Robust Autonomous Vehicle Navigation

by

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B.S., Systems Engineering
U. S. Naval Academy, 1993

Submitted to the Department of Ocean Engineering
in partial fulfillment of the requirements for the degree of

Master of Science in Ocean Engineering

at the

MASSACHUSETTS INSTITUTE OF TECHNOLOGY

May 2002

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Abstract
Autonomous Underwater Vehicle (AUV) performance is highly dependent on the quality and interpretation of navigation data available to the vehicle. It is common practice to combine multiple input sources such as compass or gyro information with sensor information that is external to the vehicle, such as long baseline transponder travel times and GPS information, to derive the best estimate of the vehicle’s position. This thesis explores a variety of issues that can affect AUV navigation and describes a navigation system that can be used to achieve more robust AUV navigation. Two main approaches are used to increase the robustness of the navigation system. The first method relies on creating a sound navigation filter with a redundant feature that can be used to monitor performance. The primary component of this navigation system is an extended Kalman filter (EKF). A bounding model referred to as the pessimistic model is used to bound the performance of the primary filter and act as a safeguard against filter divergence. The other main goal of this navigation system was to use reliable outlier rejection techniques to prevent bad data from even making it to the filter. Two methods (nearest neighbor gating and joint compatibility) are used in the primary navigation filter. Outlier rejection techniques for the least squares filter for the pessimistic model are also discussed. In addition, hypothesis testing was applied to both the joint compatibility and least squares outlier rejection methods to increase their capabilities. The results of this navigation filter were evaluated using both simulation and real experimental data from actual AUV missions.

Thesis Supervisor: John J. Leonard
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Acknowledgments

There are so many people that I should thank for their support in writing this thesis. The person that deserves the greatest acknowledgment is my loving wife, Krystee. Without your tireless dedication and tremendous support, I do not know how I managed this task. You have always been there for me. Likewise, I want to recognize how important my children Robyn and Jeremy were. Even though (at times) you slowed the actual writing process, you both helped keep everything in perspective and helped me stay focussed on what was truly important in life.

Next, I want to thank my family for their support. Mom and Dad, you have always given me every opportunity and have helped in so many ways. There is no way to thank you enough. Also, Susan, you have always been there to help us whenever we have needed it, thanks.

Thank you John, for the advice and support as my advisor. You did a great job of emphasizing family needs over academic work. This was so important to me. Paul, I can not thank you enough for your time and sharing some of your wisdom. I was a sincere pleasure to work with you.

To my fellow lab-mates in the Marine Robotics Laboratory, thank you for all of the support and good times. You all helped make this a fun experience and are great friends. I would have been lost without your help, Rick, Joon, and Mike B. Mike S., thanks for the help and good luck with your career in the Navy. I am sure you will do well. Tim, thank you for sharing your insight and perspective on the world.

To the Sea Grant AUV lab, thank you Rob, Joe, Jim, Sam, and Justin for the good times and support. I had a great time working with you all.

Thank you to the National Defense Science and Engineering Fellowship Program for making my life so much easier here.

Thank you to the faculty and staff of the Ocean Engineering department. In particular, thank you Kathy for your all your help.

Finally, to those that I have failed to mention here personally, please forgive me and thank you.
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Nomenclature

\( \delta(t) = \) delta time
\( c_{sw} = \) speed of sound in seawater
\( r = \) range
\( s = \) vehicle speed
\( s_w = \) water speed or current
\( u = \) control input
\( x = \) the state vector
\( \hat{x} = \) the state estimate
\( \hat{x}_{ls} = \) least squares state estimate
\( \hat{x}_{PM} = \) pessimistic model state estimate
\( \hat{x}(k|k) = \) \( \hat{x} \) at time \( k \), given the measurements through time \( k \)
\( \hat{x}(k + 1|k) = \) \( \hat{x} \) at time \( k + 1 \), given the measurements through time \( k \)
\( z = \) measurements
\( \hat{z} = \) predicted measurements
\( P = \) the covariance matrix
\( P(k|k) = \) \( P \) at time \( k \), given the measurements through time \( k \)
\( P(k + 1|k) = \) \( P \) at time \( k + 1 \), given the measurements through time \( k \)
\( Q = \) process covariance
\( R = \) sensor covariance
\( \Delta T = \) time between transmission and receipt of LBL signal
\( T_{tau} = \) turnaround time
\( (X, Y, Z) = \) Transponder location
\( \text{COU} = \) Circle of Uncertainty (for Pessimistic Model)
Chapter 1

Introduction

1.1 Background

Quite simply, navigation is the process of knowing the location of an object. However, this basic definition is at the heart of one of the most complex problems faced in robotics today. This problem has been extremely intriguing to humans from the earliest recorded time and is especially demonstrated through the development of maritime technology. The ability to navigate out of sight of land was one of the key factors that led to a remarkable increase in exploration and discovery and has directly led to the development of large ocean going vessels found today. Now, autonomous underwater vehicles (AUVs) exist and are being used to both investigate and utilize the ocean. It is a challenging problem to provide a reliable navigation system that prevents the vehicle from becoming lost and helps it more effectively perform its mission.

Several approaches exist to provide positioning information to an AUV. However, this is not a "solved problem" because many of these systems are cumbersome to use and are not always reliable. Even as we continue to develop new techniques for navigation, there must be a continued effort to improve the existing methods by applying new ideas to make them more effective.
1.2 Autonomous Underwater Vehicles

Before delving into the specifics of the navigation system design, it is important to have an understanding of the type of platforms on which it will be employed. There are many different types of AUVs that are designed to perform a variety of missions. First, there will be a review of some of the important missions that AUVs perform to demonstrate the importance of accurate navigation. Then a basic description of the Odyssey II and Odyssey III AUV are provided. These vehicles are typical of the type of AUV that the navigation system described in this thesis is designed to guide. Finally, a description is provided for typical sensors and positioning systems used with AUVs.

1.2.1 AUV Missions

Autonomous Vehicles are used for a variety of missions. Most of these missions support scientific or military needs. The reason that many of these missions are now being done by AUVs is primarily due to cost or because the mission is inherently dangerous such as mine hunting. A brief description of typical AUV missions are listed below. This list does not cover the entire realm of AUV missions, but is intended to familiarize the reader with typical missions that depend heavily on accurate and robust navigation systems.

Mine Hunting

There has been considerable effort by the U.S. Navy to develop AUVs as a viable platform for the detection of naval mines. Recent events in the Persian Gulf have demonstrated the power of even the crudest mines. Several modern U.S. Navy ships including the USS Samuel B. Roberts and the USS Princeton have been heavily damaged by mines. Mines are also considered to be a very credible threat to submarines.

