DOPPLER-BASED LOCALIZATION FOR MOBILE AUTONOMOUS UNDERWATER VEHICLES

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ABSTRACT OF THE THESIS

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A novel algorithm for localization of Autonomous Underwater Vehicles (AUVs) operating in under-the-ice environments is proposed along with a mathematical analysis for the same. The objective is to accurately predict the position of a mobile AUV via cooperation with neighboring vehicles by utilizing a Doppler-based approach. Current existing localization techniques require either an anchor or surfacing AUV to acquire a GPS fix or rely on a system of expensive and difficult to deploy hardware. Our Doppler-based approach is based on observed Doppler shifts, which are measured opportunistically from ongoing communications between AUVs. These observed Doppler shifts can be used to project the subsequent positions of the AUV and limit the internal uncertainty associated with traditional localization techniques. An AUV's internal uncertainty is the uncertainty in the position of a mobile vehicle as estimated by itself, e.g., via localization techniques. In addition, this Doppler-based approach has minimal network overhead when compared to traditional localization techniques and does not require synchronization between AUVs. The main focus of this thesis is to quantify (via simulations) the solution behavior as well as its sensitivity to possible sources of errors.

Acknowledgements

Dedication

To my father John

my mother Dianne

my sisters, Courtney and Brianna

and my fiancé Rae

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Chapter 1

Introduction

Over the last century, robots and autonomous vehicles have allowed mankind to explore, survey and conduct research in some of the most extreme and remote environments known to man. These environments are now routinely investigated via unmanned air, land, space, and sea explorations. As a result, unmanned explorations have had unprecedented growth in recent years and are becoming commonplace. The majority of these unmanned missions were typically accomplished with simple drones and remotely operated vehicles (ROV). However, over the years the sophistication and capabilities of these vehicles has increased and many are becoming autonomous in nature.

Unmanned aerial vehicles (UAVs) are aircraft which have the ability to fly either autonomously or via control from a remote location. Currently UAVs are primarily utilized in military applications for a variety of purposes, particularly surveillance and reconnaissance. A great deal of research has been conducted into UAVs and a number of UAVs are either in development or currently in use. One UAV currently under development by BAE systems is Taranis [2], which is an autonomous stealth combat aircraft. While Northrop Grumman's RQ-4 Global Hawk [3], which is currently deployed, is capable of flying completely autonomous high altitude long endurance missions. UAVs generally utilize the Global Positioning System (GPS) and inertial sensors to achieve full autonomy.

Unmanned land missions using robotic vehicles has been around for several decades. However, recent developments have led to the replacement of human controlled and driven vehicles with fully autonomous ones. Several famous competitions have been held by various government defense departments including the United States' DARPA Grand Challenge and Germany's European Land-Robot Trial. Similar vehicles are

also currently being developed for use by the general public. General Motors (GM) announced back in 2008 that they plan to begin testing driverless cars by 2015 and that they could be on the road by 2018 [4]. These vehicles typically rely on a large number of integrated sensors and guidance systems to achieve autonomy. These systems typically include GPS, infrared detectors, laser ranging, radar, and sometimes primitive cameras.

Space has always been an environment conducive to robotic and autonomous exploration. One of the most famous robotic space explorations has been the Mars Exploration Rover Mission (MER). This ongoing research mission currently involves two rovers, Opportunity and Spirit. These rovers have gained an unprecedented amount of notoriety and press over the last decade. This can be attributed to their unparalleled success in exploring the martian surface, in fact the range of the rovers was predicted to be limited to a few meters but they have traveled several kilometers with extended life spans. These rovers have and continue to achieve much more than their originally intended missions. These rovers initially utilized both a star scanner and sun sensor for navigation when landing on the martian surface. These sensors enabled the vehicles to know their orientation in space via the positioning of the Sun and other stars. Currently both Opportunity and Spirit are capable of navigating autonomously via an auto-navigation system. This system utilizes dual stereo camera pairs which take pictures of the surrounding terrain. 3-D maps are then applied to the terrain and the rover evaluates its current position and its best future route for travel [5].

Robotic submersibles have been around for the better part of the last half century. However, very little attention has been directed toward the oceanic exploration done by these submersibles. Oceans cover nearly 71% of the earth's surface and still 95% of the world's oceans remain unexplored. The lack of attention can be attributed to the apparent lack of success. In 1960, the Bathyscaphe Trieste reached Challenger deep with a two-man crew [6]. Challenger deep is the deepest surveyed point in the oceans, with a depth of approximately 35,800 feet or approximately 6.8 miles. The Trieste crew remains the only human beings to ever reach the bottom of Challenger Deep. However, two robotic submarines have recently revisited that depth in order to conduct research.

The most successful vessel being Nereus, which was the first remote vehicle to reach the depth since Trieste. Nereus over the course of 10 hours collected data and sent live video back to the ship through a fiber-optic tether [7]. This was accomplished in spite of great difficulties associated with underwater exploration, such as extraordinary pressures and subzero temperatures.

A common feature among all of these technological achievements is the ability of these robotic vehicles to accurately determine and report back their coordinates or current position in an environment. This process is known as localization. Robotic and autonomous vehicles use a variety of techniques to localize their position; most terrestrial techniques utilize GPS while space based applications use various optical techniques, such as cameras and laser tracking. These techniques do not apply to an underwater environment due to the high absorption of electromagnetic waves and scattering of light. Acoustic waves are used in underwater applications, and while terrestrial electromagnetic waves propagate at the speed of light, $3 \cdot 10^8$, the speed of sound in an underwater environment is approximately 1500 m/s. This means acoustic communication is five orders of magnitude slower than terrestrial radio frequencies. This greatly increases the propagation delay and severely complicates network routing and localization protocols. Therefore the implementation of an effective, accurate, and efficient localization technique is often of crucial importance.

1.1 Autonomous Underwater Vehicles

Autonomous Underwater Vehicles (AUVs) are underwater robotic devices that are driven through water by a propulsion system and are controlled by an onboard computer. AUVs contain their own power supply and usually control themselves while attempting to accomplish a defined task. AUVs are maneuverable in three dimensions and have typical speeds ranging from 0.5 to 4.0 m/s with a battery life lasting anywhere from 8-50 hours [8]. Sensors onboard the AUV take time correlated measurements as the AUV follows its designed trajectory. In order for this sensor data to be statistically relevant, the location of the AUV must be determined with a high degree of certainty.

AUVs can operate remotely in underwater environments with varying degrees of autonomy. The level of autonomy chosen is an interesting dilemma. Completely autonomous AUVs utilize a preprogrammed trajectory and can only be redirected by its own algorithm while a mission is underway. GPS (when surfaced), an acoustic positioning system or some other localizing technique is used to ensure the AUV is following its programmed path. Partially autonomous AUVs allow for the active redirection of the AUV. However this comes with an inherent drawback, the less autonomous the AUV is, the higher the operational cost [8]. It is important to note that an AUV differs drastically from an Unmanned Undersea Vehicle (UUV), which requires constant and consistent communication to achieve its mission.

AUVs are widely believed to be revolutionizing oceanography and are enabling research in environments that have typically been impossible or difficult to reach [9]. Given recent advances in processing power, data storage and batteries, AUVs are now extraordinarily capable and also affordable to deploy. The increasing commercialization of these vehicles will lead to expanded system reliability and cost-effective components in the near future [10]. As a result these vehicles have become exceedingly useful and crucial in a growing number of mission critical oceanic applications [11].

The following paragraphs will cover the two main classes of AUVs along with their specific benefits, drawbacks, and capabilities. Following that we will go into depth on the various applications of these AUVs. The choice of the application will strongly influence the necessitated accuracy for localization.

1.1.1 Classes

AUVs are comprised of two main classes of vehicles: Propeller Driven Vehicles (PDVs) and buoyancy-driven gliders. These classes of vehicles are usually positively buoyant so that in the case of a catastrophic failure the AUV will surface. This means that in order for the AUV to stay submerged it must be traveling forward with some velocity. The cruising velocity of an AUV can vary anywhere from 1 to 4 m/s. The choice of the AUV platform strongly depends on the end user's application.

Figure 1.1: Two Bluefin AUVs awaiting deployment.

Propeller Driven Vehicles

PDVs were initially the first AUVs developed. They have a long slender body, closely resembling that of a torpedo, and are driven by a smaller propeller located on the rear of the craft. Their primary drawback is their limited lifespan and coverage. PDVs have a life span ranging from several hours to a few days and can traverse distances of several hundred kilometers. These distances and life spans are limited due to the powered propeller and limited battery capacity. The main benefit to using PDVs is that they have the ability to cover a large amount of distance in a short amount of time. In addition, their trajectory can also be adjusted on the fly by an onboard computer.

Gliders

Gliders have been a relatively recent development and closely resemble PDVs minus the propeller. They have allowed for missions spanning several months and thousands of kilometers. Gliders follow a saw tooth like trajectory underwater and travel at speeds of 0.4 m/s horizontally and 0.2 m/s vertically [12]. Glider movement is accomplished by manipulating its internal mass, which causes the glider to ascend or descend, while wings on the glider control its direction and trajectory. The main benefits to gliders are their range, operating life, and low cost deployment. Several drawbacks to gliders are their low velocities and lack of maneuverability.
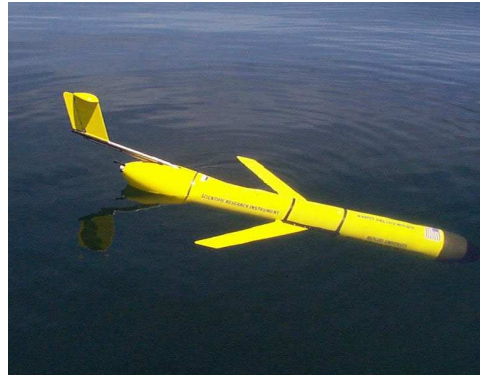
Figure 1.2: A SLOCUM glider being deployed.

Table 1.1: Commercial AUVs

Name	Manufacturer	Class Type	Run Time	Max Speed	Max Depth
Bluefin-9 (Sea Lion II)	Bluefin Robotics	PDV	12 hrs	2.60 m/s	200 m
Bluefin-12	Bluefin Robotics	PDV	20 hrs	2.60 m/s	200 m
Bluefin-21	Bluefin Robotics	PDV	18 hrs	2.60 m/s	3000 m
Gavia AUV	Hafmynd Ehf	PDV	7 hrs	3.08 m/s	>1000m
SeaOtter MK II	Atlas Maridan ApS	PDV	24 hrs	4.12 m/s	1500 m
SeaWolf	Atlas Maridan ApS	PDV	3 hrs	2.60 m/s	300 m
REMUS 100	Hydroid, Inc.	PDV	17 hrs	2.60 m/s	100 m
REMUS 600	Hydroid, Inc.	PDV	20 hrs	2.32 m/s	600 m
REMUS 6000	Hydroid, Inc.	PDV	20 hrs	2.32 m/s	6000 m
Explorer	Intl. Submarine Engin.	PDV	28-83 hrs	2.60 m/s	5000 m
HUGIN 1000	Kongsberg Maritime	PDV	17-30 hrs	3.09 m/s	1000 m
HUGIN 3000	Kongsberg Maritime	PDV	60 hrs	2.06 m/s	3000 m
HUGIN 4500	Kongsberg Maritime	PDV	60 hrs	2.06 m/s	4500 m
Iver2-580	OceanServer Tech., Inc.	PDV	>24 hrs	2.06 m/s	200 m
Spray Glider	Bluefin Robotics	Glider	>4000 hrs	0.35 m/s	1500 m
SLOCUM Electric	Webb	Glider	4 wks	0.40 m/s	1000 m
SLOCUM Thermal	Webb	Glider	3-5 yrs	0.40 m/s	1200 m
APEX	Webb	Glider	4 yrs	-	2000 m
SAUV II	Falmouth Scientific	Glider	Unlimited	1.54 m/s	500 m
Seaglider	iRobot	Glider	Months	0.25 m/s	1000 m

1.1.2   Role in Underwater Sensor Networks

Underwater Sensor Networks (UWSNs) consist of a number of nodes that interact to collect data and perform tasks in a collaborative manner underwater. These nodes can be either mobile or stationary, and are typically comprised of AUVs, which are equipped with numerous sensors for sampling. Nodes in UWSNs are dependent upon a high degree of inter-vehicular communication in order to achieve goals requiring collaboration. Designing energy-efficient and accurate localization protocols for this type of network is essential and challenging. In addition, nodes are powered by batteries, which have limited life spans. For example, REMUS-class AUVs can generally operate from 5-20 hours underwater before recharging is necessary [13].

1.1.3   Communication Techniques

Underwater communications are usually accomplished acoustically while terrestrial communications typically utilize various Radio Frequencies (RF) for communication. The characteristics of underwater sensor networks are fundamentally different from that of terrestrial networks. The speed of acoustic signal propagation in underwater acoustic channels is around $1.5 \cdot 10^3$ m/sec, which is approximately five orders of magnitude slower than radio propagation speed ($3.0 \cdot 10^8$ m/sec) in air. In addition, the acoustic propagation speed in water varies significantly with temperature, density, salinity, flow, acidity, conductivity and turbidity. This can cause the acoustic waves to travel on curved paths, also referred to as multipath [13] [14].

