we have developed a geographical routing algorithm which aims to establish the best stable route from a source node to a destination node. The optimized route is selected to achieve maximum network throughput. Extensive analysis of the network throughput when utilizing directional antennas is also presented to show the benefits of directional communication on the overall network throughput.
Design and Analysis of Underwater Acoustic Networks with Reflected Links

By

Lloyd Emokpae

Dissertation submitted to the Faculty of the Graduate School of the University of Maryland, Baltimore County, in partial fulfillment of the requirements for the degree of Doctor of Philosophy

2013
To my Parents, Roland N. Emokpae and

Carol O. Emokpae
Preface

Approximately 70% of the Earth’s surface is composed of seas and oceans making it an important area for research and exploration. Recently, the field of underwater acoustic networks has gained much interest in the research community due to its many applications some of which includes oceanic exploration, environment state monitoring, and weather prediction. From a research point of view, there is still much to be learned about establishing underwater acoustic networks. As a contribution to the growing field of underwater acoustic networks, this dissertation presents a model for communicating and establishing networks in the underwater environment. The material in this dissertation can be categorized into five main topics areas, as listed in Table I.

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Acknowledgements

“Better is the end of a thing than the beginning thereof…” (Ecclesiastes 7:8)

For the past four years, my research has taken me through uncharted territory. The quest towards a Ph.D. has been long and challenging, but ultimately rewarding. Thanks to the almighty God, what originally seemed like a daunting task has become a reality. Along the way, I received countless support from many people around me and would like to take this opportunity to express my appreciation.

I would like to thank my advisor, Professor Dr. Mohamed Younis for his unwavering guidance and support. He always encouraged me to think creatively and allowed me to explore other exciting areas of research. His thoughtful feedbacks and persistent encouragement made me a better researcher.

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Chapter 1

Introduction and Preliminaries

This chapter introduces the main problem addressed in the dissertation, highlights the assumptions, and summarizes the contribution. This chapter also presents necessary preliminaries for acoustic wave propagation, signal loss, and directional communication.

1.1 Introduction

Underwater acoustic networks (UWANs) consist of both stationary and mobile nodes that cooperate to form a network [1][2]. A node in this sense is an active communicating entity in that can transmit and receive network packets. This concept is illustrated in Figure 1-1, where we see both stationary and mobile nodes communicating to serve an application. Applications of UWANs include environmental state monitoring, oceanic profile measurements, leak detection in oil fields, distributed surveillance, and navigation. Moreover, communications between nodes rely on acoustic channels instead of radio channels, since radio waves quickly get absorbed in the water medium.
Figure 1-1: Illustration of nodes communicating underwater. Communication depends on acoustic links due to its favorable propagation properties over RF (image is in courtesy of Young H. Cho, and John Heidemann).

The underwater medium has an inhomogeneous property composing of water layers of different temperature, density, and salinity. These varying parameters affect the sound speed profile [3][4][19], which can be modeled as a function of the oceanic depth. The underwater medium can be broken into two different layers, the surface layer and the thermoncline layer as depicted in Figure 1-2. The surface layer is mainly affected by the seasonal temperature changes. On the other hand, the thermoncline layer is affected by the increase in pressure and decrease in temperature (for an increase in depth) [5]. To simplify our analysis we focus just on shallow water communication (i.e. depths < 200m). This means that we will only be concerned about the effects on the surface layer. In shallow water, acoustic waves will be greatly
affected by multipath, which ultimately leads to multiple-attenuated copies of the same signal arriving at different times [17][18][20][21]. A ray trace simulation of the multipath effect can be seen in Figure 1-3 which shows a typical sound propagation with starting angles ranging from 5 to 15 degrees. Directional communication is often used to mitigate the effects of multipath [23][27][31]. More importantly, directional communication takes advantage of the spatial spectrum available by allowing multiple transmissions to occur simultaneously within the same transmission range. However, most directional communication schemes rely on line-of-sight (LOS) links, which might not be available due to the nature of the underwater environment.

![Figure 1-2: Pacific environment sound speed profile [4]. There are two main layers namely the surface layer and the main thermocline.](image)

Furthermore, for ad-hoc formation, node localization, medium arbitration and data routing are required for proper network operation.
Node mobility becomes a challenge for node localization when directional communication constraints are placed. Even non-mobile nodes tend to change positions over time due to the water current and drift. This poses a challenge for localization techniques that depend on fixed reference nodes, often referred to as anchors, for estimating the positions of sensor nodes. In addition, establishing a relative topology using measured received-signal-strength (RSS), the time-of-arrival (TOA), the time-difference-of-arrival (TDOA), or the angle-of-arrival (AOA) requires establishing communication line of sight (LOS) links, which is not always feasible for mobile nodes. Moreover, these measurements (especially TOA and TDOA) can have errors due to multipath signals arriving sooner than expected, which decreases the accuracy of the measurement.

![Figure 1-3: Ray tracing simulation of the sound propagation using a similar pacific ocean sound speed profile with 5-15 degree starting ray angles.](image)
The multipath nature of the underwater environment and the slow propagation of the acoustic medium complicate medium access arbitration. Medium access and control (MAC) protocols for omni-directional antennas are either contention-based [56] or contention-free [57]. Contention-free protocols include time, frequency, and code division multiple access (TDMA, FDMA, and CDMA) schemes. While Contention-based protocols require each node to compete for the shared channel resulting in probabilistic coordination such as the carrier sense multiple access protocol (CSMA). Time-based contention-free medium access is inefficient due to the need for a large guard time in order to cope with the worst case propagation delay. This would result in a waste of the limited acoustic channel bandwidth. Meanwhile, the narrow acoustic band makes FDMA-based medium access sharing impractical. Furthermore, it becomes hard to predict collisions among multiple node transmissions due to the variant and slow propagation delay and thus contemporary CSMA protocols would not be able to solve the hidden terminal problem without some knowledge about the network topology. Directional MAC (D-MAC) protocols usually surpass those based on omni-transmissions in terms of bandwidth utilization and delay. Although D-MAC protocols have been studied extensively in RF environments, to date, little attention has been given to acoustic links.

Data routing is also a challenge for directional communication in a multipath shallow water environment. Thus, given the 3-dimensional nature of the underwater environment, geographical (geo) routing is often employed to leverage the known position information in the routing process [2]. A geo-routing algorithm can either serve unicast, multicast, geocast or anycast. A geocast is a special case of multicast in
which the recipients are collocated in specific geographical regions. Geocast is popular in sensors networks where queries can be disseminated to solicit data from nodes in some area or when the data is sent to a mobile sink whose trajectory is not precisely known. Anycast often serves applications in which multiple sinks exist and it is necessary to reach any of them. Distributed geo-routing protocols often employ greedy forwarding techniques, whereby the packet is forwarded to the next hop closest to the destination node. Although this strategy simplifies the routing process, it is still prone to a local minimum. A local minimum is a node that is closest to the destination than any of its neighbors, but no link exists connecting the node to the destination due to blocked line-of-sight (LOS) paths. Furthermore, most geo-routing algorithms do not take into consideration the physical layer characteristics and antenna model as cross-layer optimizations in the routing process.

![Illustration of the multipath channel with four eigenrays](image)

*Figure 1-4: Illustration of the multipath channel with four eigenrays (i.e. traveling waves) of interest which are: direct-path (DP), refracted-surface-reflected (RSR), refracted-bottom-reflected (RBR) and refracted-surface-reflected-bottom-reflected (RSRBR). When recovering NLOS links we propose using RSR and RBR eigenray for directional communication.*
To overcome this challenge we propose using directional communication that will also utilize non-line-of-sight (NLOS) links. In this dissertation, we develop a novel surface-based reflection (SBR) scheme, which uses reflections from the water surface (or bottom) to establish NLOS links. The receiver only accepts signals that are reflected once (surface or bottom) by checking the received-signal-strength (RSS) and comparing it to the calculated surface/bottom attenuation parameters. The RSS is obtained by calculating the attenuation from the recovered channel’s impulse response (IR). Furthermore, only accepting surface or bottom reflected signals is done to promote NLOS usage with directional antennas and to fully utilize the spatial spectrum between multiple nodes. Thus, a transmitter will be able to select either LOS or NLOS depending on the communication protocol used, while the receiver will be able to filter out the desired link by incorporating SBR. An illustration of the SBR scheme is shown in Figure 1-4 where the receiver B will be mainly interested in the refracted-surface-reflected (RSR) and refracted-bottom-reflected (RBR) eigenray when recovering NLOS links. An eigenray is a traveling wave that connects a transmitter to a specific receiver. A suite of protocols have been developed for node discovery and localization, medium access control and routing in order to enable efficient network operation.

1.2 Network Model: Directional Multi-hoping

Utilizing NLOS will allow for simultaneous communication. To illustrate, let us consider Figure 1-5 and Figure 1-6, where $k_{\text{LOS}}$ is the LOS transmission range. With omni-directional antennas, multiple simultaneous transmissions cannot occur when
nodes are within each other’s transmission range. As shown in Figure 1-5, while the transmissions \((B \rightarrow C \rightarrow E)\) are taking place, node \(D\) cannot send packet to node \(F\) since it will interfere with the ongoing packet traffic. With directional antennas, in Figure 1-6, two simultaneous multi-hop transfers \((A \rightarrow B \rightarrow C \rightarrow E)\) and \((D \rightarrow F)\) can take place, which increases overall network throughput. Figure 1-7 shows that NLOS links can enable unique simultaneous multi-hop transfer scenarios by bypassing node \(B\), which is the destination on another path. The scenario in Figure 1-7 is not feasible with omni and LOS-directional transmissions. In our proposed protocols, we exploit the idea of utilizing NLOS (or reflected) links in node discovery, medium access (MAC) and geographical routing to form a UWAN. In the next chapter, we will summarize the research contributions of this dissertation, which builds on this network model.

![Figure 1-5: Multi-hop Omni-directional](image1)

![Figure 1-6: Multi-hop Variant #1](image2)

![Figure 1-7: Multi-hop Variant #2](image3)

**Figure 1-5:** Multi-hop with omni-directional antennas. kLOS is the line-of-sight transmission range, shown for node A.

**Figure 1-6:** Multi-hop with directional antennas enables multiple simultaneous transmissions.

**Figure 1-7:** Enabling reflections while using directional antennas yields an increase in simultaneous transmissions.
1.3 Research Contribution

A high-level networking overview of the proposed dissertation is illustrated in Figure 1-8, where the sensor nodes aim to utilize both line-of-sight (LOS) and surface-reflected non-line-of-sight (NLOS) links to establish the best route to the desired destination.

![Underwater networking scenario showing sensors utilizing LOS and NLOS links to establish best routes to a destination (or group of destinations).](image)

**Figure 1-8:** Underwater networking scenario showing sensors utilizing LOS and NLOS links to establish best routes to a destination (or group of destinations).

The best route is obtained by incorporating our novel surface-based reflection (SBR) scheme, which uses the reflections from the water surface, and bottom, to establish communication links. The receiver only accepts signals that are reflected at the surface (or bottom) by checking the Received Signal Strength (RSS) and comparing it to the calculated reflection coefficients. The research contribution can be summarized as follows:
A. *A Novel Surface-based Reflection (SBR) Scheme*: The SBR scheme exploits the multipath nature of the acoustic channel by recovering both LOS and NLOS links. This is accomplished through the usage of directional antennas to either direct the signals energy towards the next-hop node (LOS) or to the water surface/bottom to be reflected onto the next-hop node (NLOS). Furthermore, a homomorphic deconvolution process is used to recover the channel’s impulse response, which is further used to determine the directional link type (LOS or NLOS). Advantages of the SBR method include source signal tracking avoidance, node localization, and network link extensions.

B. *Multimodal Underwater Acoustic Modem Prototype*:  
   
   A prototype modem has been developed to utilize a multimodal directional transducer for LOS and NLOS communication. The prototype has been used to validate the performance of the SBR communication model in a water tank. The prototype design could be leveraged for networking protocols such as node discovery, localization, medium access control and routing. The end result is an efficient directional acoustic communication platform that mitigates the effect of multipath propagation while fully utilizing the available spatial spectrum.

C. *Network Throughput Analysis with directional LOS/NLOS Links*: We derive an analytical bound on the achievable throughput. Our network throughput analysis will take into consideration LOS links (i.e., DP) and NLOS links (RSR and RBR). The derivation will be based on the assumption that we have a physical (PHY)
and medium-access (MAC) cross-layer optimization scheme that utilizes switch-beam directional antennae. The MAC protocol will be based on the carrier-sense multiple access protocol with collision avoidance (CSMA/CA). Published studies for the throughput of the CSMA/CA protocol have been limited to RF links. To the best of our knowledge, this is the first study for conducting throughput analysis for shallow water communication with directional antennas. More importantly, the inclusion of NLOS links especially with directional communication has never been done before for underwater acoustic communication in shallow water environments.

D. *Surface-based Anchor-free Localization:* A surface-based reflection anchor free localization (SBR-AL) algorithm is proposed to establish a coordinate system relative to the water surface. Advantages of the SBR-AL method include node discovery, ad-hoc formation, source signal tracking avoidance, and network link extensions, where additional communication paths are made available.

E. *Underwater Signal Reflection-enabled Acoustic-based Localization:* We have also developed an underwater signal reflection-enabled acoustic-based localization scheme (UNREAL) which takes advantage of directional antennas and utilizes both LOS and non-line-of-sight (NLOS) links for node localization. We then derive a closed-form angle-of-arrival (AOA) position estimation expression that considers either reference underwater nodes or reference reflection points on the water surface in order to calculate the position of a node that has drifted away from the geographically located network.
F. Reflection-enabled Directional Medium Access: We have developed a novel reflection-enabled directional MAC (RED-MAC) protocol, which to the best of our knowledge, is the first directional MAC for UW-ASNs that comprehensively addresses the various design complications of underwater medium access arbitration. The proposed RED-MAC protocol only requires one switch-beamed antenna, which can be partitioned to form segmented directional antennas and will not be dependent on the line-of-sight (LOS) path. In traditional D-MAC protocols nodes can only direct their antennas towards the known position of the receiver. As a result, traditional D-MAC schemes cannot recover if an obstacle is blocking the path of the signal. However, with RED-MAC nodes will be able to determine if an obstacle is blocking the LOS link and switch to the next best directional antenna that will be reflected from the water surface or the water bottom. RED-MAC will achieve this by incorporating the surface-based reflection (SBR) scheme which allows a receiver to establish water surface (or bottom) reflected links.

G. Signal Reflection-enabled Geographical Routing: For ad-hoc formation (i.e. Figure 1-8), we propose GORRILA, a geographical optimized reflection-enabled routing algorithm that is immune to link ambiguity. GORRILA aims to establish the best stable unicast route from a sender to a group of destination nodes within a specific geocast region as depicted in Figure 1-8. Unlike traditional Euclidean distance based routing protocols, GORRILA not only relies on the LOS link between one-hop neighbors when establishing routes, but also considers other
reflected paths while routing packets to neighbors. GORRILA factors in two NLOS links (or eigenrays), which are the refracted-surface-reflected (RSR) and refracted-bottom-reflected (RBR) eigenrays. Utilizing RSR or RBR links enables GORRILA to be robust to LOS link failures due to high network traffic or blocked paths that cause a packet to be trapped in a local minimum (i.e. voids), which has plagued most published geo-routing protocols. Although the current GORRILA algorithm currently optimizes each route to achieve maximum network throughput, we plan on extending the GORRILA algorithm to consider other routing metrics, such as: network delay, error rate and energy.

### 1.4 Sound Speed Modeling

As mentioned in the introduction, the varying underwater parameters, namely, pressure, salinity, and temperature affect the sound speed profile. We can express the sound speed profile mathematically by the following expression [5]:

\[
c = 1449.2 + 4.6T - 0.055T^2 + 0.00029T^3
+ (1.34 - 0.01T)(S - 35) + 0.016z
\]  

(1)

We see that the expression for the sound speed \( c \) is dependent on the temperature \( T \) in degrees centigrade, salinity \( S \) in parts per thousand, and depth \( z \) in meters. Although the expression (1) is accurate in most cases, it requires *priori* information about the salinity, temperature and depth. Furthermore, when modeling short-range (\( \leq 1 \)km) shallow water propagation (up to 200m depth) we can assume a sound speed profile that varies pseudo-linearly with depth as introduced by Gordon [3]:
\[ c(z) = \frac{c_w}{\sqrt{1 + 2.4z/c_w}} \]  

(2)

where \( c_w \) is the sound speed in the water surface layer. When an acoustic wave interacts with a hard bottom material, i.e., silt, sand, and gravel, we can define the sound speed in the bottom as \( c_b \), such that \( c_b > c_w \) for hard bottom mediums. We should note that the expression (2) is mainly used as an approximation only when the salinity and temperature parameters are not known. In the next two subsections (1.5, 1.5.1), we will go over the antenna model before introducing the sonar equation in 1.6. Both the antenna model and the sonar equation are important concepts needed for underwater communication.

**1.5 Acoustic Antenna Models**

A hydrophone is a microphone used as an acoustic antenna for communicating underwater, where the term “hydro” refers to a piezoelectric transducer with an acoustic impedance match to water. A single element hydrophone is Omni-directional in nature. For directional underwater acoustic communication, the antenna is composed of an array of hydrophones that can be summed up at various phases and amplitudes resulting in a beam-former [5]. A directional beam-former can be expressed by averaging the SNR to the output of the hydrophone array as follows:

\[ \frac{S^2}{N^2} = \frac{\left[ \sum_{i=1}^{m} s_i(t) \right]^2}{\left[ \sum_{i=1}^{m} n_i(t) \right]^2} = \frac{\sum_{i=1}^{m} \sum_{j=1}^{m} s_{ij}}{\sum_{i=1}^{m} \sum_{j=1}^{m} n_{ij}} \]  

(3)

where the bar represents the average over time of the \( m \) signals \( s_i(t) \) and noise \( n_i(t) \).

The array signals and noise for the \( i^{th} \) and \( j^{th} \) hydrophones can be expressed as \( s_{ij} = s^2 \hat{s}_{ij} \) and \( n_{ij} = n^2 \hat{n}_{ij} \). Thus, the beam-former can be further simplified to:
Figure 1-9: A 7-element antenna array and the corresponding beam-form pattern when combining the signals of all elements in one axis [26].

Figure 1-10: A stackable multimode piezoelectric directional transducer. Each cylinder is 2" in height with an outer diameter of 4.25" [27]. The horizontal beam pattern is shown; the vertical beam pattern depends on the number of stacks.

\[
\frac{S^2}{N^2} = \frac{s^2}{n^2} \frac{\sum_{i=1}^{m} \sum_{j=1}^{n} \hat{s}_{ij}}{\sum_{i=1}^{m} \sum_{j=1}^{n} \hat{r}_{ij}}
\]

The gain of the hydrophone array can then be expressed as:

\[
AG = 10 \log \left( \frac{S^2}{N^2} \right) = 10 \log \left( \frac{\sum_{i=1}^{m} \sum_{j=1}^{n} \hat{s}_{ij}}{\sum_{i=1}^{m} \sum_{j=1}^{n} \hat{r}_{ij}} \right)
\]

We can further define the antenna gain \(G(\theta)\) at the beam steering angle \(\theta = \theta_s\) and for an array gain of \(AG\) as:

\[
G(\theta) \approx \begin{cases} 
AG, & \text{Combined Gain} \\
DI(\theta = \theta_s), & \text{Directional Gain}
\end{cases} \tag{4}
\]

A vector hydrophone array was developed in [26] for underwater acoustic communication. Although their fabricated design used a hydrophone array that can only receive acoustic signals without transmitting them, the same concept can be extended for a hydrophone array with both sensing and emitting properties [28][29]. Figure 1-9 shows an illustration of the 7-element 3D vector sensor array with sensors.
oriented at both positive and negative axis ± (x, y, z) as well as at the origin(0,0,0). When combined together, the 7 elements can be used as an omni-directional antenna with beam pattern shown in the right side of Figure 1-9 (the dipole is the omni-directional beam oriented around the x-axis). A piezoelectric directional transducer was designed and evaluated by Butler et al [27]; their proposed transducer generates a directional pattern by combining the fundamental vibration modes of a cylindrical acoustic radiator, the fabricated transducer along with the vertical beam pattern is shown in Figure 1-10. Furthermore, the beam steering angle can be controlled electrically by changing the voltage amplitude rather than the phase, which makes it ideal for our proposed system model. The next subsection will elaborate more on the multimodal transducer concept.

1.5.1 Multimode Piezoelectric Transducer

A multimode piezoelectric transducer is a cylindrical radiating transducer that synthesizes higher order modes of operation from the lower order modes [27][30]. Figure 1-11 shows an omni-directional mode, which is a fundamental mode that occurs when we have uniform positive voltage distribution on the inner surface of the cylinder.
Such a polarized piezoelectric device will have continuous electrodes on the inner and outer surfaces of the cylinder. The resonant frequency of the omni-directional fundamental mode for a sound speed of $c$ and a mean ring diameter $D = \frac{d_{inner} + d_{outer}}{2}$ can be given by:

$$f_0 = \frac{c}{\pi D} \quad (5)$$

Thus, the fundamental frequencies for subsequent $n$ modes, i.e. Dipole, Quadrupole, etc., can be calculated from that of the omni-directional mode as shown:

$$f_n = f_0\sqrt{1 + n^2} \quad (6)$$

Furthermore, the three first modes (Omni, Dipole and Quadrupole) can be combined with different voltage weights corresponding to the normalized far-field acoustic pressure as shown in Figure 1-14. The resulting superimposed combination results in
a quadrant beam pattern as illustrated in Figure 1-15. We can express the quadrant beam pattern from the far-field complex acoustic pressure function $p(\theta)$ at the azimuth angle $\theta$ as shown:

\[
\frac{p(\theta)}{p(0)} = \frac{1 + A \cos \theta + B \cos 2\theta}{1 + A + B}
\]  

(7)

where $p(0)$, $A$, $B$ are the maximum far-field complex acoustic pressure function of the major lobe, the normalized far-field acoustic pressure due to dipole mode only and the normalized far-field acoustic pressure due to quadrupole mode only respectively. We should note that the far-field factors $(A, B)$ are real entities due to the normalization hence real voltage weights can be substituted for $(V_A, V_B)$ relative to omni-mode to characterize the shape of the resulting beam pattern.

*Figure 1-16:* Example of the voltage distribution needed to form a tri-mode configuration. The voltage distribution of $[1.5, 1.9, 0.5, 0.1]$ is only valid for the frequency band in the [15 kHz, 20kHz] range.
This concept of combining the lower order modes can be made practical as shown in [27] by modifying a piezoelectric cylinder to include segmented internal electrodes for signal voltage and one external electrode for ground.

An example of the voltage distribution can be seen in Figure 1-16. The internal voltage weights for each mode of operation can be obtained with the following set of equations:

\[
V_1 = V_o + V_d - V_q
\]

\[
V_2 = V_o + V_d + V_q
\]

\[
V_3 = V_o - V_d + V_q
\]

\[
V_3 = V_o - V_d - V_q
\]

For:

\[
V_o = 1/T_o
\]

\[
V_d = A/T_d, A = 1
\]

\[
V_q = B/T_q, B = 0.414
\]

The parameters \((T_o, T_d, T_q)\) are obtained from the complex amplitude of the transmit voltage responses (TVR) at the desired frequency for the omni, dipole and quadrupole modes respectively. We will revisit the TVR and go over in detail in section 1.6.1 of this chapter. Nevertheless, we note that with the current voltage distribution shown in Figure 1-14, the multimodal transducer can generate a 40° beam in the frequency range of 15 kHz to 20 kHz as depicted in Figure 1-10. Different voltage distributions will need to be derived if another frequency band is desired.

### 1.6 Sonar Equation and Noise

Given a source level \((SL)\), an ambient noise level \((NL)\) and a total transmission loss \((TL)\), the passive sonar equation defined in [5] is given by:
\[ SNR = SL - NL - TL \quad [dB] \quad (15) \]

where SNR is the desired signal-to-noise-ratio. The noise level (NL) can be due to ambient noise, marine noise, water surface noise, or human-made noise [87]. Surface-ships typically dominate the 20-500 Hz frequency range, while noise due to bubbles and breaking waves dominate the 500-100,000Hz range. Above 100 kHz, thermal noise caused by motion of water molecules dominates. Figure 1-17 depicts a typical noise spectral density level in the ocean environment.

Marine organisms communicate in a wide spectrum of the acoustic band 10-100,000Hz whereby some mammals, i.e. snapping shrimp, have been known to corrupt man-made signal transmission with having an individual source level of greater than 180 dB re 1 uPa at 1 meter. Toothed whales (Odontocetes) are known to communicate in the 100-100,000Hz band. Some of these mammals typically employ short clicking sounds at higher frequencies for the purpose of echo-localization.
Figure 1-17: Spectral density sound levels of marine life ambient noise from weather, wind, geologic activity, and commercial shipping [13]

To establish communication in the presence of noise, the SNR would have to be above a desired detection threshold (DT), which will need to exceed that of the noise and the acoustic transmission loss. To properly determine the desired SNR, we will go over source level (SL) determination and different parameters that make up the acoustic transmission loss $TL$. This will be the focus of the next two subsections.
1.6.1 Acoustic Source Level

Acoustic communication requires utilizing piezoelectric transducers to emit and receive sound. Every piezoelectric device can be characterized by their mechanical response, namely the transmitting voltage response (TVR) and the receiving voltage response (RVR) [87]. For the sonar equation in (15), the TVR is typically used as the acoustic source level (SL). The TVR is defined according to [31][87] as the sound pressure level experience at a range of 1 meter, generated by the transducer per 1V of input voltage over the frequency band of the transducer. The TVR effectively measures the sound pressure level in units of dB/1uPa/m during transmission. Thus, we can mathematically, represent the source level as:

\[
SL = TVR = 20 \log \left( \frac{\text{Output Response} \ (\frac{uPa}{V})}{\text{Reference Response} \ (\frac{uPa}{V})} \right) \ @ \ 1m
\]  

(16)

where the reference response is taking to be 1 uPa/V. Figure 1-18 gives a plot of the source level or the TVR of two different piezoelectric cylindrical transducers. The TVR data for both plots where obtained from [31][87]. The red line gives the source level of a piezoelectric cylindrical transducer with a resonant frequency of 40 kHz, where we see that between 38 and 43 kHz the TVR is at its peak. The blue line gives the source level of the multimodal piezoelectric cylindrical transducer described in chapter 1.5.1, which is known two resonant frequencies one at 10 kHz and the other at 36 kHz. Figure 1-19 gives a detailed TVR breakdown of the multimodal piezoelectric transducer. Recall from chapter 1.5.1 that the multimodal piezoelectric transducer combines the three fundamental modes (omni, dipole, and quadrupole) to
form a directional beam or tri-mode pattern. From Figure 1-19 we see the effects of combining the multiple modes on the total TVR of the tri-mode pattern.

![Transmit Voltage Response](image)

**Figure 1-18:** Transmit Voltage Response of two piezoelectric transducers with different resonant frequencies.

![TVR of different configurations](image)

**Figure 1-19:** TVR of the different configurations that make up the tri-mode plot [27]. The complex amplitudes from these TVR measurements were used to determine the voltage distribution in section 1.5.1.
Unlike the TVR, the RVR measures the voltage induced by a plane wave of a unit of acoustic pressure at the receiver over the frequency band of the transducer. The RVR is a measure of the sensitivity of the transducer given in units of dB/1V/uPa during reception. The sensitivity gives a ratio of the output voltage of the transducer to the sound pressure in the water fluid surrounding it. This can be expressed mathematically as shown:

\[
RVR = 20 \log \left( \frac{\text{Received Pressure} \left( \frac{V}{uPa} \right)}{\left( \frac{1}{uPa} \right)} \right)
\]  

(17)

Taking RVR measurements usually requires a reference hydrophone, reference transducer (with a known TVR) and the transducer that needs to be calibrated. Figure 1-20 shows the plot of the RVR for three different transducers, the blue and red plots depict the RVR for the multi-modal and the 40-kHz resonant frequencies respectively. The black plot gives the RVR measurement of a measurement hydrophone [89], which is a specialized transducer that can mainly receive with a relatively flat RVR spectrum over a wide acoustic spectrum (10-100,000Hz).

Hydrophones, which are mainly used for reception, are typically made from passive piezoelectric ceramics to yield higher charge sensitivity, i.e., un-modified variant of lead zirconate-titanate. These devices are typically classified as type II piezoelectric devices. According to the DOD-STD-1376A standard [88], there are 6 types of piezoelectric devices.
Figure 1-20: Plot of the receive voltage response of three different transducers

Type I devices are made of a modified variant of lead zirconate-titanate composition, they are generally recommended for medium to high power acoustic applications, both the Multi-modal and 40-kHz piezoelectric devices shown in blue/red are made of Type I piezoelectric ceramic materials. Type III devices are similar to Type I but greatly improved for high electric drive because of lower losses. Type IV devices are made from a modified barium-titanate body for use in moderate electrical drive applications. Type V devices are made of a composition intermediate to Type II and IV devices. While Type VI devices are similar to Type II but contain higher charge sensitivity and dielectric constant, this comes at the expense of a reduced Curie temperature. The Curie temperature is the temperature that induces a magnetic change in the material.
1.6.2 Acoustic Transmission Loss

In general, there are three main causes of transmission loss to an acoustic wave in an underwater environment, namely transmission loss due to multipath attenuation effects \((TL_{MULT})\), transmission loss due to spherical geometric spreading \((TL_{SGP})\) and transmission loss due to plane-wave attenuation, i.e. absorption \((TL_{WAVE})\) [5]. The total transmission loss in decibels can be expressed mathematically as:

\[
TL_{TOTAL} = TL_{MULT} + (TL_{SGP} + TL_{WAVE})
\]

\[
TL_{TOTAL} = TL_{MULT} + TL_{LOS} \quad [dB]
\]  (18)

where we have now grouped the spherical geometric spreading \(TL_{SGP}\) and plane-wave \(TL_{WAVE}\) transmission loss to what we define as the line-of-sight (LOS) transmission loss \(TL_{LOS}\). In shallow water most of the transmission loss is due to the attenuation from multipath effects. The LOS transmission \(TL_{LOS}\) (in dB) has the following frequency-distance dependent relationship:

\[
TL_{LOS} = k \cdot 10 \log(d) + d \cdot 10 \log \alpha(f) \quad [dB]
\]  (19)

for

\[
\alpha(f) = \frac{1}{1000} \left(\ddot{a}(f^3)\right)
\]

\[
\ddot{a}(f) \equiv 3.3 \times 10^{-3} + \frac{0.11f^2}{1 + f^2} + \frac{44f^2}{4100 + f^2} + 3.0 \times 10^{-4} f^2
\]

where \(\ddot{a}(f)\) can either be cylindrical \((k = 1)\) or spherical \((k = 2)\). Cylindrical spreading can be used as a simple approximation for spreading loss in a medium with upper and lower boundaries with the assumption that the sound is uniformly distributed over the surface/bottom of the cylinder; this is illustrated in Figure 1-21. Spherical spreading describes the decrease in sound level as the wave propagates away from a source.
uniformly in all directions, thus spherical spreading only considers the LOS transmission loss without any multipath effects as depicted in Figure 1-22. In our case we have adopted the spherical model since we will be closely considering the effects of multipath in a rough boundary in subsequent sections. $f$ is the frequency (in Hz) and $\tilde{\alpha}(f)$ (in dB/km) is derived for an underwater environment with temperature at $4^\circ$ C, salinity of 35 ppt, and pH of 8.0.