Modern anti-mine warfare relies on several platforms including manned mine sweepers and specialized sleds towed from helicopters. In some cases, combat divers are involved in the removal of mines. The biggest drawbacks that all of these meth-
ods have are that they are dangerous and not covert. It is important that the enemy does not know that you have surveyed a region for several reasons. Sweeping for mines may be an indication of an impending amphibious operation. Additionally, if the enemy knows that a minefield has been compromised, it may take action to introduce additional mines to the area. An example of the Navy's use of AUVs for object location is shown by Trimble [30].

Several AUVs are in development for the Navy to search for mines. These units range from small vehicles such as a variant of the REMUS AUV developed by Woods Hole to AUVs specifically designed to operate from submarines such as the Long Term Mine Reconnaissance System (LMRS). These systems all have the advantage of keeping people away from the mines. Another common attribute of these methods is the importance of maintaining an accurate navigation picture when the AUV is collecting survey information. This is necessary so that ships or submarines can obtain accurate locations of the mines, and so that other assets can be brought in to remove the mines if needed.

It is interesting to note that some of the experimental results in this thesis are from the GOATS 98 experiment, which explores new methods of using AUVs to locate mines.

Environmental Sampling

Another popular use of AUVs is environmental sampling. These missions can take many forms. For example, a typical mission may use AUVs with a high endurance to collect information on the temperature and salinity over a wide area. Other scientific missions include mapping of bottom features such as thermal vents or geological features. This can be accomplished more efficiently by an AUV than a surface ship. Just as with the mine search mission, it is usually very important that the environmental information collected by the AUV is accurately correlated to a real-world location. Therefore, the AUV must have a reliable and accurate means of navigation. A good example of an AUV that is involved in environmental sampling is the Autonomous Benthic Explorer (ABE). An ABE survey mission is described by Yoerger, Bradley,
and Walden [39]. Another discussion of underwater mapping with AUVs using the HUGIN AUV is provided by Gade and Jalving [9].

Object Location (Submarine Rescue)

This next type of mission is a more general application of the mine hunting mission. It is quite plausible to use AUVs to search for other objects besides mines on the ocean floor. These objects include items such as flight recorder boxes from airplane crashes and actual wreckage of ships, aircraft, and submarines.

One of the motivating factors for researching AUV navigation and this thesis is the potential to use AUVs to search for disabled submarines on the bottom. The loss of two American submarines in the 1960s (USS Scorpion and USS Thresher) and the recent loss of the Russian Submarine, Kursk, highlight the importance of such missions. Current submarine rescue procedures rely on the use of towed side-scan sonar systems or manned vehicle search to locate a disabled submarine on the bottom. This method is very time consuming, and time is a critical factor in rescuing trapped crewmen. An area search could be conducted much faster by a team of AUVs. It is possible to quickly deploy these vehicles from helicopters since many of them are similar in size and shape to light weight torpedoes. The biggest challenge in such a system is maintaining precise navigation to accurately report the location of a disabled submarine and to ensure that they do not leave any holes or holidays in the search areas. A big advantage of these systems is that they are similar to the type of AUVs that would be used to search for mines. Therefore, it is likely that the Navy would have a substantial inventory of equipment. It is hoped that continued efforts to improve AUV navigation systems will lead to improved rescue capabilities for submarines.
1.2.2 AUV Examples

Odyssey II AUV

The Odyssey II was developed by the AUV Laboratory at MIT Sea Grant in 1995. Figure 1-1 shows a cutaway view of the Odyssey II AUV. This diagram shows that most of the equipment is contained in two pressurized spheres. A silver-zinc battery in one of these spheres provides power to the electronics and also to the tail cone, which contains the main motor and the actuators for the control surfaces. The vehicle weighs over 400 pounds and is capable of diving to depths of 3000 meters and has a top speed of 3 knots.

Odyssey III AUV

The Odyssey III AUV is similar to the Odyssey II in many respects, but it is a more complex vehicle. The most noticeable difference is that it is much larger (almost 900 pounds). Since it has increased size, the Odyssey III is capable of carrying more sensor equipment. Another difference is in the tail cone, where the vehicle control takes place. Instead of moveable fins, the Odyssey III directs the entire thruster assembly to maneuver the vehicle. This vehicle is also able to operate down to 3000
meters and has a top speed of 4 knots.

1.3 Underwater Navigation Techniques

There are several navigation techniques available to underwater vehicles. These can be divided into two primary groups: Dead Reckoning (DR) and Positioning Systems, which are both described in more detail below. The primary difference between these methods is that DR systems sense information about how the vehicle is moving such as speed or direction, which means that the navigational uncertainty tends to grow over time. Position systems differ because they provide information of where the vehicle is relative to a point in the environment. Generally, these errors are not time dependent. It is true that the equipment does contain some time related errors due to factors such as clock drift, but these are negligible for the relatively short missions that the AUVs described above undertake. There are several references with good summaries of the navigation capabilities of underwater vehicles such as [27], [15], [37], and [34].

1.3.1 Dead Reckoning

Dead reckoning systems have evolved from the some of the earliest navigation practices that were used in ancient times. In the most simple form, the vehicle calculates its position by integrating the best estimates of its speed and direction of travel from its last known position. Some of the most widely used DR systems or
components are described below. There are many instances where a vehicle may be equipped with more than one of these sensors.

**Compass**

One of the most recognizable instruments for sensing vehicle heading is the magnetic compass. Its design is comparable to more familiar compasses that are used on land or in aircraft. The instrument relies on sensing the magnetic field of the earth and comparing it to the orientation of the sensor. While this system is fairly easy to implement, it has several disadvantages. One problem is that the sensor is affected by magnetic fields that are generated by the vehicle. The sources of these fields may also vary due to changing electrical loads. A compass is also sensitive to movements of the vehicle. For example, it is not uncommon for a compass to act erratically during a vehicle turn.

**Gyro**

Gyrosopes are used as part of an inertial measurement unit (IMU) that is used on many AUV applications. When used properly, most IMUs are more accurate than a compass. IMUs provide more than just heading or yaw information. They can sense yaw, pitch, and roll as well as the rate that these parameters are changing.

Another version of the gyro is the ring laser gyro (RLG). This sensor measures the phase difference between two beams of light that travel in a circle to determine heading. An advantage of the RLG is that it is very precise (0.0018°) when compared to a gyro compass (0.1°) or compass (1 – 10°). Additionally, it has a much lower drift (0.44°/hour) compared to the gyro compass (10°/hour) [38]. One example of a very accurate INS system for underwater vehicles (MARPOS) is described by Larson [14]. This system can achieve a positional accuracy of 0.02%-0.1% of distance travelled. The primary disadvantage of the RLG is that it is very expensive compared to the other sensors.
Doppler Velocity Sonar

A Doppler Velocity Sonar (DVS) (also known as a Doppler Velocity Log (DVL)) measures vehicle speed through the water by either tracking objects in the water column or the bottom. The measured doppler shift is a function of the vehicle speed. In addition, if the sensor is tracking the bottom, it also provides the height of the vehicle above the bottom, which is called the altitude. A good DVS system can provide very accurate speed information. Some of the drawbacks of a DVS system are that it is expensive, and it can be hard to use depending on the environment. It is sometimes difficult for the DVS to “lock on” a soft bottom.