The use of radio frequencies is impractical for AUVs operating in an underwater environment. An extra low RF signal (30Hz - 300Hz) will propagate in water but it requires an enormous antennae and a significant amount of transmission power. This makes it unsuitable for low-power AUVs and sensor nodes [14]. In addition, GPS uses radio waves in the 1.5GHz band which do not propagate in water. This is due to the high attenuation of RF in an underwater environment, thus UWSNs employ acoustic communication [13] [14] [15].

Underwater communication utilizing the transmission of optical signals has been

studied, but is impractical for long distances and typical water clarity. Optical communication requires light be transmitted with remarkably high precision in blue-green wavelengths over short distances and in near perfect water clarity [13]. This is because light is quickly scattered and absorbed by water.

Acoustics is the most viable means of communication, but it is severely affected by network dynamics, large propagation delays and high error probability. Significant progress has been made to overcome these challenges in the last two decades. A general performance limit of acoustic communications is provided as 40 km·kbps for the range rate product [16]. It is important to note that this estimate applies to vertical channels in deep water and not shallow-water or horizontal channels [13]. Generally acoustic communications have limited bandwidth due to increasing attenuation that occurs with higher frequencies.

It is important to note that acoustic communications usually require forward error correction, also referred to as error correction coding, to lower the bit error rate (BER). UWSNs suffer from a high bit error probability since phase shifts and amplitude fluctuations are common in an underwater environment [13]. Once an acoustic waveform is sent it is impacted severely by currents, turbulence, temperature gradients, salinity discrepancies and other related phenomena that can distort the waveform [17].

In underwater communications spanning long distances, it is common for shadow zones to exist or develop over time. Shadow zones are defined as geometric regions with unusually high transmission loss [13] [17]. In shadow zones, frequency specific attenuation occurs leading to a state where acoustic communication is nearly impossible. Automating repeat requests for packets in addition to spatial and frequency diversity can be used to overcome shadow zones [17].

It is important to note that propagation delays can be estimated in underwater communications. This is due to the fact that propagation delays are relatively constant for a given depth, salinity and temperature [13].

1.1.4 Applications

Over the last several decades AUV technology has shifted from proof of concept to routine operational use. Current research is now focusing on new sampling and localization strategies. A characteristic S curve can be associated with the evolution of AUV technology over the last three decades [18]. AUVs reached an operational state nearly ten years ago, and as the technology has matured they have become a part of the commercial mainstream in the ocean industry [18]. The forecast for AUV demand over the next decade is expected to approach 1,144 AUVs, resulting in a 2.3 billion dollar market value [19].

Critical Missions

Critical missions are defined as those in which failure is not an option. These missions can include but are not restricted to missions that safeguard human and marine life, property, and national interests. UWSNs monitoring mine locations is one such application. It is crucial for AUVs in this mission to locate, coordinate and collaborate effectively. In order for this to happen, effective communication and accurate localization is necessary [11]. A swarm of AUVs can investigate a known mine field prior to a ship or submarine entering the vicinity. These AUVs act as a team to quickly identify, denote and transmit back accurate locations of the mines. The United States Navy has developed and deployed such a system called the Long Term Mine Reconnaissance System (LMRS), which is a UWSN consisting of several AUVs used for mine monitoring and discovery [10].

British Petroleum's (BP) historic oil spill in the Gulf of Mexico emphasizes the role of critical response AUVs. Woods Hole Oceanographic Institute (WHOI) deployed an Sentry AUV in the wake of the events in the Gulf [20]. This AUV sampled the amount of hydrocarbons in the ecosystems surrounding the Deep Water Horizon rig. Detailed chemical analysis from the AUV showed that there was relatively little deterioration in oil cloud plumes surrounding the rig. These estimates and their corresponding underwater locations contradicted initial government estimates. WHOI's data was utilized to

limit the damage and help in the recovery from such an unprecedented environmental disaster.

Defense

Despite AUVs recent commercial success, many AUVs are currently deployed and being developed primarily for defense purposes. The need to secure vital sea ports and passages has led to the development of AUVs capable of detecting and monitoring intruders in these acute areas. One such AUV is the United Kingdom's Talisman L. This vessel currently being built by BAE systems uses high definition forward and sideways looking sonar as well as a suite of multi-view cameras. It has high maneuverability and can operate for 12 hours at depths up to 100 meters with velocities approaching 2.60 m/s. The Talisman is capable of monitoring confined ports and harbors.

Germany plans on purchasing several Sea Otter Mk II AUVs. The Sea Otter AUV would primarily be utilized for surveillance and reconnaissance purposes, but could see an expanding role in the future. The Sea Otter has a modular design that allows its sensors and payload to be completely altered. With just a few extension modules the Sea Otter can be transformed to carry a Sea Fox mine disposal vehicle or transport divers to and from an attack submarine.

General Industrial Applications

The oil and gas industry has dominated the commercial AUV market. This industry has used AUVs as a surveying tool to evaluate pipe routes and drilling locations [10] [21]. The use of AUVs has enabled a cost savings of 59% and an order of magnitude reduction in the amount of time necessary for deep water surveys [10]. AUVs utilized in surveys were predicted to exceed $200 million dollars in revenue by the year 2004 [10]. In addition, SeeByte and Subsea 7 have developed an AUV capable of inspecting and repairing offshore oil pipelines, risers, and mooring. These systems have been developed to lower costs associated with performing tasks formerly performed by remote operating vehicles (ROVs).

The use of AUV data for hydrographic surveys and mapping is becoming an accepted

standard in many countries. Hydrographic surveys are allowing industries and countries around the globe to map vast underwater territories using high resolution precision cameras. In addition, these AUVs are being used to identify strange or unknown objects in harbors or ports, national seabed boundaries, and possible oil and gas reserves.

Oceanic Monitoring and Research

The Arctic is one of the most inhospitable and unexplored regions in the world. Year round ice coverage with temperatures approaching $-50\,^{\circ}\text{C}$ ($-58\,^{\circ}\text{F}$) make it all but impossible to use conventional oceanographic techniques for surveying, mapping, tracking, sampling and exploring this hostile region [22]. In addition, the risks and costs associated with deploying manned submersibles in the arctic region are substantial so AUVs are used extensively [22]. In 1996, an AUV known as Theseus was able to lay a fiber optic cable over a distance of 200 km (124 mi) under Arctic sea-ice [23]. Theseus also demonstrated extraordinary navigational capability and achieved an error of less than 0.5% of the distance traveled. However, this additional navigational capability came at a cost. It was comprised of several expensive precision systems including: INS, Doppler, sonar and surface transponders.

Non-arctic mapping and sampling is an equally critical process that is also being accomplished via AUV. Rutgers University recently completed a cross-Atlantic voyage with a SLOCUM autonomous underwater glider. The glider successfully traveled 7,300 kilometers over the course of 201 days [24]. The purpose of this effort was to map and track changes in large ocean ecosystems such as carbon fluctuations. Many other institutions are also pursuing similar ambitions such as Woods Hole Oceanographic Institute, which launched Spray in conjunction with Scripps Institution of Oceanography in California. This AUV is expected to gather data on temperature, currents and salinity in order to better understand the role oceans are currently playing in the global warming process.

1.2   Thesis Contributions

In this thesis, we evaluate several localization techniques that have been proposed in previous papers and promote a novel Doppler-based approach. This is carried out in an under-the-ice simulation with four specific scenarios, in which all AUVs are fully mobile. In our approach, Doppler shifts are opportunistically measured from ongoing communications and the AUV's position is projected. Currently, no literature has reported this Doppler-based approach.

This approach is used to minimize localization error in several situations. Doppler can be used to limit the error associated with lateration by correcting for RTT and currents. In underwater environments with sufficiently high packet error rates, Doppler can be used to accurately localize the AUV. In addition, this Doppler approach limits associated network overhead by utilizing sensed Doppler shifts in place of performing lateration.

1.2.1   Problem Statement

A multitude of localization techniques have been proposed for terrestrial sensor networks, but there are relatively few localization algorithms for UWSNs and even fewer for under-the-ice scenarios. We are interested in evaluating a Doppler-based approach in order to achieve suitable localization results. Current localization techniques require either the expansive deployment of beacons and anchors or expensive navigation systems, which need synchronization to perform localization. Our Doppler-based system outperforms these localization techniques without requiring additional hardware or synchronization.

1.2.2   Mobile Localization Algorithm

In this Doppler-based approach, Doppler shifts are opportunistically measured from ongoing communications and the AUV's position is projected. This projection minimizes error due to a wide variety of sources, such as round-trip time (RTT), currents, and channel conditions. In addition, this approach does not require time synchronization

between AUVs and has a limited network cost. As a result, network overhead is reduced and the battery life of the AUV is extended. This allows for a greater operating range and allows an AUV to stay submerged for longer periods of time, which is crucial when exploring an under the ice environment.

The AUV attempting to localize its position broadcasts its ID number and an indicator that it is performing localization. Neighboring AUVs, also referred to as reference AUVs, reply to the broadcast with their ID, current coordinate position, and uncertainty. It is important to note that the localizing AUV keeps a log of each reference AUV's previous two positions. Once the localizing AUV hears from at least three reference AUVs, it performs lateration with a Doppler correction. By utilizing the observed Doppler shift and logged positions, the localizing AUV can minimize the error associated with traditional localization techniques.

Underwater communications suffer from large propagation delays, multipath, and shadow zones. If packets are lost because of the channel and the localizing AUV fails to hear from at least three references, the AUV can still be localized using our Doppler-based algorithm. This is accomplished by utilizing available Doppler data from previous communications and the last two logged positions for each reference AUV. In this situation we can usually project the current coordinate position of enough references to perform localization.

1.2.3   Simulation Results

The simulation results clearly show the performance gain of our Doppler-based approach versus previously proposed techniques. In all four scenarios, our Doppler-based approach outperforms other cooperative localization algorithms and nears the performance of an expensive inertial navigation system (INS). This system utilizes a DVL and several quality inertial navigation sensors whose costs are approximately $50,000 [25] a piece.

1.2.4　Outline

The remainder of this thesis is organized as follows. In Chapter II, we provide an overview of related work for AUV capabilities, in particular sensors, navigation systems and localization algorithms. We present the motivation and underwater communication model in Chapter III. The proposed solution is in Chapter IV, followed by performance evaluation and analysis in Chapter V. Conclusions are discussed in Chapter VI.

Chapter 2

AUV Capabilities

Traditionally ocean monitoring has been accomplished via static sensors that record data and are collected after a mission is completed. This setup does not allow for real-time monitoring, system reconfiguration, or failure detection [26]. Therefore a great deal of research has been directed towards AUVs with integrated sensor suites. These AUVs allow for the real-time monitoring of oceanic regions. In addition, these AUVs can adjust their destination, speed, and trajectory based on specific data and a mission's needs at the time. AUVs' capabilities are limited by two major factors: batteries and vehicle navigation [21]. We are going to deal with vehicle navigation extensively in this thesis.

2.1 Underwater Communications

Achieving effective and efficient communications in an underwater environment is a challenging and difficult task. With this in mind, our localization protocols and algorithms have been designed and written for the Woods Hole Oceanographic Institute (WHOI) Micro-Modem. This acoustic modem is available as an integrated device with Hydroid Inc. vehicles or can be purchased as a standalone system, which can be used in experiments or integrated into an AUV [27]. This modem has been utilized in a multitude of underwater experiments [20] [28] [29] [30] and has served as an emulator/testbed for the development of team formation and routing protocols in [31] [32].

Depending on the selected packet type and the modulation scheme the bit rate of the WHOI Micro-Modem can vary significantly. The acoustic Micro-Modem has 4 primary packet types and can transmit these packet types at 4 different data rates and in 4 different frequency bands, which range from 3 to 30 kHz. The maximum achievable bit

Table 2.1: The major packet types utilized by the WHOI acoustic Micro-Modem.

Packet Type	bps	Max. Frames	Bytes per Frame	Modulation	Coding Scheme
0	80	1	32	FH-FSK	
1*	250			PSK	1/31 spreading
2	500	3	64	PSK	1/15 spreading
3	1200	2	256	PSK	1/7 spreading
4*	1300			PSK	1/6 rate block code
5	5300	8	256	PSK	9/14 rate block code

The two packet types denoted by a * indicate an unimplemented scheme.