In shallow water environments most of the transmission loss will be due to multipath or reverberation effects. We will study this in depth in chapter 3 when we go over our proposed surface-based-reflection (SBR) communication model.

1.7 Summary

In this chapter we started by introducing the networking problem and outlining the research contributions. A majority of the chapter went over necessary preliminaries needed for underwater communication, especially when utilizing directional piezoelectric transducers. A multimodal transducer concept of Butler et al. [27][30] was presented which is able to generate both omni-directional and directional beams by combining the fundamental modes of a vibrating cylinder. Thus,
the resulting transducer may be steered by changing the voltage amplitude rather than the phase of the electrodes of the cylinder. The sonar equation was also introduced, which showed that both noise and transmission loss greatly affects underwater communication. Thus, it is imperative to pick a transducer with a high transmit voltage response (TVR) for increased source level and a high receive voltage response for increased receiver sensitivity.
Chapter 2

Related Work

This chapter compares the research contributions to the state of the art on UWANs. Given the contribution of the dissertation, the discussion is divided into four sections covering NLOS communication, node localization, medium access and control (MAC), and geographical routing.

2.1 NLOS Underwater Communication

Prior research on underwater communication has considered the effects of utilizing NLOS links [38][42][43]. Optical NLOS underwater communication was proposed by Arnon and Kedar [25]. They were able to derive an expression for the expected received power by calculating the reflection coefficient of the water surface. Although the range of an optical link is limited in the underwater medium (~ 8m for 1GHz bandwidth) the authors proposed using multi-hop schemes to extend the communication range.

Recently, studies in underwater communication have pointed out the benefit of taking advantage of NLOS links, especially for node localization [42][43]. In [42], the authors proposed the use of a NLOS scheme in acoustic underwater localization. They classified the NLOS link based on a combination of the received-signal-strength (RSS), time-of-arrival (TOA) and time-difference-of-arrival (TDOA). Although the
NLOS classification scheme is promising, the TOA/TDOA technique employed requires clock synchronization, which might be difficult due to the high propagation delay in underwater environments. In [43], the authors proposed an anchor-based localization scheme with mobility prediction. Each node predicts each location by incorporating its mobility pattern and that of its neighbors.

In all directional communication schemes, it is assumed that the positions of all communicating nodes are known. These positions can either be relative (i.e. anchor-free) [40] or global (i.e. anchor-based) [42][43].

2.2 Underwater Localization

GPS-free localization, which is popular in indoor and underwater environments, uses the range measurements (RSS, TOA, and AOA) to some reference points to determine the position of nodes relative to these points [46]-[53]. Node localization in underwater environment has received some attention in recent years. Almost all published algorithms require pre-determined reference nodes in the localization process [46][49][50]. A major drawback for this approach in large and widely-spread networks is the need of many reference nodes since in most indoor and underwater environments it is not feasible to deploy many reference nodes due to cost, energy, and operational requirements. Zhou et al. [49] tried to partially address this issue by pursuing a hybrid scheme, where some nodes serve as anchors after determining their position relative to surface buoys. Thus, few buoys would be needed since the anchor would serve as reference nodes for the rest of the network.

On the other hand, in [50] the AOA assisted NLOS approach was able to use a fixed reference node and a reflected wall to determine the location of a moving
receiver by using the AOA and TOA of the reflected-path to reconstruct the lost LOS due to an obstacle interfering with the LOS communication. A drawback to this approach is that the transmitter and receiver must be initially connected through a LOS connection before an obstacle interferes forcing the receiver to use the AOA of the reflected path to reconstruct the LOS connection. On the other hand, our proposed surfaced-based anchor-free localization algorithm (SBRAL) does not depend on a LOS connection to perform the localization process. A Phero-Trail Location service protocol was also demonstrated in [52], where the path of the mobile sink node is projected onto a 2D plane on the water surface. The nodes on the water surface keep track of the projected path of the underwater mobile node, which can be used to trace the location of the mobile sink node if communication is lost at any point. This is different from the proposed SBRAL approach since the SBRAL uses the temporary intersection points on the water surface to locate mobile sensor nodes, these intersection points will change over time and will be used to fine-tune the position estimates of the sensor nodes. Similar to [52], an AUV-guided underwater localization scheme was proposed in [53]. AUVs act as mobile beacon nodes that surface periodically to obtain GPS coordinates, which are then included in beacons to locate the remaining nodes. Thus, without the mobile beacons the remaining nodes cannot obtain their position. In our proposed SBRAL algorithm, there are no beacons involved, instead each node cooperates to obtain a relative coordinate system relative to the water surface. Furthermore, the relative coordinate system can be transposed into a global system when beacon nodes are available.
2.3 Medium Access Control for UWANs

MAC protocols for omni-directional antennas are either contention-based [56] or contention-free [57]. Contention-free protocols include time, frequency, and code division multiple access (TDMA, FDMA, and CDMA) schemes. While Contention-based protocols require each node to compete for the shared channel resulting in probabilistic coordination such as the carrier sense multiple access protocol (CSMA). However, these protocols either are geared for saving energy [58] or focus on avoiding the effect of propagation delay on access collisions [56] without much care for bandwidth utilization. Meanwhile CDMA-based approaches [57] do not work well in shallow water environments. Some protocols have pursued hybrid schemes such the clustered-network architecture in [59], where nodes are grouped based on proximity. TDMA is used within the individual clusters since the distance between nodes is small and the guard time between time slots does not have to be large. Allocating distinct spreading code to each cluster prevents interference among clusters. Meanwhile, the Slotted-FAMA protocol [60] combines TDMA and CSMA in order to achieve high throughput. However, the involved handshaking may lead to low throughput in the presence of high propagation delay in the underwater acoustic channel. In addition, the protocol requires clock synchronization, which is very challenging to achieve in UW-ASNs due to the slow signal propagation. An extension has been proposed in [61] to eliminate the need for clock synchronization by adjusting the handshake time based on the distance between the communicating nodes.
R-MAC [62] strives to save energy and avoid collisions through medium access reservation. A node randomly picks its listening/sleep and transmission schedule and informs its neighbor. However, the protocol only works well as long as the network topology (i.e. neighborhood) is known and remains static. R-MAC protocol also does not take into account the large propagation delays in the UW-ASNs that may affect the transmission. Meanwhile, in Tone-LoHi (T-Lohi) [63] nodes contend to reserve the channel for the right to transmit data. Nodes will contend for access to the channel by sending a short tone and listening for a tone from other contenders to determine if the reservation was successful. The T-Lohi protocol takes into account the slow underwater signal propagation by adjusting the reservation period based on the expected propagation delay. Despite the major improvement in channel throughput and energy savings, there are still some cases of data-to-data collisions due to bi-directional deafness. T-Lohi also does not have a mechanism for detecting a hidden terminal. Furthermore, T-Lohi is based on omni-directional transmission and does not take full advantage of the available spatial spectrum.

Directional MAC protocols usually surpass those based on omni-transmissions in terms of bandwidth utilization and delay. Although directional MAC (D-MAC) protocols have been studied extensively in RF environments, to date no protocol exists for UW-ASNs. Therefore, we cover some of the RF-based D-MAC protocols that may be applied to UW-ASNs. In [64], a node uses two antennas for communication, one directional used for sending and one omni-directional dedicated for receiving. In the DtD-MAC protocol [65], each node will use a low-cost switch-beamed antenna for both transmission and reception. A transmitter continually scans
the directional antenna towards the known receiver and sends a D-RTS message when the antenna is not blocked. If the receiver’s position is not known the transmitter will sequentially send D-RTS messages on each of the unblocked antenna and then waits for a reply before continuing clockwise to the next antenna. A receiver will periodically scan each of its directional antennas for D-RTS messages by waiting for a specified amount of time (on each antenna) before switching counter-clockwise to the next antenna. This leads to increased delivery delay, and thus, would not be suitable for mediums that have slow signal propagation.

Our proposed RED-MAC protocol only requires one switch-beamed antenna which can be partitioned to form segmented directional antennas and will not be dependent on the line-of-sight (LOS) path.

2.4 Geographical Underwater Routing

The 3-D nature of the underwater environment has made geo-routing a popular choice for setting data paths in UW-ASNs. A geographical routing protocol works by using the position information to find the best route from the source to the destination. A geo-routing algorithm can either serve unicast, multicast, geocast or anycast. A geocast is a special case of multicast in which the recipients are collocated or batches in specific regions. Geocast is popular in sensors networks where queries can be disseminated to solicit data from nodes in some area or the data is sent to a mobile sink whose trajectory is not precisely known [66]. Anycast often serves applications in which multiple sinks exist and it is necessary to reach any of them [66]. Prior work on routing in UW-ASNs can be categorized based on the destination of the traffic into single [67] or multi-sink[68], on node and sink mobility [66], on path setup.
methodology into link-state based or geo-routing [69], and on the nature of the algorithm into centralized [70] and distributed [71]. The considered design objectives include energy saving [72], route robustness [73], reduced delay [71], and on-time delivery ratio [74].

We believe that the SBR communication model leverages all these routing protocols. In essence, additional SBR-based links are provided. These SBR links enable robustness by overcoming obstacles and noisy LOS links, allow for fast delivery by avoiding regions with high traffic that extends the medium access delay, facilitate the handling of voids, etc. Unlike prior work that factors the link state in the route selection, the proposed geocast protocol exploits the properties of the reflected signals to enable efficient geocast with some receivers tuning their filter differently. This is a unique cross-layer optimization that our proposed SBR communication model makes possible to employ. Furthermore, prior work fundamentally assumed that the sensors are stationary and only the sink node may be mobile. The assumed network model in our work allows all nodes to be mobile. This is a very unique feature that distinguishes our proposed routing scheme.

2.5 Summary

This chapter compared the research in this dissertation to the state of the art on UWANs. This includes NLOS communication, node localization and discovery, medium access and control (MAC) and geographical routing.
Chapter 3

Surface Based Underwater Communications

This chapter introduces and describes the surfaced-based communication model. We start by presenting an abstract version of the model before dissecting the different pieces that make up the entire model. We have also adopted scattering models that can be used with our model along with a propagation model. Moreover, simulation and tank-based experiments are presented to validate the surface-based concept. Results of experiments carried in a tank will be presented in chapter 4 where we will introduce our multimodal acoustic modem.

3.1 Communication Model

Recall from Figure 1-4 in chapter 1.1, that the shallow water acoustic channel is prone to high multipath especially when omni-directional communication is being employed. Thus, to overcome the limitations of current communication systems we propose a surface-based-reflection communication (SBR) model, which exploits the multipath nature of the acoustic channel by recovering both LOS and NLOS links. This is accomplished through the usage of directional antennas to either direct the signals energy towards the LOS or to the water surface/bottom to be reflected onto the destination.
Figure 3-1: High-level view of the proposed system model. The transmitter modulates the desired data to be transmitted on the acoustic channel. The receiver applies recovery mechanisms to obtain the transmitting data and the channel impulse response. 

The proposed communication model can be summarized in Figure 3-1, which shows a transmitter and receiver block for an acoustic link utilizing the known antenna beam pattern. The transmitting node applies a digital modulation scheme, to the desired data to generate $e(t)$. The signal is then convolved with the acoustic channel $h(t)$, which can be modeled using ray tracing, resulting in a noise-free signal of $s(t)$. Upon reception, the signal is typically mixed with an additive white Gaussian noise (AWGN) [21][23][24] signal $w(t)$. The block diagram in Figure 3-1 shows four design inputs to the SBR model. The transmission loss $\{TL_{LOS}, TL_{RSR}, TL_{RBR}\}$ includes both the line-of-sight $TL_{LOS}$ and non-line-of-sight $\{TL_{RSR}, TL_{RBR}\}$ parameters which will be derived from different scattering models. Moreover, the statistics of those parameters can be estimated by sampling the water surface/bottom. Thus from Figure 3-1, we see that SBR will serve two different purposes; the first
will be to recover the transmitted signal $e(t)$ depending on the desired link option (LOS or NLOS), which will be determined by the transmission loss parameters $\{TL_{LOS}, TL_{RSR}, TL_{RBR}\}$ and the recovered channel impulse response $h(t)$. The second purpose will be to obtain the range measurements $\{r_A, r_B\}$, which will be used in the SBR-AL localization algorithm described in chapter 4.

We will begin by describing two models for the multipath transmission loss in the acoustic channel (blue box) which we will build upon in the communication model.

### 3.2 Shallow Water Acoustic Loss

As alluded to earlier, most of the transmission loss in shallow water is due to multipath effects. In underwater acoustics [5], the surface-area (i.e., water surface or bottom) and volume (i.e. plane-wave) scattering strength $S$ is typically used as a conventional parameter of reverberation. Reverberation is the total sum of all scattering contributions in the medium due to the inhomogeneities in the sea boundaries. The total scattering strength is defined as the ratio in decibels of the intensity of the sound scattered by a unit surface area or volume, referenced to a unit distance, $I_{\text{scat}}$, to the incident plane-wave intensity $I_{\text{inc}}$ as:

$$S = 10 \log \frac{I_{\text{scat}}}{I_{\text{inc}}} \text{ [dB]}$$

(20)

Scattering is a mechanism for acoustic transmission loss and interferences. Different empirical scattering models have been designed and employed with success [5][7] [8][9][10]. The Raleigh model [5][7] is valid for low acoustic frequencies ($\leq 1$ kHz) and small surface heights. The Navy Research Laboratory (NRL) model [8][9] is valid for slightly higher frequencies ($\leq 10$ kHz) and also factors in wave
bubbles. The Applied Physics Laboratory of the University of Washington (APL-UW) model [10] is valid at much higher frequency intervals (10 – 100 kHz) but has only been verified at a narrower frequency interval (20 – 50 kHz). The APL-UW model also requires that the measured wave height be at most 10m. Both NRL and APL-UW models require both the acoustic frequency \( f \) in kilohertz and the wind speed \( U \) in meters/second. The wind speed is used as a parameter for both NRL and APL-UW because it is easily and reliably measured and is the best known environmental parameter that correlates with sea surface conditions. In our simulations and analysis of our SBR model, the Raleigh model has been adopted since it requires less information about the sea state. Moreover, the analysis presented in this dissertation can further be extended to include other scattering models. The next two subsections will go over both the Raleigh and NRL methods for modeling multipath transmission loss.

### 3.2.1 Raleigh Model

The Raleigh model has been shown to be suitable for modeling scattering in shallow water environments [21][5]. The Raleigh total multipath transmission loss \( TL_{\text{MULT}} = RTL_{\text{MULT}} \) can be determined by modeling the shallow water environment as a homogeneous fluid-fluid media as demonstrated in [21] and illustrated in Figure 3-2.
The top layer is the water layer and the bottom layer is the oceanic bottom in a shallow water environment. In the water layer the parameters \(\{c_w, p_w, \theta_w\}\) corresponds to the speed of sound (in m/s), the density (in kg/m\(^3\)) and grazing angles (in radians). The same applies for the parameters \(\{c_b, p_b, \theta_b\}\) in sea bottom. Thus we can now describe the multipath transmission loss \(TL_{MULT}\) for the different link option (RSR, RBR and LOS) by calculating the Raleigh reflection coefficients (using Snell’s Law) as follows:

\[
R = \frac{p_b c_b / \sin\theta_b - p_w c_w / \sin\theta_w}{p_b c_b / \sin\theta_b + p_w c_w / \sin\theta_w}
\]

\[
\hat{R}_{bottom}(\theta) = R e^{-0.5\Gamma^2}
\]  \hspace{1cm} (21)

\[
\hat{R}_{water}(\theta) = -e^{-0.5\Gamma^2}
\]  \hspace{1cm} (22)

\[
TL_{MULT}(\theta) = \begin{cases} RTL_{RSR}(\theta) & \text{RSR} \\ RTL_{RBR}(\theta) & \text{RBR} \end{cases}
\]  \hspace{1cm} (23)

For

\[
RTL_{RSR}(\theta) = -10 \log \left( |\hat{R}_{water}(\theta)|^2 \right)
\]  \hspace{1cm} (24)
\[ R_{TL, \text{RBR}}(\theta) = -10 \log \left( |R_{\text{bottom}}(\theta)|^2 \right) \]  

(25)

where \( R \) is the reflection coefficient for a flat bottom for a Raleigh roughness parameter defined as:

\[ \Gamma = 2k \sigma_{\text{RMS}} \sin \theta \]  

(26)

The Raleigh roughness parameter \( \Gamma \) depends on the wavenumber \( k = 2\pi f / c \), where \( c = c_w \) or \( c_b \). The roughness parameter also depends on the root-mean-square (RMS) roughness \( \sigma_{\text{RMS}} \) and the grazing angle \( \theta = \theta_w \). The assumption according to [5] is that the expression for the roughness parameter \( \Gamma \) is only valid for small \( k \) and \( \sigma_{\text{RMS}} \). We can express the RMS roughness parameter for a 2D sampled water surface as shown:

\[ \sigma_{\text{RMS}} = \sqrt{\frac{1}{NM} \sum_{i=1}^{N} \sum_{j=1}^{M} \sigma_{ij}^2(t)} \]  

(27)

Such that \( \sigma_{ij}(t) = (h_{ij}(t) - \bar{h}) \) and \( h_{ij}(t) \) is the water surface height for the \( i \)th and \( j \)th sample relative to the mean value of the rough surface height \( \bar{h} \). If the height variance \( \sigma_{ij}^2(t) \) for each sample isn’t known, we can approximate the RMS roughness from the surface wind speed with the Pierson-Moskowitz (PM) or with the Pierson-Neumann (PN) models [6] given that we have prior knowledge of the wind speed \( v_w \) in \([\text{kn}]\) (1 kn = 0.514 m/s) as shown:

\[ \sigma_{\text{RMS-PM}} = \sqrt{1.4 \cdot 10^{-5} v_w^4} \]  

(28)

\[ \sigma_{\text{RMS-PN}} = \sqrt{0.341 \cdot 10^{-5} v_w^5} \]  

(29)

Furthermore, we see that the multipath transmission loss (23) is mainly dependent on the grazing angle \( \theta \) for fixed underwater parameters \( \{c_w, p_w, c_b, p_b\} \).
Figure 3-3: Multipath transmission loss for a silt-like rough bottom and a rough water surface with rms roughness of 0.1 depicting a critical angle of 33.6° for the RBR eigenray.

Figure 3-4: Impact on the RMS height variation on the water surface transmission loss showing higher effect on the surface roughness for high grazing angles.

Figure 3-5: Impact of the RMS height variation on the rough bottom.
Figure 3-3, Figure 3-4 and Figure 3-5 show plots of the Raleigh multipath transmission loss $RTL_{MULT}$ due to a rough water and bottom surfaces (i.e. RSR and RBR) as we vary the grazing angle $\theta = \theta_w$ and the rms roughness $\sigma_{RMS}$. The sound speeds in the shallow water environment were set to $\{c_w = 1500, c_b = 1800\}$, while the densities where set to model a silt-like bottom surface (i.e. $p_b/p_w = 1.7$). With acoustic wavelengths of $\lambda_w = 1.5\, m$ and $\lambda_b = 1.8\, m$ which implies a carrier frequency of 1 kHz. We see that rougher surfaces will greatly impact the multipath transmission loss due to higher scattering especially when we exceed the critical angle of $\theta_c$. In addition, we see that the transmission loss from the water bottom far exceeds that of the water surface, this is especially true since the silt-bottom tends to be an absorber of sound with transmission loss in the range of $\{40, 60\}$ dB as also reported with the APL-UW model [5][10]. On the other hand, hard surfaces such as gravel will reflect most of the acoustic energy, resulting in a lower transmission loss in the range of $\{10, 20\}$ dB [5]. In chapter 6, we present an algorithm for using the water surface in node discovery and localization due to its low signal loss and time-varying properties.

Thus, given our expression for the multipath transmission loss using the Raleigh model (23) the total received power can be described as follows:

$$A(d, f, \theta) = 10^{\frac{TL_{TOTAL}}{10}} = d^2 a(f)^d \left(\frac{R(\theta)}{\theta}\right)^{-1}$$

$$P_{RX} = P_{TX} \cdot A(d, f, \theta) \cdot G(\theta)$$

(30)

where $R$ is the reflection coefficient for the water bottom or surface in (21) and (22).
respectively. \( G(\theta) \) is the antenna gain which can be deduced from the antenna model described in chapter 1.5.1 and from equation (4) in chapter 1.5. In the next subsection, we go over the NRL scattering model which is suitable for slightly higher frequencies \((\leq 10 \text{ kHz})\) and also factors in wave bubbles.

### 3.2.2 Navy Research Laboratory Bistatic-Scattering Model

The NRL has developed a 3D interface-scattering model that factors in bubble waves and is parameterized solely by the wind speed. The bubble wave’s act as an absorber at moderate to high grazing angles, this absorption leads to acoustic energy loss. Also, any noise generated at the air-to-sea interface must propagate through the bubble layer before reaching the receiver. The bistatic scattering NRL (BiS-NRL) model is defined by adding the bubble scattering intensity \( I_{\text{bubble}} \) to the scattering strength expression in (20) as shown:

\[
\text{BiS}_{\text{NRL}} = 10 \log \left( \frac{I_{\text{scat}}}{I_{\text{inc}}} + I_{\text{bubble}} \right) \quad \text{[dB]} 
\]

(31)

A bistatic system requires both the transmitter and receiver to be separated by a distance that is comparable to the expected target (i.e. surface) distance. To be consistent with previous definitions, we define the bistatic total multipath transmission loss \( BTL_{\text{MULT}} \) as:

\[
BTL_{\text{MULT}} = -\text{BiS}_{\text{NRL}} \quad \text{[dB]} 
\]

(32)

To determine the intensities \((I_{\text{scat}}, I_{\text{inc}}, I_{\text{bubble}})\), we first give an illustration of the scattering model in Figure 3-6 which is shown for the ocean bottom. Note that for the ocean surface, the geometry is inverted, so that positive \( z \) corresponds to the depth below the surface.
Figure 3-6: Illustration of the scattering geometry used in NRL’s bistatic scattering calculations. $\theta_{inc}$ is the incident grazing angle, $\theta_{scat}$ is the scattered grazing angle and $\phi_{bi}$ is the bistatic angle.

In this case, $k$, $q$, $\theta_{inc}$, $\theta_{scat}$, and $\phi_{bi}$ corresponds to the incoming wavevector, outgoing wavevector, incident grazing angle, scattering grazing angle and bistatic angle, respectively. The bistatic angle is the difference in azimuth between the incident and scattered directions. The two wavevectors can be written in terms of both the incident and scattering angles for an acoustic wavenumber of $k_0 = 2\pi f / c_0$ as shown:

$$k = k_0 (\cos \theta_{inc} \hat{x} - \sin \theta_{inc} \hat{z})$$
$$q = k_0 (\cos \theta_{scat} \cos \phi_{bi} \hat{x} + \cos \theta_{scat} \sin \phi_{bi} \hat{y} + \sin \theta_{scat} \hat{z})$$

With unit vectors:

$$v_k = [\cos \theta_{inc} \ 0 \ - \sin \theta_{inc}]^T$$
$$v_q = [\cos \theta_{scat} \cos \phi_{bi} \ \cos \theta_{scat} \sin \phi_{bi} \ \sin \theta_{scat}]^T$$

Thus, the interface scattering $I_{int} = I_{scat}/I_{inc}$, depends on the horizontal and vertical
magnitudes of the difference in the two wavevectors, i.e. \( k - q = (Q_h, Q_z) \) with magnitudes defined as follows:

\[
|Q_h| = k_0 \sqrt{\cos^2 \theta_{\text{inc}} + \cos^2 \theta_{\text{scat}} - 2 \cos \theta_{\text{inc}} \cos \theta_{\text{scat}} \cos \phi_{bl}} \\
Q_z = -k_0 (\sin \theta_{\text{inc}} + \sin \theta_{\text{scat}})
\] (35) (36)

With this definition, the interference scattering \( l_{\text{int}} \) is obtained by using the lowest-order small-slope approximation (SSA) [7] of the rough surface as shown:

\[
l_{\text{int}} = \frac{l_{\text{scat}}}{l_{\text{inc}}} = \frac{1}{8\pi} \left| \frac{\beta}{|Q_h| \cdot Q_z} \right|^2 \cdot I
\] (37)

where \( \beta \) corresponds to the boundary conditions prevailing at the interface and \( I \) is an integral involving the spatial spectrum of the roughness. The expression (37) can be approximated by using a first-order perturbation theory resulting in:

\[
l_{\text{int}} = \frac{l_{\text{scat}}}{l_{\text{inc}}} \approx \left| \frac{\beta}{2} \right|^2 \cdot W(Q_h)
\] (38)

Such that \( W(Q_h) \) is the 2D roughness spectral density of the rough bottom and surface which is taken to be a Gaussian random process described as:

\[
W(Q_h) = \frac{w_2}{(h_0|Q_h|)^{\gamma_2}}
\] (39)

For the ocean surface, we can assume \( \gamma_2 \in (2,4) \) and \( w_2 = A_2 U \) with the subscript representing a 2D random process. Such that \( U \) is the wind speed (in m/s) at an elevation of 10m and \( A_2 \in (5 \times 10^{-5}, 20 \times 10^{-5}) \text{m}^3 \text{s}^{-1} \). The parameter \( h_0 \) is the normalizing reference distance of 1m. Furthermore, \( \beta \) is calculated for the ocean surface by using Dirichlet boundary conditions [7] as shown:

\[
\beta = -4k_0^2 \sin \theta_{\text{inc}} \sin \theta_{\text{scat}}
\] (40)

Hence, the interference scattering \( l_{\text{int}} \) for the water surface is expressed as:
\[ I_{\text{water}} = I_{\text{int}} = \left| \frac{-4k_0^2 \sin \theta_{\text{inc}} \sin \theta_{\text{scat}}}{2} \right|^2 \frac{A_{S}U}{(h_0|Q_h|)^{\gamma_2}} \] (41)

This only depends on four environmental parameters which are \((c_0, U, A_S \text{ and } \gamma_2)\).

Furthermore, the bubble intensity was determined empirically in [8] to be:

\[ I_{\text{bubble}} = \frac{0.0019d^{5.15}k_0^{-0.6}k_{v,i}^2k_{v,s}^2}{2(1 + k_{v,i}^2d^2)(1 + k_{v,s}^2d^2)[1 + (k_{v,i} - k_{v,s})^2d^2][1 + (k_{v,i} + k_{v,s})^2d^2]} \] (42)

where, \(k_{v,i} = -k_0 \sin \theta_{\text{inc}} \) and \(k_{v,s} = -k_0 \sin \theta_{\text{inc}}\). Thus, the bubble intensity only depends on two parameters \(c_0 \) and \(d \) for \(d \) derived empirically in [9] as:

\[ d = \begin{cases} 
0.557 - 0.117 \cdot U + 0.0109 \cdot U^2 & U > 7.5 \text{ m/s} \\
-0.19509 + 0.06503 \cdot U & 3 \leq U \leq 7.5 \text{ m/s} \\
0 & U < 3 \text{m/s}
\end{cases} \] (43)

We now define the multipath transmission loss derived with the B-SSS model as shown:

\[ BTLMULT(\theta, \phi) = -\text{Bi}_{\text{NRL}} = \begin{cases} 
BTL_{\text{RSL}}(\theta, \phi) & \text{RSR} \\
BTL_{\text{RBR}}(\theta, \phi) & \text{RBR}
\end{cases} \] (44)

For:

\[ BTL_{\text{RSL}}(\theta, \phi) = -10 \log(I_{\text{water}} + I_{\text{bubble}}) \] [dB] (45)
\[ BTL_{\text{RBR}}(\theta, \phi) = -10 \log(I_{\text{bottom}} + I_{\text{bubble}}) \] (46)

Given our expression for the multipath transmission loss using the B-SSS NRL model the total received power can be described as follows:

\[ A_B(d, f, \theta, \phi) = 10^{\frac{TL_{\text{TOTAL}}}{10}} = d^2 \alpha(f)^d \left( \frac{l_{\text{scat}}}{l_{\text{inc}}} + I_{\text{bubble}} \right)^{-1} \]
The NRL model can be used in a simulated environment to determine the transmission loss of the water surface (i.e. RSR) and water bottom (RBR). Furthermore it can also be used in a simulated environment to study the effects on the network throughput. However, in practice it might not be feasible to obtain the ocean state parameters, i.e. \((c_0, U, A_s\) and \(\gamma_2\)). To circumvent this, each communicating node can obtain statistical information on the water surface and bottom by sending pings towards the surface/bottom and measuring the mean and variance of the transmission loss. In section 3.5, we will describe a mechanism for obtaining the statistics of the multipath transmission loss \((TL_{RSR}, TL_{RBR})\) from pinging the water surface and bottom. Before we do that, we will elaborate the received signal model of Figure 3-1 in the next two subsections.

### 3.3 Received Signal Model

Ray propagation model is a widely-accepted method for modeling signal propagation in shallow water [5][23][24]. According to Paul C. Etter [24] there are typically four basic types of eigenrays that are of interest, namely: refracted-surface-reflected (RSR), refracted-bottom-reflected (RBR), refracted-surface-reflected-bottom-reflected (RSRBR), and the direct-path (DP). Florian Schulz [21] went on to describe the length of each eigenray, which is reflected at the surface first before being reflected \(i\) times during the entire propagation as:

\[
r_i = \sqrt{(D_{TX} + a_i D_w + b_i D_{RX})^2 + d^2}
\]  

\[(48)\]
The geometrical descriptions of the transmitter and the receiver are illustrated in Figure 1-4. The coefficients for $a_i$ and $b_i$ are given in (49), (50), and (51).

\begin{align*}
    a_1 &= 0 \\
    a_{i+1} &= a_i + (1 + (-1)^{i+1}) \\
    b_i &= (-1)^{i+1}
\end{align*}

Figure 3-7: Communication model revisited. Focusing on the received signal

Given an approximation for each eigenray $r_i$, the received signal $r(t)$ is simply a convolution of the transmitted signal $e(t)$ with the acoustic channel $h(t)$ with an additive white noise $w(t)$ as shown:

\[ r(t) = e(t) \ast h(t) + w(t) \]

\[ r(t) = s(t) + w(t) = \sum_{k=1}^{K} \beta_k e(t - \tau_k) + w(t) \]  

where “$\ast$” is the convolution operator, and $\tau_k$, $\beta_k$ corresponds to the time delay and attenuation factor for the $k$-th path respectively. The time delay can be determined by the geometry information of the transmitter and receiver depth $\{D_{TX}, D_{RX}\}$, water
depth $D_w$ and LOS distance $d$ as shown below:

$$
\tau_k = \frac{r_k}{\bar{c}_{ij}} = \frac{\sqrt{(D_{TX} + a_k D_w + b_k D_{RX})^2 + d^2}}{\bar{c}_{ij}}
$$

(53)

For an eigenray (traveling wave) length of $\tau_k$ that is dependent on the average sound speed $\bar{c}_{ij}$ between the two connected nodes $\{i, j\}$. The attenuation factor $\beta_k$ can be modeled for the k-th path as:

$$
\beta_k = 10^{\frac{TL_{TOTAL}}{10}} = 10^{\frac{TL_{MULT(k)}+TL_{LOS}}{10}}
$$

(54)

where, $TL_{TOTAL}$ is the total attenuation in the shallow water environment. In the next subsections, we will go over our proposed scheme used to recover the channel impulse response $h(t)$ and consequently the transmitted signal $e(t)$.