Other Speed Measurement

There are other methods available to measure vehicle speed. One method involves measuring the rate that the propeller turns and using this number to calculate the speed based on a pre-determined ratio (turns-per-knot ratio). Some devices rely on a small propeller that turns due to the movement of water past the vehicle. The rate that it rotates is proportional to the speed. Another option is to estimate speed by the motor current or control input. An example of calculating speed based on motor RPMs is shown by Matos and Cruz [18].

1.3.2 Positioning Systems

Several types of positioning systems are available to correlate the vehicle location to global coordinates. Several of these methods are listed below. It is important to note that other methods exist, and there are different techniques that can be employed when using the methods that are listed. In this thesis, a distinction is made between positioning systems and tracking systems. Tracking systems are a subset of positioning systems that do not provide information directly to the mobile robot. Instead another platform determines the vehicle location. Then this information can then be relayed to the AUV via an underwater communication system. A brief comparison of the various acoustic positioning systems is provided by Vickery [34],
Global Positioning System

The Global Positioning System (GPS) is probably the best known positioning system because of its widespread use. However, GPS is not an ideal navigation source for AUVs because it can only be used when the vehicle is on the surface or trails an antenna near the surface. However, there are several instances where GPS is very valuable for AUV missions. GPS receivers are relatively small and easy to incorporate into most AUV systems. The published capability of GPS states that the system is able to provide a vehicle position that is accurate to 100 meters with the standard position service or 22 meters with precision positioning service (military GPS) [13] when the vehicle is on the surface before or after a mission. Standard GPS accuracy can also be increased to 33 meters using differential GPS (DGPS). However, position data is generally more accurate. With selected availability turned off, GPS is usually accurate to within 5 to 15 meters. Accuracies of less than 5 meters are possible with differential GPS. One plausible use of GPS is that a vehicle operating near the surface utilizing GPS can serve as a master platform to guide other (deeper) AUVs. Since such a system has not been tested, it will rely on advances in multiple vehicle technology. GPS can also be used to initialize the AUV position before diving.

Long Baseline

Long baseline (LBL) navigation systems are one of the most widely used underwater tracking systems. A detailed description of LBL systems is provided by Send [26]. The system operates on the principle of triangulating the time of flight ranges between the AUV and a field of two or more transponders. There are many different configurations for LBL systems. In its most basic form, the vehicle emits an interrogation pulse on a discrete frequency. Each transponder replies on a unique frequency after a fixed delay or turn around time. The range from the vehicle to each transponder is found by:

\[ R = \frac{c_{sw}(\Delta T - T_{lat})}{2} \]  

(1.1)
Figure 1-3: Basic LBL Description: The AUV is in the center of an array of transponders (T1, T2, and T3). R1 is the slant range between transponder 1 and the vehicle.

Each range measurement results in a set of possible positions where the vehicle could be. In reality, this produces a sphere centered on the transponder. However, in practice, the depth of the vehicle is known through the use of a depth sensor. An independent depth measurement constrains the possible position to points on a circle. The intersection of these circles describes the position of the vehicle. Section 2.2 provides a description of one method to calculate the vehicle position from the intersection of these circles.

The operation of a traditional LBL system requires prior knowledge of the transponder positions. This is usually obtained through a careful and time consuming calibration process with a surface platform. A good description of the LBL surveying process is provided by Send [26]. While it may be possible to find transponder positions with a GPS system, it is not ideal and usually results in a higher inaccuracy in
the system compared to typical calibration techniques. The number of transponders used in an LBL array also varies. Typically, three or four transponders are used. An idea for using one LBL transponder in conjunction with dead reckoning information is presented by Larsen [14].

One of the inherent problems with LBL information is that the vehicle moves between the transmission and receipt of the timing signal. This means that the signal from vehicle that is 700 meters away from a transponder will have a total travel time of nearly a second. The vehicle may move an appreciable distance in this time.

A primary characteristic of an LBL system is its operating frequency. This affects both the accuracy and the range of the system. For example, a 12 kHz system may have a range of 5-10 km with a precision of 0.01-10 m, while a 300 kHz system has a range of approximately 100 m, but may achieve a precision of less than a centimeter [38] [40].

1.3.3 Acoustic Tracking Systems

The main difference between positioning systems and tracking systems is that a tracking system does not provide information directly to the vehicle. It is possible to transmit this information to the AUV via an underwater communications system. Another important use of tracking systems is that they provide information that can be used when post-processing AUV mission data, which results in a more reliable and confident navigation solution.

Ultra Short Base Line

Ultrashort base line (USBL) operates with a single transmitter and array of receivers. In operation, the AUV transmits an omni-directional signal when it receives an interrogation pulse from the tracking vehicle. The reply signal is sensed by the receiver on the tracking platform that is composed of several receiving elements spaced less than 10 cm apart. By sensing the phase difference of the AUV’s signal, the bearing to the vehicle can be calculated with Equation 1.2, where $\phi$ is the measured phase
angle and \( d \) is the distance between receiving elements.

\[
\theta = \arcsin\left(\frac{\phi \lambda}{2\pi d}\right)
\]  

(1.2)

An advantage of this type of system is that it is not hard to use and does not take much time to set up after the equipment has been installed and calibrated on the ship. However, this initial calibration is critical to proper operation of the USBL system.

**Underwater GPS**

The ACSA system, GPS Intelligent Buoys (GIB), has been used recently as a tracking system for AUVs. In many aspects, the system is similar to the LBL system described above. Instead of relying on an acoustic interrogation signal, the system relies on the AUV emitting an acoustic signal that is controlled by a precise timing system. The buoys that receive this signal are on the surface and are equipped with GPS receivers. They are able to transmit their position along with the time of flight data to a master station, which triangulates the AUV’s position. One advantage of the underwater GPS system is that it does not require an extensive calibration like an LBL system, making it much easier to use. This system is simpler to employ than a USBL system because there is no interface between the system and support ship that requires calibration. Thomas [29] provides more detailed information on the use of underwater GPS tracking system.

**Underwater Communications**

An important aspect of using a tracking system for AUV navigation is the underwater communication system. The most common system for this application is the acoustic modem. The WHOI micromodem users manual [12] provides a good example of an underwater acoustic modem. This modem is able to reliably transmit 40-80 bits per second. At this data rate, the amount of information that can be exchanged is fairly limited. An important to consideration is information travels at the speed of
sound in water. Therefore, any position information that is relayed to the vehicle is delayed. Some of the complications with working with acoustic communications are covered by Catipovic [6] and Baggeroer [2].