Table 2.2: Transmission Delay time for the major packet types implemented on the WHOI Micro-Modem. Data is calculated for a PSK bandwidth of 5kHz and an FSK bandwidth of 4kHz. [1]

Packet Type	Transmission Delay
0	12.15 s
1*	3.38 s
2	3.25 s
3	3.65 s
4*	3.45 s
5	3.34 s

The two packet types denoted by a * indicate an unimplemented scheme.

rate is 5300 bps, which illustrates the limited data rate of an underwater environment. The range of the WHOI modem depends on the frequency selected typically 10kHz works out to 6km to 12km, 15kHz works out to 5km-8km, and 25kHz works out to 2km-4km depending on acoustic conditions [33] [34] [35] [36]. The modem's power amplifier is a class-D topology and was selected due to its efficient and simplistic characteristics, as a result the power output of the Micro-Modem is fixed at 50 Watts [27]. Control of the WHOI Micro-Modem is achieved via NMEA commands [37]. Each modem is programmed via serial port (RS-232) and has an OpenEmbedded Linux system. Each of these systems is equipped with a Gumstix Motherboard (GM) and has a Marvell PXA255 400 MHz processor, 64 MB RAM, and 1 GB of SD disk storage [38]. In addition, each modem is designed for an operating temperature ranging from $-40^{o}C$ to $+70^{o}C$ [35].

2.1.1 Communications Cost

The average number of localization messages sent per node in an UWSN is commonly referred to as communication overhead. In order to localize the position of an AUV, the AUV must receive a broadcast of each anchor node's current calculated position.

The communication cost per node becomes critical as the number of anchor nodes and AUVs in the UWSN increases. The number of messages sent per node have been analyzed for Dive and Rise Localization (DNRL), Proxy Localization (PL) and Large-Scale Localization (LSL), but it was done without any suggestions for minimizing associated network costs [39]. Minimizing the number of localization messages sent to and from the AUV can extend an AUVs operating time in an underwater environment. This communication overhead is proportional to the total energy spent. Therefore, an efficient localization scheme which limits the number of localization messages is necessary. This proposed Doppler-based approach satisfies these requirements.

2.2   Sensors

AUVs are typically equipped with several sensors, which vary based on the price and application of the AUV. These sensors are utilized in data collection, localization and other mission critical processes. Given the significant number of sensors available for AUVs we will concentrate on sensors used in aiding navigation.

Pressure Sensors

A pressure sensor, also known as a depth sensor, provides the pressure readings for the depth of an operating AUV. This pressure corresponds to a specific depth and has an accuracy range that varies from 0.01 to 1.0 m depending on the quality of the sensor. In addition, pressure sensors have a relatively high update rate of 1 Hz [40]. This allows a three dimensional problem to be transformed into two dimensions. Therefore all UWSN localization problems with respect to AUVs are stated in two dimensions.

Doppler Sensing

The WHOI Micro-Modem is capable of detecting Doppler shifts during communications between a transmitter and receiver. The Doppler shift is calculated by the modem and given in m/s. This is the calculated relative speed between the receiver attached to the modem and the transmitting transducer [37]. The main drawback is that the

modem detects the cumulative Doppler shift, so the Doppler shift is susceptible to ocean currents and other oceanic phenomena.

Flow Meters

Flow meters are used to calculate a vehicle's relative speed in an underwater environment. Typically a propeller fixed to the AUV is rotated by the vehicle moving through the water. A sensor attached to this propeller detects the number of rotations per minute (RPMs), flow speed is then calculated, and therefore the vehicle's speed in the underwater environment can be deduced [28].

Magnetic and Gyro Compasses

A compass is usually a part of the basic navigation suite of an AUV. These devices typically consume little power and are able to provide the local magnetic fields' 3-D vector [28]. The primary drawback of a magnetic compass is that in order to locate true north, which is a point on the Earth's rotational axis as opposed to magnetic north, the compass requires calibration to the vehicle's region of operation. In addition the performance of the compass is affected by its position on the AUV and the presence of local magnetic fields [28]. A standard magnetic compass was not reliable enough for use in several experiments in the Arctic due to near vertical magnetic field lines [41].

A gyrocompass is an electrically powered compass capable of finding true north while being impervious to external magnetic fields which deflect normal compasses. This is accomplished by exploiting the rotation of the earth. This rotation deflects the compass via gyroscopic precession, which is defined as a change in the orientation of the gyro's rotational axis. Modern gyrocompasses typically implement an orthogonal triad of fibre optic or ring laser gyroscopes, which use an optical path difference to determine the Earth's rate of rotation [42].

Attitude Heading Rate Sensor

An Attitude Heading Rate Sensor (AHRS) typically consists of a 3-axis linear accelerometer in addition to the aforementioned gyrocompass and magnetic compass. An AHRS

system uses the compasses to detect the vehicle's attitude and heading while using an accelerometer to compute the three linear and angular accelerations [28]. In addition, since the acceleration, heading, and attitude are known the vehicle's velocity can be computed.

Inertial Navigation System

Inertial Navigation Systems (INS) are comparable to AHRS except that they include information from absolute position sensors [28]. INS systems utilize the information from these absolute sensors in coordination with data provided by the rate sensors to derive a vehicle's position. INS systems tend to be more expensive than AHRS systems, but they generally have sensors less susceptible to noise [28]. INS systems are constrained by error growth over time and/or distance traveled; this error is also known as INS drift [43] [28]. The most accurate INS systems are controlled by the military and are highly classified, but their accuracy is estimated to be approximately 0.01 km/hr [28].

Doppler-Velocity Log

Doppler-Velocity Log (DVL) units provide an estimate of an AUV's velocity relative to the ocean floor. These DVL units utilize at least three but typically four downward facing transducers [40]. The sensed Doppler shifts are then used to calculate the AUVs velocity underwater. In addition if the starting position is known, the AUV's velocity can be integrated over time to calculate its subsequent position. This method when used in combination with an INS unit is accurate to less than 5 meters per hour of operation. However, this comes with an additional hardware cost and the integration of DVL data leads to a cumulative error.

Sensor Performance at Arctic Latitudes

There are many other constraints to consider when examining AUV exploration in the Arctic. Equipment at such extreme latitudes tends to not operate as originally designed. Three systems underwent a thorough testing at Arctic latitudes: Ring-laser

gyroscopic INS with DVL assistance, gyro-compass AHRS, and a traditional magnetic AHRS system [41]. The magnetic AHRS struggled due to the nearly vertical magnetic field lines. The inertial instruments also became increasingly difficult as a function of the secant of latitude [41]. In addition to those constraints, gyro-compasses tend to be less accurate at high latitudes.

2.3   Localization

In underwater sensor networks (UWSNs), determining the location of each sensor is of critical importance and is often done by utilizing localization techniques. Localization is the process of estimating the location of each node in a sensor network. While various localization algorithms have been proposed for terrestrial sensor networks, there are relatively few localization schemes for UWSNs and even fewer for polar environments under ice.

Numerous localization protocols currently exist for terrestrial applications. However, there are prohibitive obstacles which prevent the application of terrestrial-oriented localization techniques to an underwater environment. UWSNs have a substantially higher propagation delay. These delays are experienced by acoustic channels and are not present in Radio Frequency (RF) terrestrial channels. Most terrestrial localization techniques have been designed for a fast and reliable channel. Despite these shortcomings it is still essential to understand the fundamental localization techniques utilized in a terrestrial RF network.

2.3.1   Terrestrial Sensor Network Localization

Global Positioning System

The Global Positioning System (GPS) is a space based navigation system composed of a constellation of 24 medium earth orbiting (MEO) satellites [44]. Each GPS satellite is equipped with an atomic clock, typically composed of Rubidium [45]. These satellites transmit the time, orbital information, system health and an almanac, which estimates the orbits of all other GPS satellites. A GPS receiver then calculates its position by

correlating the time of flight (TOF) for the signal transmitted from each satellite in orbit. There are three numerical methods are utilized in the computation of position for a GPS receiver: 1) trilateration and one dimensional numerical root finding 2) multidimensional Newton-Raphson calculations 3) Using more than four GPS satellites leads to an overdetermined system and no unique solution, which requires least-squares method or a similar technique [46] [47]. Terrestrial applications often make use of GPS since it is easy to use, available, and accurate.

Convex Optimization

The Convex Optimization localization technique was proposed to estimate the position of unknown nodes based on connectivity constraints of given seed nodes [48]. In this centralized technique, geometric constraints between nodes are represented as Linear Matrix Inequalities (LMIs). The LMIs for the entire network are combined to form a single semi-definite program. The semidefinite program is mathematically solved for each node position. The advantage of this scheme is in its relative simplicity and elegance. However, high delay, computational cost and inability to use range data limit the practical applications of this centralized scheme.

Sequential Monte Carlo Method

A Sequential Monte Carlo (SMC) method to achieve localization for mobile nodes has been studied in [49] [50]. The SMC method is a recursive Bayes filter that estimates the posterior distribution of a node's positions conditioned on sensor information. It is a two-step process. In the *prediction step*, the node uses a motion model to predict its possible location based on previous sample and its movement. In the *filtering step*, the node uses a filtering mechanism to eliminate those predictions that do not match the sensor information. This scheme requires no ranging hardware on the nodes. An improved version of a range-free SMC algorithm has been proposed for a heterogenous network of static and mobile nodes [51]. However, the effects of different mobility models on location estimates were not considered.

Dual and Mixture Monte Carlo Methods

Dual Monte Carlo (DMC) and Mixture Monte Carlo (MMC) methods for sensor localization on static and mobile nodes have been studied in [52]. DMC method is the logical inverse of the SMC method. The DMC uses a prediction step and the distributed filtering mechanism in SMC, while the second filtering step uses the prediction step distribution in SMC. The MMC method is the combination of both SMC and DMC methods [49]. Simulation results showed that localization estimation was improved in DMC and MMC methods compared to SMC method. This improvement comes at the expense of increased computation time. This is primarily due to the detailed sampling process employed in DMC and MMC methods. In addition, all Monte Carlo schemes suffer from two short-comings: 1.) A high density of nodes are required for each method. This density cannot be assumed in an UWSN due to the sparse deployment of sensors [26] [53]. 2.) Monte Carlo methods have a slow convergence time.

2.3.2 Localization in UWSN

A number of localization schemes have been proposed to date which take into account a number of factors like the network topology, device capabilities, signal propagation models and energy requirements. However, most localization schemes require the location of some nodes in the network to be known. There have been a few UWSN localization protocols proposed [2][3][4], but none of these protocols are designed with any consideration on how localization can be used to estimate subsequent positions of AUV.

Range-based Schemes

In range-based schemes, in order to estimate the location of nodes in the network, measurements are made. These measurements need to be precise in order for the localization results to be accurate and useful. Range based schemes include distance and angle measurements. These schemes, use Round-Trip Time (RTT), Time of Arrival (ToA), Time Difference of Arrival (TDoA), Received-Signal-Strength (RSS), or Angle

of Arrival (AoA) to estimate their distances to other nodes in the network. Any scheme that relies on ToA or TDoA requires tight time synchronization between the transmitter and the receiver clocks, whereas RTT does not. However, RTT comes with a higher network cost and associated error. RSS has been implemented in [54], but it comes with an additional network cost.

In order to calculate locations, range based protocols can estimate the absolute point-to-point distance (i.e., range) or angle estimates [55] [56] [57] [58] [59] [60] but at the cost of external hardware which in turn increases the network cost.

An hierarchical localization scheme involving surface buoys, anchor nodes and ordinary nodes was proposed in [61]. Surface buoys are GPS based, and used as references for positioning by other nodes. Anchor nodes communicate with surface buoys while ordinary nodes only communicate with the anchor nodes. This distributed localization scheme applied 3D Euclidean distance and recursive location estimation method for the position calculation of ordinary nodes. However, mobility of the sensor nodes was not considered in the position estimate.

A relative position estimate was proposed in [15] [57] [62] [63] [64] [65] [66] through a combined process of node discovery and localization. In this technique, a seed (originator) node broadcasts discovery messages to determine neighbors and eventually all other nodes in the network. Once an unknown node has attained three seed nodes as neighbors, its location is estimated. This node can now become a seed for other unknown nodes. Coverage increases as nodes with newly estimated positions join the reference node set, which is initialized to include anchor nodes. However, there are several short-comings of this proposal such as the criteria for selecting the first seed, the method applied for measuring the distance between nodes, the effect of node mobility and inherent delay in node discovery as a result of high message exchange.

A recent proposal uses surface based signal reflection for underwater localization [54]. This approach attempts to overcome limitations imposed by line of sight (LOS) range measurement techniques such as RSS, TOA, and AoA. These limitations are caused by multipath, line of sight attenuation and required reference nodes. The receiver in this approach accepts only signals that have been reflected off the surface. It accomplishes

this by applying homomorphic deconvolution to the signal to obtain an impulse response, which contains RSS information. The algorithm then checks the RSS and compares it to calculated reflection coefficients [54]. This algorithm has several strengths, in that it allows for mobility and has a high accuracy. The main drawback is that this algorithm can not be applied to an under the ice environment since icebergs tend to have varying depths below the water surface. In addition, this algorithm is computationally intensive and has a large amount of communication overhead associated with it.