### 3.3.1 Deconvolution with Cepstrum Lifting

SBR aims to utilize directional antennas to recover LOS and NLOS links by minimizing unwanted reflections. However, to classify the desired reflection we need to resolve all components of the channel by recovering channels impulse response (IR), namely $h[n]$. To recover the channel IR, we can utilize a homomorphic deconvolution through cepstrum analysis to undo the convolution operator:

$$
r(t) = e(t) * h(t)
$$

A *cepstrum* is the result of taking the inverse Fourier transform of the logarithm of a waveform, which in our case is the received or transmitted signal. A homomorphic deconvolution is the process of de-convolving the transmitted signal $e(t)$ from the channel $h(t)$ in the cepstrum domain. Oppenheim and Shafer in [11][12], originally defined this process. Moreover, the logarithm operation needed to compute the
cepstrum creates a nonlinear mapping from the spectrum to the cepstrum domain. We can represent this process mathematically by first taking the z-transform of the noise-free received sampled discrete signal $\hat{s}[n] \approx s[n] = s \left( n \frac{1}{F_s} \right)$ as shown:

$$\hat{S}(z) = Z(\hat{s}[n]) = E(z)H(z) \quad (55)$$

where $F_s$ is the sampling frequency used to convert the continuous waveform into a discrete signal. From this point on we will be using the notation $[\cdot]$ instead of $()$ to represent the discrete samples of the signal. Continuing with our expression in (55), we then convert the noise-free spectrum $\hat{S}(z)$ to the cepstrum domain by taking the logarithm resulting in the following:

$$\log[\hat{S}(z)] = \log[E(z)] + \log[H(z)]$$

$$\hat{S}(z) = \hat{E}(z) + \hat{H}(z)$$

$${\hat{s}}[n] = D_c[e[n] * h[n]] = \text{IFFT} \left( \hat{S}(z) \right)$$

$$= \hat{e}[n] + \hat{h}[n] \quad (56)$$

The function block $D_c[\cdot]$ obtains the complex cepstrum of the noise-free signal $\hat{s}[n]$, results in the addition of the two signals $\hat{e}[n]$ and $\hat{h}[n]$ which are the complex cepstrum of the transmitted sequence and channel IR respectively. The *complex cepstrum* preserves the phase information of the signal with phase unwrapping [11]. Given the additive nature of (56), we can apply a linear filter to filter out $\hat{e}[n]$ from $\hat{s}[n]$ resulting in an estimate for $\hat{h}[n]$, i.e.,

$$\hat{h}[n] \approx \hat{s}[n] \cdot l_H[n] \quad (57)$$

For $l_H$, which is the high-pass linear filter used to filter-out the complex cepstrum of
the transmitted signal, namely \( \hat{e}[n] \). In the cepstrum domain, a linear filter is often referred to as a \textit{lifter}. Continuing on, the inverse complex cepstrum \( D_z^{-1}[\ast] \) can then be used to recover the channel IR as shown:

\[
h_r[n] = D_z^{-1}[\hat{h}[n]] = IFFT\left(\exp\left(FFT\left(\hat{S}(z)\right)\right)\right) \approx h[n]
\]  

(58)

The high-pass linear filter operation can either be done in the time domain or in the frequency domain. In the time domain, the high-pass filter \( l_{h}[n] \) is described mathematically for \( N \) total samples as shown:

\[
l_{h}[n] = \begin{cases} 
1 & N_1 \leq n \leq N - N_2 \\
0 & \text{Otherwise}
\end{cases}
\]  

(59)

The value of \( N_1 \) is initialized to accommodate the worst-case propagation delay based on the line-of-sight (LOS) range between communicating nodes, while the value of \( N_2 \) can be set based on the number of echoes or eigenrays we would like to recover, i.e.:

\[
N_1 = \frac{k_{\text{LOS}}}{\bar{c}} \times \frac{1}{T_s}
\]  

(60)

\[
N_2 = r_k
\]  

(61)

During cepstrum liftering, the parameters \( N_1, N_2 \) will be used as window parameters for the high-pass filter, where \( N_1 \) depends on \( k_{\text{LOS}} \), which is the LOS transmission range, \( \bar{c} \) is the average sound speed between communicating nodes and \( T_s = 1/F_s \) is the sampling frequency. Furthermore, \( N_2 \) depends on the worst-case eigenray length, such that the initial value of \( N_2 \) is chosen when \( k \gg 1 \) to recover multiple eigenrays. It is important to note that if both \( \hat{e}[n] \) and \( \hat{h}[n] \) are in different quefrencies (measurement of time in samples), the high-pass filter will result in a good approximation for \( \hat{h}[n] \). Similarly, the transmitted data can be recovered by applying
a low-pass linear filter $l_L$ to filter-out the complex cepstrum of the channel’s impulse response. This can be represented in the time domain as shown:

$$l_L[n] = \begin{cases} 1 & 0 \leq n \leq N_1 \\ 0 & \text{Otherwise} \end{cases}$$

(62)

![Real Cepstrum of Convolution](image)

**Figure 3-8:** Plot of real cepstrum of the noise-free signal showing an ideal filter window used for deconvolution when both the cepstrum of the data and the channel are separable

Figure 3-8 gives a plot of an ideal case whereby both the cepstrum of the channel and the data do not overlap too much. In this case, an ideal filter window size based on eqns. (60) and (61) can be used to filter out the complex cepstrum of the data.
Figure 3-9: Plot showing the simulated and recovered channel IR with the RSR speech signal for the non-varying simulation parameters.

Figure 3-10: Plot of the noise-free received signal (and its complex cepstrum) that shows the effects of the multipath channel on the received signal.

A simulated performance of the liftering method can be seen in Figure 3-9 and Figure 3-10 with the transmitter-receiver geometry parameters \((D_{TX}, D_{RX}, D_w)\) shown in the top row plots for a sound speed of 1520 m/s. The water surface/bottom densities \((p_w, p_b)\) and LOS distance \((d)\) are shown in the bottom row plots. In the top plot of Figure 3-9, the impulses correspond to the arrival times of the multipath signal. The first TOA corresponds to the RSR eigenray which is attenuated to about 0.28, all other impulses corresponds to eigenrays that are reflected by the water bottom and are attenuated even more as shown. The noise free transmitted signal is depicted in Figure 3-10, whereby the transmitted signal was a 10 kHz sampled signal. From Figure 3-9, we see that the recovered channel IR resembles the simulated channel IR for filter parameters of \(N_1=66\) and \(N_2=2048\). The amplitude fluctuations from the 128\(^{th}\) sample to about the 300\(^{th}\) sample are due to a small overlap in the cepstrum domain of the transmitted signal and channel IR, i.e. \(\hat{e}[n]\) and \(\hat{h}[n]\), from
the ideal as illustrated in Figure 3-8. Nevertheless, we can minimize this effect by optimally fine-tuning the window parameters $N_1$ and $N_2$.

![Simulated Channel IR](image1)

**Figure 3-11:** Simulated and recovered channel IR with mobile nodes using lifting method

Figure 3-11 shows another simulated performance of the lifting method when just recovering the channel IR. For this simulation, the transmitted signal was a frequency-shift-keying (FSK) modulated 40-bit signal. We also varied the relative velocities of the transmitter and receiver, which induced a small Doppler frequency shift at the receiver. The top-half plot is the simulated channel for a known transmitter-receiver geometry that utilizes the estimated eigenray length as defined in (53). The first pulse corresponds to the arrival time of the line-of-sight (LOS) signal while the second pulse corresponds to the arrival of the refracted-surface-reflected (RSR) signal. Unlike our previous analysis, the simulation does not contain any bottom reflections but only a surface reflection. The bottom-half of Figure 3-11
shows the recovered channel IR after apply a window size large enough to recover up to ten eigenrays or NLOS reflections. Thus, we see that the channel IR was recovered successfully despite the induced Doppler shift. In section 3.3.4 of this chapter, we go over a method for handling Doppler shifts which will occur when nodes are mobile, in fact due to the non-linear waveguide of the channel (i.e. Figure 1-3) there could exist a Doppler shift even when nodes are not mobile [5]. Looking closely at Figure 3-11, we do note that there exist fluctuations in the recovered channel IR as shown in the bottom-half of Figure 3-11 which are a result of both $\hat{e}[n]$ and $\hat{h}[n]$ being relatively close together in the same quefrency domain. This limits the high-pass filters performance in filtering out $\hat{e}[n]$ from $\hat{h}[n]$. To prevent overlap in the cepstrum domain during liftering, the next subsection will go over a priori-based subtraction (PBS) method that builds upon the cepstrum concept.

### 3.3.2 Deconvolution with Cepstrum Subtraction

Assuming that we have prior knowledge of the transmitted signal, i.e. $e[n]$ in the form of a synchronization frame, we propose utilizing a priori-based subtraction (PBS) cepstrum method to recover the channel IR and by extension subsequent transmitted signals. We recall that the complex cepstrum of the noise-free received signal is defined in (56) as:

$$\hat{s}[n] = \hat{e}[n] + \hat{h}[n]$$

Instead of utilizing a high-pass filter, which may not be suitable if both $\hat{e}[n]$ and $\hat{h}[n]$ are in the same quefrency, we can determine the complex cepstrum of the channel IR by assuming the complex cepstrum of the data sequence is known by subtraction.
\[
\hat{h}[n] = \hat{s}[n]_{\text{observed}} - \hat{e}_{\text{known}}[n]
\] (63)

Thus, given the known frame synchronization sequence \(e[n]\) and have observed samples of the convolved signal \(\hat{s}[n]_{\text{observed}}\), the receiver will simply compute two complex cesptrums, i.e.

\[
\hat{s}[n] = \hat{s}[n]_{\text{observed}} = D_x[\hat{e}_{\text{known}}[n] * h[n]] = IFFT(S(z))
\]

\[
\hat{e}_{\text{known}}[n] = D_x[e_{\text{known}}[n]] = IFFT(\hat{E}_{\text{known}}(z))
\]

The channel IR can then be recovered by applying (58). Tank experiments were conducted to validate the cepstrum subtraction approach. The tank had dimensions of 1.27m (L) x 0.6m (W) x 0.8m (H), side walls of the tank were covered with a 20dB sound absorbing material since we are only interested in surface and bottom reflections. The acoustic surface and bottom were effectively flat throughout the experiment. In addition, there were no external noise sources in the water tank with the noise floor being well below the communication level. The tank-based experiment setup can be seen in Figure 3-12, whereby the transmitter and receiver were separated by approximately 1 meter. The transmitted signal consisted of a low-voltage (3-Vpp) amplitude shift keying (ASK) modulated signal with a custom transducer. The low-voltage signal was then picked up from a hydrophone receiver. In chapter 4, we will elaborate on the custom acoustic modem prototype and the tank setup.
Figure 3-12: Complete test setup showing the transmitter and receiver placement in the tank. Sound absorbing materials were placed along the sidewalls of the tank to attenuate unwanted reflections. This setup uses an un-calibrated modem with a low-voltage transmitting source (3-Vpp).

Figure 3-13 depicts the transmitted 8-bit ASK modulated acoustic signal, ASK modulation was chosen for the ease of analysis when viewing the recovered channel IR and data. A binary bit ‘1’ would be used to analyze the channel IR for that bit; the plot also depicts an effective bit rate of 10bps. The digital sampling rate was 100 kHz.

Figure 3-13: Tank testing using ASK modulated data sequence with 10KHz carrier frequency and a bit rate of 10bps. Binary bit ‘1’ is used for IR recovery.
Figure 3-14 shows the recovered channel IR when with a priori-set Cepstrum subtraction, i.e. eqn. (63). Due to the low-voltage of the acoustic signal with respect to the transmission voltage response (TVR) of the chosen transducer, we employed a filtering mechanism to recover the data that is used in the channel estimation in (63). From Figure 3-14, we see the result of the normalized channel IR recovery in the bottom half plot, it depicts a multipath (or NLOS) spread of approximately 0.006 seconds which is consistent with our expectations, thus we can effectively achieve a bit rate of 166 bps with this environment/modulation without errors. More importantly, we see that the cepstrum-subtraction deconvolution enhancement works very well in recovering the channel IR which contains both LOS and non-line-of-sight (NLOS) components.

To determine the difference in channel IR when the LOS is blocked, we repeated the same experiment, except this time we placed a 20 dB sound absorbing material to block the LOS link between the transmitter and receiver. The result of the experiment is shown in Figure 3-15. The channel IR recovery resulted in consistent normalized amplitude comparable to that obtained in Figure 3-14, except this time we only notice one impulse, which corresponds to the bottom reflection since the LOS link was blocked from the water surface leaving only the bottom reflection available. The results show that even with a low-voltage acoustic signal, we are able to recover the channel IR to be used in the SBR process.
We repeated the same experiment for a higher voltage acoustic source (10 Vpp) with two acoustic modems. A normalized time and frequency plot of a received omni-

Figure 3-14: Recovered ASK data and channel IR. The channel IR shows multipath components for LOS and NLOS reflections. The results are for a low-voltage acoustic signal during the early stages of the acoustic modem design.

Figure 3-15: Plot of the recovered data and channel IR when LOS link was blocked with a 20dB attenuation material, leaving only the bottom reflection available. The result depicts consistent NLOS recovery despite using a low-voltage acoustic signal.

Figure 3-16: Normalized plot of band-pass filtered data received with an omni-directional beam when using the finalized acoustic modem design. It shows a center frequency of 17 kHz which is the resonant frequency of the transducer. The received signal was around 4-Vpp before filtering and normalization.
directional ASK signal can be seen in Figure 3-17 where the delay spread was found to be approximately 7 milliseconds. The digital sampling rate used in this experiment was set to 250 kHz. For this experiment, the acoustic modem design was finalized which utilizes the multi-modal directional transducer design described in section 1.5.1 to transmit both omni-directional and directional beams. More details of the acoustic modem design and calibration can be found in chapter 4 of this dissertation. For this test, a bit of ‘1’ was modulated for 1 millisecond where a bit of ‘0’ (i.e. no amplitude) was modulated for 4 milliseconds. This was done to give the channel enough time to settle. Figure 3-17, Figure 3-18, Figure 3-19 and Figure 3-20 show plots of the time and channel IR recovery when utilizing the cepstrum subtraction technique for both directional and omni-directional links. In Figure 3-17, we see a plot of the reference ASK wave overlaid on the received omni-directional wave when the LOS link was not blocked. The normalized channel IR recovery is shown in the bottom half of the same plot, which shows consistent channel IR recovery for each pulse.

**Figure** 3-17: Time and channel IR plot of the ASK burst signal with omni-directional beam. The LOS link was not blocked in this case.

**Figure** 3-18: Time and channel IR plot of the ASK burst signal with a 40° directional beam. The LOS link was not blocked in this case. The plot shows a significant reduction in the number of reflections from the omni-directional case.
The effect of blocking the LOS link on the ASK omni-directional signal can be seen in Figure 3-18 which clearly shows a decrease in the normalized channel IR amplitude. We should note that at the communication frequency of 17 kHz, the 20 dB material only provides at about 10 dB of attenuation. Nevertheless, we note that we obtain a consistent channel IR, which shows the effects of blocking a LOS link on the communication channel.

Communication with a directional link improves the channel IR quality and reduces the number of unwanted reflections. This phenomenon is validated in Figure 3-19 and Figure 3-20 when we generated a 40º directional beam using the multi-modal concept. In Figure 3-19, we see that for each ASK pulse we only get two reflections, which is a significant drop from the result of the omni-directional analysis. Furthermore, the normalized channel IR amplitude remains consistent for each ASK pulse. When we block the LOS link during directional communication, we notice a similar drop in the magnitude of the channel IR pulses to our previous analysis for omni-directional communications; this effect is captured in Figure 3-20.

Figure 3-19: Time and channel IR plot of the ASK burst signal with omni-directional beam. The LOS link was blocked with a 20 dB material.

Figure 3-20: Time and channel IR plot of the ASK burst signal with a 40º directional beam. The LOS link was blocked with a 20 dB material.
The results shown demonstrate the deconvolution ability of the cepstrum subtraction method. The obtained channel IR can be further used to determine the statistics of transmission loss [$T_{LOS}$, $T_{RSR}$, $T_{RBR}$] needed for our link classification covered in section 3.4 of this chapter and for our SBR-based protocols covered in the later chapters of this dissertation. The cepstrum method described will work well when the white noise level is low and can be neglected. However, when the white noise level is significant, care needs to be taken to ensure that it has been handled properly. In the next subsection, we will go over a generalized adaptive cepstrum method that can be used to recover both the channel IR and signal in the presence of additive noise.

### 3.3.3 Adaptive Cepstrum Deconvolution with Noise Approximation

![Communication model for adaptive cepstrum deconvolution](image)

**Figure 3-21**: Communication model for adaptive cepstrum deconvolution which aims to update the initial channel IR estimate obtained from the PBS approach.
A block diagram of the developed adaptive cepstrum deconvolution (ACD) method can be found in Figure 3-21, which aims to fine-tune the channel IR cepstrum estimate from the previous approach with a gradient operation. Recall from (52) that the transmitted signal will be corrupted with additive white noise $w[n]$, this is further expressed below:

$$ r[n] = s[n] + w[n] = e[n] * h[n] + w[n] $$

If we take the $z$-transform of the noisy received sampled discrete signal $r[n]$ we get the following expression:

$$ R(z) = Z(r[n]) = E(z)H(z) + W(z) $$

Continuing on, taking the logarithm of both sides and using the properties of logs yields the following:

$$ \log[R(z)] = \log(E(z)H(z) + W(z)) $$

$$ \log[R(z)] = \log(E(z)H(z)) + \log\left(1 + \frac{W(z)}{E(z)H(z)}\right) $$

$$ \log[R(z)] = \log(E(z)) + \log(H(z)) + \log\left(1 + \frac{W(z)}{E(z)H(z)}\right) $$

$$ \hat{R}(z) = \hat{E}(z) + \hat{H}(z) + \log\left(1 + \frac{W(z)}{E(z)H(z)}\right) $$

Hence, we can define the complex cepstrum of the received signal for three special cases as shown:
where:

\[ \hat{\alpha}[n] = \text{IFFT} \left( \log \left( 1 + \frac{W(z)}{E(z)H(z)} \right) \right) \]

For the first condition, the transmitted signal and multipath spectrum greatly exceeds that of the noise which is equivalent to the noise-free expression (56) used in our analysis in sections 3.3.1 and 3.3.2. The second condition assumes that the noise level is much greater than the signal, which ultimately results in an undetectable signal. In the third case, the signal to noise ratio is high enough but is still corrupted by noise. The remainder of this section will focus on deriving an iterative method for estimating the complex cepstrum of the channel \( \hat{h}[n] \) under the third case of the expression (67).

In a similar fashion to our analysis in section 3.3.2, we assume that both the transmitter and receiver will agree on a known frame synchronization sequence \( e[n] \), which gives us knowledge of its complex cepstrum, namely \( \hat{e}[n] \). Furthermore, since we can observe the noisy signal \( \hat{r}[n] \), our goal during channel estimation is to find the complex cepstrum of the channel \( \hat{h}[n] \) that minimizes the following objective function:

\[
\min_{\hat{h}[n]} \left| \hat{h}[n] - \hat{r}[n] - \hat{e}[n] - \hat{\alpha}[n] \right|^2
\] (68)
We can determine the optimum $\hat{h}[n]$ that minimizes the objective function through Newton’s method, which aims to find the minimum solution by through iteration as shown:

$$\hat{h}[n]_i = \hat{h}[n]_{i-1} - \frac{f(\hat{h}[n]_{i-1})}{f'(\hat{h}[n]_{i-1})} \quad (69)$$

where, $\hat{h}[n]_i$ is the estimate for the current iteration, $\hat{h}[n]_{i-1}$ is the estimate for the previous iteration, $f(\hat{h}[n]_{i-1})$ is the objective function and $f'(\hat{h}[n]_{i-1})$ is its derivative which are evaluated for the previous iteration estimate. Continuing with our definition in (69) and letting $(x = \hat{h}[n]_{i-1}, a = \hat{r}[n], b = \hat{e}[n]$ and $c = \hat{a}[n])$ for ease of readability, we have:

$$f(x) = |x - (a - b - c)|^2 = x^2 - 2x(a - b - c) + (a - b - c)^2$$

$$f'(x) = 2x - 2(a - b - c)$$

We note that $x$ and $c$ in $f'(x)$ are jointly related in the cepstrum and frequency domains, this relationship can be recognized by recalling their definitions as below:

$$x = \hat{h}[n]_{i-1} = \text{IFFT}(\log H(z)) \quad (70)$$

$$c = \hat{a}[n]_{i-1} = \text{IFFT} \left( \log \left( 1 + \frac{W(z)}{E(z)H(z)} \right) \right) \quad (71)$$

where we observe that the channel spectrum $H(z)$ is common to both $\hat{h}[n]_{i-1}$ and $\hat{a}[n]_{i-1}$. To iteratively evaluate (69), we will need to provide instantaneous estimates for $W(z)$, $E(z)$ and $H(z)$. We first observe that since we have knowledge of the transmitted sequence, we also have knowledge of $E(z)$ in expression. Secondly, we can estimate the noise spectrum $W(z)$ by collecting noise samples over a period of time and obtaining the noise variance, the variance will then be used to generate a
pseudo-random sequence used to approximate $W(z)$. Thirdly, after we have obtained an estimate for the channel cepstrum through subtraction, i.e., (63), we use that estimate to approximate the channel’s spectrum. Thus, our final iteration expression now becomes:

$$\hat{h}[n]_i = \hat{h}[n]_{i-1} - \frac{f(\hat{h}[n]_{i-1})}{f'(\hat{h}[n]_{i-1})}$$

$$= \hat{h}[n]_{i-1} - \frac{\hat{h}[n]^2_{i-1} - 2\hat{h}[n]_{i-1}(\hat{r}[n] - \hat{e}[n] - \hat{a}[n])^2 + (\hat{r}[n] - \hat{e}[n] - \hat{a}[n])^2}{2\hat{h}[n]_{i-1} - 2(\hat{r}[n] - \hat{e}[n] - \hat{a}[n])}$$

(72)

We have compared the performance of both the priori-based subtraction (PBS) method and the adaptive cepstrum deconvolution (ACD) method through simulation. We generated an FSK modulated data sequence with a mark frequency of 8 kHz (bit ‘1’) and a spacing frequency of 28 kHz (bit ‘0’) which is depicted in Figure 3-22. A reference channel IR was obtained from a previous work done Benson et al [87], which was performed in a lake. Varying additive noise levels where then added after convolving the modulated FSK data with the channel, Figure 3-23 gives a plot of the channel IR recovery with both ACD and PBS respectively with an SNR of 60 dB. The plot shows that for that high of an SNR, the mean squared error between the PBS method and the ACD isn’t distinguishable. This further validates the first case in (67), which states that the complex cepstrum of the noisy signal can be approximated to just $\hat{e}[n] + \hat{h}[n]$ when $E(z)H(z) \gg W(z)$.
In Figure 3-25, we decrease the SNR to 30 dB, where we notice that the ACD method provides a lower mean squared error over the PBS method. This scenario is an example of the third case in (67) which now considers the effects of the noise on
the channel IR estimation. Recall that with ACD, we use the last channel IR estimate from PBS to instantaneously estimate the noisy-channel spectrum, the noise variance is also estimated which is used to further generate an estimate of $\hat{\alpha}[n]$. The iterative process is also depicted in the same plot, which shows a convergence at about the 20th iteration. Figure 3-24 gives an average performance of both PBS and ACD over a wide SNR range, which clearly shows the advantage of ACD for lower SNRs.

### 3.3.4 Doppler Shift Mitigation

![Doppler Shift Mitigation Diagram](image)

**Figure 3-26:** A Doppler resistant chirp symbol preamble. An up-chirp signal represents that the next data word is the frame sync.

As alluded to earlier in this chapter, node mobility will lead to frequency Doppler shifts. In addition, the waveguide of the channel can induce Doppler shifts at long ranges even when nodes are not mobile. To eliminate the effects of Doppler shifts, we can represent the transmitted data as a chirp symbol. The modulated received signal is passed into a frame synchronizer detector which checks to see if the received tone
contains a frame synchronization packet. The detector at the receiving end works by requiring the transmitter to transmit a chirp symbol followed by the modulated data/training sequence. The single-band chirp signal is illustrated in Figure 3-26 and is described by the following signal:

\[ e(t) = A \cos(\omega_o t + \pi ut^2), \quad 0 < t \leq T \] (73)

Such that:

\[ |u| = \frac{|f_e - f_o|}{T} = \frac{B}{T} \]

where \( f_o, f_e, u, T, A \) and \( B \) are the initial frequency, end frequency, slope rate, time duration, amplitude, and bandwidth of the chirp signal respectively. An up-chirp signal signifies that the next word contains frame synchronization information while a down-chirp signifies that the remaining sequences are data words. The preamble chirp signal is also Doppler resistant which allows the receiver to properly recover channel IR when mobile. Once the preamble chirp signal has been detected, the receiver will recover the channel IR by filtering, in the absence of frame synchronization or using a priori-set.
3.4 Acoustic Link Classification

![Acoustic Link Diagram](image)

**Figure 3-27:** Receiver focused communication model, this time we are interested in classifying the acoustic link from the known transmission loss parameters ($T_{LOS}$, $T_{RSR}$, $T_{RBR}$) and the channel IR $h[n]$.

Given that we have recovered the channel $h_r[n]$ either through cepstrum lifting (59), priori-based subtraction (63), or adaptive cepstrum deconvolution (72) the estimated multipath loss ($E_{MULT}$) can be determined from the recovered channel IR as shown:

$$E_{MULT} = -10 \log(|h_r(t = \tau)|) \ [dB]$$  \hspace{1cm} (74)

where, $\tau$ is the delay-spread of the first multipath signal. Therefore, given that we have knowledge of the acoustic transmission losses ($T_{LOS}$, $T_{RSR}$, $T_{RBR}$), we can classify the acoustic link by applying the following mathematical condition:

(I) $E_{MULT} \leq T_{LOS}$ \hspace{1.5cm} LOS

(II) $T_{LOS} < E_{MULT} \leq T_{LOS} + T_{RSR}$ \hspace{1cm} RSR  \hspace{1cm} (75)

(III) $T_{LOS} + T_{RSR} < E_{MULT} \leq T_{LOS} + T_{RBR}$ \hspace{1cm} RBR

The key parameters in the receiver section are also illustrated in Figure 3-27. Expression (75) implies that $T_{RBR} > T_{RSR}$ which is common in underwater
acoustics as we explained in section 3.2.1 when we analyzed the Raleigh multipath transmission loss. Moreover, the transmission losses can either be obtained from one of the scattering models described in subsections 3.2.1/3.2.2 or they can be measured and averaged over time by pinging the water surface and bottom. A mechanism for sampling (i.e. pinging) the water surface/bottom will be presented in the next section of this chapter.

3.5 Surface Sampling and Recovering Mechanism

As alluded to in the previous section we can sample the water surface (and bottom) to empirically determine the transmission losses when no prior knowledge about the sea state (i.e. roughness, wind speed, etc.) are known. Another benefit of sampling the water surface is that we can utilize this information for localization (or positioning). This will become evident when we present our localization scheme in chapter 5. The transmission losses \( (T_{L_{LOS}}, T_{L_{RSR}}, T_{L_{RBR}}) \) can then be interpolated once we have both the LOS and NLOS ranging information.

For a known LOS link, i.e. \((75)\)-I, the range information is simply the round-trip time-of-arrival (TOA) \( \tau_{LOS} \) multiplied by the average sound speed \( \bar{c} \) between communicating nodes as shown \( \{i, j\} \):

\[
d_{ij} = \bar{c} \ast \tau_{ij} = \bar{c} \ast \tau_{LOS}
\]

\( (76) \)

We can obtain The RSR (or RBR) range information by taking advantage of the 3D nature of the underwater environment by representing the transmitted signal \( r[n] \) as a vector in \( \mathbb{R}^3 \) as and described in \( (77) \).

\[
\vec{r}_A = r_{Ax} \hat{x} + r_{Ay} \hat{y} + r_{Az} \hat{z}
\]

\( (77) \)
\[
\vec{r}_B = \vec{r}_A - 2(\vec{r}_A \cdot \vec{n})\vec{n}
\] (78)

where, the “\(*\)” operation represents the dot product operator and \(\vec{n}\) is the normal vector that is normal to the water surface. Note that the notation \(\vec{r}_A\) also means the same as \(r_A\), which is the transmitted eigenray from the transmitter node \(A\). In this analysis we will be using the \(\vec{r}_A\) notation to represent the vector. Moreover, we focus on sampling and recovery of the water surface and note that a similar method can be used to sample the water bottom. Using the laws of reflection, we can determine the reflected vector (78) unto the node \(B\) (i.e., \(\vec{r}_B\)) if we know the normal vector to the water surface at the intersection point \((x_{Ri}, y_{Ri}, z_{Ri})\). We can solve for the normal vector \(\vec{n}\) by solving for the gradient of the water surface \(S(x, y, z)\) as follows:

\[
\nabla S(x, y, z) = \left(\frac{\partial S}{\partial x}, \frac{\partial S}{\partial y}, \frac{\partial S}{\partial z}\right); \vec{n} = \nabla S(x, y, z)|_{(x_{Ri}, y_{Ri}, z_{Ri})}
\]

The water surface can also be expressed as a 3D surface equation of the form \(z = S(x, y)\), Where \(R_i = (x_{Ri}, y_{Ri}, z_{Ri})\) is the intersection point of the normal vector with the surface. Thus, for a known surface function \(S(x, y)\), the receiver will be able to determine the reflected vector as shown in (78).