1.3.4 Concurrent Mapping and Localization

Concurrent Mapping and Localization (CML) is relatively new technique that involves having a mobile robot enter a new area without a-priori knowledge and map the new features, while at the same time using this information to navigate. CML is also referred to as feature-based navigation or Sequential Localization and Mapping (SLAM). This technology is very applicable to AUVs since so much of the ocean floor is unmapped, and it does not rely on external positioning systems and their associated logistical problems. It has an advantage over inertial navigation systems because it is designed to produce a result with a bounded error.

One of the major limitations of CML is that it is very difficult to consistently observe and recognize objects on the ocean floor. In short, data association is complex. CML is now being tested in AUV applications using LBL transponders in unknown locations. Therefore, the vehicle must map the transponders before it can utilize them for navigation purposes.

This thesis does not address CML issues directly. However, it is suggested that the techniques covered in this thesis can be applied to CML navigation using transponders as features. Leonard and Feder [16] describe a CML application operating in an underwater environment.

1.4 Environmental Effects on Navigation

Evaluating and explaining the effects that the ocean environment has on underwater navigation is a vast subject. A few of the major topics are discussed below.

First, the ocean environment compels us to rely on acoustic signals because of how quickly radio waves and light are absorbed. This is the reason that GPS is not effective just below the surface. The absorption quality of the ocean has a significant
effect on acoustic signals and limits the equipment that is available for navigation. Higher frequency signals are much more attenuated by the ocean, and therefore, they can not be used over long distances compared to signals with lower frequencies. However, higher frequency systems have the advantage of a much higher resolution because they have a shorter wavelength.

The reliance on acoustic signals necessitates that the speed of sound in water is an important consideration. Typically, the sound velocity in water is around 1450 m/s. Milne [20] provides a variety of different methods that can be used to calculate sound velocity. The velocity is affected by temperature, pressure, and salinity, which means that rarely is there a constant sound velocity profile (SVP) through the water column. This varying SVP causes the sound waves to diffract or bend, which results in complex travel paths. This effect can also cause regions called shadow zones that can not be reached by sound waves from a certain position. Unless the SVP is constant, the sound waves will not travel in a straight path. Generally, this effect is most noticeable with large changes in the SVP or over long ranges. Therefore, it is usually not significant with an LBL system with transponders with baselines near 1000 m.

Perhaps one of the most significant effects for the type of AUV navigation scenarios considered in this thesis is multi-path. This occurs when several acoustic signals from the same source arrive at the same point, but travel different paths. This effect is discussed in greater detail in Chapter 4 because it has a significant effect on why outliers occur with LBL data. The impact of multi-path is a recurrent theme in the tracking of underwater vehicles [30].

1.5 Conventions

It is important to clarify some of the conventions used in this thesis. Vehicle state parameters are always referenced to a global coordinate system with a North-South y-axis and an East-West x-axis. The vertical z-axis is 0 at the surface and is increasingly positive as vehicle depth increases. The AUV heading ($\theta$) is 0 in the positive y direction. Normally, the heading term is maintained between 0 and $2\pi$ to simplify
wraparound problems. There is no need to define a vehicle coordinate system in this paper. A simplified assumption is made that all sensors are co-located at the center of the vehicle. It is possible to define a vehicle coordinate system that is used to track the precise location of the sensors on the vehicle and then transform this position to the world coordinate frame. One other item to note is that the term AUV is used to refer to underwater vehicles in general because many of the ideas presented are also applicable on manned submersibles or Remotely Operated Vehicles (ROVs) [40].

1.6 Summary

This chapter offers a basic description of some of the equipment that pertains to AUVs and AUV navigation. In addition, some AUV missions are described to illustrate the importance of accurate and reliable navigation. In the following chapters, details will be provided of how such a system can be realized.
Chapter 2

Algorithm Design

2.1 Overall Approach

The primary goal of this navigation algorithm is to integrate information from several sources and output the best estimate of the AUV location. In an ideal situation, all of the data provided to the robot is clean and unambiguous, and the problem is reduced to an optimization issue. However, in the real world this is not always true because data is often corrupted and not clear. This is especially true with AUVs and the associated systems described in the previous chapter. Therefore, the navigation system must be able to achieve an optimum estimate of position in the presence of noise and uncertainty. To achieve this, a two pronged approach is used. The first part of the problem concerns how bad data is rejected by the navigation system. This process is described in Chapter 4. The second part of the problem is building an algorithm that can detect when the primary filter is diverging and reset it if needed. This error detection was achieved by implementing the Pessimistic Model (PM), which is described below.

Before examining the details of the navigation algorithm design, it is important to understand the overall structure of the system. Figure 2-1 shows this basic structure. Sensor inputs are received from various sources, and they are then processed by the navigation filter. The primary role of the filter is to produce estimates of the vehicle position, not to use this data to control the vehicle’s motion. That function is left to
Figure 2-1: Overall Navigation System: The navigation system receives information from dead reckoning sensors and positioning systems and computes the best estimated position. This information is passed to the higher level vehicle control program.

Another program, which is labelled the Vehicle Behavior Algorithm. A good analogy exists to the way that many large human-controlled ships operate. A quartermaster is a person whose primary responsibility is to use information from all available sources to plot the ship's position and make recommendations to the Officer of the Deck (OOD). Then, it is the OOD's responsibility to take this information, evaluate it, and direct the ship's actions. Essentially, the primary purpose of the navigation filter described in this thesis is to act as the quartermaster.

The heart of the navigation filter is the Extended Kalman Filter (EKF). This was chosen because it is a proven and effective technique for combining data from several sources to provide a best estimate of the vehicle state. However, the EKF has some inherent problems that may cause trouble for the navigation algorithm. These are described in more detail below.

In addition to the EKF, other techniques were used to estimate the vehicle position from the available navigation data. For example, least square filtering is used to
estimate positions for the PM.

### 2.2 Least Squares Filtering

A least squares filter provides a straightforward method to calculate the vehicle position from a set of ranges produced by an LBL system. One method of using this LBL data to calculate vehicle position is shown here. A more detailed explanation of this derivation is shown by Milne [20].

Referring to Figure 1-3, it is seen that the unknown vehicle position \((x, y)\) is calculated from a set of known transponder positions \((X_1, Y_1)\), \((X_2, Y_2)\), and \((X_3, Y_3)\) and ranges \(r_1, r_2,\) and \(r_3\). The two-dimensional range is represented by \(r\) and any depth difference has been accounted. Each one of the circles can be described by an equation (shown for transponder 1):

\[
r_1 = (x - X_1)^2 + (y - Y_1)^2 \tag{2.1}\]

By expanding these circle equations and subtracting the pairs then the following equations are obtained:

\[
-2(X_1 - X_2)x - 2(Y_1 - Y_2)y = (r_1^2 - r_2^2) - (X_1^2 - X_2^2) - (Y_1^2 - Y_2^2) \tag{2.2}
\]

\[
-2(X_2 - X_3)x - 2(Y_2 - Y_3)y = (r_2^2 - r_3^2) - (X_2^2 - X_3^2) - (Y_2^2 - Y_3^2) \tag{2.3}
\]

\[
-2(X_1 - X_3)x - 2(Y_1 - Y_3)y = (r_1^2 - r_3^2) - (X_1^2 - X_3^2) - (Y_1^2 - Y_3^2) \tag{2.4}
\]