In submarines and other related vehicles positioning system, localization systems are based on Short Baseline systems (SBL) and Long Baseline systems (LBL) [67]. External transducer arrays are employed in both systems to aid localization. In SBL system, position estimate is determined from measurement of the range and angle of acoustic transponder beacon to the vehicle. In addition, these vehicles can randomly interrogate the beacon from which distance is computed. In LBL systems, array of transponders are tethered in the ocean bed with fixed location. Any vehicle interrogation is returned by transponder beacons enabling position computation. UWSN nodes are bounded by cost-constraints, hence both SBL and LBL schemes with their added signal processing and hardware complexity are not suitable.

Anchor-based and anchor-free localization schemes are sometimes referred to as beacon-based or seed-based localization. In these schemes unknown nodes estimate their position from anchor nodes, which have known positions. Once unknown nodes have estimated their position within a specified region, they too can become anchor nodes. In anchor-free localization systems, nodes exchange packets with neighbors to generate a relative map for node positions [68].

A bounding box algorithm defines a rectangular region with the intersection of the distance estimates ($w.r.t$ node and anchor positions) [15]. It requires two messages from positions that are non-aligned. The performance of this algorithm is strongly dependent on anchor-node position. In order to achieve an accurate localization, messages are required to be sent from either side of the box. The algorithm achieves localization for a large number of nodes but with a substantially high error rate.

A proposal that studied underwater localization in both static and mobile nodes was described in [69]. A Dive-N-Rise (DNR) beacon obtains coordinates while on the ocean surface and then sinks, while simultaneously distributing its coordinates to unknown nodes. This scheme assumes synchronized nodes in which nodes listen for several beacons before applying message TOA scheme for range measurement. However, the results are incomplete since a random model depicting high variability of shallow and deep water scenarios were not incorporated in the study [14] [69].

In [70], AUV Aided Localization (AAL) was proposed to address node mobility, limited message exchange and 3D coverage. This approach utilizes two-way ranging and does not require synchronization. In this approach, a timer begins when the packet is sent and stops when the packet is received. This timer value is then multiplied by the speed of sound and then divided by two for the distance estimate. The response packet includes AUV coordinates so when a node hears three localization messages that are non-coplanar it performs lateration.

Comparisons for the performance of three localization techniques known as Dive and Rise Localization (DNRL), Proxy Localization (PL) and Large-Scale Localization (LSL) have been carried out in [39]. DNRL, PL and LSL are distributed, range-based localization schemes, which are suitable for three dimensional, mobile UWSNs. However, since PL and LSL techniques are primarily for large scale localization so we focus on DNRL. In DNRL, an anchor (originator) node broadcasts localization messages to neighbors and all other nodes in the network. Once an unknown node has attained three anchor nodes as neighbors, its location is estimated. If the node receives updated coordinates, these coordinates overwrite old records and localization is performed again.

An AUV serving as an Communication and Navigation Aid (CNA) is proposed in [29]. This proposed approach attempts to predict the location of an AUV by using ranging information acquired via RTT. This is a linear prediction technique in which previous position estimates are utilized. In addition, this approach has an online correction technique but is strongly dependent upon receiving ranging information from the support AUV.

Range-free Schemes

Range-free schemes do not use range or bearing information; that is, they do not make use of any of the techniques mentioned above (RTT, ToA, TDoA and AoA) to estimate distances to other nodes. The centroid scheme [64], DV-Hop [68] and Density aware Hop-count Localization (DHL) [71] fall under this category. The area in which the node is located is computed by a server or anchor to determine the sensors location. The granularity of the scheme is determined by the size of areas, which the sensor nodes fall within and this is adjusted by varying a number of power levels used. Range-free schemes make no assumptions about the availability or validity of range information [64] [68] [72] [73]. Range-free schemes can only provide coarse position estimates, but do not need additional hardware support.

Dead reckoning makes use of an AUV's onboard sensors in order to predict a vehicle's location. It accomplishes this by integrating the vehicle's heading and speed over time. An AUV is assumed to be surfaced at the start of the mission and its coordinates are known via GPS. Once an AUV is submerged its speed can be measured directly with a flow meter, estimated with accelerometers, or determined experimentally. The vehicle's heading is extracted from either a compass, AHRS, or INS with varying degrees of accuracy. In order for dead reckoning to be effective it requires a suite of highly accurate sensors, especially since magnetic navigation systems are subject to local variations in the magnetic field and gyro's are subject to drift over time. Quality inertial navigation sensors cost approximately $50,000 [25] a piece. In addition, dead reckoning is subject to error propagation over time since its velocity is integrated with respect to time. Extended Kalman Filters (EKF) can be used to minimize system noise, but dead reckoning is typically only accurate for a short period of time [74] [75].

Bathymetry localization matches the depths of an underwater terrain to available bathymetric maps in order to better localize an AUVs position [43]. Traditional INS suffer from drift, and the authors attempt to overcome this by exploiting available bathymetric data. This technique generates a position estimate based on two primary systems: a maximum likelihood estimator which uses in-situ measurements of ocean
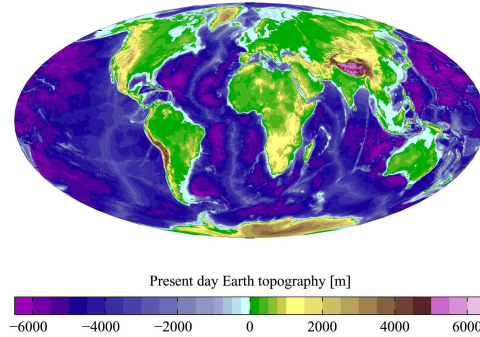
Figure 2.1: Bathymetry map of the Earth from the National Geophysical Data Center's TerrainBase Digital Terrain Model.

depth and an INS and/or DVL system [43]. These systems when used in combination can greatly constrain INS drift and lead to an accurate localization that does not decay with time. The primary problem with this localization method occurs when there are limited geographic features on the ocean bottom, in other words there is a limited variation of the sea floor's depth.

Simultaneous Localization and Mapping

Simultaneous Localization and Mapping (SLAM), also known as Concurrent Mapping and Localization (CML), attempts to merge two traditionally separated concepts, map building and localization. SLAM has been investigated using an imaging sonar and DVL in combination with dead reckoning [76]. However, despite recent research efforts this technology is still in its infancy and many obstacles still need to be overcome. As of November 2010, there have been several simulations carried out [77], but currently there is no operating solution to the AUV SLAM problem.

Probabilistic Localization

Several proposals have utilized a particle filter approach as an estimating technique for Bayesian models. A particle filter is used to represent the vehicle state, which can then be used to estimate an AUV's position via Bayes filter, which is essentially a probability distribution [78]. The particle filter approach has two distinct advantages. The first being that it can handle errors that are not modeled as gaussian. The second

is the particle filter does not require any knowledge of an AUVs initial position or orientation. Particle filters are not easily implemented in real missions with small scale AUV networks. This is due to a particle filter's required computational complexity and the large number of particles necessary to define a sample space, which may not be available in a real mission. Particle filters struggle to perform localization in regions with limited or unknown maps.

2.3.3 Under the Ice Localization

Relatively few under the ice localization techniques have been proposed and many standard underwater localization techniques do not apply to an under the ice environment. Recent efforts have been made by Kongsberg Maritime and Wireless Fibre Systems (WFS) to develop an effective wireless communication system for locating and communicating with AUVs under the ice wirelessly [79]. Despite these efforts the technology remains expensive and out of reach for most universities and industries. Current techniques employed in an under ice environment include: combinations of either dead-reckoning using inertial measurements [23] [41] [80], sea-floor acoustic transponder networks such as SBL or LBL [81], and/or a DVL that can be either seafloor or ice relative [23] [41] [80] [82]. These current approaches require external hardware, are cost prohibitive, and suffer from error propagation. Therefore an accurate and affordable localization technique is needed in an under the ice environment.

In our simulation, we implement an INS system with a DVL to constrain error over time. This serves as our performance baseline. An INS system equipped with quality sensors and a DVL can achieve suitable localization results with an error of about 8 meters over the course of 4,000 seconds [83].

A major barrier to entry for under the ice exploration is the risk of losing an AUV vehicle. Suggestions toward reducing the risks associated with under the ice exploration have been made in [84]. Accurate navigation is considered one of the important prerequisites for achieving safe under the ice operations. Modern AUVs, such as the HUGIN 1000, use a sophisticated INS system that must be supported/aided by either DVL, SBL, LBL, or terrain referenced navigation in order to constrain error due to

drift [84]. Our proposed Doppler approach consistently constrains the error in localizing

AUVs in under the ice environments.

Chapter 3

Mobile Localization

3.1 Motivation

In this thesis, we are interested in performing the localization of a mobile UWSN comprised of several AUVs. Our motivation is that few localization techniques exist for mobile sensor networks, and most are not designed with any consideration for how mobility can be exploited to achieve localization. We designed a localization scheme that utilizes a Doppler-based approach in tandem with the lateration technique to perform localization. Currently, no literature has reported this approach.

Currently the only Doppler-aided localization technique leveraging Doppler shifts is known as bottom lock Doppler or DVL. DVL works by bouncing sound waves off either the seafloor or the bottom of an ice pack [82]. The sound waves are emitted by an external transducer array. It then senses the Doppler shifts observed in the sonar signal. This provides the AUV with its velocity, which when combined with a heading, can be integrated over time to get position. There are several drawbacks to this approach. It requires a close proximity to the seafloor or ice pack to operate. In addition, the external transducer array used in this approach increases the energy use, costs, and complexity of the AUV. Our proposed approach has no external hardware requirement since Doppler functionality is built into modern underwater modems, such as the WHOI modem [37].

We make comparisons to several other localization approaches in our simulation. The approaches that were implemented in our simulation were DNRL, AAL, CNA, and INS. These techniques were covered with greater detail in Chapter II, but we will summarize each approach and how it was implemented in our simulation.

A major detail in any localization scheme is the selection of anchors or reference AUVs. In any of the localization schemes, an unlocalized AUV may hear from a number of reference AUVs. It is assumed that three references are enough, but perhaps the node hears from five. It is possible to use all of these referenced locations when performing lateration to better localize position. However, Erol's two major localization algorithms' (DNRL & AAL) prefer to implement the simplest lateration, which is trilateration. In other words, these approaches are using three reference AUVs. So, the selection of references becomes the next problem. It is possible to chose references randomly or first arrival or last arrival. Here both DNRL and AAL utilize the last three references to arrive, since all AUVs are mobile the latest information has less possibility to be outdated.

Here is how we implemented DNRL. There are three mobile anchor AUVs that will serve as references for all other (non-anchor) AUVs. When the total number of AUVs in the system is greater than six then four mobile anchor AUVs are utilized and not three. Each mobile anchor AUV is equipped with an expensive INS system with DVL to keep track of their position. These references are referred to as 'mobile anchors', because they have the same purpose as a Dive'N'Rise anchor with a GPS fix except they are mobile. These anchor AUVs serve to localize all other AUVs in the system. Unlocalized AUVs record every new anchor AUV coordinate and the related distance estimate in a table unless it comes from a coplanar anchor. When the number of entries reaches three it does lateration. If the AUV receives new coordinate updates from an anchor AUV already stored, then the new message overwrites on the old records. The limited number of anchor AUVs limits the overall accuracy and coverage of this scheme. Over time if the AUVs are not kept in a formation they will travel and drift further and further apart. This can cause a disconnected network and creates issues of lost packets and inaccurate localization, especially if there are relatively few AUVs serving as anchors. Additionally, the INS system onboard the anchor AUVs use expensive inertial sensors that can cost upwards $50,000 [25].

AAL differs from DNRL in several distinct ways. The first is that anchor AUVs are no longer utilized and all mobile AUVs are eligible to be used as references in

localization. In addition, two-way ranging is utilized to relax any synchronization requirements. The process starts when an AUV hears a broadcasted localization message (short message to indicate that an AUV is in their transmission range and performing localization), when the reference AUV hears this message it replies with its current coordinates and ID number. The localizing AUV stops an internal timer when the response is received. The timer value is multiplied by the speed of sound and divided by two to get a distance estimate. When a localizing AUV receives three messages from reference AUVs it checks if the coordinates are non-coplanar, and if so proceeds to lateration. If three references are not received the localizing AUV utilizes stored coordinates for an additional reference so that lateration can be performed. This introduces a great degree of error. In addition, since a two-way approach is utilized the localizing AUV will travel tens of meters before its position can be determined. At this point the position determined is no longer the localizing AUV's current position.

The CNA approach attempts to predict the location of an AUV by using ranging information acquired via RTT. This is a linear prediction technique in which previous position estimates are utilized. This alternative approach considers a system in which a single submerged AUV (with accurate dead reckoning instrumentation, such as an INS/DVL system) communicates with a fleet of much less accurately localized AUVs so as to improve the positioning of the latter [29]. This is very similar to the moving long base line (MLBL) approach, which utilizes several submerged vehicles to serve as mobile anchors for one or more AUVs [85]. The CNA technique also bears a striking resemblance to the previously covered DNRL approach, which uses three mobile anchor AUVs to constrain localization error. The CNA approach also implements an online correction technique but it is strongly dependent upon receiving ranging information from reference AUVs.