Figure 3-28: Sampling process showing the sensor node measuring its depth of a moving water surface
To determine the surface function $S(x, y)$, SBR models the water surface as a moving wave. Assuming a known water surface direction ($\vec{v}$), a node can obtain a 2D sample of the surface by looking up, re-transmitting to the water surface and measuring the round-trip TOA ($\tau_{RTT}$) at intervals of $\Delta t$ with a sampling frequency of $f_s = \frac{1}{\Delta t}$. This is illustrated in Figure 3-28, where the measured depth at each interval can be expressed as:

$$z_{xy} = \left(\frac{c_w \times \tau_{RTT_{xy}}}{2}\right)$$  \hspace{1cm} (79)

The 3D coordinate system is also shown in Figure 3-28 with $\theta$ being the elevation angle and $\phi$ the azimuthal angle. Here, the dotted lines represent the sampled depth measurement from the water surface to the node $S_0$. Hence, we are assuming that each node will have up to $\Lambda$ acoustic transducers sending ping signals to the water surface and listening for the echoed signal. The ideal continuous water surface at a time $t$ can be expressed as:

$$z_{xy}(t) = S(x, y)|_t$$  \hspace{1cm} (80)

Each node will then obtain time-varying depth samples to the water surface bounded by a maximum grid size of $[X, Y]$ for $x = 0,1,..X$ and $y = 0,1,..Y$, the resolution of $x$ and $y$ (1 in this case) will depend on the number of directional transducers used and the directivity of the measurements. Moreover, the node’s depth will impose a limit on both the maximum sampling frequency $f_s = 1/\Delta t$ and the maximum grid size $[X, Y]$. For example the deeper the node is relative to the water surface, the maximum sampling frequency decreases and the maximum grid size increases. On the other hand, the closer the node is to the water surface, the maximum
sampling frequency will now increase and the maximum grid size will be smaller. In addition, the node’s depth from the water surface will determine the resolution of the water surface grid. The minimum resolution can be determined by using the relationship between the elevation grazing angle $\theta$ and the transmitting node’s depth $D_{TX}$, such that the $x$-coordinate of the steered i-th directional beam can be determined as:

$$x_i = \sqrt{\left(\frac{D_{TX}}{\sin \theta_i}\right)^2 - D_{TX}^2}$$  \hspace{1cm} (81)

where $\theta_i = \theta_{i-1} + \Delta \theta$ is the grazing angle with a beam directivity of $\Delta \theta$. The minimum grid scale resolution $\Delta = \Delta x = \Delta y$ is determined by taking the minimum of difference between all $x$-coordinates of the steered beam given by the following expression:

$$\Delta = \min \bigcup_{i=1}^{G} x_i - x_{i-1}$$  \hspace{1cm} (82)

Figure 3-29: Relationship between the directivity and the minimum grid scale resolution.
Figure 3-29 gives a plot of the feasible grid scale sizes for varying antenna directivity at different node depths. We see that in order to obtain a grid scale resolution of $\Delta = 1\,\text{m}$, the transducer or antenna directivity $\Delta \theta$ needs to be less than or equal to $5^\circ$ which is hard to achieve in practice. Nevertheless, we note that the closer the node is to the water surface the finer the grid scale resolution.

Moreover, we assume that each node will have a limited view of the water surface with grid size of $[N, M] \leq [X, Y]$ and a scale resolution of $\Delta$, such that $n = 0, \Delta, \ldots N$ and $m = 0, \Delta, \ldots M$. This implies that each node will be limited to the view of the following continuous water surface at time $t$.

$$z_{nm}(t) = S(n, m)|_t$$  (83)

We can represent the sampling process mathematically as $z_{(n,m)}[k] = z_{(n,m)}(k\Delta t)$, with a 2D sampling index of $k = 0, 1, \ldots K$ and a sampling frequency of $f_s = \frac{1}{\Delta t}$. The time-varying sampled depth function can now be represented as:

$$z_{nm}[k] = (S(n, m)|_{k\Delta t} + z_{(0,0)}[k])$$

$$z_{nm}[k] = \left(S(n, m)|_{k\Delta t} + \frac{c_w \tau_{RTT(0,0)}}{2}[k]\right)$$  (84)

Also, we note that during water surface sampling, the true depth of the node for each sample $k$ will be added to the amplitude of the water wave. In realistic underwater environments, the continuous water surface function $S(x, y)|_t$ will be composed of multiple waves with different frequencies, phases and amplitudes. In fact, this can be viewed as classical sampling and reconstruction scheme used in digital signal processing (DSP). The sampling process will resolve the phase and the amplitude, while the frequencies in the surface function can be resolved with Fourier
Transformation. To simplify illustration, we can assume a continuous water surface function with multiple frequency components as shown:

\[
S(x,y)|_t = \sin(2\pi(2xt + 4yt)) + \sin(2\pi(4xt + 2yt)) + \sin(2\pi(xt + yt))
\]  

(85)

The sampled water surface function for our limited grid of \([N,M] \leq [X,Y]\) becomes:

\[
S(n,m)|_{k\Delta t} = \sin\left(2\pi k\left(\frac{2}{f_s}n + \frac{4}{f_s}m\right)\right) + \sin\left(2\pi k\left(\frac{4}{f_s}n + \frac{2}{f_s}m\right)\right) + \sin\left(2\pi k\left(\frac{1}{f_s}n + \frac{1}{f_s}m\right)\right)
\]

Here the highest frequency component is \(\kappa = 4Hz\) and the sampling frequency is \(f_s = 1/\Delta t\). Due to the direction of the water wave and the size of the limited sampling space \([N,M]\) for \(n = 0,1,\ldots N \leq X\) and \(m = 0,1,\ldots M \leq Y\) we will only obtain a limited view of the water surface as it passes on. Also, we cannot assume that the water surface function is periodic due to the non-deterministic nature of the environment. Hence, we need to know the direction and speed of the water wave, and the parameters of the water (density, pressure, permittivity, and permeability) to determine the effect of the sampled water surface on the entire water surface space (within the specified geo-located boundary). This can be translated into a finite-difference time-domain (FDTD) problem that solves Maxwell's wave propagation equation as shown in [78][79]. The finite difference method approximates the differential operations in the Maxwell wave equation with finite differences over a discrete computational mesh or grid. Thus, to recover the water surface function for a
larger grid area that extends beyond the nodes view at a specific time $t = t_0$, we convolve the FDTD transformed sampled water surface measurement $S_{FDTD}(x, y)$ with the low-pass filter with impulse response $h_I(x, y)$ as shown:

$$S(x, y)|_{t=t_0} \approx \sum_{y=0}^{Y} \sum_{x=0}^{X} S(x, y)|_{t=t_0} h_I(x - k\Delta t, y - k\Delta t)$$ (86)

Both the $x^{th}$ and the $y^{th}$ samples are based on the sampling period $\Delta t$. Using a 2-pole Butterworth low-pass filter design with normalized cut off frequency of $\omega_c = 2\pi \frac{K}{F}$ for $h_I(x, y)$ and a sampling frequency of 80 Hz, the estimated water surface function of (86) after $t = \tau = 6$ seconds using FDTD is shown in Figure 3-30. Here we see the effect of a sampled moving water surface for a $[N, M] = [40m, 40m]$ sample space on the entire geo-located boundary $[X, Y] = [80m, 80m]$ after applying FDTD and the low-pass filter. Furthermore, we note that the recovered water surface in Figure 3-30 uses a grid scale resolution of $\Delta = 1m$, which implies an antenna directivity of less than or equal to $5^\circ$. Although this is very hard to realize in practice, increasing the grid scale to $\Delta = 5m$ (directivity of $25^\circ$) will be feasible with the directional transducer presented in section 1.5.1 assuming sixteen internal voltages. This result in an obvious lower water surface resolution shown in Figure 3-31, however we note that the water surface pattern and flow is essentially the same as the ideal grid scale size of $\Delta = 1m$. 


Figure 3-30: An illustration of the recovery of the water surface function by using FDTD and a two pole Butterworth low pass filter on a water wave moving at 10 m/s.

Figure 3-31: Recovered water surface with a grid scale of Δ=5m depicting a decrease in resolution but similar water surface pattern/flow to the ideal grid scale.
3.6 Summary

In this chapter we introduced the surface-based reflection (SBR) communication model, which exploits the multipath nature of the acoustic channel by recovering both LOS and NLOS links. Different scattering models were presented which were used to analyze the acoustic transmission loss when interacting with the water surface or bottom. We have also presented a channel impulse response (IR) recovery mechanism that utilizes homomorphic deconvolution through cepstrum analysis to recover the channel information. This information is then used to classify the acoustic link as either LOS or NLOS. Furthermore, we have presented a method for sampling and reconstructing the water surface (or bottom), which can be used to empirically measure the acoustic transmission loss. The sampled water surface will also be used in the localization algorithm in chapter 6 of this dissertation.
Chapter 4

Prototype for Validating Surface-Reflected Communication Links

In this chapter, we will present on the prototype suite used for validating surface reflected links, i.e. SBR-based communications and networking. The first half of this chapter focuses on the multimodal acoustic modem prototype used as a node in UWAN communications. The second half talks about the test bed prototype used for validating both the communication and networking models.

4.1 Multimodal Underwater Acoustic Modem Prototype

Commercially-available acoustic modems are very expensive due to their application-specific design, inflexible to enable the validation of the SBR model and SBR-inspired protocols, and bulky for a lab-based use. Therefore, this section will discuss on work done towards the design of an acoustic modem that overcomes these shortcomings and serves the project objective. This design was inspired by a low-cost modem design in [87], which utilizes a field-programmable-gate-array (FPGA) and an Omni-directional transducer. Unlike the design in [87], our design utilizes a multimodal piezoelectric transducer described in section 1.5.1. The design employs commercial-off-the-shelf components and utilizes an FPGA device to handle all required digital signal processing. Directional communication, i.e., beam-forming,
will be based on the multimodal piezoelectric directional transducer concept described in section 1.5.1, which generates a directional pattern by combining the fundamental vibration modes of a cylindrical acoustic radiator. This allows the transducer to be electrically controlled to create both omni and directional beam patterns.

![Functional block diagram of the proposed architecture](image)

**Figure 4-1:** Functional block diagram of the proposed architecture depicting both the acoustic modem and the directional transducer. The DSP-FPGA will handle the modulation/demodulation and required digital filtering.

A summary of the acoustic node functional diagram can be found in Figure 4-1. This design was inspired by a low-cost modem design in [87] which utilizes an FPGA and an Omni-directional transducer. Unlike their design, our design will utilize a directional transducer and will allow for wireless/wired application-layer access via Bluetooth and RS-232. To the left of the figure we have the acoustic modem block diagram. The DSP-FPGA will handle all the modulation and demodulation required to communicate effectively on the acoustic channel. This also includes carrier symbol synchronization, clock generation, channel IR filtering (SBR) and band-pass filtering.
needed to ensure that the generated acoustic signal is within the frequency band of the piezo-electric transducer.

Figure 4-2: Acoustic Modem Block Diagram

A realization of the functional block diagram can be found in Figure 4-2, which shows the acoustic modem design flow and board block diagram. The design utilizes an Altera Cyclone IV FPGA device to handle all required digital signal processing (DSP). Some of the DSP requirements includes: noise filtering, SBR-based channel equalization, SBR-based channel estimation, and acoustic link classification. In addition to DSP functions, the FPGA handles digital modulation/de-modulation and directional beam forming needed to establish SBR-based line-of-sight (LOS) and non-line-of-sight (NLOS) communication. The FPGA also contains a soft-core processor, which will be used to implement SBR-inspired networking protocols for ad-hoc formation. The soft-core processor running inside the FPGA will be able to perform SBR-based localization algorithms (chapters 6 and 7), which include both anchor-based and anchor-free methods. For medium access and control, the soft-core
processor will be used to arbitrate our proposed reflection-enabled directional medium access protocol (chapter 8), which utilizes the directional beam former and link classification to establish a star-like network. To promote ad-hoc formation and allow for multi-hop networking, the soft-core processor running inside the Cyclone IV FPGA will be able to maintain a directional network allocation vector (DNAV) table and perform the required routes based on our proposed routing optimization algorithm presented in (chapter 9).

The block diagrams to the right of the Cyclone IV FPGA in Figure 4-2 describe the analog flow. As can be seen, the acoustic modem prototype will include the necessary digital-to-analog-converter (DAC) and analog-to-digital-converter (ADC) with the required dynamic range for the application. For transmission, the output of the DAC drives a two-stage variable gain amplifier with a bandwidth of 10 KHz – 50 KHz. The bandwidth has been chosen to be able to support a wide range of piezoelectric transducers, which will cater to different applications. The output of the two-stage variable gain amplifier is then connected to an opto-coupled replay, which will be controlled by the FPGA to enable transmission. Thus, the current design is half-duplex and the modem cannot send and receive at the same time. Furthermore, for transmission (and reception) there are eight analog lanes, which are essential for directional beam-forming. During reception, the eight analog signals from the electrodes on the transducer are the interface to eight parallel two-stage pre-amplifiers. The pre-amplifier provides up to 40dB of pre-amplification and operates at the acoustic band of 10 KHz – 50 KHz. Each electrode signal corresponds to a look-direction or angle-of-arrival (AOA) in the azimuth direction. The electrode
signal can either be individually selected, or summed to provide an additional 40dB of pre-amplification. When summed, the single analog output also increases the signal-to-noise-ratio (SNR), which allows for more efficient communication at the expense of AOA knowledge. The received analog signal (summed or selected) then drives the ADC, which is periodically sampled by logic elements in the FPGA.

The acoustic modem prototype can be seen in Figure 4-3. At the current configuration, the design dimensions are 9.1in x 7.6 in. The bottom part of the figure shows the digital portion of the design, which includes the FPGA, memory, and IO. The bottom section also contains the necessary power supply needed to power both the digital and analog sections. The top portion contains the analog design for an eight-channel transmission and reception beam-forming system. We should note that a large portion of the board area is taken up by the analog piece in the design. Shielded connectors are also provided to allow for low-noise with piezoelectric transducers. To evaluate a single-channel of the analog portion, we developed an Arduino stackable analog front-end shield that is shown in Figure 4-4. The Arduino interface is an open-source platform that utilizes an Atmel microcontroller and has IO
pins that can be accessible via stacks or connectors. The design shown in Figure 4-4 builds from the Arduino concept. This allows us to easily validate and evaluate the analog portion of the proposed acoustic modem prototype. The next subsections will go over analog design considerations for transmission and reception.

### 4.1.1 Analog Transmission Design

Transmission of analog signals entails amplifying the signal received from the DAC to a power level high enough for the desired communication range. Table II lists some requirements for the analog amplifier for a mid-to-short range (less than 100 meters) acoustic communications. The wide bandwidth was chosen to allow the modem to interface with different transducers.

<table>
<thead>
<tr>
<th>Requirements</th>
<th>Value</th>
</tr>
</thead>
<tbody>
<tr>
<td>Bandwidth</td>
<td>10 kHz to 50 kHz</td>
</tr>
<tr>
<td>Power Efficiency</td>
<td>80-90%</td>
</tr>
<tr>
<td>Voltage Output</td>
<td>10-30Vpp</td>
</tr>
<tr>
<td>Distortion (Linearity Indication)</td>
<td>&lt; 5%</td>
</tr>
</tbody>
</table>

There are different classes of power amplifiers, some of which includes class A, B, AB, C, and D [87][98]. An amplifier is linear if it preserves the signal wave-form, while an amplifier is efficient if a majority of the signal power is delivered to the load. Class A amplifiers are linear in nature and consist of a single transistor for its output stage but are not very efficient (50%). Class B amplifiers consist of two complimentary transistors with each one handling both half of the waveform, the amplifier provides the same low efficiency of a Class A but it isn’t very linear. Class AB amplifiers combines the best of both the Class A and B amplifiers, it includes two
transistors that are allowed to conduct at the same time. The efficiency of a Class AB amplifier is also around 50%. Class C amplifiers are effectively class B amplifiers that are tuned to operate at a single fixed frequency, mainly used for RF transmitters. The class D amplifiers are a class of *switching amplifiers*, which consist of a comparator, MOSFET-based switching state and a low-pass filter. The design of the class D amplifier allows for 90-95% efficiency.

Based on the system requirements in Table II we decided to go with a class D amplifier.

Figure 4-5: Class D amplifier circuit. The design uses the TPA3123 IC.

Figure 4-5 gives an image of a single channel analog transmitter. The design uses the TPA3123D2 chip, which has four selectable closed-loop gains of 20, 26, 32 and 36 dB. The power supply was approximately 15V, which gives a maximum efficiency of about 93%. The effective bandwidth of the amplifier is from 1 kHz to 50 kHz. The output of each channel shown in Figure 4-5 is connected to an opto-isolated relay,
which is turned on when transmission is enabled. When enabled the output then goes to an impedance matching circuit, which mainly consist of a parallel inductance to make the piezoelectric load appear resistive. Figure 4-6, Figure 4-7, Figure 4-8 and Figure 4-9 gives time and frequency plots of the output of the amplifier after going through the impedance matching circuit for frequencies of 10 kHz, 20 kHz, 30 kHz and 40 kHz.

**Figure 4-6:** Time frequency analysis of transmit amplifier at 10 kHz

**Figure 4-7:** Time frequency analysis of transmit amplifier at 20 kHz

**Figure 4-8:** Time frequency analysis of transmit amplifier at 30 kHz. The unwanted spikes can be reduced by adjusting the output filter.

**Figure 4-9:** Time frequency analysis of transmit amplifier at 40 kHz. The unwanted spikes can be reduced by adjusting the output filter.
We see that the harmonic distortion is approximately 5% in the pass-band but starts to increase as we get close to the high-pass cut-off frequency of 50 kHz. For directional transmission, we will use four dual-channel class D amplifiers to form an eight channel voltage distribution needed to form the directional beam as described in section 1.5.1 and re-illustrated in Figure 4-10. The actual transducer wiring on a custom made multi-modal transducer can be found in Figure 4-11. The next subsection will go over design considerations and requirements for analog reception.

![Figure 4-10: Re-illustration of the voltage distribution needed to form a directional beam pattern](image)

![Figure 4-11: Transducer wiring for multi-modal communication](image)

### 4.1.2 Analog Reception Design

To properly establish a reliable underwater communication system, we will need to first calibrate the acoustic modem to pre-amplify the low-voltage incoming acoustic signal from the piezoelectric transducer. One way of doing this is to exploit the known transmitting voltage response (TVR) and receiving voltage response (RVR) of the transducer. Given that we know the TVR and RVR of the communicating transducer, along with the separation attenuation (A) and transmitted voltage ($V_{TX}$) we
can determine the voltage at the receiving transducer ($V_{RX}$) during communication as follows:

$$V_{RX} = 10^{rac{TVR+RVR-A}{20}} \cdot V_{TX}$$

(87)

where, (87) was derived from the following expression [87]:

$$TVR = 20 \log_{10} \left( \frac{V_{RX}}{V_{TX}} \right) - RVR + A$$

$$= 20 \log_{10} \left( \frac{V_{RX}}{V_{TX}} \right) - RVR + k \cdot 10 \log d$$

The expression describes the fact that the collected data sampled at the receiving transducer represents the combination of the transmitting voltage response (TVR) plus the receiving voltage response (RVR) and the effects of attenuation due to separation distance, where $d$ is the separation distance in meters and $k = 1$ is the spreading factor. Thus, to determine the amount of gain needed during the pre-amplification stage of the acoustic modem, we will need to first solve for the receive voltage and determine the minimum gain ($G_{min}$) needed for proper analog-to-digital-converter (ADC) quantization. We define this gain as follows:

$$G_{min} = 20 \log_{10} \left( \frac{V_{ADC}}{V_{RX}} \right)$$

(88)

### Table III: Required preamplifier gain for a transmission of 10 Vpp

<table>
<thead>
<tr>
<th>Frequency (kHz)</th>
<th>TVR (dB/1uPa/m)</th>
<th>RVR (dB/1V/uPa)</th>
<th>$A$ (k=1) (dB)</th>
<th>$V_{RX}$ (V)</th>
<th>$V_{ADC}$ (V)</th>
<th>$G_{min}$ (dB)</th>
</tr>
</thead>
<tbody>
<tr>
<td>30</td>
<td>132</td>
<td>-195</td>
<td>10</td>
<td>2.239 x 10^{-2}</td>
<td>1</td>
<td>53</td>
</tr>
<tr>
<td>35</td>
<td>136</td>
<td>-195</td>
<td>10</td>
<td>3.548 x 10^{-3}</td>
<td>1</td>
<td>49</td>
</tr>
<tr>
<td>40</td>
<td>142</td>
<td>-191</td>
<td>10</td>
<td>11.220 x 10^{-3}</td>
<td>1</td>
<td>39</td>
</tr>
<tr>
<td>45</td>
<td>141</td>
<td>-192</td>
<td>10</td>
<td>8.913 x 10^{-3}</td>
<td>1</td>
<td>41</td>
</tr>
<tr>
<td>50</td>
<td>139</td>
<td>-198</td>
<td>10</td>
<td>3.548 x 10^{-3}</td>
<td>1</td>
<td>49</td>
</tr>
<tr>
<td>55</td>
<td>127</td>
<td>-202</td>
<td>10</td>
<td>0.562 x 10^{-3}</td>
<td>1</td>
<td>65</td>
</tr>
</tbody>
</table>
Table III shows an example for the required gain for a transmission voltage of 10 Vpp whereby the TVR and RVR where obtained from the 40-kHz transducer described in section 1.6.1, i.e. Figure 1-18 and Figure 1-20 respectively. The attenuation of 10 dB assumes a separation distance of 10 meters with a cylindrical spreading loss. From the table, we see that in order to establish a reliable communication at that range and resonant frequency of 40 kHz, we will need a minimum gain of 39 dB. Moreover, when picking a preamplifier care needs to be taken to ensure that the amplifier meets the following criterion:

- Low noise
- Low input offset voltage (10 – 100 uV)
- High gain-bandwidth product (10 MHz – 100 MHz)

The current configuration of the acoustic modem uses a two stage fixed gain preamplifier with each stage providing 40 dB of amplification. Furthermore, a band-pass filter is employed prior to the first stage to filter out frequencies that are outside of our communication range.

![Image](image.png)

Figure 4-12: Receiver Transducer and Hydrophone used in testing
Figure 4-13: Time frequency analysis comparison of pre-amplified signal at 17 kHz. Node separation is 1 meter. The blue plot is the 19 kHz transducer, the dotted black plot is for the measurement hydrophone.

Figure 4-14: Time frequency analysis of pre-amplified signal at 19 kHz showing comparable but slightly better SNR from the 19-Khz transducer over the hydrophone.

Figure 4-15: Time frequency analysis of pre-amplified signal at 21 kHz. Since we are operating further from the transducers resonant frequency, the hydrophone will exhibit better SNR performance.
Figure 4-13, Figure 4-14 and Figure 4-15 show plots of the pre-amplified signal after the first stage of receive amplification for both the reference hydrophone [89] and the lab assembled transducer as depicted in Figure 4-12. The hydrophone is a specialized transducer that can mainly receive with a relatively flat RVR spectrum over a wide acoustic spectrum (10-100,000Hz). The test was performed in tank we cover in more detail in section 4.2 of this chapter. In this test, transmitter (with a resonant frequency of approximately 19 kHz) was placed approximately 1 meter away from the reference hydrophone, which transmitted a continuous wave at 10 Vpp. In all three cases, we note that the amplified voltage is around 1.6 Vpp for the hydrophone with a total SNR of approximately 60 dB, which is quite sufficient for establishing a reliable underwater link. On the other hand, the lab made transducer exhibits a higher amplified voltage of around 4 Vpp with a lower SNR at frequency bands outside of its resonant frequency. Thus, the lab-made transducer is more sensitive at frequencies close to its resonant frequencies yielding higher output voltages but is more prone to noise unwanted noise. The SNR was calculated by fitting the noisy received signal through least squares and applying the signal-to-noise and distortion ratio (SINAD) as defined in [94] as shown:

\[
\text{SNR} = \text{SINAD} = 20 \log \frac{A_{\text{rms}}}{\text{NAD}}
\]  

(89)

where \(A_{\text{rms}}\) is the root-mean-squared (rms) amplitude of the signal and is equal to the peak amplitude of the fitted sine wave divided by \(\sqrt{2}\). The noise rms and distortion (NAD) parameter is defines according to the following expression:
Such that $x[n]$ is the sampled noisy data set, $\hat{x}[n]$ is the data set of the best-fit wave and $N$ is the number of samples. Hence, we see from the figure above that the preamplifier succeeds in amplifying the low voltage acoustic signal received at the transducer. Given that we can properly communicate and sample analog data in the underwater medium, the resulting sampled data can then be used in our SBR analysis described in the previous chapter (chapter 3) and by extension used in the SBR-based protocols (chapters 6, 7, 8 and 9). In the next section, we will go over the prototype test bed used for validating the acoustic modem and the SBR-based concept.

4.2 Test-bed Prototype

Figure 4-16: Test-bed architecture showing an example network of four nodes. The walls of the water tank will be layered with acoustic absorbing materials.

Figure 4-17: Front view of the water tank showing the wave pump and 3D camera
To validate the (SBR) model along with the SBR-inspired networking protocols, we have built a test-bed suite that can be summarized in Figure 4-16. The test-bed consists of a tank, acoustic modems, directional transducers, sensors (i.e. water temperature/salinity measurement, Kinect-based surface-function measurement) and distributed hosts (i.e., laptops). The directional transducers are to reside inside a 75-gallon water tank [95], while the acoustic modem is to be mounted outside of the tank. Suites of sensors are used to ensure proper calibration of the water tank. Water-proof temperature and salinity sensors [96][97] are mounted inside the water tank and are accessible in real-time by any of the host (i.e. laptops) to provide an estimate of the sound speed, empirical measurements are also carried out to obtain the sound speed in the water tank. An acoustic wave maker is used to generate surface waves to increase the water surface roughness; this enables us to study the effect of a rough surface on the recovery of reflected surface links. Furthermore, a Microsoft 3D Kinect sensor [92][93] is mounted above the water tank as shown in Figure 4-16 to measure the water surface function as a base-line reference; this is also used to accurately measure the surface roughness parameters. In addition, the tank bottom is to be covered with sand or gravel depending on the desired bottom attenuation. The walls are covered with acoustic absorbing materials since we are only interested in surface/bottom reflections.

The next section will go over some analysis of the SBR communication model while using the acoustic modem prototype. The experiments were carried out with the test-bed tank summarized in Figure 4-16.
4.3 Summary

In this chapter, we presented two main prototypes that were designed for evaluating the SBR concept. The first was an acoustic modem, which was designed to utilize both omni-directional and the multi-modal directional transducer concept. The acoustic modem utilizes a field-programmable-gate-array (FPGA) to handle all required signal processing. The FPGA also includes a soft-core processor to allow for both higher-level protocols to be implemented on the modem. On the analog side, the acoustic modem provides both transmission and reception capabilities with a half-duplex mode. The transmitter is based on a class D amplifier with an effective bandwidth of 50 kHz. Furthermore, for directional operation four dual-channel class D amplifiers are selectively controlled to interface with the multi-modal directional transducer. The receiver is composed of a two-stage pre-amplifier circuit design with each stage providing 40dB of amplification. This allows the receiver to pick up very low acoustic voltages and thus increasing the communication range.

The second prototype was the acoustic test bed suite used for validating the SBR concept and the SBR-inspired protocols. The test bed consist of a water tank, acoustic modems for communication, a pump for generating surface waves, a 3D camera for measuring the water surface roughness, sensors, and a series of hosts (i.e. PCs). This gives us a platform for validating our work in a repeatable and controlled manner.
Chapter 5

Network Throughput Analysis

Given our proposed SBR scheme, which aims to incorporate NLOS signal-reflected links, we can further analyze the combined physical-MAC layer network throughput when utilizing NLOS SBR links. In this chapter, we will go over our published manuscript on the throughput analysis for shallow water communication [75]. The derivations will be based on the assumption that we have a PHY/MAC cross-layer utilizing a switch-beam directional antenna with CSMA/CA protocol. Although such analysis has been conducted before for RF links [76][77], no studies exist for acoustic links with directional antennas. Most importantly, we study the effect of utilizing NLOS (or signal-reflected) links with directional communication. It is important to note that the throughput analysis only considers the Raleigh scattering model described in section 3.2.1 to reduce the complexity of the analysis, the derivations that will be presented in the chapter can be further extended to consider other scattering models.

5.1 CSMA/CA Saturation Network Throughput

The saturation throughput for CSMA/CA MAC protocol is defined according to [76] as the ratio of the average payload transmitted during one slot to the average slot duration as shown:

\[
TH = \frac{\text{Average payload transmitted during one slot}}{\text{Average slot duration}}
\]
\[ TH = \frac{p_{tr} p_s E[P]}{(1 - p_{tr}) \sigma + p_{tr} (1 - p_s) T_c + p_{tr} p_s T_s} \]  

(91)

Such that \( E[P], T_c, T_s \) and \( \sigma \) correspond to the average payload size, the average collision duration, the average successful transmission duration, the duration of an empty time slot, respectively. The terms \( p_{tr} \) and \( p_s \) correspond to the probability that at least one node is actively transmitting, and the probability of a successful transmission, respectively. The average payload size and the transmission/collision durations can be calculated for a packet length of \( L(\cdot) \) in bits, an acoustic modem data rate of \( \mu \) in bps, a LOS transmission range of \( k_{\text{LOS}} \) in meters, and an average sound speed between all contending nodes of \( \bar{c} \) in meter/sec as follows:

\[ E[P] = \frac{L(P)}{\mu} + \frac{k_{\text{LOS}}}{\bar{c}} \]

\[ T_s = \frac{L(\text{RTS}) + L(\text{CTS}) + L(P) + L(\text{ACK})}{\mu} + \frac{k_{\text{LOS}}}{\bar{c}} \]

\[ T_c = \frac{L(\text{RTS})}{\mu} + \frac{k_{\text{LOS}}}{\bar{c}} \]

If the CSMA/CA MAC implements a constant back-off mechanism with a window size of \( W \) for \( N \) contending node where \( \tau = \frac{2}{W + 1}, p_{tr} \) can be easily calculated as:

\[ p_{tr} = 1 - (1 - \tau)^N \]  

(92)

Furthermore, in [76] it was shown that the back-off window size that maximizes the system throughput for \( N \) contending nodes can be expressed as \( W_{\text{opt}} = N \sqrt{2T_c} \). From [77], the probability of a successful transmission \( p_s \) can be calculated using \( p_{tr} \),
the outage probability $p_o$ and the capture probability for $N$ contending nodes $p_{CAP}(N)$, as follows:

$$p_s = \frac{\Pr\{\text{Frame RSS} > \text{threshold}\} + \Pr\{\text{Frame is captured}\}}{p_{tr}}$$

$$p_s = \frac{N\tau(1 - \tau)^{N-1}(1 - p_o) + p_{CAP}(N)(1 - (1 - \tau)^{N-1})}{p_{tr}}$$ \hspace{1cm} (93)

In the balance of this chapter we define those two probabilities, derive their expressions for shallow water environments while factoring in the multipath effects, and analyze their effect on the throughput.

### 5.2 Outage Probability

The outage probability $p_o$ is defined as the probability that the received signal strength of a packet is lower than the required threshold due to large propagation attenuation. This probability is evaluated only when one node tries to transmit to the next hop neighbor $H_j$ without any other competing nodes involved. This can be expressed as $p_o = \Pr\{\text{SNR} < z_T\}$, where $z_T$ is the required received SNR threshold and will depend on the modulation scheme. We can further expand the probability for a shallow water environment with the received power defined in Equation (30) as follows:

$$p_o = \Pr\{\text{SNR} < z_T\}$$

$$p_o = \Pr\left\{\frac{P_{RX}y}{N_T} < z_T\right\}$$

$$p_o = \Pr\left\{\frac{P_{TX} \cdot A(d, f, \theta) \cdot G(\theta)y}{N_T} < z_T\right\}$$
The total attenuation \( A(d, f, \theta) = 10^{T_{TOTAL}} \) was derived in (30) for the Raleigh model and in (47) for the NRL Bistatic model in sections 3.2.1 and 3.2.2 respectively. If you recall, the total attenuation was also found to be dependent on the LOS distance \( d \), the communication frequency \( f = f_c \) and the grazing angle \( \theta \). More importantly in shallow water environments we found that the multipath attenuation parameters for surface-reflected (RSR) and bottom-reflected (RBR) signals will be dependent on the sound speeds, densities, and grazing angles as demonstrated in (21) and (22). In Equation (94), \( y \) is a random variable with unit power and is modeled after a Raleigh distribution with cumulative distribution function (CDF) of \( F_y(y) = 1 - e^{-y} \), \( P_{TX} \) is the transmission power (in dB), \( N_T \) is the received noise power and \( G(\theta) \) is the antenna gain.