Now let:

\(A_1 = -2(X_1 - X_2)\)

\(B_1 = -2(Y_1 - Y_2)\)

\(D_1 = (r_1^2 - r_2^2) - (X_1^2 - X_2^2) - (Y_1^2 - Y_2^2)\)

Next, the system of equations can be written in matrix form:

\[
Ax = B \tag{2.5}
\]
Where the following terms are defined:

\[
A = \begin{bmatrix} A_1 & B_1 \\ A_2 & B_2 \\ A_3 & B_3 \end{bmatrix}, \quad B = \begin{bmatrix} D_1 \\ D_2 \\ D_3 \end{bmatrix}, \quad x = \begin{bmatrix} x \\ y \end{bmatrix}
\]  

(2.6)

Finally, the solution to the unknown position of the vehicle can be solved by:

\[
x = (A^T A)^{-1} (A^T B)
\]

(2.7)

The input to the least squares calculation is the \( \Delta T \) between the transmission and receipt of the LBL signal, and the \( r \) term is replaced by:

\[
r = \frac{1}{2} c_{sw} \Delta T - T_{lat}
\]

(2.8)

While this method is fairly easy to implement, it does have some drawbacks. For example, it relies on the receipt of signals from at least two different beacons. With only two beacons, there also needs to be a determination of which side of the baseline that the vehicle is located. Another problem is that the algorithm needs to process information at the same time. One of the inherent problems with LBL information is that the vehicle moves between the transmission and receipt of the signal. Therefore, it is possible that the least squares calculation is performed on data that is received at different times due to different distances between the vehicle and the transponders.


### 2.3 Kalman Filter

A Kalman filter was selected as the primary component of the navigation filter for several reasons. It is able to combine the measurements from several sources. This is true even if only one ping is received from the LBL system or if a series of pings
are received in different time steps. The Kalman filter is also useful because it tracks the uncertainty associated with the estimates that it calculates. In navigation, it is almost as important to know the confidence level of the estimated position rather than just the location. One of the drawbacks with the Kalman filters used in many AUV applications is that they can fail or diverge when given poor data. While closed loop stability has been shown for the EKF [10], the properties for stability can not be guaranteed for the types of filters used in AUV navigation applications. Once bad information is inserted into these filters, it is very difficult to remove or compensate for it. This can have disastrous results. It is this consequence that motivates the techniques discussed in this thesis to improve the reliability of navigation systems.

2.3.1 Overall Filter Description

Several factors are considered for the design of the filter. One goal was to make a filter that is flexible or generic so that it could be applied on different types of vehicle without significant modification. Another driving factor is that, ultimately, the navigation program needs to be run in real-time on the vehicle. Currently, the processing power on the available vehicles is very limited compared to the average home PC [30]. Another reason for simplifying the model as much as possible is that a minimalistic model paves the way for a low complexity algorithm with a high degree of robustness and accuracy [7]. Based on these and other requirements, an EKF with a simplified model was chosen. Figure 2-2 shows the basic structure of the EKF that was used. Several references ([3], [19], and [5]) were useful for building the structure of the filter and standardizing the nomenclature.

2.3.2 Definition of Terms

In this section, the terms used in the navigation EKF are described using Figure 2-2 as a guide. First, the state vector \( \mathbf{x} \) is defined below in equation 2.10 and \( \hat{\mathbf{x}} \) is the estimate of \( \mathbf{x} \). There are a few aspects to note about the state vector. One is that it may seem cumbersome to define velocity terms in both directions instead of
Figure 2-2: EKF Outline: This flowchart shows how the EKF processes information.

\[
\begin{align*}
F(k) &= \frac{\partial f(k)}{\partial x} \\
H(k) &= \frac{\partial h(k+1)}{\partial x}
\end{align*}
\]
just using a speed term. This was done to aid in the analysis of the various terms. It is easier to determine what is having the most impact on the overall speed of the vehicle. An assumption is made that there is little motion in the z-direction, so the rate of depth change is not factored into the speed calculation. Another aspect of the state equation is that $\theta$ is defined as zero in the positive y direction. This is done to maintain the convention used in ship navigation where a course of 000 is to the North. Since speed is a commonly used term, it is defined by $s$ to simplify notation as shown below:

$$s(k) = \sqrt{x(k)^2 + y(k)^2}$$ \hspace{1cm} (2.9)

$$\begin{bmatrix} x \\ y \\ z \\ \theta \\ \dot{x} \\ \dot{y} \\ \dot{\theta} \end{bmatrix} = \begin{bmatrix} x(k) + s(k)\delta(t) \sin(\theta) \\ y(k) + s(k)\delta(t) \cos(\theta) \\ z(k) \\ \theta + \delta(t) \dot{\theta} \\ \dot{x} \\ \dot{y} \\ \dot{\theta} \end{bmatrix}$$ \hspace{1cm} (2.10)

Next, the state transition equation $f()$ is:

$$\begin{align*}
  x(k + 1) &= x(k) + s(k)\delta(t) \sin(\theta) \\
  y(k + 1) &= y(k) + s(k)\delta(t) \cos(\theta) \\
  z(k + 1) &= z(k) \\
  \theta(k + 1) &= \theta + \delta(t) \dot{\theta} \\
  \dot{x}(k + 1) &= \dot{x} \\
  \dot{y}(k + 1) &= \dot{y} \\
  \dot{\theta}(k + 1) &= \dot{\theta}
\end{align*}$$ \hspace{1cm} (2.11)

This is not a complicated vehicle motion representation since acceleration is not modelled. There is no pre-defined observation space that is always used by the filter. Equation 2.12 shows a typical observation vector for an observation that includes
data from the compass, DVL, and three transponders. A similar measurement model for LBL time of flight times is shown by Vaganay, Bellingham, and Leonard [31], [33]. Another important characteristic is that even though depth is tracked in the state vector, it is not correlated with any other state. The primary reason behind this choice is that depth is assumed to be available from an on-board source. Some experiments are conducted with saving states to help correct for LBL timing problems and it is important to record the full three-dimensional estimate. Another reason that depth is tracked in the state vector is to facilitate future modifications to the filter or support more advanced process models. The arrangement of relying on a depth detector to track the vehicle in the z-axis, while concentrating the filter on x-y coordinates only is also utilized by Cruz and Matos [18].

\[
\begin{bmatrix}
\theta_{\text{compass}} \\
 s_{\text{DVL}} \\
 \Delta T_1 \\
 \Delta T_2 \\
 \Delta T_3 \\
\end{bmatrix}
\]

(2.12)