3.2   Underwater Model

In this section we introduce the UWSN environment that our proposal is based on and state related assumptions. Suppose the network is composed of a number of AUVs that are collecting data in a collaborative manner. Barring currents these vehicles travel at

fairly constant horizontal speeds, ranging from 0.20-0.40 m/s see Table 1.1.1 and know their heading via a magnetic compass or gyroscope. However, these instruments perform poorly at extreme latitudes [41]. Therefore the ability of these vehicles to complete tasks collaboratively depends on their ability to locate and communicate effectively. Underwater communications are impacted severely by path loss, propagation delay, temperature, salinity, and pressure see section 1.1.3 for more details.

A coarse approximation for underwater acoustic wave propagation is the Urick model. The Urick model provides path transmission loss $TL(l, f)$ in dB and can be modeled as,

$$TL(l, f) = \kappa \cdot 10log(l) + \alpha(f) \cdot l, \tag{3.1}$$

where κ is the spreading factor, l is the distance between the transmitter and receiver, and f is the carrier frequency. κ is taken to be 1.5 for practical spreading, and $\alpha(f)$ $[dB/m]$ represents an absorption coefficient that increases with f [86]. The spreading of sound energy caused by the expansion of the wavefronts is known as *geometric spreading*[1] and is accounted for in the first term, $\kappa \cdot 10log(l)$, of (3.1). Geometric spreading is independent of frequency, but increases with propagation distance. It is important to note that a spreading factor of $\kappa = 2$ is used for spherical spreading, $\kappa = 1$ for cylindrical spreading, and $\kappa = 1.5$ for the so-called practical spreading. The second term, $\alpha(f) \cdot l$, accounts for *medium absorption*, where $\alpha(f_0)$ $[dB/m]$ represents an absorption coefficient. This absorption coefficient defines the dependency of the transmission loss on frequency.

In reality, acoustic propagation speed varies with water temperature, salinity, and depth. These acoustic waves can travel on curved paths and are also reflected from the water's surface and off the sea floor. Such an uneven propagation of waves results in shadow (convergence) zones which may receive much more (or less) transmission loss than predicted by the Urick model. A detailed description is provided in the paragraph

---

[1]There are two kinds of geometric spreading: *spherical* (omni-directional point source, spreading coefficient $\kappa = 2$), and *cylindrical* (horizontal radiation only, spreading coefficient $\kappa = 1$). Cases that are in-between show a spreading coefficient κ in the range of $(1, 2)$, depending on link length and water depth.

below, but more details can be found in [87].

A *surface duct* is a zone below the sea surface where sound rays are refracted toward the surface and then reflected back downward. These rays alternate between being refracted and reflected along the duct and are carried out to relatively far distances [88]. Regions in a water column where the speed of sound initially decreases to a minimum and then increases due to pressure is known as a *sound channel.* Above the depth of minimum value, sound rays are bent downward while below the depth of minimum value, rays are bent upward. This results in the rays being trapped in the channel, which permits their detection at quite a large distance from the source, also called SOFAR [88]. A *convergence zone* is a region in the deep ocean where sound rays, refracted from the depths, return to the surface. They are focused at or near the surface in successive intervals. A *shadow zone* is a region in which very little sound energy penetrates. This depends on the strength of the lower boundary of the surface duct and is usually bounded by the aforementioned lower boundary and a limiting ray. There are two shadow zones: 1) the sea surface, in which a shadow is cast beneath the surface in the sound field of a shallow source. 2) deep-sea bottom, in which a shadow zone is produced by the upward-refracting water above it.

It is due to these phenomena that the Urick model is insufficient to represent the underwater channel for AUV communications. To overcome these shortcomings in our simulation, a Bellhop model has been implemented. This model is a complete ray tracing tool for underwater environments and can accurately model the aforementioned phenomena [89]. Once the Bellhop model is provided with a sound speed depth profile, transmission loss can be calculated via three-dimensional acoustic ray tracing. A numerical solution to the Bellhop is provided by HLS Research, which solves the differential ray equations to provide the transmission loss [89]. The Bellhop model is only used to simulate the underwater acoustic environment since it requires extensive environmental information that an AUV will not be able to provide.

An additional important characteristic of underwater environments are currents. While the majority of ocean currents can be mapped and accounted for in most situations [90], it is still crucial to understand each localization technique's performance

in these scenarios. These underwater currents have a profound impact on localization techniques and can be mitigated by utilizing observed Doppler shifts. The main situation in which currents go un-detected is one in which the majority of AUVs are under the influence of the same current. Two customized current models are utilized throughout our simulation, one with variable currents of 1 to 3 cm/s and another with extreme currents of 4 to 6 cm/s. These current models are based off data provided for the Bering Strait [91] and Arctic [90] [92].

We also implement an empirical ambient noise model in our simulations similar to that implemented by Baozhi Chen in [32]. This empirical model is calculated by integrating the power spectrum density (psd) over the current frequency band. The power spectrum density (psd) implemented is a 'V' type structure, as shown in [86]. A propagating sound wave underwater creates changes in pressure, which are detected at the receiver. A pressure level of $1\mu Pa$, serves as relative reference for the power (source) level, which is expressed in decibels (dB). The power level (dB) at a distance of $1\ m$, $SL\ re\ \mu Pa$ is given by

$$SL = 170.77 + 10\log P, \qquad (3.2)$$

where P is a compact source of power in watts.

Chapter 4

Proposed Approach

This proposed localization solution is for a distributed UWSN comprised of several mobile AUVs performing a collaborative task under ice. Initially all AUVs were deployed at the surface in a two dimensional volume of 1250 by 1250km. Each AUV has an initial velocity between 2.5 and 4 m/s and varies over time. Our proposed approach is a novel Doppler-based algorithm for the localization of AUVs in an UWSN, specifically under-the-ice scenarios.

We make following assumptions:

1. There are N reference AUVs : n = 1, 2, ... N

2. Each AUV is assumed to have a unique integer ID and an onboard clock

3. An AUV's ID in this thesis is provided as, AUV_1 for AUV 1, AUV_2 for AUV 2, etc. and to simplify notation we use AUV_i for the localizing AUV and AUV_n for any reference AUV

4. The localizing AUV coordinates are provided as

   $P_i = (x_i, y_i, z_i)$

5. Reference (neighboring) AUVs are considered to be at position

   $P_n = (x_n,\ y_n,\ z_n)$

6. Subscripts indicate the AUV's ID number (Ex : P_1 indicates the position of AUV 1)

7. Superscripts indicate the time instants (Ex : P^k indicates position at time 'k')

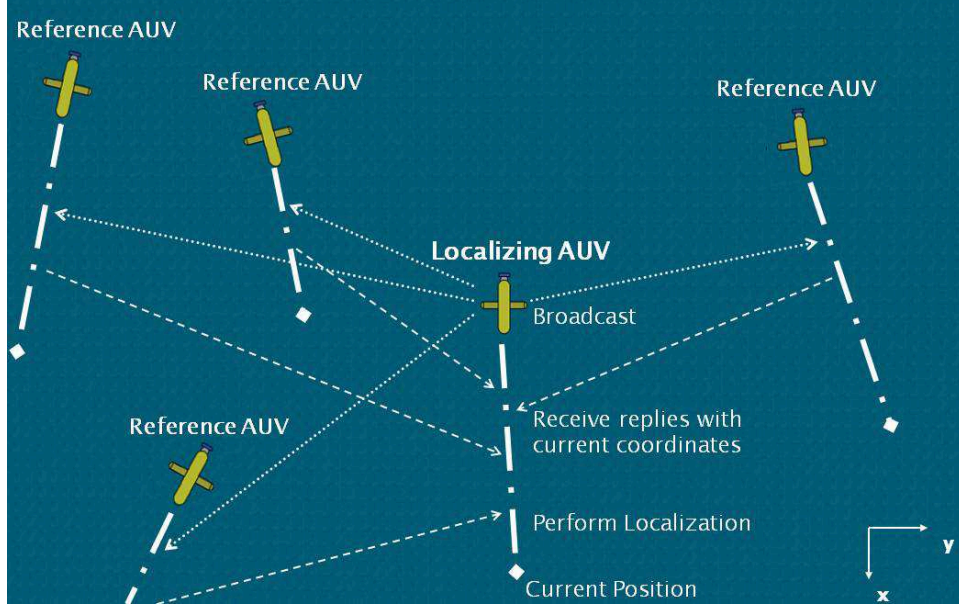8. Thus $P_n{}^{k+1}$, would signify the position of reference AUV 'n' at a time instant 'k+1'

Figure 4.1: Overview of Localization Protocol

9. All AUVs are equipped with storage capabilities, such that a localizing AUV_i maintains a log of its references' $AUVs_n$ last two positions

This typically three dimensional localization problem can be transformed into two dimensions since each AUV is assumed to have a pressure sensor, which provides the z distance or depth of the AUV. We utilize RTT to calculate the distance from the localizing AUV_i to a reference AUV_n. This alleviates the need for synchronization between AUVs. When AUV_i broadcasts that it is performing localization, it starts an internal timer or records the current time from its internal clock. As localization messages are received from references they are timestamped with the time they were received. The difference in time between when the message was sent and received is the RTT of the message.

The RTT_{in} from AUV_i to a reference AUV_n is given as

$$RTT_{in} = \left(\frac{\|\overrightarrow{P_iP_n}\|}{c} + (T_p + T_t) \right) \cdot 2 \qquad (4.1)$$

where $\|\overrightarrow{P_iP_n}\|$ is the distance between the AUVs, T_p is the time needed for processing, T_t is the transmission delay given by Table 2.2, and c is the speed of sound. It is important

to note that the speed of sound fluctuates as a function of several variables, in particular temperature, salinity, and depth. Mackenzie developed an empirical equation for the speed of sound in sea water [93] given as

$$c(T, S, z) = a_1 + a_2T + a_3T^2 + a_4T^3 + a_5(S - 35) + a_6z + a_7z^2 + a_8T(S - 35) + a_9Tz^3$$

where a_1=1448.96, a_2=4.591, a_3=-5.304·10^{-2}, a_4=2.374·10^{-4}, $a5$=1.340, a_6=1.630·10^{-2}, a_7=1.675·10^{-7}, a_8=-1.025·10^{-2}, a_9=-7.139·10^{-13}. This simple empirical equation was utilized in the simulation for a more accurate modeling of the speed of sound. Mackenzie's model, assumes a water temperature and salinity that varies with depth. A temperature range of -2 to 2^oC and a salinity between 32.5-35% was implemented in our simulation.

The distance between AUV_i and AUV_n can now be calculated as

$$d_p = \frac{RTT_{in} - 2 \cdot (T_p + T_t)}{2} \cdot c \qquad (4.2)$$

where RTT_{in} is the measured round trip time, T_p is the time needed for processing, T_t is the transmission delay given by Table 2.2, and c is the estimated speed of sound. This provides the total distance, d_p, between AUV_i and AUV_n. However, by the time AUV_i receives the positional information from reference AUV_n, AUV_n has already moved at a rate of $\upsilon_n \cdot (RTT_{in}/2)$.

The Doppler-shifted frequency f_n observed at AUV_i can be expressed as

$$f_n = f_s \left(1 \pm \frac{\upsilon_{(R)}}{c}\right) \qquad (4.3)$$

where

$\pm$ is representative of whether the source and reference are moving towards or away from each other, $\upsilon_{(R)}$ is the inter-vehicular velocity of the AUV_i w.r.t to the reference AUV_n, f_s is the frequency of the source, and c is the speed of sound.
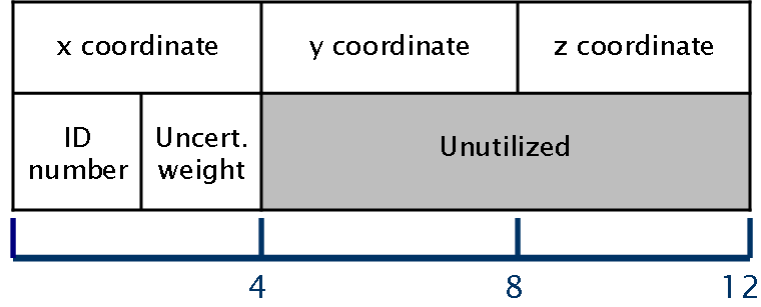
Figure 4.2: Localization packet structure in bytes.

$$\Delta f = f_n - f_s = \left(\frac{v_{(R)}}{c} \right) \cdot f_s \tag{4.4}$$

where Δf is the frequency shift. In UWSNs, Doppler shifts can be observed for AUVs whose inter-vehicular velocity differs only slightly. This is in stark comparison to observed terrestrial Doppler shifts, which require a substantial inter-vehicle velocity. This characteristic can be attributed to the speed of sound underwater, which is five orders of magnitude slower than terrestrial RF. In terrestrial applications, c $(3 \cdot 10^8 m/s)$ dominates in equation 4.4 unless $v_{(R)}$ is sufficiently large. The WHOI Micro-Modem is able to provide an inter-vehicular Doppler velocity in terms of m/s [37]. This velocity is utilized by our Doppler-based algorithm.