To evaluate Equation (94), we assume a random deployment scenario whereby the deployed nodes will form a cluster that is normally accumulated (or distributed) around the geographical boundary. In some cases [43], this assumption is also true for position estimation, which is also required for directional communication. Thus, we assume that all contending nodes are normally distributed with zero mean (\( \mu = 0 \)) and variance \( \sigma = 1 \) around next-hop node \( H_j \) (with transmission range \( k_{LOS} \)) such that the distance \( d \) and incident angles \( \theta \) can be modeled with the following probability density functions (PDFs):

\[
f_d(d) = \frac{1}{\sqrt{2\pi}} \exp\left(-\frac{d^2}{2}\right)
\]
\[ f_\theta(\theta) = \frac{1}{\sqrt{2\pi}} \exp \left( -\frac{\theta^2}{2} \right) \]

Given the bivariate distribution between \( \{d, \theta\} \), we can further evaluate Equation (94) by computing the joint probability distribution of the continuous random variables \( \{d, \theta\} \) as

\[ p_o = \text{Pr}\{ -k_{LOS} \leq d \leq k_{LOS}, -\theta_{3dB} \leq \theta \leq \theta_{3dB} \} \]

\[ p_o = \text{Pr}\{ 0 \leq d \leq k_{LOS}, -5^\circ \leq \theta \leq 5^\circ \} \]

\[ p_o = \int\int f_{D,\theta}(d, \theta) d_d d_\theta f_d(d) f_\theta(\theta) \]

\[ p_o = \int_{-k_{LOS}}^{k_{LOS}} \int_{-\theta_{3dB}}^{\theta_{3dB}} f_{D,\theta}(d, \theta) d_d d_\theta f_d(d) f_\theta(\theta) \]

Since we are only considering positive distances (i.e., \( 0 \leq d \leq k_{LOS} \)), we have:

\[ p_o = \int_0^{k_{LOS}} \int_{-\theta_{3dB}}^{\theta_{3dB}} f_{D,\theta}(d, \theta) d_d d_\theta f_d(d) f_\theta(\theta) = \]

\[ = \int_0^{k_{LOS}} \int_{-\theta_{3dB}}^{\theta_{3dB}} F_Y \left( \frac{Z_T N_T}{P_{TX}} (A(d, f, \theta))^{-1} G(\theta)^{-1} \right) d_\theta d_d f_d(d) f_\theta(\theta) \]

\[ = \int_0^{k_{LOS}} \int_{-\theta_{3dB}}^{\theta_{3dB}} \left( 1 - \exp \left[ -\frac{Z_T N_T}{P_{TX}} (d^2 \alpha(f)^d (\hat{\theta}(\theta)^2)^{-1})^{-1} G(\theta)^{-1} \right] \right) \]

\[ \cdot d_\theta d_d f_d(d) f_\theta(\theta) \]

To improve readability, we let:

\[ \gamma = \frac{Z_T N_T}{P_{TX}} \]

\[ A = (d^2 \alpha(f)^d (\hat{\theta}(\theta)^2)^{-1})^{-1} \]

\[ B = G(\theta)^{-1} \]

And
\[ p_o = p_o(1) - p_o(-\gamma AB) \]

Yielding:
\[
p_o = \int_0^{k_{LOS}} \int_{-\theta_{3dB}}^{\theta_{3dB}} (1 - \exp[-\gamma AB]) \, d_\theta \, d_d \, f_d(d) \, f_\theta(\theta) \]
\[
p_o(1) = \int_0^{k_{LOS}} \int_{-\theta_{3dB}}^{\theta_{3dB}} 1 \, d_\theta \, d_d \, f_d(d) \, f_\theta(\theta) \]
\[
p_o(1) = \int_0^{k_{LOS}} \frac{1}{\sqrt{2\pi}} \exp\left(-\frac{d_e^2}{2}\right) \int_{-\theta_{3dB}}^{\theta_{3dB}} \frac{1}{\sqrt{2\pi}} \exp\left(-\frac{\theta^2}{2}\right) \, d_\theta \, d_d \]

This can be approximated by the Gaussian Q-function as:
\[
Q(x) = \int_x^{\infty} \frac{1}{\sqrt{2\pi}} \exp\left(-\frac{t^2}{2}\right) \, dt \approx \frac{1}{\sqrt{2\pi x}} \exp\left(-\frac{t^2}{2}\right) 
\]
\[
p_o(1) = [Q(0) - Q(k_{LOS})][Q(-\theta_{3dB}) - Q(\theta_{3dB})] \approx 1 
\]

Hence:
\[
p_o = 1 - \frac{1}{2\pi} \int_0^{k_{LOS}} \int_{-\theta_{3dB}}^{\theta_{3dB}} \exp\left(-\frac{d_e - \theta}{2} - \gamma AB\right) \, d_\theta \, d_d \quad (95) 
\]
Figure 5-1: Outage probability when varying the half-power beam-width

Figure 5-2: Outage probability when varying the transmission power

Figure 5-3: Outage probability when varying the grazing angle
The outage probabilities are shown in Figure 5-1 through Figure 5-3 for line-of-sight (LOS), surface-reflected (RSR), and bottom-reflected (RBR) links using the physical/MAC-layer parameters in Table IV. We will also be referring to Table IV when we analyze the capture probability and the normalized throughput. The underwater density parameter $p_b$ was obtained for a silt-like water bottom, while the water surface is modeled as a rough surface with RMS value shown in Table IV. In Figure 5-1 we vary the directivity of the acoustic antenna model, namely the half-beam-width $\theta_{3dB}$ and study the effects on the outage probability. We see that as we increase the directivity (i.e. decreasing $\theta_{3dB}$) of the directional antenna the outage probability decreases. This is expected since highly directed signals will be more likely to be above the SNR threshold (i.e. not subject to outage). In the same figure we notice that LOS signals have the least outage probabilities followed by RSR and RBR. This is because the LOS signal does not experience any multipath attenuation, which will increase its likelihood of being above the SNR threshold. However, since RBR signals are attenuated more than RSR signals, the outage probability will be higher as depicted in Figure 5-1. In Figure 5-2 we vary the transmission power $P_{\text{TX}}$ to see the effects on the outage probability. This plot shows that as we increase the transmission power the outage probability (signal is below SNR threshold) decreases for a half-power beamwidth of $\theta_{3dB} = 5^\circ$. This is expected, since when utilizing a highly directed antenna ($\theta_{3dB} = 5^\circ$) we increase the probability that the signal will be above the SNR threshold (i.e. $1 - p_o$) by simply increasing the transmission power towards the desired destination. Furthermore, we see that LOS links provide the best option followed by RSR links, then RBR links.
Table IV

THROUGHPUT ANALYSIS PARAMETERS

<table>
<thead>
<tr>
<th>$k_{\text{LOS}}$</th>
<th>$\theta_{3dB}$</th>
<th>$c_w$ (m/s)</th>
<th>$c_b$ (m/s)</th>
</tr>
</thead>
<tbody>
<tr>
<td>1000m</td>
<td>5°</td>
<td>1500</td>
<td>1800</td>
</tr>
<tr>
<td>$\sigma_{\text{RMS}}$</td>
<td>$z_T$</td>
<td>$p_w$ (kg/m³)</td>
<td>$p_b$ (kg/m³)</td>
</tr>
<tr>
<td>0.5</td>
<td>-1dB</td>
<td>1000</td>
<td>1700</td>
</tr>
<tr>
<td>$P_{\text{TX}}$</td>
<td>$N_T$</td>
<td>$\theta_s$</td>
<td>$N$</td>
</tr>
<tr>
<td>20dB</td>
<td>-90dB</td>
<td>33°</td>
<td>5</td>
</tr>
<tr>
<td>$f_c$ (kHz)</td>
<td>$W$</td>
<td>$u$ (bps)</td>
<td>$\bar{c}$ (m/s)</td>
</tr>
<tr>
<td>1</td>
<td>100</td>
<td>1000</td>
<td>1430</td>
</tr>
<tr>
<td>$\sigma$</td>
<td>$\lambda_w$ (m)</td>
<td>$\lambda_b$ (m)</td>
<td>RTS(bits)</td>
</tr>
<tr>
<td>0</td>
<td>1.5</td>
<td>1.8</td>
<td>100</td>
</tr>
<tr>
<td>CTS(bits)</td>
<td>$P$ (bits)</td>
<td>ACK (bits)</td>
<td></td>
</tr>
<tr>
<td>100</td>
<td>5200</td>
<td>100</td>
<td></td>
</tr>
</tbody>
</table>

$k_{\text{LOS}}$: Line-of-sight transmission range
$\theta_{3dB}$: Half-power beamwidth
$c_w$: Sound speed in the water surface layer
$c_b$: Sound speed in the water bottom layer
$\sigma_{\text{RMS}}$: Root-mean-squared water surface roughness
$z_T$: Received signal threshold
$p_w$: Density in the water surface layer (continental shelf)
$p_b$: Density in the water bottom layer (silt-like bottom)
$P_{\text{TX}}$: Transmission power
$N_T$: Noise power
$\theta_s$: Beam-steering angle
$N$: Number of contenders
$f_c$: Acoustic carrier frequency
$W$: CSMA Window size
$u$: Acoustic modem data rate
$\bar{c}$: Average sound speed between contending nodes
$\sigma$: Empty slot time
$\lambda_w$: Water surface acoustic wavelength (meters)
$\lambda_b$: Oceanic bottom acoustic wavelength (meters)
We study the impact of the grazing angle $\theta_w$ (i.e. angle of incident to the surface/bottom) in Figure 5-3, recall that the effects of the grazing angle can be controlled by adjusting the beam steering angle $\theta_s$ when utilizing directional antennas. In Figure 5-3, we see that as we decrease the incident angle to the water surface below the critical angle $\theta_c = 33.6^\circ$, the outage probability diminishes, which mean that the signal is likely to be above the SNR threshold. However, if we decide to operate above the critical angle, the outage probability increases and then saturates. The critical grazing angle is found from Snell’s Law, which is defined below:

$$\theta_c = \arccos\left(\frac{c_1}{c_2}\right) = \arccos\left(\frac{c_w}{c_b}\right)$$

Thus, given an antenna design with enough fidelity over the beam steering angles, it is best to operate at angles right below the critical angle.

### 5.3 Capture Probability

The capture probability $p_{CAP}(N)$ is defined in [77] as the probability that the received signal power of the RTS / CTS / ACK / DATA frame exceeds the interference power of the frames from other contending nodes ($N-1$). Thus, we have the following relationship:

$$p_{CAP}(N) = N \cdot \Pr\left\{ y > z_T \sum_{i=2}^{N} P_i \right\}$$

$$p_{CAP}(N) = N \cdot \Pr\left\{ y > z_T \sum_{i=2}^{N} \left( \frac{d_l^2 \alpha(f)^d (\hat{R}(\theta_i)^2)^{-1}}{\hat{R}(\theta_1)^2} \right) G(\theta_i)^{-1} y_i \right\}$$

The summation takes into account the interference that a node $S_1$ experiences from
all other sensor nodes, where $P_i$ is the interference power from node $S_i$ and $y_i$ is a random variable with unit power which is modeled after a Raleigh distribution as stated earlier. Similar to evaluating $p_o$ in Equation (94), we can solve for the capture probability by assuming normal distribution among all contending nodes $N$ based on the condition that we know their proximity $d$ and incident angles $\theta$ as shown:

$$p_{CAP}(N) = \int_{0}^{k_{LOS}} \int_{-\theta_{3dB}}^{\theta_{3dB}} N[p_{CAP,1}(N, d_1, \theta_1 | d, \theta)] d_\theta d_\phi f_\phi(d) f_\theta(d)$$

The conditional probability $p_{CAP,1}(N, d_1, \theta_1 | d, \theta)$ is based on the fact that we know the distances $(d_2, d_3, ..., d_N)$, and incident angles to the next-hop node $H_j$ from all other contending nodes. This assumption is valid since each node will know the position information to their one-hop neighbors by applying appropriate localization mechanisms [42][43]. Given the mutually independent nature of the interference from all contending nodes, the conditional probability $p_{CAP,1}(N, d_1, \theta_1 | d, \theta)$ can be simplified into a moment generating function of the form:

$$p_{CAP,1}(N, d_1, \theta_1 | d, \theta)$$

$$= \int_{0}^{\infty} \int_{0}^{\infty} \exp \left(-z_T \sum_{i=2}^{N} y_i Y \right) e^{-y_2} e^{-y_N} dy_2 .. dy_N$$

$$= \int_{0}^{\infty} \int_{0}^{\infty} \exp \left(- \sum_{i=2}^{N} y_i (1 + \eta) \right) dy_2 .. dy_N = \prod_{i=2}^{N} \frac{1}{1 + \eta}$$

where:

$$\eta = z_T Y$$

and
As a result, the capture probability is determined by:

\[ Y = \left( \frac{d_l^2 \alpha(f)^d (\hat{R}(\theta) \hat{R}(\theta)^2)^{-1}}{d_l^2 \alpha(f)^d (\hat{R}(\hat{R}(\theta)^2)^{-1})} \right) G(\theta) \]

Hence:

\[ p_{\text{CAP}}(N) = N \cdot \int_0^{k_{\text{LOS}}} \int_{-3 \text{dB}}^{3 \text{dB}} \prod_{i=2}^{N} \frac{1}{1 + \eta} d\theta d_d f_d(d) f_{\theta}(\theta) \]

Each node \( S_l \) will know the positions (global or relative) of its neighbors. Therefore, \( S_l \) will only need to compute the conditional capture probability, namely \( p_{\text{CAP},l}(N, d_1, \theta_1|d, \theta) \) since it knows the relative distances and angle-of-arrivals of the \( N \) contending nodes. Figure 5-4 shows a plot of the SNR threshold to the capture probability for the different link option (LOS, RSR, RBR) using the parameters in Table IV. We see that as we increase the SNR threshold required for communication, the capture probability decreases. This is because the higher the SNR is, the tighter the requirement for communication would be which effectively decreases the capture probability. From the same plot we see that as we increase the multipath effect, the capture probability decreases, i.e., for no multipath (LOS) we have the highest capture probability while for bottom reflected signals we have the lowest capture probability. From the same plot, we see that when utilizing directional antennas we obtain high capture probabilities since sharply directed signals from the source node will overpower the interference from all other contending nodes.
Figure 5-4: SNR threshold to capture probability for the different link variants. Plot also shows confidence level averaged over ten runs with each run having a random node distribution.

Figure 5-5: The effects of the number of contenders on the capture probability. Plot also shows confidence level averaged over ten runs with each run having a random node distribution.

Figure 5-6: The effect of the grazing angle on the capture probability
Figure 5-5 plots the relationship between the number of contending nodes to the next hop node $H_j$ and the capture probability. The plot agrees with the findings in [77] and indicates that as we increase the number of contenders around the next-hop node the capture probability decreases which is expected. We also see that a link that experiences high multipath (i.e. RBR) will also have a low capture probability, with the LOS link providing the best option for communication. More importantly, we see that utilizing directional antennas will boost the capture probability since it decreases the total interference power from all other contending nodes.

Furthermore, we see in Figure 5-6 that as long as the grazing angle $\theta_w$ is less than the critical angle $\theta_c = 33.6^\circ$ we will be able to obtain the best capture probability when utilizing NLOS links (i.e. RSR and RBR).

5.4 Effects on Throughput

Recall from (91) that the normalized network throughput will be dependent on the outage probability $p_o$ and the capture probability $p_{CAP}$. The throughput effects are shown in Figure 5-7, Figure 5-8 and Figure 5-9. We start by examining the effect of the root-mean-squared (RMS) roughness parameter $\sigma_{RMS}$ on the normalized throughput. Recall in Equation (27) that the RMS roughness is used to estimate the rough water surface and bottom, higher $\sigma_{RMS}$ values means that the signal is prone to high scattering which ultimately increases the multipath transmission loss defined in Equation (23). Therefore, we see that for high $\sigma_{RMS}$ values the network throughput decreases. We also see that utilizing directional antennas such that the angle of incident is less than the critical angle (i.e. $\theta_s \approx \theta_w < \theta_c$) will increase the network
throughput as shown in Figure 5-9.

In Figure 5-8 we see the effect of the number of contenders on the normalized throughput for the parameters defined in Table IV. We see that the network throughput is at the maximum for a network density of about 5 nodes (i.e. N=5) and decreases for large network densities due to low probability of successful transmission. From the same plot we see that utilizing the LOS link will yield the highest network throughput since it experiences no multipath attenuation, the RSR link yields the second-best throughput followed by the RBR link as expected. We also notice that utilizing directional antennas with the LOS link yields the best option for communication since it provides the best SNR, which increases the effective throughput.

Lastly, we capture the impact of the grazing angle on the network throughput in Figure 5-9. We see that for grazing angles that are above the critical angle the network throughput drops rapidly due to high signal loss.
Figure 5-7: RMS roughness effect on the normalized throughput. Plot also shows confidence level averaged over ten runs.

Figure 5-8: Plot showing the effects of the network density on the normalized throughput for directional and omni-directional antennas. Plot also shows confidence level averaged over ten runs.

Figure 5-9: Grazing angle effect on the normalized network throughput
5.5 Summary

In this chapter, throughput analysis for shallow water communication with directional antennas was presented. Unlike traditional directional communication, our approach factors in non-line-of-sight (NLOS) links to the analysis, namely RSR and RBR. We derived an expression for the network throughput when communicating with a PHY/MAC cross-layer when utilizing a switch-beam directional antenna in the PHY layer. The MAC layer is based on the carrier-sense with multiple-access and collision avoidance (CSMA/CA) protocol. Our results show that using directional antennas greatly improves the network throughput due to its low outage probability and high capture probability. Our analysis has also concluded that utilizing highly directional antennas will minimize the chance of exceeding the critical angle, which promotes the usage of NLOS links. The next four chapters will be dedicated to SBR-inspired networking protocols, which builds upon the concepts and derivations discussed thus far.
Chapter 6

SBR-based Anchor-free Localization

As demonstrated in the previous chapter, directional transmission is the most efficient scheme for inter-node interaction in UWANs. In addition, localization is needed for node discovery and ad-hoc formation of the network. However, node mobility in UW-ASNs poses a challenge for directional communication among nodes. To form relative topologies in underwater environments, node localization algorithms are often employed [52] [80][81]. These algorithms are GPS-free, meaning that they do not require any GPS information but rely on acoustic range measurements to establish a relative coordinate system. Node localization algorithms usually rely on measured received-signal-strength (RSS), time-of-arrival (TOA), time-difference-of-arrival (TDOA) or angle-of-arrival (AOA) calculations for node positioning. Unfortunately, due to the multipath nature of the underwater environment, i.e. shallow water, those measurements are prone to errors from line-of-sight (LOS) instabilities. In addition, most node localization algorithms for UW-ASNs only consider omni-directional transducers and hence do not exploit the spatial spectrum and ranging accuracy obtained with directional transducers.

Traditional localization algorithms work by using LOS range measurements. Due to the unavailability or instability of the LOS links in underwater setups, a practical solution for underwater localization is needed. Moreover, node localization can either be anchor-free or anchor-based. In this chapter we address the node localization
problem with an anchor-free approach. Hence, the result of the localization algorithm that will be described is a relative coordinate system.

### 6.1 Localization Problem and SBR-AL Overview

As mentioned earlier, traditional relative localization algorithms work by using LOS range measurements. To illustrate this let us consider the Local Position Discovery (LPD) algorithm described in [51] as illustrated in Figure 6-1.

**Figure 6-1:** Establishing relative coordinate system, where the distances \( d_{ij} \) correspond to the LOS distances between the nodes \( i \) and \( j \).

The relative coordinate system is formed by the origin node (or gateway node) \( S_0 \) first assuming the origin position \((0,0)\) and attempts to locate its one-hop neighbors through a node discovery process. The first neighbor that \( S_0 \) locates, say \( S_4 \) forms the x-axis of the relative coordinate system and the position of the first neighbor becomes \((d_{04},0)\), where \( d_{04} \) is the LOS distance. The LOS distance can be obtained from the time-of-arrival measurement as \( d_{04} = \bar{c} \cdot \tau_{04} \), where \( \bar{c} \) can be represented as the average sound speed and \( \tau_{04} \) is the time-of-flight or TOA of the LOS signal from the node \( S_0 \) to \( S_4 \). The second neighbor that is discovered namely \( S_2 \)
completes the triangle only if $S_2$ is a non-collinear neighbor to both $S_0$ and $S_4$ respectively as shown in Figure 6-1. The LOS distances $d_{02}$ and $d_{42}$ are obtained the same way as before, however this time the position $(x_2, y_2)$ of the node $R_2$ is determined through the law of cosines using:

$$x_2 = \frac{d_{02}^2 + d_{04}^2 - d_{42}^2}{2d_{04}}, y_2 = \sqrt{d_{02}^2 - x_2^2}$$

The positions of all other nodes are obtained through the same steps or through multilateration. The LPD algorithm then uses a least squared error minimization scheme to fine-tune the position estimates. Thus we see here that the range estimates that are used to obtain the positions are simply the LOS range estimates $\tau_{ij}$ for each node-pair $S_i$ and $S_j$. It is obvious that without an accurate measure of the LOS range information $\tau_{ij}$ the performance of the LPD algorithm will be drastically affected. Most importantly in a 3D underwater environment there are no guarantees that the LOS (or direct-path) will be available due to the multi-path effects of the underwater channel as discussed earlier.

Since LOS links are not guaranteed in shallow water environments, a new localization algorithm is needed. In this section we present the SBR-AL algorithm which will create a relative coordinate system using the RSR range measurements $\{r_A,r_B\}$ obtained from SBR coupled with LOS ranging (when available). Recall from the previous section that our approach will use the vectors namely $r_A$ and $r_B$ as range measurements instead of time-of-flight information as is common to most localization algorithm. The diagrams in Figure 6-2, Figure 6-3 and Figure 6-4 summarize a detailed view of the localization process.
Figure 6-2: State-machine of water surface reconstruction mechanism which runs in parallel with the SBR-AL algorithm (Figure 6-3)

Figure 6-3: SBR-AL stages showing the stages performed by each sensor node $S_i$. One of the criteria for evaluating each of the variants will be the localization error.

Figure 6-4: Neighbor Discovery With SBR, which uses the known surface function (from FDTD) to create a GRID-MAP of intersection points. Discovery messages are sent to obtain range estimates from one-hop neighbors
The state machine of the water surface recovery mechanism can be seen in Figure 6-2, which initially samples the water surface to obtain an initial wave for the finite-difference time domain (FDTD) process. The surface recovery mechanism (Figure 6-2) runs in parallel with the SBR-AL state machine in Figure 6-3. In SBR-AL each sensor node (S_i) will create a relative coordinate system where the node S_i will assume a center position. In Figure 6-3, we see that SBR-AL consists of four phases, namely, node discovery, range estimation using signals reflected from the water surface, anchor-free localization, and optimization to minimize the localization errors. From Figure 6-3, we see that depending on the variants of SBR-AL and the range information provided we might need to re-discover the neighboring nodes (as shown in Figure 6-4) to increase the accuracy of the localization process, which exploits the time variability of the water surface function. Each SBR-AL variants will be evaluated according to the following criterions; (i) Localization complexity, (ii) Localization overhead, (iii) Sensitivity to mobility, and (iv) Localization error. We will revisit these criteria in section 6.5 of this chapter.

In the next subsection we will go over the node discovery mechanism used in SBR-AL in detail, which is summarized in Figure 6-4. A detail pseudo-code of the node discovery mechanism can be found in Appendix B of this dissertation.

### 6.2 Node Discovery and Range Estimation

Recall from section 1.5 that we will be utilizing Λ = M directional antennas that can be combined to form an Omni-directional beam pattern. This allows us to utilize the wider beam pattern for LOS range estimation and the narrower beam pattern for both LOS and NLOS range estimation during node discovery phase. During node
discovery, each node will first utilize an Omni-directional beam pattern to locate all one-hop neighbors by sending a DISCOVERY\textsubscript{DP} message beamed in all directions. The receiving node will then apply (75)-case I to determine if the received signal was not reflected before replying with an ACK-DISCOVERY\textsubscript{DP} message. If more range measurements are needed (see Figure 6-4) or if the transmitting node did not receive a response within a specified period of time, it switches to node discovery with directional antennas, which will aim each directional antenna to the water surface as described in the remainder of this subsection.

To discover all adjacent nodes in NLOS node discovery, we propose using the moving water surface to discover one-hop neighbors. To do so, the node \( S_t \) will increase the angle \( \theta \) in all directions and retransmit a DISCOVERY\textsubscript{RSR} message towards the known water surface \( S(x,y) \) while the receiving node \( S_j \) will use the reflection point from the water surface to solve for the reflection vector \( \vec{r}_d \). If a node receives the DISCOVERY\textsubscript{RSR} message prior to reflecting from the water surface, the localization mechanism will revert to traditional LOS-based schemes, i.e. \([46][51]\), otherwise the receiving node will compute the reflected vector \( \vec{r}_B \) based on (9). Keep in mind that the water surface is assumed to be moving with time \( t \) as shown in Figure 6-2 with a known wave direction, and is continually updated in time by the FDTD algorithm (86). Thus we can also represent a time-dependent water surface function after a time period \( \tau \) as follows:

\[
S(x,y)|_{t=\tau} = S(x,y)
\]  

(98)

Given the 3D environment, the interesting question is how to determine the direction and the increment in \( \theta \) value given the infinite number of choices. To
determine a set of discrete values, SBR-AL implements a grid that is essentially a 2D map of the water surface where each cell in the grid corresponds to the depth of the node relative to the 2D plane that contains the node $S_i$. Taking node $S_0$ in Figure 6-5 as an example, the node is currently at $z$-position $(0,0,z_0)$ and will project a virtual cone with an angle of $\theta$ to the water surface. Thus, for a sine wave water surface with $(\text{max}, \text{min})$ amplitudes of $(-1,1)$ and a frequency on the $y$-axis we see that one possible intersection point to the water surface is $(0,0,0)$.

By looking up into the FDTD recovered water surface from node $S_i$ we can generalize the following grid map of the water surface (see Figure 6-6), where each cell in the grid corresponds to a specific intersection point on the water surface. Here, the grid cell size ($\Delta = \Delta x = \Delta y$) is taken to be $1m \times 1m$ ($\Delta = 1$) which is a representation of the acoustic transmitter resolution when adjusting the projected angle onto the water surface function $S(x,y)$. Recall from SBR we are interested in the point $(x_{RI}, y_{RI}, z_{RI})$ on the water surface function $S(x,y)$ which will be reflected
and it was shown that one possible intersection point to the water surface (relative to node $S_0$) is the point (0,0,0). We note that the $z$-axis for each cell can be expressed as $z_{xy} = S(x, y) - z_0$ relative to the depth $z_0$ of node $S_0$. Recall from (79) that the sampling process added the depth of the node to the sampled continuous water surface function, thus to obtain the true water surface amplitude we simply subtract the node’s depth from the FDTD recovered surface function $S(x, y)|_{t=T}$. The node’s true depth (relative to a FLAT surface) can be estimated by averaging over the recovered water surface amplitude. Hence, we can show that $z_{00} = 0$ for the sine wave shown in Figure 6-5.

From Figure 6-6 we see that the maximum transmit angle at (0,0,$z_{00}$) is $\theta(0) =$ $\theta_{(0,0,z_{00})} = 90^\circ$, where the point (0,0,$z_{00}$) is referred to as level 0 in the SBR-AL node discovery phase. Each level in the discovery phase consists of a series of intersection points that is represented by the transmit angle at that point. So, in level 1 we have the lighter cells representing the 8 possible points of intersection. Each intersection point allows us to compute both the $\vec{r}_A$ and $\vec{n}$ vectors. Hence, we can write an expression for the number of levels $l = \{0,1,2,...,L\}$ and the number of possible intersection points ($IP_l$) as shown below:

$$IP_l = \text{corners} + (2(l - 1) + 1) \cdot \text{sides}; \text{ for } l > 0$$

$$IP_l = 4 + (2(l - 1) + 1) \cdot 4; \text{ for } l > 0$$

Each intersection point will be scaled by the grid cell size ($\Delta$), which affects the transmission angle at that point. The transmission angle can be expressed by relating the base of the cone projected onto the water surface with the following expression:
\[
\theta_{(x,y,z_{xy})} = \sin^{-1}\left(\frac{|\bar{r}_{(x,y,z_{xy})}|}{k_{LOS}}\right) \leq \sin^{-1}\left(\frac{z_0}{k_{LOS}}\right)
\]

such that \( |\bar{r}_{(x,y,z_{xy})}| \leq k_{LOS} \) where \( k_{LOS} \) is the line-of-sight transmission range.

Given the expression for the transmission angle, we can determine the value at each level within the surface grid. The maximum transmission angle at each level \( l = \{0,1,2,\ldots,L\} \) is the maximum of all the possible transmission angles resulting from each \( \bar{r}_A \) vector (this will occur at the extreme intersection points). By picking out the four corners at each level we can write the following expression for the maximum transmission angle for that level:

\[
\theta(l) = \max \left[ \theta_{(-l,z_{-l})}, \theta_{(l,z_{l})}, \theta_{(-l,z_{-l})}, \theta_{(-l,z_{-l-l})} \right]
\]

We now define \( \Delta \theta \) as the change in angle as we iterate with/through the levels until reaching the maximum achievable angle \( \theta_{\text{MAX}} \), as shown:

\[
\Delta \theta = \theta(l) - \theta(l - 1); \quad \text{for } l > 0
\]

\[
\theta_{\text{MAX}} = \theta(N) = \sin^{-1}\left(\frac{z_0}{k_{LOS}}\right)
\]

We can express the magnitude of the \( \bar{r}_A \) vector by computing the radius \( r \) of the projected cone for a node depth \( z_0 \) as:

\[
r = z_0 \tan \frac{\theta_s}{2}
\]

\[
|\bar{r}_A| = \sqrt{r^2 + z_0^2}
\]

where \( \theta_s \) is the beam steering angle of the antenna pattern as defined in (4). The magnitude of the \( \bar{r}_B \) vector is simply the magnitude of expression (9). Hence, we see
that the node $S_i$ will increase its transmission angle by $\Delta \theta$ to attempt to locate new nodes until reaching $\theta_{\text{MAX}}$. Also note that, the selection of $\overrightarrow{r_A}$ will be dependent on the grid mapping of the water surface as illustrated in Figure 6-6, which depicts a grid cell size of $(\Delta = \Delta x = \Delta y = 1)$. Smaller grid cell size will lead to more accurate $\overrightarrow{r_A}$ measurements however this is limited by the directivity of the antenna model as illustrated in Figure 3-29. To study the upper bound on the localization performance, we assume a highly directional piezoelectric transducer $(\Delta = 1)$ in the evaluation of the localization algorithm in section 6.6. In theory, the directional transducer model described in section 1.5.1 can be designed to achieve higher acoustic directivity by increasing the number of internal electrode sectors to 180 ($2^\circ$ beam) from the original value of 8 ($45^\circ$ beam). The calculation of $\overrightarrow{r_B}$ is mainly dependent on the accuracy of the normal vector at the specified intersection point to the water surface. The simulation section (section 6.6.1) discusses the sources of error in obtaining the range measurements $\{\overrightarrow{r_A}, \overrightarrow{r_B}\}$.