The corresponding predicted measurement equation is:

\[
\begin{bmatrix}
\theta \\
 s \\
 2r_{S1}/c_{sw} + T_{tat} \\
 2r_{S2}/c_{sw} + T_{tat} \\
 2r_{S3}/c_{sw} + T_{tat} \\
\end{bmatrix}
\]

(2.13)

In the above equation, \( r_S \) refers to the slant range between the vehicle and the transponder and is given by:

\[
r_S = \sqrt{(\hat{x} - X)^2 + (\hat{y} - Y)^2 + (\hat{z} - Z)^2}
\]

(2.14)
2.3.3 System Noise

The system noise (also called the plant noise or process noise) term in the filter \((Q)\) represents uncertainty that exists due to errors in modelling the vehicle’s dynamics. For example, changes in vehicle acceleration will have an impact on the velocity and position states, but the model does not directly factor in accelerations. Using Bar-Shalom and Li [3] as a guide, a constant white acceleration model is assumed. From this, the process noise is described by:

\[
Q = \begin{bmatrix}
\frac{1}{4} \delta t^4 & 0 & 0 & \frac{1}{2} \delta t^3 & 0 & 0 \\
0 & \frac{1}{4} \delta t^4 & 0 & 0 & \frac{1}{2} \delta t^3 & 0 \\
0 & 0 & \frac{1}{4} \delta t^4 & 0 & 0 & \frac{1}{2} \delta t^3 \\
\frac{1}{2} \delta t^3 & 0 & 0 & \delta t^2 & 0 & 0 \\
0 & \frac{1}{2} \delta t^3 & 0 & 0 & \delta t^2 & 0 \\
0 & 0 & \frac{1}{2} \delta t^3 & 0 & 0 & \delta t^2 \\
\end{bmatrix}
\]

\[
\sigma_v^2 \\
\tag{2.15}
\]

In Equation 2.15, the \(\sigma_v^2\) term is one of the filter design factors that needs to be specified for a particular AUV. Normally, this term is the same magnitude of the maximum possible acceleration that the vehicle may experience. For practical purposes, this is usually set to \(1 \text{ m}^2/\text{s}^4\). The system noise is also dependent on the sample interval time \((\delta t)\). For this reason, it is re-calculated at each time step since the time interval may vary.

2.3.4 Measurement Noise

Just as there is uncertainty associated with the vehicle motion, there is also uncertainty with the sensor measurements. One of the advantages of using an EKF is that this uncertainty can be quantified. However, this is somewhat limited because we assume that any errors have a zero mean normal distribution. The measurement noise (also called observation error) is represented by \(R\), and may have a significant impact on the filter performance. There are many instances where a sensor (for example, a compass) will have a non-zero bias. This error is not modelled in this navigation
filter, but it could be added later. Brookner [5] discusses tracking a sensor bias in the filter state vector.

One facet of LBL measurements is that they are usually not zero-mean Gaussian. Normally, acoustic returns are not received earlier than expected. It is possible that returns may be delayed due to multi-path effects. However, if we consider multi-path returns to be outliers, it is appropriate to model the direct path returns in the same manner as other measurements. This subject is covered in greater detail in Chapter 4.

It is generally true that the size of $R$ will vary during each filter time step because the observation vector is usually not constant. Another assumption is that the observations are not correlated so that there are only diagonal terms in $R$. A typical measurement noise vector for an observation that contains a compass reading, DVL measurement, and two LBL signals looks like:

$$
R = \begin{bmatrix}
\sigma_{\text{compass}}^2 & 0 & 0 & 0 \\
0 & \sigma_{\text{DVL}}^2 & 0 & 0 \\
0 & 0 & \sigma_{\text{LBL1}}^2 & 0 \\
0 & 0 & 0 & \sigma_{\text{LBL2}}^2
\end{bmatrix}
$$

(2.16)

### 2.3.5 EKF Operation

This section describes the basic operation of the EKF, but is not intended as a review of Kalman filtering theory. The filter is designed to be as flexible as possible so that it can be used in a variety of situations. Even though it is written as a general navigation filter, there are still AUV and sensor specific design factors that must be specified. Table 2.1 lists these design factors and shows typical values that are used.

<table>
<thead>
<tr>
<th>Design Factor</th>
<th>Symbol</th>
<th>Typical Value</th>
</tr>
</thead>
<tbody>
<tr>
<td>System Noise Variance</td>
<td>$\sigma_n^2$</td>
<td>$1 \text{ m}^2/\text{s}^4$</td>
</tr>
<tr>
<td>Heading Variance</td>
<td>$\sigma_{\text{hdg}}^2$</td>
<td>$0.0025 \text{ rad}^2$</td>
</tr>
<tr>
<td>Speed Variance</td>
<td>$\sigma_{\text{spd}}^2$</td>
<td>$0.04 \text{ m}^2/\text{s}^2$</td>
</tr>
<tr>
<td>LBL Variance</td>
<td>$\sigma_{\text{LBL}}^2$</td>
<td>$2.2\times10^{-6} \text{ sec}^2$</td>
</tr>
</tbody>
</table>

Table 2.1: Filter Design Parameters
It is also important that the filter is properly initialized, which includes providing an initial state estimate for the vehicle. Since this code has been only run on AUV data in post-processing, the initial state estimate was taken from the data set. If possible, it is ideal to initialize the vehicle position when it is still on the surface with a positioning system such as GPS. Another alternative is to use a least squares method similar to the filter in the PM to initialize the primary filter.

Figure 2-2 describes how the filter processes information. The first step is to project the state and error covariance matrix and then predict the observation vector based on this. The predicted observation is then compared with the real observation to determine the innovation. Finally, the Kalman gain is calculated and used to update the state vector and state covariance matrix.

2.4 Pessimistic Model

Kalman filters have been used in many navigation applications because of their ability to optimally fuse multiple sources of data. However, a hidden danger exists because the filter may diverge, which could have disastrous implications for an underwater vehicle. One idea to help prevent this potential problem is the use of the PM to bound the performance of the primary navigation filter.

The principle behind the PM is to assume that an estimated position of the vehicle can be bounded by a circle of uncertainty (COU) that defines any probable position of where the vehicle actually could be. The radius of this circle is essentially the 99% confidence level of the position estimate. It is true that the actual probability distribution is not a circle, but it greatly simplifies the computational complexity and is adequate for this purpose. The model is referred to as pessimistic because it tries to assume a worst-case error approach in establishing the bounds of the COU. The PM provides a position estimate that can be compared with the primary filter estimate. If the primary filter estimate does not fall within the COU, there is likely a problem with either the filter or some component of the navigation system. There is no way to prove that the true vehicle position is really inside the COU. However
as the vehicle moves, the COU grows due to a combination of heading and speed errors and the estimated effect of the ocean current. Since it is based on the worst "expected" errors, if the vehicle is found to be outside of this boundary, the filter may then be diverging.