In this approach, the localizing AUV_i broadcasts its ID and an indicator that it is performing localization to other neighboring AUVs in range. Each AUV in the UWSN does this broadcast periodically every 60 s defined as ΔT. Neighboring AUVs who successfully receive the broadcast reply to the message with their ID, current coordinates, and positional uncertainty see Figure 4.2. All localization messages are assumed to be transmitted and received by a WHOI Micro-Modem aboard the AUVs. These modems are rated for an operating temperature of $-40^o C$ and have been used in deep cold water experiments such as Nereus' exploration at a depth of 11,000 m [35] [94]. All communications are done at a frequency of 10kHz since the AUVs are sparsely deployed in the UWSN and communications span great distances. Communications

using 10kHz work out to 6km to 12km depending on acoustic conditions [33] [36]. In addition 10kHz is part of the modem's standard band (Band A) [33] [94]. Since we are transmitting less than 32 bytes, we need not worry about sending multiple frames when dealing with the various packet types available with the Micro-Modem. The Micro-Modem's Packet Type 2 with a phase-shift keying (PSK) modulation scheme is utilized for our localization messages. Type 2 was chosen given its minimal packet error rate at a relatively low Signal-to-Interference-plus-Noise Ratio (SINR) [32].

If the localization message sent from a reference is successfully received by the localizing AUV_i, this information is then stored until AUV_i hears from at least three references, $AUVs_n$. The pseudocode can be found in the General Localization Protocol at the end of the chapter. Please note that it is possible to hear from more than three AUV references. In this case the next crucial element of the algorithm is reference selection.

We adopt a weighted framework where the localizing AUV_i ranks the received references $AUVs_n$ in terms of their associated uncertainty. The pseudocode for this uncertainty calculation can be found at the end of the chapter. Our model implements an acceptable threshold and discards all references who are below it, we perform this as long as we have at least three references. The time window to receive references from the point of broadcast is sixty seconds.[1] The pseudocode can be found in Reference Selection Algorithm at the end of the chapter.

If packets are lost due to the channel and the localizing AUV_i fails to hear from at least three references, the AUV_i can still be localized using our Doppler-based algorithm. This is accomplished by utilizing the latest Doppler data from previous communications and the last two logged positions for each reference AUV_n. Since the logged coordinates for each reference AUV_n has an associated timestamp[2], we are able to sort the $AUVs_n$ in order of those with the most recently logged coordinates, essentially a last in first out (LIFO) scheme. The algorithm then ensures there are enough reference $AUVs_n$ to

---

[1]The time between receiving a localization message and performing lateration is stored as T_{Ln}.

[2]An associated timestamp is defined as the time a localization message was received from a reference AUV_n.

perform lateration.

Once reference selection has taken place we can calculate AUV_i's current position. The range vector from AUV_i to its reference AUV_n is $\overrightarrow{P_iP_n}$ where the range $d_n = P_iP_n = \|\overrightarrow{P_iP_n}\| = [(x-x_n)^2 + (y-y_n)^2 + (z-z_n)^2]^{\frac{1}{2}}$ From the reference $AUVs_n$ we can formulate an overdetermined system of equations.

The general equation between the AUV_i and reference $AUVs_n$ can be written in 3D as a **system of equations**,

$$\begin{bmatrix} d_1^2 = (x-x_1)^2 + (y-y_1)^2 + (z-z_1)^2 \\ \\ \\ . \\ \\ \\ . \\ \\ \\ d_n^2 = (x-x_n)^2 + (y-y_n)^2 + (z-z_n)^2 \end{bmatrix}$$

where d_n is the distance between AUV_i and AUV_n, (x,y,z) are the coordinates of the localizing AUV_i and (x_n, y_n, z_n) are the coordinates of the nth reference AUV, referred to as AUV_n. The only unknowns are x and y since the z position is provided by the on board pressure sensor, the d_n between the AUVs can be accurately estimated, and the AUV_n's coordinate position is known.

Since the AUVs travel at different speeds and the inter-vehicular velocity between AUV_i and AUV_n is not zero, we can utilize the Doppler velocity to compute an updated distance estimate between them. Each AUV is assumed to be equipped with a modem, capable of detecting the Doppler-shift associated with a reply message, such as the Woods Hole Oceanographic Institute's Micro-Modem [37]. AUV_i's modem detects the Doppler-shift associated with the received signal and calculates the AUV's relative inter-vehicle velocity, $v_{(R)}$ (this value is positive or negative based on whether the AUVs are moving toward or away form each other). This inter-vehicle velocity when multiplied by half the RTT (transmission, processing, and propagation delay) plus T_{Ln} (the time between receiving the reference AUV_n's localization message and performing lateration) provides the difference in distance, Δd_d, between the distance

prior to Doppler correction, d_p, and the current distance, d_n.

$$\Delta d_d = v_{(R)} \cdot T_{Ln} \tag{4.5}$$

where $v_{(R)}$ is the inter-vehicle velocity and T_{Ln} is the time between receiving the reference AUV_n's localization message and performing lateration. The current distance between the localizing AUV_i and the reference AUV_n can now be updated as

$$d_n = d_p + \Delta d_d \tag{4.6}$$

where Δd_d is the difference in distance between the distance prior to Doppler correction, d_p, and the current distance, d_n.

It is assumed that each AUV stores the last two positions for all other AUVs in the UWSN, which is realistic given that the WHOI Micro-Modem provides SD storage [32] [37]. The localizing AUV_i now uses the current position x'^k_n, y'^k_n, z'^k_n and stored position x^{k-1}_n, y^{k-1}_n, z^{k-1}_n for each reference AUV_n to compute AUV_n's component velocities, v_{x_n}, v_{y_n}, and v_{z_n}.

$$\widehat{\vec{v_n}} = \frac{\overrightarrow{P^{k-1}_n P'^k_n}}{\Delta T_r} = \frac{(x'^k_n - x^{k-1}_n, y'^k_n - y^{k-1}_n, z'^k_n - z^{k-1}_n)}{\Delta T_r} \tag{4.7}$$

where ΔT_r is the time difference in seconds between the last time localization was performed and the time the coordinates for the reference were received. We now end up with the component velocities for the reference AUV

$$v_{x_n} = \frac{x'^k_n - x^{k-1}_n}{\Delta T_r}$$

$$v_{y_n} = \frac{y'^k_n - y^{k-1}_n}{\Delta T_r}$$

$$v_{z_n} = \frac{z'^k_n - z^{k-1}_n}{\Delta T_r}$$

These velocity components when multiplied by T_{Ln} and added to the coordinates received from the reference AUV_n provide the current coordinates at each localization

interval. The coordinates received by the reference AUV are $x_n'^k$, $y_n'^k$, $z_n'^k$. The corrected current coordinates are computed as

$$x_n^k = x_n'^k + v_{x_n} \cdot \left(\frac{RTT_{in}}{2} + T_{Ln} \right)$$

$$y_n^k = y_n'^k + v_{y_n} \cdot \left(\frac{RTT_{in}}{2} + T_{Ln} \right)$$

$$z_n^k = z_n'^k + v_{z_n} \cdot \left(\frac{RTT_{in}}{2} + T_{Ln} \right)$$

Now that we have the updated coordinates and distances, the previous **system of equations** can be linearized.

$$
(x - x_{n-1})^2 + (y - y_{n-1})^2 + (z - z_{n-1})^2 - d_{n-1}^2
$$
$$
= (x - x_n)^2 + (y - y_n)^2 + (z - z_n)^2 - d_n^2
$$
(4.8)

$$
2x(x_{n-1} - x_n)^2 + 2y(y_{n-1} - y_n)^2
$$
$$
= x_{n-1}{}^2 - x_n{}^2 + y_{n-1}{}^2 - y_n{}^2 + z_{n-1}{}^2 - z_n{}^2 - 2z(z_{n-1} - z_n)^2 + d_n^2 - d_{n-1}^2
$$
(4.9)

This can be expressed in matrix form as a linear system ,

$$A\phi = b \tag{4.10}$$

where

$$
A = \begin{bmatrix}
2(x_1 - x_n) & 2(y_1 - y_n) \\
& \\
\cdot & \cdot \\
& \\
\cdot & \cdot \\
& \\
2(x_{n-1} - x_n) & 2(y_{n-1} - y_n)
\end{bmatrix}
$$

$$b = \begin{bmatrix} x_1{}^2 - x_n{}^2 + y_1{}^2 - y_n{}^2 + z_1{}^2 - z_n{}^2 - 2z(z_1 - z_n)^2 + d_n^2 - d_1^2 \\ \\ \cdot \\ \\ \\ \cdot \\ \\ x_{n-1}{}^2 - x_n{}^2 + y_{n-1}{}^2 - y_n{}^2 + z_{n-1}{}^2 - z_n{}^2 - 2z(z_{n-1} - z_n)^2 + d_n^2 - d_{n-1}^2 \end{bmatrix}$$

$$\phi = \begin{bmatrix} \hat{x} \\ \hat{y} \end{bmatrix}$$

where ϕ can be solved for.

The Least Squares (LS) solution corresponding to $A\phi = b$ is given by

$$\phi = \left(\mathbf{A}^T \mathbf{A} \right)^{-1} \mathbf{A}^T \mathbf{b} \tag{4.11}$$

General Localization Protocol 1 General localization protocol utilized by the AUVs. Here T is total time underwater, T_{end} in our simulation is $10600s$, ΔT is the localization interval of $60s$, T_{wind} is the time to start listening for replies, ΔT_{wind} represents the time window to receive replied localization messages and is set to $60s$

1: **while** $T \leq T_{end}$ **do**
2:     *Broadcast request for information to neighboring AUVs*
3:     $T_{wind}=T$
4:     **for** $T_{wind} \leq T_{wind} + \Delta T_{wind}$ **do**
5:         *Listen for incoming replies*
6:         *Store replies from references*
7:         $T_{wind} = T_{wind} + 1s$
8:     **end for**
9:     *Estimate distances via RTT*
10:     *Run reference selection algorithm*
11:     *Perform localization*
12:     *Determine uncertainty*
13:     *Update positional coordinates*
14:     $T = T + \Delta T$
15: **end while**

Reference Selection Algorithm 2 Reference selection algorithm. Here N_{ref} represents the number of reference AUVs (essentially the number of neighboring AUVs who's localization message have been received successfully), AUV_n represents the reference AUVs, ω_n represents each reference's uncertainty, ω_a represents the average uncertainty for the top three references, and τ_d represents the defined threshold which is 5% (0.05) in our simulation.

1: **if** $N_{ref} > 3$ **then**
2:     *Sort reference $AUVs_n$ by their uncertainties (ω_n)*
3:     *Select the top three and calculate*
$$\omega_a = \tfrac{1}{3} \sum_{i=1}^{3} (\omega_n)$$
4:     **for** N_{ref} not in the top three **do**
5:         **if** $1 - \left(\frac{\omega_n}{\omega_a}\right) \leq \tau_d$ **then**
6:             **if** $i == 1$ **then**
7:                 *Write top three $AUVs_n$ to a references list*
8:             **end if**
9:             *Append AUV_n to the list*
10:             $i=i+1$
11:         **end if**
12:     **else**
13:         *Write top three $AUVs_n$ to a references list*
14:     **end for**
15: **else**
16:     *Use all available $AUVs_n$*
17: **end if**

Uncertainty Algorithm 3 Uncertainty algorithm. Here T is total time underwater, ΔT is the localization interval of $60s$, N_{ref} represents the number of reference AUVs, ω_i is the current AUV's uncertainty, and ω_n represents each reference's uncertainty.

1: **if** $T \leq \Delta T$ **then**
2:    *Initial uncertainty*
3:    **if** $N_{ref} \geq 3$ **then**
4:       $\omega_i = 100$
5:    **else**
6:       $\omega_i = \frac{N_{ref}}{3}$
7:    **end if**
8: **end if**
9: **if** $T > \Delta T$ **then**
10:    **if** $N_{ref} \geq 3$ **then**
11:       $\omega_i = \frac{1}{N_{ref}} \sum_{i=1}^{N_{ref}} (\omega_n)$
12:    **else**
13:       $\omega_i = \frac{1}{3} \sum_{i=1}^{N_{ref}} (\omega_n)$
14:    **end if**
15: **end if**

Chapter 5

Performance Evaluation

5.0.1 Evaluation Metric

The difference in position for Euclidean 3D space is used to evaluate performance. Localization error is defined as the distance between the actual AUV position and the estimated AUV position. Real time (one simulation run) localization results can be found in Figures 5.3-5.6 (a). The deviation for the AUVs is also computed. This deviation is the amount the localization error deviates from the total averaged error and is modeled as,

$$\sigma = \sqrt{\frac{1}{N} \sum_{i=1}^{N} \left(E_i - \bar{E}\right)^2} \tag{5.1}$$

where N is the number of AUVs in the UWSN, E_i represents the localization error[1] for each AUV operating in the UWSN at that particular time. $\bar{E}$ represents the average localization error over the course of the simulation $(10{,}600s)$ for all AUVs and is given by,

$$\bar{E} = \frac{1}{L_t} \sum_{j=1}^{L_t} \left(\frac{1}{N} \sum_{i=1}^{N} (E_i)\right) \tag{5.2}$$

here L_t is the number of times the localization is performed, such that $L_t = \frac{T_{end}}{\Delta T}$, N is the number of AUVs in the UWSN, and E_i represents the localization error for each AUV at that time.