Upon receiving the transmitted DISCOVERY$_{\text{RSR}}$ message from $S_i$ containing the intersection point and projection area to the water surface, node $S_j$ will respond with an ACK-DISCOVERY$_{\text{RSR}}$ on all of its directional antennas indicating that it received the reflected signal. If the receiver $S_j$ did not receive the reflected surface signal after the period $\tau$ but received the direct-path (DP) or LOS signal it will instead respond with an ACK-DISCOVERY$_{\text{DP}}$ message on all directional antennas. This is done so that the localization algorithm can use the LOS link when the receiver is within the line-of-sight of the transmitting antenna. Recall from section 3.4 (link classification) that the receiver will be able to tell the difference from the LOS to the RSR signal
through the filtering process described in (75). Hence, depending on the messaged received (ACK-DISCOVERY$_{RSR}$ or ACK-DISCOVERY$_{DP}$); the range estimation will either be LOS or NLOS. The entire node discovery process can be summarized in Figure 6-4, which shows the different states involved in the process.

Thus at the conclusion of node discovery for a specified time period $t = \tau$ the transmitting node will have a list of $\{\overrightarrow{r}_A, \overrightarrow{r}_B\}_{ij}$ vectors and temporary intersection points $(x, y, z)_{ij}$, where the subscript $ij$ refers to the measurement connecting the source node $S_i$ to the destination node $S_j$.

We have shown the node discovery mechanism that SBR-AL uses to discover its one-hop neighbors which was performed for a specific time interval $t = \tau$. The node discovery phase will employ the SBR filtering that allows us to obtain either LOS round-trip time of flight range measurements or vector-based NLOS range measurements $\{\overrightarrow{r}_A, \overrightarrow{r}_B\}$ for a time-varying water surface after a specified period $\tau$. These range measurements will be used depending on the localization variant (SBR-CAL, SBR-DAL, SBR-EAL); where in the corporative case (SBR-CAL) we only require one $\{\overrightarrow{r}_A, \overrightarrow{r}_B\}_{ij}$ pair connecting two nodes $\{S_i, S_j\}$ and in both directed cases (SBR-DAL or SBR-EAL) we will need multiple $\{\overrightarrow{r}_A, \overrightarrow{r}_B\}_{ij}$ pairs required for the multilateration process. We will start by first describing the anchor-free localization mechanism in the corporative case in the next subsection. A detailed pseudo-code of both the node discovery mechanism and the localization process can be found in Appendix C.
6.3 Anchor-free Localization

The remainder of this section will be used to present our anchor-free localization schemes. The surface-based anchor-free localization (SBR-AL) protocol comes in three different variants that can be exploited to achieve the desired performance in terms of coverage and error.

6.3.1 Coorporative Anchor-free Localization: SBR-CAL

In the corporative scheme, the node that is building the local coordinate system will require range measurements from multiple nodes in order to estimate the relative positions similar to [46][51]. However, unlike [46][51], SBR-CAL will use the RSR range measurements, i.e. the $\{\vec{r}_A, \vec{r}_B\}$ vectors instead of the LOS range information if the LOS range information is not available. The local coordinate system is built by each node $S_i$ where each node assumes a center position $(0,0,z_i)$ based on its depth information, equation (79), and builds a 2D triangle by projecting the difference in depth information to its discovered one-hop neighbors as shown in Figure 6-7.

![Figure 6-7: Local coordinate system for the node S0 showing the 2D projected node position estimates for nodes S2 and S4 (3D network example shown in Figure 6-5).](image-url)
The x-axis is formed by selecting the node $S_4$ where the distance $d_{04}$ is the estimated LOS distance from the $\overrightarrow{r_A}, \overrightarrow{r_B}$ vectors after applying it to the eigenray calculation (53) from section 3.3 as shown:

$$d_{04} = \sqrt{r_{RSR}^2 - (D_{TX} + D_{RX})^2}$$

$$d_{04} = \sqrt{\left(\left|\overrightarrow{r_{04}}^A\right| + \left|\overrightarrow{r_{04}}^B\right|\right)^2 - (z_0 + z_4)^2} \quad (102)$$

The notation $\overrightarrow{r_{04}}^A$ refers to the transmitted vector from node 0 to node 4, while $\overrightarrow{r_{04}}^B$ refers to the reflected vector from node 0 to node 4. Note, the expression (102) above can also be replaced with the true LOS measurement (76) in section 3.5. This will allow the localization algorithm to use the true LOS estimate if it exists, otherwise the estimated LOS from the expression (102) is used. Hence, we see that the initial position estimate for the node $S_4$ is simply $(d_{04}, 0, z_0 - z_4)$.

To obtain the position estimate for the second node $S_2$ we calculate the LOS estimates $d_{02}$ and $d_{42}$ as done in (102) by replacing the vectors with the $\{\overrightarrow{r_A}, \overrightarrow{r_B}\}_{02}$ to calculate $d_{02}$ and $\{\overrightarrow{r_A}, \overrightarrow{r_B}\}_{42}$ to calculate $d_{42}$. The position of $S_2$ is then obtained by using the law of cosines, which becomes $(x_2, y_2, z_2) = (x_2, y_2, z_0 - z_2)$. So for all other nodes that are connected to $S_0$, SBR-CAL will locate the node by using the law of cosines as shown for node $S_2$. The identified position for all adjacent nodes will be referred to as the initial position matrix denoted as:

$$P_{S_i} = \begin{bmatrix}
x_{i,0} & y_{i,0} & z_{i,0} \\
x_{i,1} & y_{i,1} & z_{i,1} \\
\vdots & \vdots & \vdots \\
x_{i,m-1} & y_{i,m-1} & z_{i,m-1}
\end{bmatrix} \quad (103)$$
6.3.2 Directed Anchor-free Localization: SBR-DAL

In the directed scheme (SBR-DAL), the node $S_i$ that is building its local coordinate system will not require multiple neighbors to be involved in the localization process. Instead we exploit the fact that there will be a list of temporary intersection points upon completion of the node discovery phase. The transmitted node discovery messages will reflection these intersection points unto the node we are trying to locate (i.e. $S_j = S_1$).

![Diagram of Directed Anchor-free Localization](image)

**Figure 6-8:** Standard Triangulation problem with the reference nodes (as shown in the left). On the right we have the equivalent problem using the water surface intersection points as temporary reference nodes.

This is illustrated in Figure 6-8 where we see a standard multilateration problem to the left with multiple reference nodes \{R_1, R_2, R_3, R_4\} whose positions $(X_1, Y_1, Z_1); (X_2, Y_2, Z_2); (X_3, Y_3, Z_3); (X_4, Y_4, Z_4)$ are used to locate a discovered a sensor node $S$ at the unknown position $(U_x, U_y, U_z)$. Thus, similar to [46] we can obtain the position of the unknown sensor node “$S_j$” by solving the following system of equations:
Given that we know the water surface function and have a grid that contains the reflection points to the unknown sensor node for a given maximum transmission angle $\theta_{\text{MAX}}$, this can be translated into a multilateration problem by using the intersection points to the water surface as reference nodes $\{R_1, R_2, R_3, R_4\}$ whereby the water surface is centered around the originating node $(S_0)$. The system of equations will solve for the x-y positions of the unknown node $S_j$ since the z-coordinate of $S_j$ is known from its depth as shown in (79). Thus we can define the range measurements $\{d_1, d_2, d_3, d_4\}$ as $d_i = |\vec{r}_{B_i}|$. The position of the unknown node $(S_j)$ is then obtained via multilateration and is added to the initial position matrix $P_{S_i}$ as shown:

$$
\begin{bmatrix}
(X_1 - U_x)^2 + (Y_1 - U_y)^2 + (Z_1 - U_z)^2 \\
(X_2 - U_x)^2 + (Y_2 - U_y)^2 + (Z_2 - U_z)^2 \\
\vdots \\
(X_n - U_x)^2 + (Y_n - U_y)^2 + (Z_n - U_z)^2
\end{bmatrix} = \begin{bmatrix}
d_1^2 \\
d_2^2 \\
\vdots \\
d_n^2
\end{bmatrix}
$$

(104)

6.3.3 Enhanced-directed Anchor-free Localization: SBR-EAL

We can improve on the SBR-DAL scheme by aiming to solve for the positions of two nodes $S_i$ and $S_j$ concurrently instead of assuming $S_i$ to be at the origin (as was required in both SBR-CAL and SBR-DAL). SBR-EAL only requires the z-coordinate of the temporal intersection point (which is known from node discovery) and the transmission angle $\theta_i$ from node $S_i$ to calculate the x and y coordinates of the intersection point. The system of equations required to determine the positions of nodes $S_i$ and $S_j$ can be represented as:

$$
P_{S_i} = \begin{bmatrix}
0 & 0 & z_0 \\
U_x & U_y & U_z \\
\vdots & \vdots & \vdots \\
x_{n-1} & y_{n-1} & z_{n-1}
\end{bmatrix} = \begin{bmatrix}
x_0 & y_0 & z_0 \\
x_1 & y_1 & z_1 \\
\vdots & \vdots & \vdots \\
x_{n-1} & y_{n-1} & z_{n-1}
\end{bmatrix}
$$
both $S_i$ and $S_j$ will now require four LOS measurements\{\(d_{1i}, d_{1j}, d_{2i}, d_{2j}\}\}. Where the first subscript corresponds to the temporal reference node index and the second subscript is the sensor node index as illustrated in Figure 6-9. Hence, SBR-EAL eliminates the error due to the reflection by simply using the LOS distances from each sensor node to the temporal intersection points.

Figure 6-9: Illustration of the enhanced-directed anchor-free localization that aims to use two reference nodes and the LOS distances to each of the references in the localization, eliminating the error due to reflection.

We can express the system of equations required to obtain the position for the unknown sensor node $S_i = S_1$ as shown:

\[
\begin{bmatrix}
(U_{x0} - x_1)^2 + (U_{y0} - y_1)^2 + (z_0 - z_1)^2 \\
(U_{x1} - x_1)^2 + (U_{y1} - y_1)^2 + (z_1 - z_1)^2 \\
(U_{x0} - x_2)^2 + (U_{y0} - y_2)^2 + (z_0 - z_2)^2 \\
(U_{x1} - x_2)^2 + (U_{y1} - y_2)^2 + (z_1 - z_2)^2
\end{bmatrix} = \begin{bmatrix}
\frac{d_{1i}^2}{d_{1j}^2} \\
\frac{d_{2i}^2}{d_{2j}^2}
\end{bmatrix}
\]

(105)

where the coordinates \((x_1, y_1, z_1)\) and \((x_2, y_2, z_2)\) corresponds to the positions of the temporal reference nodes $R_1$ and $R_2$ respectively. The variables \(\{U_{x0}, U_{y0}\}\) are the
unknown x-y coordinates of the node $S_i = S_0$ while $\{U_{x1}, U_{y1}\}$ are the unknown x-y coordinates of the node $S_j = S_1$. Note that the z-coordinates of both sensor nodes $S_i$ and $S_j$ are known and is simply their depths to the water surface. From the expression above we see that we have four equations and four unknowns, which are sufficient to solve for the x-y coordinates for the two sensor nodes. The LOS range measurements $\{d_{1i}, d_{1j}, d_{2i}, d_{2j}\}$ are simply the magnitude of the $\overrightarrow{r}_A$ vectors as described in (101).

### 6.4 Localization Optimization

In all three variants of SBR-AL we build an initial position estimate matrix $P_{S_i}$ for each sensor node $S_i$. In this phase we are interested in determining the optimized position matrix $P$ that minimizes the least squared localization error $E(P)$ based on the initial position estimates as shown below:

\[
E(P) = \sum_{j=1}^{m-1} \sum_{k=1}^{j-1} \left( \tilde{R}(j, k) - R(j, k) \right)^2
\]

where $R$ is an $(m \times m)$ matrix representing the true inter-node RSR range measurements from the TOA information and $\tilde{R}$ is another $(m \times m)$ matrix representing the estimated RSR range measurement after SBR-AL localization. We can express the matrix $R$ as shown below:

\[
R = \begin{bmatrix}
    r_{00} & r_{01} & \cdots & r_{0n} \\
    r_{10} & r_{11} & \cdots & r_{1n} \\
    \vdots & \vdots & \ddots & \vdots \\
    r_{(m-1)(0)} & r_{(m-1)(1)} & \cdots & r_{(m-1)(m-1)}
\end{bmatrix}
\]

Such that the true inter-node measurement from node $S_i$ to $S_j$ is $r_{ij} = \bar{c} \cdot \tau_{ij} = \bar{c} \cdot \tau_{\text{RSR}}$ and $\tau_{\text{RSR}}$ is the TOA of the RSR signal, we have also defined $\bar{c}$ as the average
sound speed between the nodes $S_i$ and $S_j$. The $\hat{R}$ matrix representing the estimated inter-node RSR range measurement can be determined as shown:

$$
\hat{R} = \begin{bmatrix}
\hat{r}_{00} & \hat{r}_{01} & \ldots & \hat{r}_{0n} \\
\hat{r}_{10} & \hat{r}_{11} & \ldots & \hat{r}_{1n} \\
\ldots & \ldots & \ldots & \ldots \\
\hat{r}_{(m-1)(0)} & \hat{r}_{(m-1)(1)} & \ldots & \hat{r}_{(m-1)(m-1)}
\end{bmatrix}
$$

Moreover, the estimated inter-node RSR range measurement $\hat{r}_{ij}$ between the nodes $S_i$ to $S_j$ is expressed as:

$$
\hat{r}_{ij} = \sqrt{(z_i + z_j)^2 + d_{i,j}^2}
$$

SBR-CAL then uses all available range estimates (the set of P matrices of the $m$ adjacent nodes) to find the most accurate positions of all $m$ by minimizing $E(P)$. However, both DAL and EAL will not require range estimates from neighbors to minimize the $E(P)$. A gradient descent has been proposed as a suitable method for performing the minimization of $E(P)$ [51]. A comparison of the three SBR-AL variants to LPD (a LOS localization scheme) can be found in Table V.

**Table V**: Comparison of traditional LOS schemes to the three SBR-AL variants

<table>
<thead>
<tr>
<th>Localization Method</th>
<th>Range Measurements</th>
<th>Main Techniques</th>
</tr>
</thead>
<tbody>
<tr>
<td>LPD</td>
<td>LOS</td>
<td>Law of Cosines + Multilaterization</td>
</tr>
<tr>
<td>SBR-CAL</td>
<td>LOS + NLOS</td>
<td>Law of Cosines + Multilaterization</td>
</tr>
<tr>
<td>SBR-DAL</td>
<td>NLOS</td>
<td>Multilaterization</td>
</tr>
<tr>
<td>SBR-EAL</td>
<td>NLOS</td>
<td>Multilaterization</td>
</tr>
</tbody>
</table>
6.5 Analytical Evaluation

This subsection evaluates the three SBR-AL variants according to the following criterions; (i) Localization Complexity, (ii) Localization Overhead, and (iii) Sensitivity to mobility. The localization error is evaluated in section 6.6.1, 6.6.2 and 6.6.3.

Localization Complexity: The computation complexity ($CP$) for SBR-AL takes into consideration the different phases of the localization algorithm which are: water surface recovery, node discovery and position estimation. Each variant will require the same computation for the water surface recover and node discovery, however their position estimation complexity will be different. Recovering the sampled water surface function $S[m, n] = S(m\Delta t, n\Delta t)$ has a time complexity of $O(N^2)$, for equal sampling space in both directions $m = n = 0, 1, \ldots N$. On the other hand, performing the node discovery has a complexity of $O(l \cdot M_t) \leq O(\Lambda)$, where $\Lambda$ is the total number of directional antennas available. Hence, we have the following complexities for each of the SBR-AL variants:

$$
CP_{\text{CAL}} = O(N^2 + \Lambda + k)
$$

$$
CP_{\text{DAL}} = O(N^2 + 2\Lambda)
$$

$$
CP_{\text{EAL}} = O(N^2 + 2\Lambda)
$$

$$
k = d + (d - 3)
$$

where $k$ is the number of LOS links to $d$ destinations needed to form a 2D triangle as required for SBR-CAL. Thus, we see that for large network densities, i.e., large node degree $d$, the complexity of SBR-CAL exceeds both DAL and EAL. Both directed schemes (DAL and EAL) have equal complexities since in worst case each requires
up to \( l \cdot M_l \leq \Lambda \) system of equations to solve for the position of the discovered sensor node. Hence, we can express the relationships between the complexities of the SBR-AL variants as shown:

\[
\begin{cases}
  k = \Lambda & CP_{\text{CAL}} = CP_{\text{DAL}} = CP_{\text{EAL}} \\
  k > \Lambda & CP_{\text{CAL}} > (CP_{\text{DAL}} = CP_{\text{EAL}})
\end{cases}
\]

(108)

Although SBR-CAL results in higher localization complexity as shown in (108) for large number of range estimates, it is also more likely to result in higher localization accuracy due to the increase in the amount of range measurements used. Furthermore, it was shown in [44] that a maximum equilateral triangle (MET) resulted in higher localization accuracy than a triangle with a low-aspect ratio (LAR). Thus, the initial position estimates is more likely to form an equilateral triangle when we have more range measurements from neighboring nodes as is common with SBR-CAL.

**Localization Overhead:** The overhead \((OV)\) needed by each sensor node \(S_i\) in each of the SBR-AL variant for a packet size of \((p)\) bytes are determined by the following mathematical relationships:

\[
OV_{\text{CAL}} = k\Lambda p \\
OV_{\text{DAL}} = \Lambda p \\
OV_{\text{EAL}} = 2\Lambda p
\]

The parameter \(k\) is the number of LOS links \((107)\) to \(d\) destinations. We see that DAL requires the least localization overhead since it does not require range measurements from its neighbor, on the other hand EAL requires both communicating nodes to exchange LOS range measurements of the temporal intersection points to the water surface. Hence, we can compare the overhead required for each SBR-AL variant as shown:
Localization Sensitivity to Mobility: We define the localization sensitivity to mobility \((SM)\) as the inaccuracy of the estimated initial positions \((103)\) of a mobile node moving at speed \(u\) after time \(T = CP\) (the computational time) as shown:

\[
SM = \left| 1 - \frac{1}{1 + \Delta} \right|
\]

For:

\[
\Delta = \begin{cases} 
0 & uT \leq 1 \\
uT & uT > 1 
\end{cases}
\]

Such that \((\Delta)\) is the effect on the sensitivity induced by the mobile node. A larger SM means the node’s mobility will have greater impact on the localization accuracy, while smaller SM values leads to minimal effects on the position estimates. Hence, we see that if the algorithm executes before the node moves one unit distance it will have no effect on the localization position estimates, otherwise the localization accuracy becomes affected depending on the computational time of the SBR-AL algorithm. Recall from \((108)\) that CAL takes the longest to execute since it requires range information from its neighbors, while both DAL and EAL have similar complexities. Thus, we can compare the localization sensitivities of each of the variants as shown:

\[
\begin{cases} 
\Delta = 0 & SM_{CAL} = SM_{DAL} = SM_{EAL} \\
\Delta > 0 & SM_{CAL} > (SM_{DAL} = SM_{EAL}) 
\end{cases}
\]
6.6 Numerical Evaluation

The next two sections will report on the performance of the SBR-AL algorithm as we vary the maximum transmission angle ($\theta_{\text{MAX}}$) on the localization error defined in equation (106) and the coverage (the percentage of discovered nodes). We also compare the performance of the each of the SBR-AL variants to the LPD algorithm of [51]. The simulation environment consists of 30 nodes that are randomly placed in an underwater cube with dimensions $50m \times 50m \times 50m$ with a controlled water surface. Every node utilizing any of the SBR-AL variants can either use LOS or RSR links as described in (75), while LPD only have access to LOS links since it utilizes an omni-directional antenna model. Recall from section 6.2 that during the node discovery phase the transmitter will direct its antennas towards the water surface and send DISCOVERY$_{\text{RSR}}$ messages. The receiving node will respond with ACK-DISCOVERY$_{\text{DP}}$ message if it receives the LOS signal as demonstrated in (75), otherwise it will respond with an ACK-DISCOVERY$_{\text{RSR}}$ if it receives the RSR reflected signal. The simulation results currently focus on single-hop localization since SBR-AL does not currently support multi-hop.

The grid cell resolution ($\Delta = \Delta x = \Delta y$) is taken to be $1m \times 1m$ ($\Delta = 1$). The localization error is scaled by the LOS transmission range and the number of nodes $N=30$, i.e., $E(P)/(k_{\text{LOS}} * N^2)$, where $k_{\text{LOS}} = 50m$ for SBR-AL utilizing the directional antenna model (section 1.5) and $k_{\text{LOS}} = 25m$ for LPD utilizing omni-directional antenna model. The plot also show the confidence intervals of the data (deviation) for each value of $\theta_{\text{MAX}}$, where we observe that with a 90% confidence level the ranging localization error stays within 10% of the sample mean. The lengths
of the confidence interval are calculated as $C_l_{\text{length}}(\theta) = (\frac{\sigma(\theta)}{\sqrt{14}}) * 1.65$, such that $\sigma(\theta)$ is the standard deviation for the current water surface for a given transmit angle $\theta$ over fourteen runs. The beam steering angle $\theta_s$ was also varied as we iterated through each grid-map level without considering specific antenna beam patterns. The underwater simulation parameters such as the densities $\{p_w, p_b\}$ and speeds $\{c_w, c_b\}$ were obtained from our previous SBR experiment. We first study the effects on a static water surface where the simulated water surface functions are flat surface, $\sin(X)$, $\sin(2X)$, $\sin(3X)$, $\sin(4X)$ and $\sin(5X)$. We then study the effects on a water surface moving at 10 m/s for the continuous water surface function defined in (85) for a fixed $\theta_{\text{MAX}} = 150^\circ$. The simulation experiments were conducted using MATLAB. In both cases we plot the root-mean-square (rms) height variation $\sigma_{\text{RMS}}$ of the water surface function as defined in (27).

### 6.6.1 Effects of Varying the Transmission Angle

In this subsection, we study the effects of varying the maximum transmission angle on a static water surface. Figure 6-11, Figure 6-12, Figure 6-13 and Figure 6-14 show plots for the localization error for LPD, SBR-CAL, SBR-DAL, and SBR-EAL respectively, were the result indicate that we increase the transmission angle we locate more nodes which decreases the total localization error in all cases. SBR-CAL yields the least error since nodes work together to exchange range measurements that will be used to fine-tune the position estimates. Both DAL and EAL have similar error profiles and outperform LPD since LPD only has access to LOS links through its local one-hop neighbor, while both DAL and EAL have access to LOS and RSR.
links in the node discovery phase. We also note that EAL incurs less localization error than DAL (especially for low frequency water waves) since EAL also tries solving the position of the center node instead of assuming the origin position. From the same plots we see that as we increase the frequency of the sine wave (in all cases) the localization error increases due to the decrease in the number of intersection points. Thus each of the SBR-AL variants will perform well as long as the water surface frequency is low.

Figure 6-15 shows a plot of the localization coverage (the percentage of discovered nodes) for the sine-wave with the lowest frequency were SBR-CAL results in the highest coverage followed by LPD due to their corporative nature. Recall from section 5 that SBR-CAL uses the water surface to discover its neighbors and exchanges the range information to obtain the initial position matrix, this will eventually lead to an increase in the coverage since every node (within the LOS communication radius) will be involved. On the other hand, both SBR-DAL and SBR-EAL attempt to locate one neighbor at a time, which reduces the localization overhead since we now avoid the handshakes between neighbors.
Figure 6-10: RMS height variation

Figure 6-11: LPD localization error

Figure 6-12: SBR-CAL localization error

Figure 6-13: SBR-DAL localization error

Figure 6-14: SBR-EAL localization error

Figure 6-15: Coverage for SIN(X)
6.6.2 Effects of a Mobile Water Surface

In this subsection we study the effects of a mobile water surface presented in section 3.5, i.e. Figure 3-30, on the localization error and coverage while fixing the transmission angle. In this experiment, it is assumed that each node knows \textit{a priori} the time-varying water surface function $S(x, y)$ to be used for node discovery and localization. We report the results after 20 seconds of wave propagation in a 50m x 50m geo-located space such that at time zero the rms wave height variation is approximately flat. In all cases we fix the maximum transmission angle (to $\theta_{\text{MAX}} = 140^\circ$). Figure 6-16 shows the plot for the rms wave height variation for a time period of [0, 20] seconds, such that at time zero the water wave can be perceived as almost flat. We expect that as the water wave completely occupies the geo-located space the rms wave height variation will stabilize as demonstrated when we studied the water frequency (see Figure 6-10). We see that between [0, 6] seconds we have more fluctuations in the height variations since the water wave has not occupied most of the geo-located space due to the existence of flat spots. Hence we see that within that same period of time each of the SBR-AL variants remain stable since we do not have more intersection points to obtain additional range measurements (Figure 6-17 and Figure 6-18). However we notice that LPD’s localization error in Figure 6-17 decreases slightly within that same period since there are less scattering affecting the LOS communication.
After 6 seconds of wave propagation the rms wave height variation begins to stabilize, which means that the water surface now behaves like the multi-frequency component wave (85). We now notice that the error incurred for LPD starts to increase, since there is more scattering due to the rms roughness. However, the error incurred by both SBR-DAL and SBR-EAL begins to decrease (Figure 6-17) since we now have more intersection points that will reflect unto the node that we are trying to locate. SBR-CAL shows a similar increase in error (to LPD) since it only uses one intersection point to the unknown node. Recall from section 6.3.1 that SBR-CAL builds a relative coordinate system by estimating the LOS length from the \( \{\overline{r_A}, \overline{r_B}\} \) vectors, the rough surface will cause the \( \{\overline{r_A}, \overline{r_B}\} \) vectors to vary which will lead to variance in the LOS estimate in (102). On the other hand both SBR-DAL and SBR-EAL exploit the fact that the rough surface will lead to more vectors, which can be used to solve the system of equations and thus reducing the total error. The coverage plot is also shown (see Figure 6-18) which depicts that as the surface becomes rough after 6 seconds of wave propagation we locate more nodes for both SBR-DAL and SBR-EAL.
In all cases, SBR-CAL provides the best coverage (up to 90%) since every node is involved in the localization process. However this comes at the expense of communication overhead.

6.6.3 Prototype-based Evaluation

This section reports the performance of the SBR-AL algorithm with semi-empirical tank measurements. Our experiment setup can be summarized in Figure 6-19, which consists of a water tank, Microsoft 3D Kinect camera, water pump and a computer running Matlab. The water pump will be used to generate water waves, which will be characterized by the tarp that was placed on top of the water. Furthermore, the tarp was placed right below the 3D camera to allow the camera to measure the distance to the tarp over time, which gives us an estimate of the water surface roughness.

![Figure 6-19: Experiment setup with a water tank, 3D camera, wave generator and MATLAB processing shown on the left. The projected view of the 3D Kinect sensor unto the tarp (right image) is used to create a scaled 3D underwater environment.](image)
The 3D camera was then calibrated to only see the tarp which uses 49×37 pixels. The 3D camera will also give us distance to each pixel in mm at a sampling rate of 30Hz. The sampled water surface was then used in the Matlab simulation took the entire 49×37 pixels and formed a 3D underwater environment consisting of a 49m × 37m × 50m cube which is a scaled view of our tank setup, where 50m was the chosen depth of the underwater environment relative to the water surface. We then randomly placed 30 nodes inside the 3D underwater environment and compared the localization performance for all three SBR-AL variants. The grid scale resolution was set to a size of Δ= 1 which assumes a highly directive transducer and the maximum transmission angle was set to θ_{MAX} = 140°. The Ecotech wave pump generator [99] was set to generate a water wave that will oscillate at a certain frequency, due to the size of the water tank and the strength of the pump, the water wave we found that the water wave will begin to oscillate at the specified frequency approximately three seconds after being turned on. This effect is captured in, Figure 6-21, which shows a plot of the RMS roughness of the Kinect sampled water wave over 90 total samples for a run time of approximately 3 seconds. We see that at about the 80th sample, the RMS roughness saturates due to the oscillating frequency of the set wave. Figure 6-20, Figure 6-22, and Figure 6-24 give snapshots of the water surface settling effect, we see from Figure 6-20 that the water surface can be approximated as flat when the pump was initially turned on. Figure 6-21 shows the change in the wave height during the ramping stage of the pump while Figure 6-22 shows the sinusoid water wave after settling at the predefined frequency set by the pump.
Figure 6-20: Sample view of the water surface at frame 5 which shows a relative low change in wave height.

Figure 6-21: Plot of the RMS roughness of the water samples from the 3D Kinect camera over time.

Figure 6-22: Sample view of the water surface at 35 frames into the test. We can now see a significant change in the wave height.

Figure 6-23: Plot showing the localization performance over time. We see that the cooperative approach (SBR-CAL) achieves best performance. The slight increase in slope from frame 80 to 90 is due to the high RMS roughness variance.

Figure 6-24: By the 85th water sample frame, the water surface effectively settled to a continuous sinusoid corresponding to the setting of the wave generator. The RMS roughness of the water wave effectively saturates at this point.

Figure 6-25: Despite the relative swing in the RMS roughness between frames 20 and 60, the localization coverage for all three approaches is within 20% over time.
The localization error performance is given in Figure 6-23, which shows that the cooperative SBR-AL approach achieves the best results over time. This is due to the fact that more nodes are involved in the localization process and will effectively reduce the total error. We also notice that the performance of SBR-EAL is only 20% worse than SBR-CAL due to the added enhancement. The localization coverage also depict promising results, which shows that for a highly directive acoustic transducer with resolution of $\Delta = 1$, we can discover and locate over 80% of nodes over time with the cooperative SBR-CAL approach. Although we did not run the experiment, we have shown in our earlier manuscript [41] that smaller grid resolution (i.e. $\Delta > 1$) will increase the localization error for water waves that is composed of lower frequency contents. Further work needs to be done to study the effects of different grid scale resolution for wider beam directional transducers on the localization performance. In theory, the multimodal directional transducer model described in section 1.5.1 can be designed to achieve higher acoustic directivity by increasing the number of internal electrode sectors to 180 (2° beam) from the original value of 8 (45° beam). The results presented in the paper gives us an approximate upper bound on the localization performance under highly directional communication where we observe that the cooperative SBR-AL approach gives us the best result.