As the vehicle moves, the COU must grow to account for uncertainty that occurs due to errors in steering, currents, or other effects. Figure 2-3 illustrates this growth. One aspect of the PM is to describe how this uncertainty grows with time. In the model, the following sources of error are considered: current (set and drift), speed errors, and compass errors. Equation 2.17 describes how COU growth is computed at each time step. Note that $s$ is the vehicle speed, and $s_w$ is the speed of the water or maximum expected current. Also notice that a design factor of three times the standard deviation of the expected heading and speed errors is used. If this is found to be too limiting, consider using a smaller design factor. Figure 2-4 graphically shows how the part of the error due to measurement errors is derived. The bottom part of the line shows the starting position of the vehicle in a given time step and where it is expected to be at the end due to normal dead reckoning motion.

$$COU(k + 1) = COU(k) + \delta t (s_w + \sqrt{(s \arctan(3\sigma_{heading}))^2 + (3\sigma_{speed})^2}) \quad (2.17)$$

AUV movement is handled by dead reckoning using the most recent heading and speed measurement in each time step. If the current $s_w$ direction and magnitude is known or accurately estimated, it can be used to correct the dead reckoning position. A potential problem with using dead reckoning within the PM is that it is vulnerable to mistakes if there is a problem with the heading or speed sensors. Ultimately,
Figure 2-4: Circle of Uncertainty Error Source: The speed and heading contribution to COU growth is calculated by assuming that the associated error estimates are the worst expected. The "error" is added to the ocean current estimate to determine COU growth.

This problem should be evident when fix updates do not fall within the COU. An alternative is to advance the estimated position using the commanded input rather than the sensor measurement. An advantage of using this method is that the COU is based on the expected error of the sensors, and this error is a function of how well the vehicle is able to achieve its ordered course and speed. If an error does occur because an accurate primary filter estimate lies outside of an incorrect PM estimate and COU, there is a problem because the AUV is not going where it is ordered. The dead reckoning equations for the PM are given below.

\[
x_{PM}(k + 1) = x_{PM}(k) + \delta t(s \sin \theta_{heading})
\]

\[
y_{PM}(k + 1) = y_{PM}(k) + \delta t(s \cos \theta_{heading})
\]

Naturally, if not corrected, the COU would grow without bound to the point where it does not provide any useful information. There must be some method to periodically shrink the COU. This is accomplished by utilizing a fix obtained from a positioning system. As mentioned before, a characteristic of a positioning system is that its errors do not change with time. Ideally, this means that each fix should have the same uncertainty associated with it regardless of when it occurs. The vehicle fix is obtained by using a least squares filter as described in Section 2.2. After the fix
has been calculated, it is validated using methods described in the next chapter. If it passes this validation, the PM position estimate is updated, and the COU is reduced to reflect the uncertainty of the fix.

2.5 Implementation

The navigation system is designed so that it can be used in real-time on an AUV or to post-process data after a mission. Even though the primary filter and the PM run in parallel they are not necessary coupled. The goal of this navigation system is to produce a best estimate of the vehicle position and a means to monitor the “health” of the overall system. The navigation algorithm can be configured to automatically reset the primary filter based on the PM if the estimate of the primary filter falls outside the COU. Alternatively, the primary control algorithm can detect a disagreement between the two estimation methods. Then it can initiate a corrective action or decide to terminate the mission. More information on implementing filter reset is found in Chapter 3.
Chapter 3

Filter Modifications

3.1 Introduction

Chapter 2 provides the framework for the primary navigation system and PM. Several modifications to the primary system that were tested that improve the system reliability and accuracy. These modifications are discussed in a separate chapter because they can be viewed as improvements and not the basis of the system. It may be useful to refer to Chapters 5 and 6 because they provide examples that demonstrate the effectiveness of some of the methods discussed in this chapter.

3.2 LBL Delay

As mentioned in Chapter 1, one of the problems with using an acoustic LBL system is that there is normally an appreciable delay between transmitting an interrogation signal and receiving a reply from the transponder. During this time, the vehicle continues to move. Therefore, the LBL system measures a time of flight that is also a function of vehicle movement. Figure 3-1 shows an exaggerated view of this effect. The green line shows the path that the acoustic signal travels. Vectors $\vec{V}_1$ and $\vec{V}_2$ are calculated by the program. It is important to recognize that $|\vec{V}_2| \ll |\vec{V}_1|$ so that the angle $\theta$ is nearly constant along the region of interest on $\vec{V}_2$. The corrected distance $D$ is shown on the figure as “correction” and is determined with the following
equation:

\[ D = \frac{1}{2} |\vec{V}_2| \frac{\vec{V}_1 \cdot \vec{V}_2}{|\vec{V}_1||\vec{V}_2|} \]  

(3.1)

which is equivalent to:

\[ D = \frac{1}{2} |\vec{V}_2| \cos \theta \]  

(3.2)

In the algorithm, whenever an LBL ping is transmitted by the vehicle, the current vehicle state estimate is saved. Later, when the reply from the transponders is received, the information in the saved state can be used to calculate vectors \( \vec{V}_1 \) and \( \vec{V}_2 \). Now the corrected distance is calculated as shown above. Finally, the corrected distance is applied to the estimated range measurement. The overall effect is the same as a running fix from traditional ship navigation [4].

### 3.3 Kalman Filter Resets

As mentioned in Chapter 2, one of the primary reasons for implementing the PM is that it can be used to monitor the primary filter performance and act as a guard to protect against filter divergence. This may be needed if reliable positioning updates are not available at the beginning of a mission and dead reckoning is not reliable. This may occur if the AUV must transit a considerable distance to a region of interest. During this transit, the vehicle may be unable to receive consistent positioning information, and errors such as ocean currents or an undetected compass bias may cause the true position to fall outside of the uncertainty bounds of the filter. If this occurs, then most outlier rejection methods such as nearest neighbor gating or joint compatibility are likely to reject the positioning system measurements. This unwanted rejection occurs because the residual between the measurement and estimated measurement will be too large. In such a situation, it is unlikely that the vehicle will achieve accurate navigation. A real example of this can be found in the GOATS experiments described in Chapter 6.

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Figure 3-1: Effects of AUV Motion with LBL: In this instance, the AUV is driving toward the beacon so that the receipt leg of the acoustic signal is shorter than the transmission. It is assumed that the LBL return provides the most information about the vehicle position in the middle between the transmit and receive. Therefore, the correction factor is the distance toward or away from the beacon that is used to adjust the predicted measurement.
The decision to reset the filter is based on a comparison of the primary filter state (\(\hat{x}\)) and the PM state estimate (\(\hat{x}_{PM}\)) as shown by:

\[
\gamma < |\hat{x} - \hat{x}_{PM}|
\]  

(3.3)

Normally, the threshold (\(\gamma\)) is set to the current COU. If this threshold is exceeded, the filter estimated state is set to the PM estimated state, and the state covariance matrix \(P\) is reset to reflect the estimate uncertainty of the least squares fix used in the PM.