The deviation plotted over time can found in Figures 5.3-5.6 (b) down below. In addition, in order to obtain results of statistical significance, 250 trials were conducted for varying numbers of AUVs. In all trials, the localization error was accumulated and

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[1]Localization error is defined as the 3D Euclidean distance between the AUV's estimated position and its actual position.
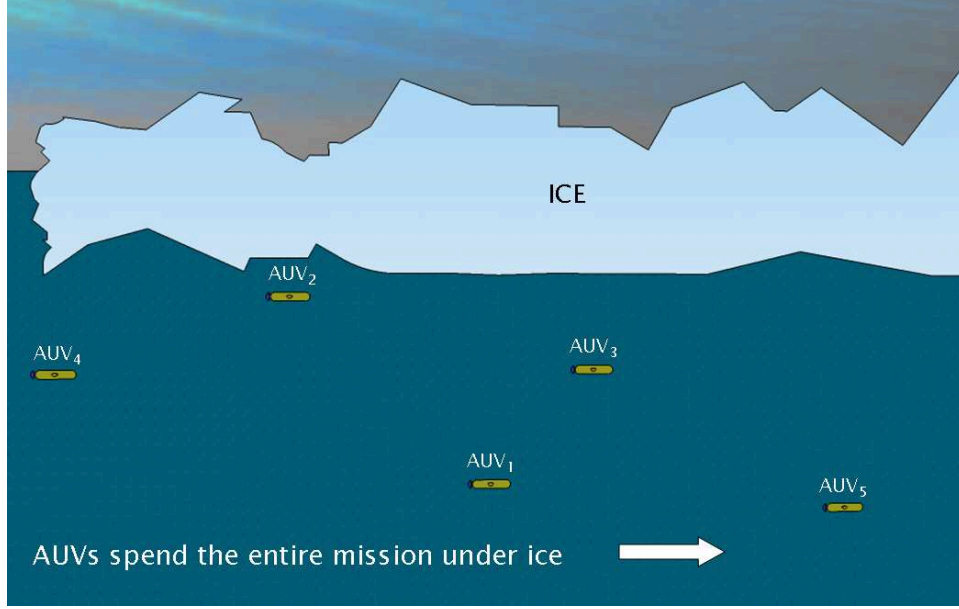
Figure 5.1: Scenario 1

then averaged for each simulation and over all runs. The average errors for the AUV's predicted location can be found in Figures 5.3-5.6 (c).

5.0.2 Specific Scenarios

The developed simulation allows for the adjustment of the number of AUVs, scenarios, runs, 3D deployment region, time interval, total time, water temperature, salinity, and currents all of which can be found in Table 5.1. We utilize two specific scenarios with two different underwater currents in our simulation.

- **Scenario One** *with Typical Currents*: This scenario involves a team of AUVs who collaboratively explore an underwater region located under ice. These AUVs remain under-the-ice for the duration of the mission and do not return to the surface until the mission is completed. Typical currents ranging in speed from 0.01-0.03 m/s [90] [92] were implemented.

- **Scenario One** *with Severe Currents*: This is scenario one with severe currents implemented. These currents range in speed from 0.04-0.06 m/s [90] [92].

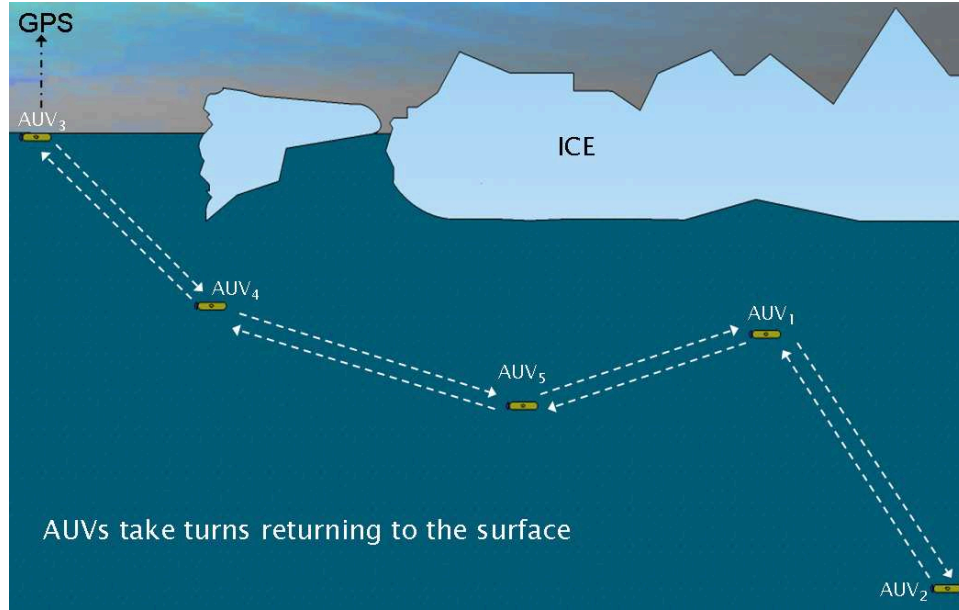- **Scenario Two** *with Typical Currents*: The second scenario is similar to the first

Figure 5.2: Scenario 2

except that individual AUVs will periodically surface to update their positioning via GPS. These AUVs take turns returning to the surface according to a predefined interval, which is $1800s$ in our simulation. In order to avoid ice cover, these AUVs return to the edge of the ice sheet where they were deployed. Once an AUV surfaces, it acquires a GPS fix and updates its current coordinate position. The number of AUVs that return to the surface depends on the number of AUVs deployed. If there are six or fewer AUVs then only one AUV will surface periodically. If there are more than six AUVs deployed, then teams of two will return to the surface periodically. The order in which the AUVs return to the surface is sequential according to the AUV's ID number. Typical currents ranging in speed from 0.01-0.03 m/s were implemented.

- **Scenario Two** *with Severe Currents*: This is scenario two with severe currents implemented. These currents range in speed from 0.04-0.06 m/s.

Table 5.1: Simulation Parameters

AUV Localization	
Number of Simulated Runs	250
Total Time	10600 s
Scenario 2 Surface Interval	1800 s
Time Interval, ΔT	60 s
Deployment 3D Region	1250(L)x1250(W)x0(H)m^3
Confidence Parameter, α	0.05
AUV Velocity	0.25-0.40 m/s
AUV Depth Range	[0,1000] m
Typical Currents	0.01-0.03 m/s
Severe Currents	0.04-0.06 m/s
Water Temperature Range	[-2,2]^{o}C
Salinity Range	[32.5,35] %

5.0.3   Evaluation Results

Scenario One

It can be seen that our Doppler-based technique performs closely in terms of localization error over time to the expensive INS hardware system [2]. In addition, as the number of AUVs increases the localization error drops across the board for all techniques. This can be attributed to the fact that as the number of AUVs increases there are more references to chose from when performing localization. Also the number of localization messages lost due to path loss, channel conditions, and etc. is minimized since the number of AUVs has increased, thus enhancing coverage. AAL clearly outperforms all other cooperative localization approaches other than the Doppler-based technique. This AAL approach also performs dramatically better with a larger number of AUVs. It is not surprising to see DNRL and CNA perform the worst in terms of localization error. Their poor performance can be attributed to their use of a limited number of AUVs equipped with expensive dead reckoning systems. All the algorithms perform the same for the first half hour or so, but as time passes and the AUVs travel further and further, DNRL and CNA begin to struggle. Since only a select number of AUVs are designated as anchors in these two approaches, it has limited coverage and it is clear

---

[2]This INS system serves as a performance baseline. An INS system is composed of several INS sensors in combination with a DVL to constrain error over time. INS sensors cost upwards of $50,000 [25].

why they would struggle over longer periods of time. DNRL and CNA are best served in team formation techniques with reliable underwater channels (few lost packets). The performance of all the localization techniques perform at an acceptable level even with severe currents. It is interesting to see that the localization error can not be minimized by increasing the number of AUVs in the UWSN as was the case with typical currents. Stronger currents limit the effectiveness of adding more AUVs to the UWSN. Currents take place in specific underwater regions and adding more AUVs just increases the number of AUVs influenced by the currents not necessarily bettering the localization.

Scenario Two

The results for the second scenario closely resemble the results attained for the first. However, the second scenario clearly limits the error for each localization technique. This second scenario shares many of the same characteristics as the first scenario; all localization schemes fail to significantly minimize error with an increasing number of AUVs when the currents are severe. This changes dramatically for typical currents, where the performance for all techniques is greatly improved with a larger number of AUVs. Once again DNRL and CNA performed comparably, and our Doppler-based scheme was similar to the INS approach.

5.0.4 Error Analysis

There are several uncertainties that are associated with the localization techniques presented: propagation delay, anchor positions and channel conditions, hardware, underwater acoustic speed, and Doppler shift all play a key role in affecting localization accuracy.

- *Propagation Delay*: RTT errors are prevalent for message transmission due to non-determinism in the latency estimate of message delays.Propagation latency, encoding/decoding time and receiving time all contribute to RTT error. This is mitigated by our Doppler-based approach since we can project the position of the reference AUV.

- *Channel Conditions*: Multipath, shadow zones, path loss, geometric spreading,and poor reliability all hamper underwater communications.

- *Transmission Time*: Transmission time in underwater environments is on the order of several seconds. Specifically the WHOI Micro-Modem takes approximately 3 seconds depending on packet type to transmit [37].

- *Hardware Measurement*: The depth, z, is measured by a pressure sensor which is known to be accurate to 0.01%.

- *Speed of Sound*: The speed of sound, c, is a complex function of water temperature, salinity, and depth. Mackenzie's empirical formula is used to model this. It provides a relatively accurate speed of sound for each time increment while minimizing processor cost.

- *Error in Doppler-shift*: Doppler-based errors include sensor error in echo detection and measurement, which affects Doppler's long term accuracy [95]. The precision and accuracy of a Doppler sensor is a complex function of signal power, frequency, pulse length, velocity of sound accuracy, transducer alignment and spectral estimating techniques. The variance of a frequency shift estimate is given in [95].
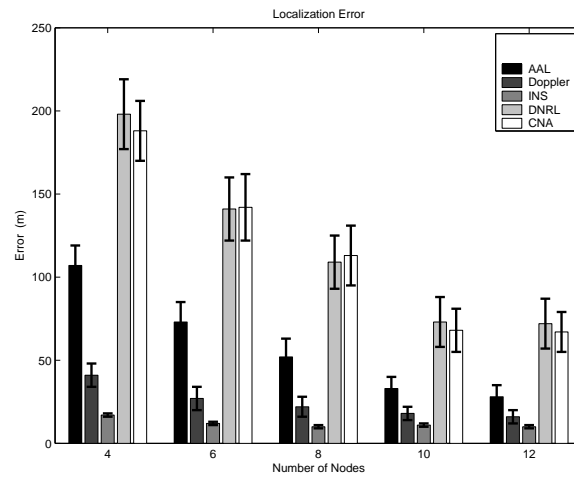
These errors were modeled in Python using the equations and methods mentioned above.
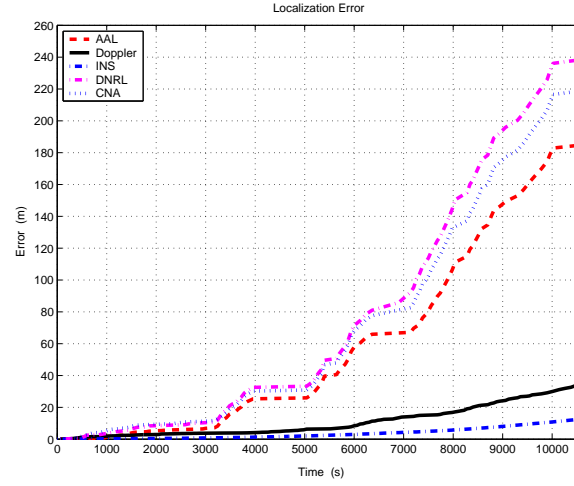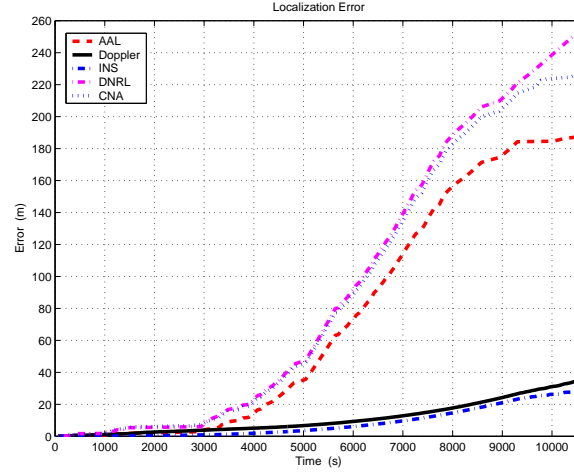
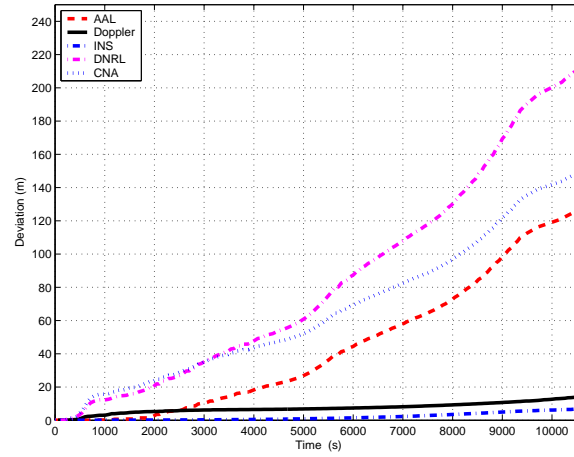(a) Localization error comparison for 4 AUVs
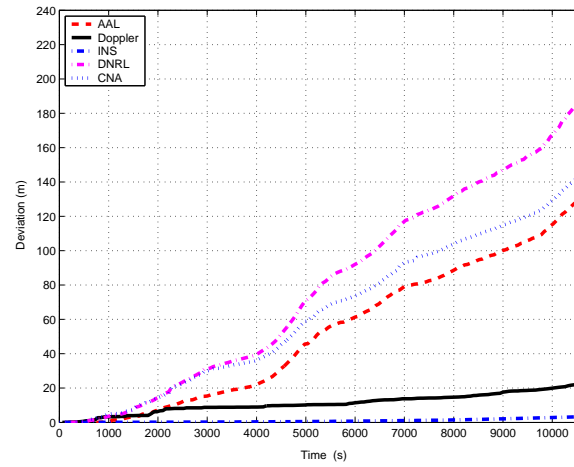
(b) Deviation comparison