### 6.7 Summary

In this chapter, we have presented the surface-based anchor-free localization (SBR-AL) protocol, which leverages the SBR model and comes in three different variants that can be exploited to achieve the desired performance in terms of coverage and error. The distributed scheme (SBR-CAL) provides the best option in terms of
coverage (up to 90%) while the directed SBR-DAL and SBR-EAL schemes opt to provide moderate coverage (up to 40%) without requiring much network overhead. The simulation results have shown that the SBR-CAL outperforms contemporary LOS-based approaches since it utilizes both LOS and SBR links in the localization process. The simulation experiments show that the frequency of the water surface affects the localization error due to the decrease in the number of reference points obtained for high frequency water waves; hence SBR-AL will perform well for low-frequency water waves. The results also show that both SBR-DAL and SBR-EAL perform well when the water wave is mobile and the rms wave height variation stabilizes, since more intersection points that will reflect unto the destination node will be obtained. Prototype based validation were also carried out to capture the localization performance over time for 3D camera sampled water wave. The results are consistent with expectations showing that at the cooperative SBR-AL approach can locate over 80% of nodes with low error under highly rough water wave heights. This is due to the fact that more range measurements are used to effectively reduce the localization error. Furthermore, since all three localization variants exploit the variability of the water surface, we are able to obtain relatively steady localization performance over time.
Chapter 7

SBR-based Anchor Localization

In the previous chapter, we presented an anchor-free localization scheme, which doesn’t require any reference (or anchor) nodes to form a relative topology. In this chapter, we focus on using reference nodes that have already been located with an appropriate anchor-free localization scheme, i.e. SBR-AL, to locate a lost node that have drifted away from the network. We consider an underwater network that operates in shallow water environment, as depicted in Figure 7-1. The network consists of a base station (BS) node, geographically positioned (GP) nodes, and lost-drifted (LD) nodes. The goal of UNREAL algorithm is to locate all LD nodes, where it is assumed that we will only locate one LD node at a time. The BS node resides close to the water surface while utilizing its antenna array to periodically measure the water surface function as demonstrated in section 3.5 and re-illustrated in Figure 7-1. Both the BS and GP nodes are equipped with directional piezoelectric underwater transducers, similar to the ones mentioned in section 1.5, which allow for both elevation and azimuth angle-of-arrival (AOA) angle measurements. On the other hand, an LD node is only equipped with an Omni-directional transducer.
Figure 7-1: Network model of the proposed scheme. UNREAL uses both LOS and NLOS AOA range information to locate a lost-drifted (LD) node that has drifted away from the network. The water surface function is used for NLOS position estimation.

Figure 7-2: Illustration of an anchor-free localization scheme used to locate the geographical-positioned (GP) nodes. The located BS/GP nodes will then be used as reference nodes to locate an LD node that has drifted away from the network.
Recall from the directed variant of SBR-AL in section 6.3.2, the reflection points unto the water surface (and the BS) can be used as reference points to solve a standard triangulation problem. So given our network model for the UNREAL algorithm in Figure 7-1, the position of the i-th GP node \((GP_{xi}, GP_{yi}, GP_{zi})\) is determined by applying the multilateration expression in eqn. (104) of section 6.3.2 as follows:

\[
\begin{bmatrix}
(X_1 - GP_{xi})^2 + (Y_1 - GP_{yi})^2 + (Z_1 - GP_{zi})^2 \\
(X_2 - GP_{xi})^2 + (Y_2 - GP_{yi})^2 + (Z_2 - GP_{zi})^2 \\
\cdots \\
(X_n - GP_{xi})^2 + (Y_n - GP_{yi})^2 + (Z_n - GP_{zi})^2
\end{bmatrix} = 
\begin{bmatrix}
d_1^2 \\
d_2^2 \\
\vdots \\
d_n^2
\end{bmatrix}
\]  

(112)

where, \((X_i, Y_i, Z_i)\) is the i-th reflection point unto the water surface which is used as a temporary reference point. The expression (112) also requires the ranging information \(d_i = c \cdot \tau_i/2\) from the GP node to each reflection point which is known since each GP node maintains its own water surface function estimate.

Thus, after initial anchor-free localization, the BS and GP nodes will be used as reference points to locate the LD node that has drifted away due to the water current. In this case, we now only rely on the surface function from the BS node. The lost or LD node will send broadcast omni-directional ping messages with a reference packet number which will reach a subset of reference nodes (BS and GP). Each GP node then will classify the link as line-of-sight (LOS) or surface-reflected non-line-of-sight (NLOS). In this phase, the GP nodes will not need to maintain a water surface function since the BS node will assume that responsibility. Each GP node will also
determine the azimuthal (θ) and elevation (φ) AOAs of the received ping messages from the lost node. Depending on θ and φ the GP will classify the link to the LD node as LOS or NLOS, i.e., pointing towards the surface. A collection of the classified link (LOS/NLOS) and AOAs will then be sent to the BS node to be used to centrally locate the drifted node. The calculated node position will then be broadcasted throughout the network until it reaches the LD node. The proposed underwater reflection-enabled acoustic-based localization scheme (UNREAL) is summarized in Figure 7-1. For the sake of clarity, we make the following assumptions: (I) The proposed UNREAL scheme will only locate one LD node at a time; (II) The BS/GP nodes can differentiate between multiple LD nodes from the packet header information in the case that multiple LD nodes want to join the network; (III) The positions of the BS/GP nodes are determined a priori at network setup by applying a suitable anchor-free location schemes, i.e. SBR-AL as discussed in chapter 6, and is maintained throughout the life of the network. In the three sections, we will go over the UNREAL method in detail.

7.1 UNREAL Angle of Arrival Measurements

As mentioned earlier, traditional relative localization algorithms work by using LOS range measurements. To locate the LD node that has drifted away, we propose an AOA-based closed-form solution that aims to use the antenna array of the reference GP/BS nodes in the localization process. According to [54], AOA ranging restricts the source location along the line of bearing (LOB). Hence the location of the source node is obtained from the intersection of multiple LOBs to each reference node. Due to the 3-dimensional nature of the underwater environment, we assume that azimuth
(θ) and elevation (φ) AOA measurements are obtained from up to N reference BS/GP nodes. This information along with the classified link type is sent to the BS. We also assume that the AOAs, i.e. {θᵢ, φᵢ}, measured at each reference node will be subject to errors denoted by {εᵢ, ϵᵢ}. Thus, the measured AOAs between each reference i-th node at known position \( \mathbf{p}_i = [x_i y_i z_i]^T \) and lost node at unknown position \( \mathbf{p} = [x \ y \ z]^T \) can be expressed as shown:

\[
\theta_i = \tan^{-1}\left( \frac{y - y_i}{x - x_i} \right) + \epsilon_i \\
\phi_i = \cos^{-1}\left( \frac{z - z_i}{r_i} \right) + \epsilon_i
\]

(113)

\[
\phi_i = g_i(\mathbf{p}) + \epsilon_i
\]

(114)

where, \( f_i(\mathbf{p}) \) and \( g_i(\mathbf{p}) \) are functions that describe the non-linear relationship between the AOA measurements and the lost node position \( \mathbf{p}, r_i \) is the LOS distance between the reference node and the lost LD node as follows:

\[
r_i = \sqrt{(x - x_i)^2 + (y - y_i)^2 + (z - z_i)^2}
\]

### 7.2 Closed Form Least Squares Position Estimation

Given that we have a collection of \( \mathbf{\theta} = [\theta_1 \theta_2 \ldots \theta_N]^T \) and \( \mathbf{\phi} = [\phi_1 \phi_2 \ldots \phi_N]^T \) measurements that is corrupted with zero-mean uncorrelated Gaussian noise terms \( \mathbf{\epsilon} = [\epsilon_1 \epsilon_2 \ldots \epsilon_N]^T \) and \( \mathbf{e} = [e_1 e_2 \ldots e_N]^T \), we can derive a closed-form solution that uses the antenna array of the reference nodes to locate the nodes. In the
next two subsections, we will go over the proposed closed-form solution for LOS and NLOS positioning.

### 7.2.1 Line-of-sight Localization

![Coordinate System](image)

Figure 7-3: LOS Position estimation illustration showing the collection of angles from each sensor node.

As mentioned earlier, we assume that azimuth and elevation AOA measurements are obtained from all \( N \) reference nodes. This information along with the classified link type is sent to the BS. Assuming LOS link classification in (75) for up to \( N \) reference nodes, i.e. Figure 7-3, we arrange the AOA measurements into two vectors, which results in:

\[
\theta = f(p) + \epsilon
\]  

(115)
\[
\phi = \mathbf{g}(\mathbf{p}) + \mathbf{e}
\]  

(116)

Such that, \( \mathbf{\theta} = [\theta_1 \theta_2 \ldots \theta_N]^T, \mathbf{e} = [\varepsilon_1 \varepsilon_2 \ldots \varepsilon_N]^T \) and \( \phi = [\phi_1 \phi_2 \ldots \phi_N]^T, \mathbf{e} = [\varepsilon_1 \varepsilon_2 \ldots \varepsilon_N]^T \). Thus, estimating both \( \mathbf{f}(\mathbf{p}) \) and \( \mathbf{g}(\mathbf{p}) \) will allow us to solve for the position of the lost node. To determine \( \mathbf{f}(\mathbf{p}) \), we linearize the non-linear AOA function by performing a Jacobian linear map described by \( \mathbf{J}_F(\mathbf{p}) \), which can be used to give us the best linear approximation for \( \mathbf{f}(\mathbf{p}) \) near the reference point \( \mathbf{p}_0 \) as shown:

\[
\mathbf{f}(\mathbf{p}) \approx \mathbf{f}(\mathbf{p}_0) + \mathbf{J}_F(\mathbf{p}_0)(\mathbf{p} - \mathbf{p}_0)
\]  

(117)

The Jacobian matrix of a 3-dimensional spherical coordinate system with:

\[
x = r \sin \phi \cos \theta \quad y = r \sin \phi \sin \theta \quad z = r \cos \phi
\]

Is defined as:

\[
\mathbf{J}_F(\mathbf{p}) = \begin{bmatrix}
\frac{\partial x}{\partial r} & \frac{\partial x}{\partial \phi} & \frac{\partial x}{\partial \theta} \\
\frac{\partial y}{\partial r} & \frac{\partial y}{\partial \phi} & \frac{\partial y}{\partial \theta} \\
\frac{\partial z}{\partial r} & \frac{\partial z}{\partial \phi} & \frac{\partial z}{\partial \theta}
\end{bmatrix}
\]

(118)

With unit vectors:

\[
\mathbf{v}_1 = \begin{bmatrix}
\cos \phi \cos \theta & r \cos \phi \cos \theta & -r \sin \phi \sin \theta \\
\sin \phi \sin \theta & r \cos \phi \sin \theta & r \sin \phi \cos \theta \\
\cos \phi & -r \sin \phi & 0
\end{bmatrix}^T
\]  

(119)

\[
\mathbf{v}_2 = \begin{bmatrix}
\cos \phi \cos \theta \cos \phi \sin \theta & -\sin \phi \\
-\sin \phi \sin \theta & \sin \phi \cos \theta \cos \phi \sin \theta & 0
\end{bmatrix}^T
\]  

(120)
If we rearrange the system of equations corresponding to the linear estimation and select the second unit vector needed to approximate \( f(p) \), we get the following linear system:

\[
b(\phi, \theta) = H(\phi, \theta) \cdot p
\]  

(121)

where,

\[
H(\phi, \theta) = \begin{bmatrix}
-\sin \phi_1 \sin \theta_1 & \sin \phi_1 \cos \theta_1 & 0 \\
& \ldots & \ldots \\
-\sin \phi_N \sin \theta_N & \sin \phi_N \cos \theta_N & 0
\end{bmatrix}
\]

And

\[
b(\phi, \theta) = \begin{bmatrix}
-x_1 \sin \phi_1 \sin \theta_1 + y_1 \cos \phi_1 \sin \theta_1 - z_1 0 \\
& \ldots \\
-x_N \sin \phi_N \sin \theta_N + y_N \sin \phi_N \cos \theta_N - z_N 0
\end{bmatrix}
\]

Hence, we estimate the \( (x, y) \) position of the lost node \( p \approx \tilde{p} = [x \ y \ 0]^T \) by computing the least squared solution to (121) as shown:

\[
\tilde{p}_{\text{LOS}} = \left( H(\phi, \theta)^T H(\phi, \theta) \right)^{-1} H(\phi, \theta)^T b(\phi, \theta)
\]  

(122)

The \( z \)-coordinate of the lost node can be solved by substituting the solution in (122) to \( r_i \) and into (116) which gives us an approximation for \( g(p) \). We then solve the resulting quadratic equation for the unknown \( z \)-coordinate resulting in:

\[
z = \frac{-2z_i \pm \sqrt{(2z_i)^2 - 4(z_i^2 - \beta_i)}}{2}
\]  

(123)

For:

\[
\beta_i = \frac{((x - x_i)^2 + (y - y_i)^2) \cos^2 \phi_i}{1 - \cos^2 \phi_i}
\]  

(124)
7.2.2 Non-line-of-sight Localization

Due to the lower transmission loss of water surface links over bottom links (see Figure 3-3 in section 3.2.1) and the variability of the water surface, we only focus on NLOS positioning for surface-reflected links. Assuming that the links for a set of BS/GP nodes has been classified as surface-reflected NLOS by selecting option II in (75), the goal of the location algorithm will be to estimate the position of the LD node by only using the AOA measurements.

Since the LD node is equipped with an omni-directional transducer, we will have multiple reflection points that correspond to one broadcast signal. Hence, we will need to determine the transmitted vector for each reflection point as illustrated in Figure 7-4. This will be used in our closed-form expression to solve for the position of the LD node. We can express the spherical unit vector ($\vec{v}_i$) of the received reflected
signal for the i-th reference node by relation to the Cartesian coordinate system as shown:

$$\vec{v}_i = \begin{bmatrix} \hat{\rho} \\ \hat{\phi} \\ \hat{\theta} \end{bmatrix} = \begin{bmatrix} \sin \phi_i \cos \theta_i & \sin \phi_i \sin \theta_i & \cos \phi_i \\ \cos \phi_i \cos \theta_i & \cos \phi_i \sin \theta_i & -\sin \phi_i \\ -\sin \phi_i & \cos \theta_i & 0 \end{bmatrix} \begin{bmatrix} \hat{x} \\ \hat{y} \\ \hat{z} \end{bmatrix}$$  \hspace{1cm} (125)

The reflected ray ($\bar{r}_i$) for each reference node can then be determined by the following expression:

$$\bar{r}_i = p_i + t\vec{v}_i$$  \hspace{1cm} (126)

where, $p_i$ is the known position i-th reference node, $t$ is the ray parameter which measures the distance along the ray and $\vec{v}_i$ is the direction vector. Also, note that we are using the arrow ($\vec{}$) to denote the vectors that interact with tangent plane $T(v)$ of the known surface function for $v = (x, y, z)$. We can compute the ray parameter $t$ for the intersection point of $\bar{r}_i^2(t)$ to the tangent plane as:

$$T(\bar{r}_i^2) = 0$$

$$t = \frac{(R_i - p_i) \cdot \vec{n}}{\vec{v}_i \cdot \vec{n}}$$  \hspace{1cm} (127)

Such that $R_i$ is the intersection/reflection point on the tangent plane that satisfies the equation and $\vec{n}$ is the normal vector at the intersection point. The normal vector to the known water surface function can be determined by picking out three points $(P_1, P_2, P_3)$ that lie on the tangent plane on the water surface as shown:

$$\vec{n} = (P_1 - P_2) \otimes (P_1 - P_3)$$  \hspace{1cm} (128)
where $\otimes$ is the cross product operator. We then calculate the transmitted reflected vector $\vec{t}_i = [x_{ti} y_{ti} z_{ti}]^T$ at the intersection normal vector as follows:

$$\vec{t}_i = \vec{r}_i / |\vec{r}_i|$$

We can now approximate our NLOS AOA ranging from the reflection point unto the LD node as:

$$\theta_{Ri}(\text{azimuth}) = \tan^{-1} \left( \frac{y_{ti}}{x_{ti}} \right)$$

$$\phi_{Ri}(\text{elevation}) = \cos^{-1} \left( \frac{z_{ti}}{|\vec{t}_i|} \right)$$

where $|\vec{t}_i|$ is the magnitude of the transmitted reflected vector. Hence, if we have a collection of $\theta_R = [\theta_{R1} \theta_{R2} ... \theta_{RN}]^T$ and $\phi_R = [\phi_{R1} \phi_{R2} ... \phi_{RN}]^T$ angles, we can estimate the $(x, y)$ position of the lost node $\vec{p} \approx \vec{p} = [x \ y \ ?]^T$ by utilizing the closed-form least squares expression derived earlier as shown:

$$\tilde{\vec{p}}_{\text{NLOS}} = \left( H(\phi_R, \theta_R)^T H(\phi_R, \theta_R) \right)^{-1} H(\phi_R, \theta_R)^T b(\phi_R, \theta_R)$$  (132)
In a similar fashion to LOS positioning, the z-coordinate of the lost node is determined by utilizing the expression \((123)\) and substituting a single reference reflected elevation angle \(\phi_{ri}\) into \((124)\) for \(\beta_i\).

### 7.3 Prototype-based Evaluation

![Figure 7-5: Similar experiment setup used in validating SBR-AL was used for this experiment. As with before, the projected view of the 3D Kinect sensor unto the tarp is used to create a scaled 3D underwater environment.](image)

In this section, we validate the performance of the localization algorithm for both LOS and NLOS AOA ranging by using the same prototype setup used in validating SBR-CAL in chapter 6. The setup can be summarized in Figure 7-5, which consists of a water tank, Microsoft 3D Kinect camera, water pump and a computer running Matlab. The water pump will be used to generate water waves, which will be characterized by the tarp that was placed on top of the water. Furthermore, the tarp
was placed right below the 3D camera to allow the camera to measure the distance to the tarp over time, which gives us an estimate of the water surface roughness. We define the root-mean-squared (RMS) roughness $\sigma_{RMS}$ of the 2D sampled water surface as follows:

$$\sigma_{RMS} = \sqrt{\frac{1}{XY} \sum_{i=1}^{X} \sum_{j=1}^{Y} \sigma_{ij}^2(t)}$$

Such that $\sigma_{ij}(t) = (h_{ij}(t) - \bar{h})$ and $h_{ij}(t)$ is the water surface height for the $i^{th}$ and $j^{th}$ sample relative to the mean value of the rough surface height $\bar{h}$. The 3D camera was then calibrated to only see the tarp which uses $49 \times 37$ pixels. The 3D camera will also give us distance to each pixel in mm at a sampling rate of $30Hz$. The sampled water surface was then used in the Matlab simulation took the entire $49 \times 37$ pixels and formed a 3D underwater environment consisting of a $49m \times 37m \times 50m$ cube which is a scaled view of our tank setup, where 50m was the chosen depth of the underwater environment relative to the water surface.

We then simulated a network with one lost node and up to eight reference nodes, which includes both BS and GP nodes. All the nodes where randomly placed inside the defined 3D cube. Each node had the same line-of-sight (LOS) transmission range $k_{LOS}$, which was used to determine connectivity between nodes. The lost node will then broadcast a message, which will reach a subset of the reference nodes either through LOS or surface-reflected NLOS. In both LOS and NLOS case, the azimuth $\theta$ and elevation $\phi$ AOAs will be measured by each reference node, which will be corrupted by errors with a known variance. We then evaluate the LOS, NLOS and
combined LOS/NLOS localization performance by defining the least squared error function $E(P)$ as shown:

$$E(P) = \sum_{i=1}^{M} (\tilde{p}_i - p_i)^2$$  \hspace{1cm} (134)

where, $p = [p_1 p_2 ... p_M]^T$ is a vector of the true lost node position for $M$ simulation runs and $\tilde{p} = [\tilde{p}_1 \tilde{p}_2 ... \tilde{p}_M]^T$ is another vector of the estimated lost node position after applying the closed-form regression analysis defined in (122) and (132).

Figure 7-6: Localization performance as we vary the AOA variance for LOS operation. The variance for both azimuth and elevation AOAs are assumed to be the same. Results depict low localization error when we have enough reference nodes.

Figure 7-7: Localization performance as we vary the AOA variance for NLOS operation. The result depicts an improved performance over LOS since the number of reflection points exceeds the true number of reference nodes.

Figure 7-6 shows the observed localization error as we vary the AOA error variance for an average of eighty runs. For this test, we assume that both the azimuth and elevation AOAs will experience the same error variance. We see from Figure 7-6 that as we increase the variance, the localization error generally increases which is expected, since errors induced in both the azimuth $\theta$ and elevation $\phi$ AOAs will
affect the closed-form estimation in (122). On the other hand, we notice that as we obtain more reference nodes, the localization error will decrease despite high AOA variance. This is because we now have more data points, which will be used to increase the position accuracy. Furthermore we note that the localization performance with 6, 9, and 10 reference nodes are relatively close to each other, this is mainly due to the chosen cubic dimensions of 49m × 37m × 50m which limits the number of unique references that can be used for localization. Due to space constraints, we were not able to show results for larger underwater environments. Nevertheless, the results depict a linear improvement in the localization error.

The NLOS localization performance can be seen in Figure 7-7 for an AOA variance range of 0 to 20. Similar to the LOS performance, we note that as we increase the number of reference nodes the localization error decreases. More interestingly, we note that the NLOS error for 6, 9 and 12 reference nodes outperforms that of the LOS. The increased number of reference points possible for NLOS than for LOS explains this phenomenon. Recall from Figure 5 that during NLOS positioning, the acoustic signal from the LD node will reflect unto the water surface at multiple intersection points. This means that the set of intersection points \( \{R_1, R_2, ..., R_r\} \) will be larger than the set of true reference/sensor nodes \( \{S_1, S_2, ..., S_s\} \) especially when the water surface is not flat (i.e. rough). Thus the NLOS localization (132) will outperform the LOS when we have more reflection points than true reference/sensor nodes.
Figure 7-8: Combined localization error for varying number of reference nodes.

Figure 7-9: Localization error projection over time. The left plot is the sampled water surface obtained from the 3D camera, the top-right plot shows the projected effects of the water surface roughness on the localization error.
Figure 7-8 gives the combined LOS/NLOS localization error as we increase the AOA variance averaged over three runs. The plot essentially shows that when combining LOS and NLOS, the localization performance will be bounded by the NLOS especially the water surface is rough. In other words, the multipath AOA variation of the acoustic channel will dominate any variation seen in the direct path. Another interesting study would be to see the effects of the water surface roughness on the localization error by utilizing the sampled water surface function obtained from the 3D camera. Figure 7-9 gives an estimated localization performance of the NLOS error for 9 and 12 reference nodes. The error assumes that the AOA variance is proportional to the water surface roughness. The left portion gives the water surface sample from the 3D camera for the 10th frame, the top right plot gives the water surface roughness over time, which starts of relatively mild and contains two rough peaks at frames 32 and 64. We see that the localization error remains sturdy over time except at those peaks, which is a result of the variability in the localization performance at those frames.

7.4 Summary

In this chapter, we have presented a novel underwater signal reflection-enabled acoustic-based localization scheme (UNREAL) that utilizes both line-of-sight (LOS) and surface-reflected non-line-of-sight (NLOS) links to locate a lost node that has drifted away from the network. The reference nodes consist of base-stations and geographical-positioned nodes that utilize directional acoustic transducers to determine the angle of arrivals (AOA) to the lost node. The AOAs consist of azimuth and elevation pairs that can either be LOS or surface-reflected NLOS. A closed-form
least-squares solution was then used to locate the lost node. Simulation experiments were carried out by using the projection of a 3D camera to create a 3D underwater networking environment. Results show promising localization performance for both LOS and NLOS.
Chapter 8

Reflection-enabled Directional MAC Protocol

The last two chapters were focused on locating nodes in an UWAN which is needed for proper ad-hoc formation. However, in order for nodes to efficiently share the acoustic channel, medium access arbitration is required. Recall from the networking model in section 1.2 that utilizing reflected links with directional antennas will greatly increase the number of simultaneous transmissions, this is re-illustrated in Figure 8-1.

*Figure 8-1: Enabling reflections while using directional antennas yields an increase in simultaneous transmissions. Here $k_{LOS}$ is the line-of-sight (LOS) transmission range of each node.*
To take advantage of this, we have developed a novel MAC protocol that takes advantage of the multipath reflections in the underwater environment. In this chapter, we introduce and analyze our proposed reflection enabled directional medium access control (RED-MAC) protocol. RED-MAC only requires one switch-beamed antenna which can be partitioned to form segmented directional antennas, an example of such an antenna is the multimodal piezoelectric transducer described in section 1.5.1. Moreover, our proposed RED-MAC protocol will not be dependent on the LOS path but will combine both LOS and NLOS to efficiently share the acoustic channel.

In traditional directional medium access (D-MAC) protocols, nodes can only points their antennas towards the known position of the receiver, consequently traditional D-MAC schemes cannot recover if an obstacle is blocking the path of the signal. However, with RED-MAC nodes will be able to determine if an obstacle is blocking the LOS link and switch to the best available directional antenna that will be reflected from the water surface or bottom. RED-MAC is broken up into two phases namely, (I) node discovery (II) and directional antenna allocation (DAA) for data transfer. In node discovery, each node will use the water surface (or bottom) to locate its one-hop neighbors; this is accomplished by using a tone-induced directional carrier sensing protocol which is described below. Each node will be aware of its position and where its neighbors are by applying an appropriate localization algorithm such as the SBR-AL described in chapter 6 or the UNREAL algorithm described in chapter 7. The DAA phase is to determine the best way to allocate the directional antenna for data transfers. A high level overview of the RED-MAC transmitter operation is shown in Figure 8-2.
8.1 Node Discovery

To access the medium during this phase, each node will adhere to the following tone-induced directional carrier sensing protocol. The protocol starts by requiring each node to sense each directional antenna before sending tone-discovery (TD) messages to locate its one-hop neighbors. The right block in Figure 8-2 describes the transmitter operation during the node discovery phase. A node will start by sensing the sectors of the antenna (those pointing towards the water surface) for a period of $t_{\text{SENSE}} = 2 * t_{\text{max}}$, where $t_{\text{max}} = k_{\text{LOS}}/c_w$ is the maximum one-way propagation delay.
between any two nodes within the specified transmission range $k_{LOS}$. Within the $t_{SENSE}$ period, if the node detects another tone or a data transfer on the specified directional antenna, the node will mark that antenna as blocked for a period of $t_{DATA}(d_i)$. The transmitter will then perform an active node discovery by sending TD pings on each of the free directional antennas, and listening for a tone-ack (TA) on each of the directional antennas directed towards the water surface (or water bottom).

Due to the multipath nature of the underwater environment, the node will need to filter out all other signals that are reflected multiple times as defined in (75) of section 3.4. Following the TA message, there will be the data payload, which will contain the position, the movement direction, and the movement speed of the receiver on that directional antenna ($d_i$). The transmitter will use this information to change its antenna based on the movement of the receiver.

After the transmitter has received a TA message on any of its directional antennas, the node will then complete node discovery and will move to the directional antenna allocation (DAA) phase for data transfer. Upon acknowledging the discovery tone, the receiver switches to the data transfer phase. The receiver also maintains a Directional Network Allocation Vector (DNAV) table which contains information about the clear-to-send (CTS) and data transmission time of each directional antenna, the usage of the DNAV table is common in directional MAC protocols [64],[65].
8.2 Directional Antenna Allocation (DAA) For Data Transfer

After a node has discovered its one-hop neighbors, the next step will be to determine the best way to allocate its directional antennas to fully utilize the available spatial spectrum. The left block in Figure 8-2 describes the DAA phase of RED-MAC. If a transmitter has data to send to a known receiver, it will re-calculate the estimated position of the receiver if the receiver is mobile; otherwise it will simply use the last known position. The transmitter will then sense the antenna that is directed towards the receiver to see if it is blocked. This done by checking the DNAV table, which contains the heard CTS and TD messages ongoing on the blocked antennas. The receiver will respond to RTS by sending CTS on all available antennas, i.e., those, which do not interfere with ongoing communications.

Figure 8-3: A 2-dimensional example that demonstrates both phases of the proposed RED-MAC protocol. Node B wants to send data to node C while A tries to discover its neighbors, DNAV is shown for node B.
Figure 8-3 illustrates a 2D scenario whereby the node $B$ wants to send data to the node $C$. Nodes $B$, $C$, $I$, $H$ and $J$ are already discovered and node $A$ tries to join the network by sending a discovery tone to $B$. Within the same period, nodes $J$ and $H$ undergo a data transfer handshaking process, where node $J$ sends RTS to the known node $H$ and node $H$ will send a CTS on all un-blocked directional antennas. Since node $I$ moved and blocked the LOS path between nodes $B$ and $C$, for transmitter $B$ the next best directional antenna to $C$ can only be antenna 2 (since antenna 8 is also blocked), which is the antenna that will reflect unto the water surface. The transmitter $B$ will be able to determine that the node $I$ is blocking its path since it knows the movement direction and speed of node $I$. After the transmitter selects the best directional antenna (in this example antenna 2 will reflect unto node $C$), it sends the RTS on that antenna and waits for $t_{\text{SENSE}} = 2 \times t_{ij} = 2 \times r_{ij}/\bar{c}_{ij}$ period to receive the CTS message from node $C$ in order to send the data. The surface-reflected distance $r_{ij}$ is derived from (53), while the distance $d_{ij}$ is the LOS distance between the nodes $i$ and $j$ (i.e. $d_{BC}$) with depths $\{z_i, z_j\}$. RED-MAC also employs back-off mechanism (see Figure 8-2) after each successful data transfer to promote fairness on the acoustic channel.

RED-MAC has many advantages. First, it strives to maximize spatial efficiency of underwater medium by considering both reflected and LOS paths in an integrated manner when allocating the directional antennas. Second, it alleviates the hidden terminal problem that is common in directional MAC protocols since TD and the CTS messages are sent using all available directional antennas. Third, RED-MAC
leverages the node’s knowledge about the motion pattern of neighbors and enables the rediscovery of a node that loses LOS link due to unexpected motion or drift.

8.3 Performance Evaluation

In this section we will validate the performance of the RED-MAC protocol and compare it to traditional UWMAC protocols. We have adopted the network simulator of [63] to study the performance of RED-MAC and added support for both directional and omni-directional antennas. STLohi [63] and slotted-ALOHA (SALOHA) are used as baseline for comparison. In the simulation only RED-MAC utilizes the directional antenna model while the baseline protocols use omni-directional antennas. The simulation parameters are described in Table IV. Each RED-MAC node will utilize directional antennas with the option of enabling reflections (SBR). The network traffic is controlled by adjusting the network load (packets/sec). The mobility is controlled by adjusting the node speed (m/s) such that nodes with even and odd IDs will move in the x and y directions respectively. We randomly place N nodes in a 300x400 area (water depth of 300 m) with a flat-water surface and bottom. Each node randomly selects a unique destination out of the N-1 remaining nodes. We then run each simulation for 100 seconds and repeat it 300 times to study the effects of varying the simulation parameters (N, node speed, network load) on the network throughput. Finally, we report the results where we observe that within a 95% confidence level the network throughput (bits/sec) stays within 5% of the sample mean.
Figure 8-4: A higher network density boosts the throughput achieved by RED-MAC, since multiple transmissions can occur within the same communication range.

Figure 8-5: We see a stable throughput performance for low network mobility, however higher network mobility leads to packet loss.