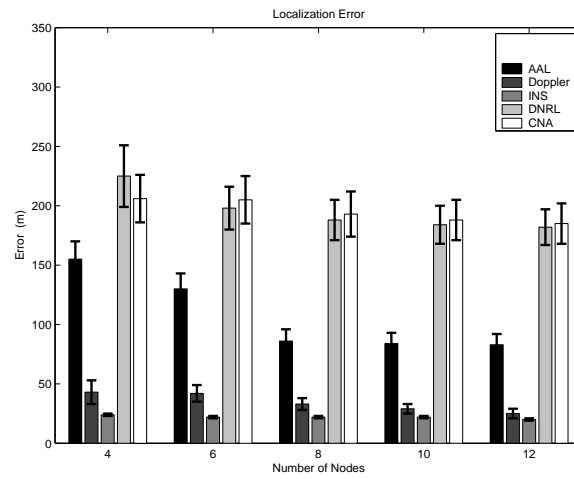
(c) Localization error for number of AUVs

Figure 5.3: **Scenario 1 with Typical Currents**: Routine under the ice mission with no resurfacing. Figure *c* was plotted with 95% confidence intervals for 250 runs.

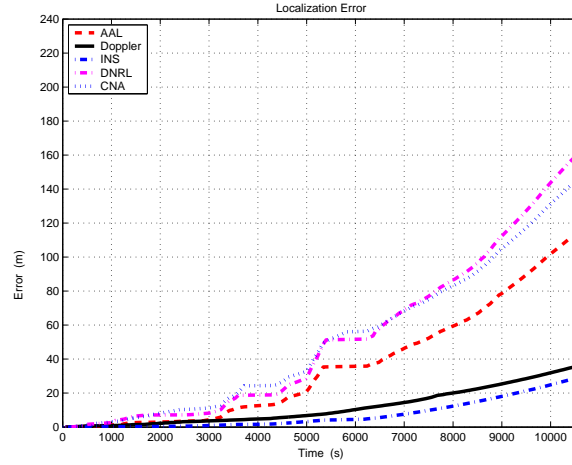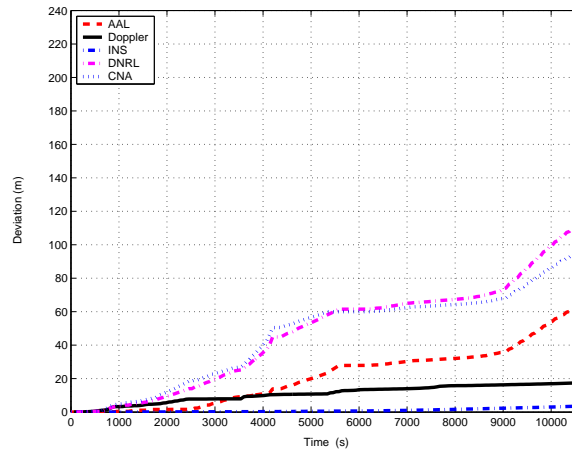(a) Localization error comparison for 4 AUVs

(b) Deviation comparison

(c) Localization error for number of AUVs

Figure 5.4: **Scenario 1 with Severe Currents**: Routine under the ice mission with no resurfacing. Figure c was plotted with 95% confidence intervals for 250 runs.

(a) Localization error comparison for 4 AUVs

(b) Deviation comparison

(c) Localization error for number of AUVs

Figure 5.5: **Scenario 2 with Typical Currents**: Under the ice mission with resurfacing and typical currents. Figure *c* was plotted with 95% confidence intervals for 250 runs.
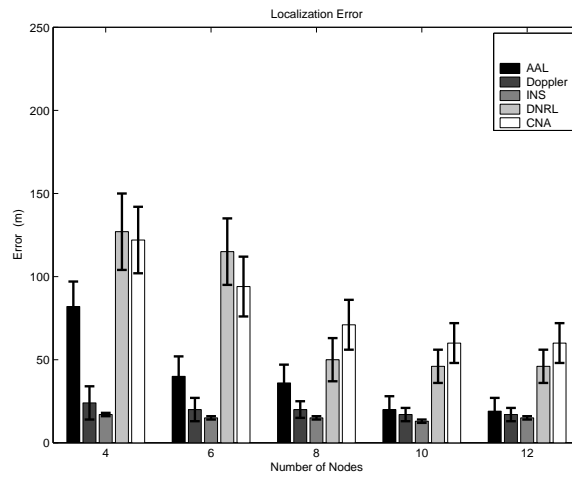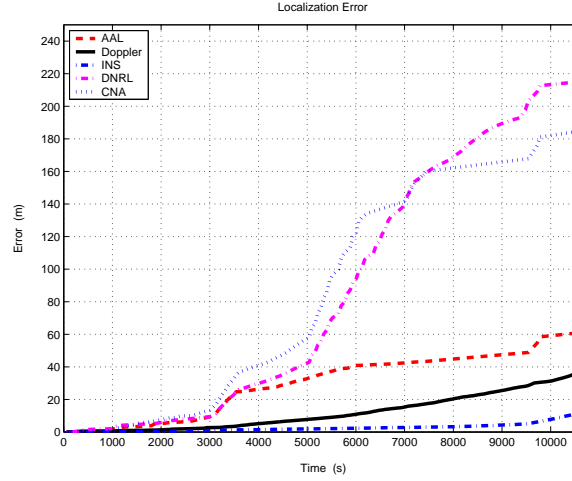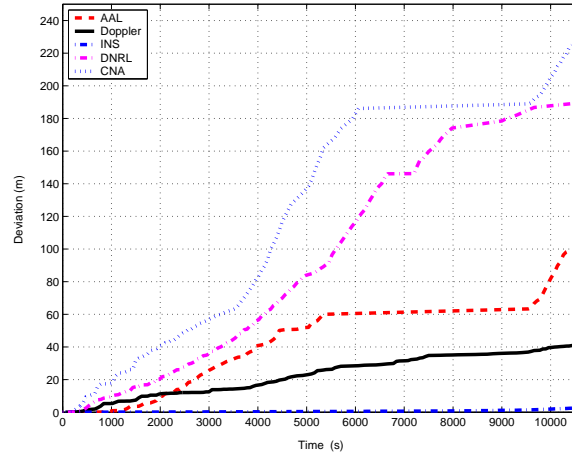
(a) Localization error comparison for 4 AUVs

(b) Deviation comparison

(c) Localization error for number of AUVs

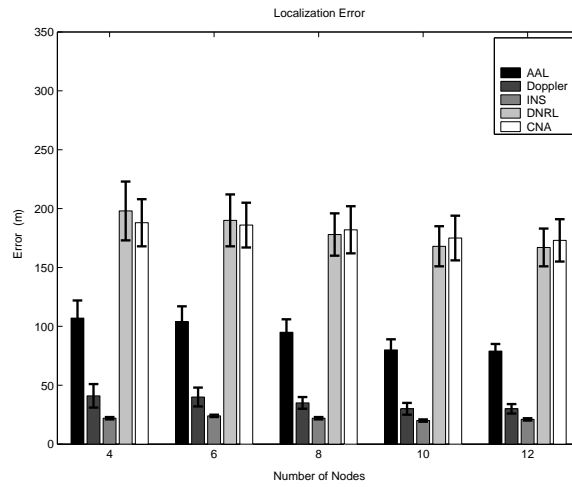Figure 5.6: **Scenario 2 with Severe Currents**: Under the ice mission with resurfacing. Figure c was plotted with 95% confidence intervals for 250 runs.

Chapter 6

Conclusion and Future Works

6.1 Conclusion

In our approach we utilize a Doppler-based approach to compute the velocity of the AUV and project subsequent positions of the AUV. In addition, we have taken into account uncertainties associated with channel conditions over time and variations in the speed of sound due to water temperature, depth, and salinity. We have successfully developed a simulation that implements an effective Doppler-based localization algorithm and studies error propagation.

This thesis discusses several localization techniques: AAL, DNRL, CNA and our novel Doppler-based approach. These techniques have been discussed in depth and are utilized in our UWSN simulation. This simulation was developed in Python and provides a detailed insight into the propagation of errors for each localization technique. An accurate Doppler-based localization algorithm has been implemented and shown to be effective when compared to other comparable localization techniques. Our approach is advantageous against other localization techniques, as it achieves excellent localization results while minimizing the number of necessary localization messages sent and received by the AUV. This alleviates some associated network overhead and lowers power consumption. It is also important to note that as the number of AUVs in the UWSN increases, the accuracy improves, but communication overhead also increases. The main benefit to using our Doppler-based approach is that it effectively limits localization error by opportunistically utilizing observed Doppler shifts from ongoing communications.

6.2   Future Works

Further development of this protocol will eventually lead to the implementation of the Doppler-based localization algorithm on the Woods Hole Oceanographic Institute (WHOI) emulation testbed developed by [32]. This emulation would provide the opportunity to test this Doppler-based approach on the actual WHOI Micro-Modem, which would be used during actual AUV deployment. The next logical step after emulation would be to implement our Doppler-based localization technique in actual field experiments. Many of the localization protocols have been written with the intent of implementing localization in actual underwater experiments. This modem has been utilized in several underwater experiments and has served as an emulator/testbed for the development of localization, team formation and routing protocols in [28] [31] [32].
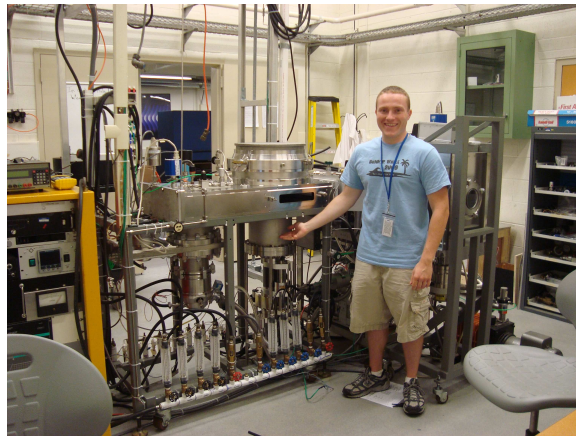
Chapter 7

Biography

Figure 7.1: Posing in front of the ECR Sputter Source at the Princeton Plasma Physics Lab.

William Somers received a B.S. degree in physics from The College of New Jersey, Ewing, NJ, in 2009 and an M.S. degree in electrical and computer engineering from Rutgers University, New Brunswick, NJ in 2011. For the past two years he has served as a Lead Engineer at the Princeton Plasma Physics Laboratory. He has recently accepted a position as an Engineer II at TASC, Inc in Virginia. His current research interests include nonlinear control and dynamics, cooperative control, mobile sensor networks, AUVs, UAVs, artificial intelligence, software development, and communication networks.

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