Figure 8-6: While each studied MAC protocol maintains a steady throughput as the mean packet load increases, RED-MAC outperforms traditional UWMAC protocols by up to 56%.
Figure 8-4, Figure 8-5 and Figure 8-6 depict the performance of the RED-MAC algorithm under varying network density and mobility. In Figure 8-4, we are shown a plot of the network throughput for four protocols (RED-MAC-no-SBR, RED-MAC-SBR, STLohi, and SALOHA), both STLohi and slotted-ALOHA are reservation-based protocols. From the plot we see that even without enabling reflections (i.e. RED-MAC-no-SBR) RED-MAC outperforms the other protocols as the network density increases by achieving up to 46% increase in throughput. This is due to the increase in the number of transmissions and successful receptions from the spatial efficiency of RED-MAC. With SBR we notice an additional 10% increase in throughput, since nodes can now utilize reflected links when the LOS links are blocked. We also notice that RED-MAC saturates around a network density of sixteen nodes, yielding a throughput of 1600 bps when SBR is employed, SALOHA saturates at 17 nodes while STLohi saturates much quicker right around 2 nodes, this is due to the conservative scheduling nature of STLohi. With SBR, RED-MAC achieves up to 56% increase in network throughput over both reservation-based protocols, since both STLohi and SALOHA saturate to a throughput of 750 bps.

In Figure 8-5, we show a plot which varies the node speed when some of the nodes in the network are mobile for a network density of N=20 nodes. We see that for low mobility the network throughput remains stable when the number of mobile nodes is low with a slight increase for higher mobile nodes; this is because the transmitting node will try to maintain a connection with the mobile receiver by utilizing both reflected and LOS links. From the same plot, we see that as we increase the number of mobile nodes the network throughput increases; this is mainly due to
the decrease in the number of collisions achieved by the increased node mobility. Therefore, we see that RED-MAC maintains a stable throughput performance for moderate node speeds (i.e. drifts). However, at high node speeds the throughput becomes less stable due to packet loss.

Finally, Figure 8-6 shows that as we increase the mean network load the network throughput remains stable for each protocol. Most importantly we notice up to a 56% increase in throughput that RED-MAC achieves over traditional omni-directional UW-ASN MAC protocols.

8.4 Summary

This chapter presented and analyzed a directional medium access protocol for UWAN. The proposed reflection-enabled directional MAC (RED-MAC) protocol utilizes a switch-beamed directional antenna and employs the surface-based reflection (SBR) recovery mechanism. This allows each node to determine if an obstacle is blocking the LOS path before switching to the next best reflected link. The simulation results demonstrate the effectiveness of the RED-MAC protocol, which achieves up to 56% increase in network throughput in comparison to traditional omni-directional MAC protocols. As a result, RED-MAC provides a spatial efficient and mobility tolerant medium access arbitration for underwater sensor networks.
Chapter 9

Reflection-enabled Geographical Routing

As alluded to in our ad-hoc networking model described in chapter 1 and re-illustrated in Figure 9-1, the ultimate goal of this dissertation is for sensor nodes to utilize line-of-sight (LOS) and surface-reflected non-line-of-sight (NLOS) links to establish the best route to the desired destination.

Figure 9-1: Underwater ad-hoc model depicting network nodes utilizing LOS and NLOS links to establish best routes to a destination (or group of destinations, i.e. geocast).

To exploit the SBR-based communication scheme described in chapter 3 while investigating multi-hop routes with reflected links, we have developed a novel
Geocast Optimized Reflection-enabled Routing Immune to Link Ambiguity (GORRILA) algorithm. GORRILA is a geographical routing scheme that not only relies on the LOS link between one-hop neighbors when establishing routes, but considers other reflected paths while routing packets to neighbors. GORRILA factors in two NLOS links (or eigenrays), which are the refracted-surface-reflected (RSR) and refracted-bottom-reflected (RBR) eigenrays. Utilizing RSR or RBR links enables GORRILA to be robust to LOS link failures due to high network traffic or blocked paths that cause a packet to be trapped in a local minimum (i.e. voids), which has plagued most published geo-routing protocols.

9.1 Algorithm Overview

GORRILA is composed of two stages. In the first stage the algorithm is executed in the source node $S_i$ and in the second stage it is executed by every node along the path to the destination. In stage 1, the source node performs a k-hop node discovery to obtain the positions and movement information of all k-hops neighbors. The anchor-free localization scheme (SBR-AL) described in chapter 6 or the anchor-based localization scheme (UNREAL) in chapter 7 can be utilized to obtain the position and movement information of all k-hops neighbors. After obtaining the position information, the node will then determine the geocast region $R$ (cubic boundary) centered on the destination node $D_j$, based on the node degree and movement information (speed and direction) of the destination. In stage 2, the packet gets routed to $R$ using an optimized unicast routing mechanism described in the next section of this chapter. The unicast route will be optimized for maximum network throughput. Once inside the geocast region, the packet is then broadcasted to all nodes within that
region until it gets to the destination mode $D_j$. The next section will go over an optimized method for selecting the best unicast route to the geographical region $R$.

9.2 Unicast Routing with Localized Delaunay Graph

Given that we know the position of nodes $k$-hops away, one can construct a planar graph from the position information to be used for unicast routing. A planar graph is a graph whereby no two edges intersect each other except at a vertex (or end point). The construction of a planar graph is important, especially when face routing is needed to recover from voids. Periodically, each node will need to construct a planar graph from the $k$-hop location information to be used in the GORRILA routing protocol. In 3D, the planar graph is constructed through Delaunay tessellation, denoted by $\text{Det}(V)$, which determines the set of tetrahedrons such that none of the points (or vertices) in $V$ are contained in any of the circum-spheres of the tetrahedrons.

To simplify the presentation, our analysis focuses on the 2D planar graph representation, namely $\text{Del}(V)$, where we have adopted the divide-and-conquer approach [85] to construct the $\text{Del}(V)$ subgraph in $O(N \log N)$ time. Although the $\text{Del}(V)$ triangulation is a planar graph, a major drawback in applying it in an ad hoc network is that it cannot be constructed locally since some edges of the Delaunay triangulation could exceed the transmission range. We overcome this by defining a new graph structure namely a $k$-localized Delaunay graph ($\text{LDeL}^k$).

When creating the $\text{LDeL}(V)$ graph from the location information of the nodes $k$-hops away, the node $S_i$ will also need to know of any obstacles blocking the LOS
links and adjust the LDel(V) graph accordingly. We refer to the inclusion of reflection points in the localized Delaunay triangulation as the LDel_R(V) planar graph. Recall from Figure 9-1 the LOS links may be blocked due to an obstacle or an unknown node, to account for this the node S_i building the LDel_R(V) graph will determine which LOS links are blocked from the information obtained from network-discovery (stage 1). Moreover, the blocked antennas/links can be inferred from the DNAV table which will be created in the MAC layer as described in our RED-MAC protocol in section 8.2 (see bottom of Figure 8-3). The node S_i will then calculate reflection points to the water surface and bottom to be used as temporary reference vertices in the LDel_R(V) graph.

After creating the planar graph, each routing node R_i will utilize the saturation network throughput (91) derived in section 5.1 for shallow water environments before selecting the next-hop node H_j that maximizes the localized saturation throughput as shown:

$$H_j = \max(TH(H_1), TH(H_2), \ldots TH(H_N))$$  \hspace{1cm} (135)

Hence, the optimized unicast route towards the desired geographical region is the route that satisfies (135). A detailed pseudo-code of the GORRILA algorithm can be found in Appendix D of this dissertation.
Figure 9-2: GORRILA illustration, showing the calculated reflection points between two connecting sensor nodes \( \{S_i, S_j\} \). The unicast route is shown, which maximizes the throughput by minimizing the number of contenders along the path.

Figure 9-3: Re-illustration from section 5.3 showing the effects of the number of contenders on the capture probability. The reflection point \( R_{69} \) in the illustration of Figure 9-2 was chosen to maximize the capture probability.

Figure 9-2 gives an illustration of the GORRILA algorithm which shows the construction of the localized Delaunay graph with reflected links. In this example, the source \( S_1 \) selects the optimized route to the destination node \( D_9 \) in the geocast region of just one node. The reflection point \( R_{69} \) was selected to minimize the CSMA/CA contention between nodes \( (S_6, S_7 \text{ and } S_8) \) while maximizing the network throughput. Recall from section 5.3 that minimizing the number of contenders for each link (LOS, RSR or RBR) will maximize the capture probability, which is the probability that the received signal power of the unicast frame exceeds the interference power of the frames from other contending nodes. This effect is re-illustrated in Figure 9-3, which show that increasing the number of contenders will decrease the capture probability.
9.3 Algorithm Evaluation

In this section we validate the performance of the GORRILA routing algorithm. The simulation experiments were conducted using MATLAB with the underwater and PHY/MAC parameters described in Table IV. The underwater environment is represented as a cube with dimensions of 200m x 200m x 200m, where the water bottom is modeled as a rough surface with a silt-like material (i.e. \( p_b/p_w = 1.7 \)). The water surface is also modeled as a rough surface with \( \sigma_{\text{RMS}} \) approximately 0.5. We then randomly place \( N \) nodes in the underwater environment and up to \( B = 40 \) obstacles that will block the LOS links between some nodes. Thus, some nodes will have LOS links available while other nodes will need to use NLOS links (i.e. RSR or RBR). Results are shown for both omni-directional and directional antennas. We then compare the network the throughput performance to the well-known greedy perimeter stateless routing (GPSR)[86], where we focus on the unicast performance with stationary nodes. Finally, we report the results where we observe that within a 90% confidence level the network saturation throughput stays within 10% of the sample mean. Other metrics, e.g. delay and energy, were considered but could not be included due to space constraints.

Figure 9-4 shows a plot of the throughput per-hop of the GORRILA algorithm for a network size of \( N = 20 \), from source \( S_1 \) to destination \( D_2 \), where we notice that utilizing directional antennas increases the throughput-per-hop due to an increase in the signal-to-interference-ratio (SIR). More importantly, we see that regardless of the antenna variant, GORRILA maintains a steady throughput at each hop due to its throughput optimization process. Figure 9-5 shows the performance of the GORRILA
algorithm in comparison with the GPSR algorithm. We see that GORRILA maintains a higher network throughput than GPSR, especially when the network density is high \((N > 20)\). At higher network densities the probability of collisions increases, leading to lower network throughput when greedy routing is employed which is not the case with GORRILA. Furthermore, the inclusion of reflected links will provide an optional hop so long as the reflected link (RSR or RBR) will sustain the LOS throughput as pointed out in section 5.4. Lastly, we see that when utilizing directional antennas the GORRILA algorithm far exceeds the greedy algorithm, which is expected.

![Figure 9-4: 3D plot of unicast route (red-line) with the throughput-per-hop.](image)

![Figure 9-5: Effect of increasing the network density on the normalized throughput](image)

### 9.4 Summary

In this chapter, we have introduced a novel geographical routing algorithm for UW-ASN that is not dependent on the line-of-sight (LOS), but utilizes reflected links in the routing process. The proposed geographical optimized reflection-enabled routing immune to link ambiguity (GORRILA) algorithm aims to establish the best stable
route from a source to a destination node. The route is also optimized to achieve the maximum network throughput. Furthermore, GORRILA can also utilize directional antennas, which boost the network throughput. Results show that the GORRILA algorithm outperforms the traditional greedy algorithm since it maintains a high network throughput at each hop during the routing process. Thus, GORRILA can be used to sustain the desired quality-of-service (QoS), i.e. network throughput.
Chapter 10

Summary and Future Work

This chapter concludes the thesis with a summary of accomplishments and recommendations for future work relating to the research area. The first section highlights the research contributions towards the goal of establishing a novel architecture design for underwater acoustic networking with reflected links. The second section recommends areas that could be extended for future work.

10.1 Summary of Contributions

This dissertation presented a novel architecture design for establishing underwater acoustic networks with reflected links. We have gone over the completed work, which builds upon the proposed surface-based-reflection (SBR) scheme. The SBR scheme exploits the multipath nature of the acoustic channel by recovering both LOS and NLOS links. This is accomplished through the usage of directional antennas to either direct the signals energy towards the next-hop node (LOS) or to the water surface/bottom to be reflected onto the next-hop node (NLOS). Furthermore, a homomorphic deconvolution process is used to recover the channel’s impulse response, which is further used to determine the directional link type (LOS or NLOS).

We have also adopted a feasible directional transducer concept, which generates both directional and omni-directional beam patterns by combining the fundamental
vibration modes of a cylindrical acoustic radiator. This allows the transducer to be electrically controlled and steered by simply adjusting the electrical voltage weights. A prototype acoustic modem was then developed to utilize the multimodal directional transducer for both LOS and NLOS communication. The acoustic modem was also used as a platform for empirically validating our SBR communication model in a tank.

Analysis on the network performance was carried out, which looked into the effects of utilizing both LOS and NLOS directional communication in a shallow water environment. Networking protocols where then developed to exploit the SBR concept for node localization, directional medium access and routing. Our network analysis was based on a PHY-MAC cross-layer design whereby the physical layer was based on a directional antenna and the MAC layer utilizes a carrier sense with multiple access and collision avoidance scheme (CSMA/CA). Our analysis showed that utilizing direct communication (i.e. LOS) will provide the best option in terms of lower outage and higher capture probabilities while maximizing the network throughput. Furthermore, we demonstrated that NLOS could also be incorporated so long as the grazing angle to the water surface/bottom is less than the critical angle; this is achieved through the usage of highly directional antennas. Thus, when utilizing NLOS links, the maximum network throughput can be sustained by increasing the directivity of the antenna model.

To achieve localization, we proposed two different techniques, one being anchor-free and the other relying on anchors (or reference nodes). For anchor-free localization, we have presented a surface-based-reflected anchor-free localization
(SBR-AL) scheme, which discovers and obtains the positions of nodes by utilizing the directional antenna and the moving water surface. The SBR-AL scheme comes in three variants depending on the link option available and desired performance. The corporative scheme (SBR-CAL) provides the best option but at a cost of higher complexity since it combines both LOS and NLOS links. The directed schemes (SBR-DAL and SBR-EAL) only utilize NLOS links and fewer overheads since only two nodes are involved in the localization process.

We have also summarized our novel directional medium access and control protocol, which utilizes the directional antenna and reflected links to maximize the network throughput. In the proposed reflection-enabled directional MAC protocol (RED-MAC) each node will be able to determine if an obstacle is blocking the LOS links to the destination and switch to the best available antenna that will be reflected to the water surface or bottom. Our simulation results demonstrate the effectiveness of the approach, which achieves up to 56% increase in throughput in comparison to traditional Omni-directional MAC protocols.

Finally, we have implemented a novel geographical routing algorithm, which aims to find the best stable route from the source node to the destination within a geocast region. The proposed Geocast Optimized Reflection-enabled Routing Immune to Link Ambiguity (GORRILA) algorithm combines both LOS and NLOS links in the routing process while maximizing the network throughput in the optimized route. Results demonstrate superior performance of the GORRILA algorithm in comparison to the well-known greedy perimeter stateless routing
(GPSR) algorithm. All of the proposed schemes have been extensively validated with both simulations and with empirical data.

### 10.2 Recommendations for Future Work

As part of our future work, we plan on investigating different modulation schemes that supports node mobility without jeopardizing the communication throughput. As mentioned in section 3.3.4, a chirp signal or linear frequency modulation enables the receiver to detect an up/down change in frequency in the presence of Doppler frequency shifts. Although this technique proved to be resistant to Doppler shifts, it greatly affects the communication bandwidth since the entire linear band is used to transmit one bit as opposed to a discrete frequency as common found in single-carrier modulation schemes. Multi-frequency or M-ary CSS (MCSS) schemes are often used to increase the communication throughput by using multiple bands to attain higher throughput [100]. This is also illustrated in Figure 10-1. However, similarly to Figure 3-26 in section 3.3.4, this scheme does not fully utilize the communication bandwidth and further limits the attainable communication throughput. To increase the communication throughput while remaining resistant to Doppler shifts we propose a Multi-frequency, amplitude and phase scheme, namely M-ary Amplitude-Phase Chirp Spread Spectrum (MAP-CSS) technique that is summarized in Figure 10-2. Instead of only applying a linear modulation of the communication frequency as is common in CSS schemes, we propose a linear modulation of the amplitude and frequency with a fixed phase. In Figure 10-2, the x-axis is the time plot for time t in seconds, the y-axis is the frequency spectrum and the z-axis is the amplitude spectrum, such that +z
contains positive amplitudes and \(-z\) contains negative amplitudes that are split into multiple bands (i.e. two bands in example).

Figure 10-1: M-ary chirp spread spectrum utilizing multiple bands to increase the communication throughput.

Comparison of the proposed CSS scheme with previous methods can be found in Table VI. Unlike previous CSS schemes, our MAP-CSS applies a linear modulation to both the amplitude and frequency of the transmitted signal while controlling the amplitude sign to implicitly change the phase. This results in a power efficient and low-complex CSS scheme that is robust to Doppler frequency shifts.

Table VI: Comparison to previous schemes to proposed MAP-CSS scheme

<table>
<thead>
<tr>
<th>CSS Methods</th>
<th>Amplitude Magnitude</th>
<th>Amplitude Sign</th>
<th>Phase</th>
<th>Frequency</th>
</tr>
</thead>
<tbody>
<tr>
<td>CSS</td>
<td>Fixed</td>
<td>Fixed</td>
<td>Fixed</td>
<td>Linear</td>
</tr>
<tr>
<td>CSS-PSK</td>
<td>Fixed</td>
<td>Modulated</td>
<td>Modulated (if phase is 0)</td>
<td>Linear</td>
</tr>
<tr>
<td>CSS-QPSK</td>
<td>Fixed</td>
<td>Fixed to +</td>
<td>Modulated</td>
<td>Linear</td>
</tr>
<tr>
<td>MAP-CSS</td>
<td>Linear</td>
<td>Modulated</td>
<td>Fixed</td>
<td>Linear</td>
</tr>
</tbody>
</table>
In addition to investigating different modulation schemes, we plan on looking into other methods of establishing routes in the underwater medium. One area of focus is to investigate the concept of multicast beam-forming techniques. The thought here is for each node in the network to adjust their antenna beam angle and signal strength to be able to form a multicast network. This is illustrated in Figure 10-3, which depict three different beam angles being formed to create a multicast route. In the same figure, we see that the link from node \(S_0\) to nodes \((S_7, S_8)\) uses a wide beam angle and stronger transmission power to be able to cover multiple nodes in just one-hop. Hence, by selectively adjusting the transmission angle and power, we can achieve a multicast route while still maximizing the network throughput and minimizing the overall network communication power. Another area of research is to utilize underwater mobile nodes to increase the network connectivity and maintain the desired quality of service (QoS). In this scenario, a mobile node could act as a mobile relay in connecting disjointed networks segments while also adjusting its beam angle and transmission power depending on the optimization criterion, e.g., minimize the distance to be traveled between segments. We also plan on looking into other QoS routing schemes, fault-tolerance and multi-transport in a multi-channel setup.

We could also investigate the trade-offs of potentially using multiple reflections instead of one. In our current model, we only accept RSR or RBR links for NLOS communication and networking. As a future work, we could look into exploiting other options such as the refracted-surface-reflected-bottom-reflected (RSRBR) link. Exploiting those multiple-bounce options could benefit ad-hoc formation. In addition, we plan on investigating the energy consumption requirements of our approach and
develop new optimization criterions for routing that factor in the energy due to transmitting, receiving and processing.

Figure 10-3: Proposed multicast routing scheme whereby each node can adjust its beam width and transmission power to establish a multicast route.

We also plan on fine-tuning our acoustic modem design to be more robust and allow for easy and quick underwater application deployment. The existing modem design can be changed from a single board to a stack-based design. The FPGA-based digital portion will be one card while the analog front end will be another card. This gives us the flexibility of just modifying the analog portion depending on the application needs. In addition, we plan on form-factoring the stackable design into a waterproof enclosure, which can then be mounted on a boat or an underwater remote controlled vehicle. This will give us a platform for pushing the limits of underwater communication and networking.
References


Personal, Indoor and Mobile Radio Communications (PIMRC 2004), Barcelona, Spain, September 2004.


[77] L. Wang, A. Chen, S. Huang, “A Cross-Layer Investigation for the Throughput Performance of CSMA/CA-Based WLANs With Directional


[91] Steiner and Martins Inc. (STEMiNC), http://www.steminc.com/


# Appendices

## Appendix A: List of Terminologies

<table>
<thead>
<tr>
<th>Terminology</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>ABC</td>
<td>Assumption based coordinate system</td>
</tr>
<tr>
<td>AOA</td>
<td>Angle of arrival</td>
</tr>
<tr>
<td>ASN</td>
<td>Acoustic sensor network</td>
</tr>
<tr>
<td>AUV</td>
<td>Autonomous underwater vehicles</td>
</tr>
<tr>
<td>CN-TOAG</td>
<td>Closest neighbor time of arrival grid</td>
</tr>
<tr>
<td>DSP</td>
<td>Digital signal processing</td>
</tr>
<tr>
<td>FDTD</td>
<td>Finite-difference time-domain</td>
</tr>
<tr>
<td>LOS</td>
<td>Line-of-sight</td>
</tr>
<tr>
<td>LPD</td>
<td>Local Positioning discovery</td>
</tr>
<tr>
<td>MFP</td>
<td>Matched field processing</td>
</tr>
<tr>
<td>NLOS</td>
<td>Non-line-of-sight</td>
</tr>
<tr>
<td>RBR</td>
<td>Refracted-bottom-reflected</td>
</tr>
<tr>
<td>RSR</td>
<td>Refracted-surface-reflected</td>
</tr>
<tr>
<td>RMS</td>
<td>Root-mean-squared</td>
</tr>
<tr>
<td>RSS</td>
<td>Received signal strength</td>
</tr>
<tr>
<td>SBR</td>
<td>Surface-based reflection</td>
</tr>
<tr>
<td>SBR-AL</td>
<td>Surface-based reflected anchor-free localization</td>
</tr>
<tr>
<td>SBR-CAL</td>
<td>Surface-based reflected corporative anchor-free localization</td>
</tr>
<tr>
<td>SBR-DAL</td>
<td>Surface-based reflected directed anchor-free localization</td>
</tr>
<tr>
<td>SBR-EAL</td>
<td>Surface-based reflected enhanced-directed anchor-free localization</td>
</tr>
<tr>
<td>SNR</td>
<td>Signal-to-noise Ratio</td>
</tr>
<tr>
<td>SRTL</td>
<td>Self-reflecting tone learning</td>
</tr>
<tr>
<td>TDOA</td>
<td>Time difference of arrival</td>
</tr>
<tr>
<td>TLM</td>
<td>Transmission line matrix</td>
</tr>
<tr>
<td>TOA</td>
<td>Time of arrival</td>
</tr>
<tr>
<td>UW-ASN</td>
<td>Underwater acoustic sensor network</td>
</tr>
</tbody>
</table>
# Appendix B: List of Parameters

<table>
<thead>
<tr>
<th>Parameter</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>$RTL_{RBR}$</td>
<td>Raleigh RBR transmission loss</td>
</tr>
<tr>
<td>$RTL_{RSR}$</td>
<td>Raleigh RSR transmission loss</td>
</tr>
<tr>
<td>$EL_{MULT}$</td>
<td>Estimated multipath transmission loss</td>
</tr>
<tr>
<td>$TL_{LOS}$</td>
<td>Line-of-sight transmission loss</td>
</tr>
<tr>
<td>$TL_{MULT}$</td>
<td>Multipath transmission loss</td>
</tr>
<tr>
<td>$\bar{a}(f)$</td>
<td>Frequency-dependent absorption</td>
</tr>
<tr>
<td>$\beta_k$</td>
<td>Bottom attenuation for the k-th path</td>
</tr>
<tr>
<td>$c_w$</td>
<td>Sound speed in water layer</td>
</tr>
<tr>
<td>$c_b$</td>
<td>Sound speed in bottom layer</td>
</tr>
<tr>
<td>$\bar{c}$</td>
<td>Average sound speed between communicating nodes</td>
</tr>
<tr>
<td>$d$</td>
<td>Line-of-sight distance</td>
</tr>
<tr>
<td>$D_{RX}$</td>
<td>Receiver’s depth</td>
</tr>
<tr>
<td>$D_{TX}$</td>
<td>Transmitter’s depth</td>
</tr>
<tr>
<td>$D_W$</td>
<td>Water depth</td>
</tr>
<tr>
<td>$f_s$</td>
<td>Sampling frequency</td>
</tr>
<tr>
<td>$G(\theta)$</td>
<td>Antenna gain</td>
</tr>
<tr>
<td>$k_{LOS}$</td>
<td>Line-of-sight transmission range</td>
</tr>
<tr>
<td>$\bar{n}$</td>
<td>Normal vector to water surface</td>
</tr>
<tr>
<td>$P_{RX}$</td>
<td>Reception power</td>
</tr>
<tr>
<td>$P_{TX}$</td>
<td>Transmission power</td>
</tr>
<tr>
<td>$\bar{r}_A$</td>
<td>Transmitted vector by node A</td>
</tr>
<tr>
<td>$\bar{r}_B$</td>
<td>Reflected vector unto Node B</td>
</tr>
<tr>
<td>$S(x,y)$</td>
<td>Water surface function</td>
</tr>
<tr>
<td>$\tau_k$</td>
<td>Time delay for the k-th path</td>
</tr>
<tr>
<td>$\tau_{LOS}$</td>
<td>Line-of-sight time delay</td>
</tr>
<tr>
<td>$\theta_{MAX}$</td>
<td>Maximum achievable angle</td>
</tr>
<tr>
<td>$\theta_s$</td>
<td>Beam steering angle</td>
</tr>
<tr>
<td>$\Delta\theta$</td>
<td>Change in transmission angle</td>
</tr>
<tr>
<td>$\lambda$</td>
<td>Acoustic wavelength</td>
</tr>
<tr>
<td>$\Lambda$</td>
<td>Number of directional antennas</td>
</tr>
<tr>
<td>$\Delta$</td>
<td>Antenna directivity</td>
</tr>
</tbody>
</table>
### Appendix C: Pseudo-code (SBR-AL)

Pseudo Code for the SBR-AL Algorithm

```plaintext
SBR-AL(Surf, current_state, next_state, num_antennas, req_measuremnts, loc_method)
1 switch (current_state)
2   if (current_state == NEIGHBOR_DISCOVERY) then
3     [range_meas_list, link_type_list] = Node_Discovery(num_antennas, Surf)
4       if (sizeof(range_meas_list) >= req_measurements) then
5         next_state = RANGE_ESTIMATION
6       else
7         next_state = NEIGHBOR_DISCOVERY // need more range meas
8     end if
9   else if (current_state == RANGE_ESTIMATION) then
10      for (i = 0; i < sizeof(range_meas_list); i++)
11         if (link_type_list(i) == LOS) then
12            los_distance(i) = t_ij*c_avg // Eqn (76)
13            LOS_available = TRUE
14         else
15            rA(i) = vector_intersect_pt(i) – [0,0,zA] // Eqn (77)
16            rB(i) = rA – 2(rA*n)n // Eqn (9)
17        end if
18      end for
19      next_state = POSITION_ESTIMATION
20   else if (current_state == POSITION_ESTIMATION) then
21      if ((LOS_available == TRUE) && (loc_method == CAL)) then
22        SBR-CAL(los_distances, rA_vectors, rB_vectors)
23      else if ((LOS_available == FALSE) && (loc_method == DAL)) then
24        SBR-DAL(rA_vectors, rB_vectors, vector_intersect_pts)
25      else if ((LOS_available == FALSE) && (loc_method == EAL)) then
26        SBR-EAL(rA_vectors, rB_vectors, vector_intersect_pts)
27      end if
28      next_state = OPTIMIZATION
29  else if (current_state == OPTIMIZATION) then
30     // Apply Eqn (31)
31  end if // end of state machine if-else structures
32 end switch
33 return next_state // Return the next state (SBR-AL should be inside loop)
```

[205]
Pseudo Code for the Node Discovery Method

```plaintext
def Node_Discovery(num_antennas, water_surface_function):
    current_state = OMNI_TRANSMIT_DISCOVERY
    current_level = 0
    while (current_state != DONE):
        if (current_state == OMNI_TRANSMIT_DISCOVERY):
            beam_angle = Combine_antenna_pattern(num_antennas)
            Transmit_message(beam_angle, DISCOVERY)
            Next_state = OMNI_WAIT_FOR_ACK
        else if (current_state == OMNI_WAIT_FOR_ACK):
            [ACK_received, toa_meas] = Check_RX(beam_angle)
            if (ACK_received == true):
                num_meas_received = size(toa_meas)
                range_meas_list.Append(toa_meas)
                link_type_list.Append(LOS)
                if (num_meas_received >= req_measurements):
                    next_state = DONE
                else:
                    next_state = DIR_UPDATE_MAP
            else:
                next_state = DIR_UPDATE_MAP
        else if (current_state == DIR_UPDATE_MAP):
            Surface_grid_map = CreateMap(surface_function, node_depth)
            next_state = DIR_TRANSMIT_DISCOVERY
        else if (current_state == DIR_TRANSMIT_DISCOVERY):
            Beam_angles = angle(corners(level(current_level))
            for (i = 0; i < 4; i++)
                Transmit_message(Beam_angles(i), DISCOVERY)
            end for
            next_state = DIR_WAIT_FOR_ACK
        else if (current_state == DIR_WAIT_FOR_ACK):
            [ACK_received, toa_meas, rb_vectors] = Check_RX(beam_angle)
            // Repeat similar check process for ACK-DISCOVERY (DP/RSR)
            // Call link_type_list.Append(LOS), for every LOS range meas
            // Call link_type_list.Append(NLOS), for every RSR range meas
            // If range measurements is enough, next_state is DONE
            // Otherwise, increment current_level
        end if
    current_state = next_state
end while
return range_meas_list, link_type_list
```

Appendix D: Pseudo-code (GORRILA)

Pseudo Code for the GORRILA Algorithm Stage II

GORRILA(V, update_graph, antenna, transmission_range, current_hop)
1     if(update_graph == true) then
2         Del = LDeL-R(V, update_graph, antenna, transmission_range)
3     endif
4     if (current_hop == destination) then
5         return current_hop
6     else
7         candidate_hops = obtain_triangle_vertices(Del, current_hop)
8         best_throughput = 0;  // Selected based on Eqn (135)
9         for (i = 0; i < length(candidate_hops); i++)
10            radius_to_destin_cand = distance(candidate_hops(i), destination)
11            radius_to_destin_curr_hop = distance(current_hop, destination)
12            throughput_cand = obtain_throughput(candidate_hops(i))  // Eqn (91)
13            if (radius_to_destin_cand < radius_to_destin_curr_hop) &&
14               (throughput_cand > best_throughput)
15               next_hop = candidate_hops(i)
16               best_throughput = throughput_cand
17         end for
18     end if
19     return next_hop  // Return the next hop that maximizes throughput
20 endif
21
LDeL-R(V, update_graph, antenna, transmission_range)
22     vector <1-byte> blocked_antennas
23     a_index = 0
24     for (i = 0; i < number_of_antennas; i++)
25        if (antenna[i].blocked == true) then
26           blocked_antennas[a_index] = i
27        end if
28     end for
29     tx_broadcast_message = {position, blocked_antennas}
30     Broadcast(tx_broadcast_message)  // send information to neighbors
31     if (ReceivedMessage() == true) then  // received message from neighbors
32        V_R = ComputeReflectionPoints(V, rx_broadcast_message)
33        Boundary_REGION = Convex_Hull(V_R)
34        Del_R = DelaunayDivideAndConquer(V_R, Boundary_REGION)
35        // Remove all edges that is not within range
36        LDeL_R = PruneEdges(Del_R, transmission_range)
37     end if
38     return LDeL_R