### 3.4 Incorporating Other Position Measurements

In Chapter 2 the primary filter is described with the measurements of heading, speed, and LBL timing information. In practice, there are times when other measurements are also available. For example, a vehicle on the surface should be able to receive accurate GPS information. If available, this should also be used in the filter. The measurement model for incorporating GPS is quite simple:

\[
\hat{z}_x = \hat{x}_x
\]

(3.4)

\[
\hat{z}_y = \hat{x}_y
\]

(3.5)

A more interesting situation occurs if the positioning measurement is available from a system such as the GIB underwater GPS system via acoustic communications with the vehicle. There is a significant delay before these measurements reach the vehicle. This delay occurs because the range calculations are conducted by a control unit that is on the surface, away from the vehicle. The position measurement must then be relayed to the vehicle, which takes time.

There are several options for handling this time delay. The simplest, but least effective method is to insert the measurement into the filter at time of receipt and
account for the uncertainty caused by the time delay by increasing the measurement covariance. A problem with this method due to the fact that measurement errors are assumed to have a zero mean Gaussian distribution. In this case, the error is very dependent on the geometry between the AUV, transponders and control unit, and the measurement errors do not have a zero mean. Another option is to estimate the time delay between the actual distance measurement and time of receipt of the information on the AUV. This position could then be advanced using methods described in Section 3.2 to the current time step of the primary filter. A more powerful, but complex alternative is to keep track of past state estimates in the state vector. If enough states are kept, the measurement can be applied directly to the filter. This approach is discussed by Leonard and Rikoski [17].

### 3.5 Smoothing

Kalman smoothing was investigated to see if it could be used to increase the accuracy of the navigation solution. Gade [9] also discusses the benefits of smoothing with a Kalman filter in AUV navigation applications. A fixed-lag Kalman smoother was implemented into the existing navigation framework. The current state is tracked along with the previous five states estimates. This filter was developed by modifying the matrices of the original primary filter. The past states are treated as stationary objects by the process model f(). However, the process model Jacobian is now written as:

\[
F = \begin{bmatrix}
F_i & 0 & 0 & \cdots \\
I & 0 & 0 & \cdots \\
0 & I & 0 & \cdots \\
\vdots & \vdots & \vdots & \ddots
\end{bmatrix}
\]  

(3.6)

In this case \(F_i\) is the process Jacobian from the original filter. Likewise, the new process noise is given by:
The measurement Jacobian was also modified by:

\[ Q = \begin{bmatrix} Q_0 & 0 & 0 & \cdots \\ 0 & Q_0 & 0 & \cdots \\ 0 & 0 & Q_0 & \cdots \\ \vdots & \vdots & \vdots & \ddots \end{bmatrix} \] (3.7)

The other important change is how the states in the state vector are controlled. In each time step, all of the states are shifted down within the state vector. Since the prediction for time step \( k+1 \) is based on the state at time \( k \), this term is in the first position of the state vector. An example of what is happening to the state vector for each time step is shown below:

\[
\begin{bmatrix}
  x(k) \\
  x(k - 1) \\
  x(k - 2) \\
  x(k - 3) \\
  x(k - 4) \\
  x(k - 5)
\end{bmatrix} \quad \rightarrow \text{predict} \quad \rightarrow 
\begin{bmatrix}
  x(k) \\
  x(k - 1) \\
  x(k - 2) \\
  x(k - 3) \\
  x(k - 4)
\end{bmatrix}
\] (3.9)

During the predication stage for a given time step, all of the prior states shift down in the state vector \( x \). The last state (in this example \( x(k - 5) \)) is removed from the state vector and considered the best estimate for that particular time. Results of the smoothed version of the filter are shown in Chapter 6.
Chapter 4

Outlier Rejection

4.1 Sources of Outliers

Outliers are measurements that do not accurately represent the entity that is being measured. In simple terms, they are “bad data”. It is important that outliers are removed or rejected because once bad information is inserted into an EKF, it is hard to compensate or correct the filter. Outliers occur for a variety of reasons, and it is impractical to classify every source, but some of the prevalent errors that may affect AUV navigation are discussed below.

Perhaps the most interesting category of outliers those that occur with LBL acoustic signals. Some of these errors occur due to background noise in the water that inadvertently triggers the LBL system or is mistaken for a transponder signal. These types of errors tend to be completely random and do not follow a recognizable pattern. Some of the most important outliers occur in LBL data due to multi-path effects. These errors may occur regularly, can be close to the expected measurement, and typically follow a definite pattern. What makes these errors more complex is that they can be similar to the expected measurement that it is easy to mistake them for good measurements. However, an LBL signal that is not traveling by the most direct path will normally take longer, and therefore, the AUV seems farther away from the transponder. Sometimes it is possible for non-direct sound waves to arrive earlier because of differences in the SVP.
Several different outlier rejection techniques are examined. One goal of this research is to investigate different methods of rejecting bad data that may degrade the AUV navigation. A description of the various methods are provided below.

### 4.2 Nearest Neighbor Gating

Nearest Neighbor Gating has been used in a number of applications [17],[21],[32]. The basic premise is that each measurement is compared with a predicated measurement and tested to see if it falls within a certain bound. For LBL data, this is straightforward because there is only one measurement (travel time) associated with each measurement. The Mahalanobis distance is calculated for each measurement using:

\[
\gamma^2 = (z - \hat{z})^T S^{-1} (z - \hat{z})
\]  

(4.1)

In this case, the innovation covariance \((S)\) is given by:

\[
S = HPH^T + R
\]  

(4.2)

Where \(H\) is the Jacobian of the measurement model with respect to the state \((\frac{\partial h}{\partial z})\) and \(R\) is the variance of the LBL measurement. A visualization of this method is that \(\gamma^2\) helps define an ellipsoid in n-dimensional space. This ellipsoid encloses a region of data that meets a given confidence level. The Mahalanobis distance calculation and other measures of distance are discussed in detail by Hall [11]. Therefore, if the Mahalanobis distance for a set of measurements exceeds a certain level, it is assumed that one or more outliers exists. Gating occurs when the calculated \(\gamma^2\) is compared to a threshold that is derived from the Chi-square distribution tables. For the nearest neighbor method, a value of 6.64 was used for the %99 confidence bound since there is only one degree of freedom.

This outlier rejection technique is not complex, and it is easy to implement. However, there are several drawbacks to using this method. It relies on an estimate of
the current state of the vehicle to calculate the estimated range \( \hat{z} \). Therefore, if there is a large error in the estimated state, it is possible that valid LBL time of flight measurements will be unnecessarily gated. In addition, this technique can not help with initializing the position of the vehicle. Another problem is this method does not account for the impact of other measurements on the validity of a measurement. This issue is covered in detail by Neira and Tardós [21] and is addressed in the next section.

4.3 Joint Compatibility

The primary navigation outlier rejection method is required to handle different sources of data. For example, it must be able to reject bad LBL times at the same time as handling an erratic compass measurement. Considering all observations simultaneously for outlier rejection is referred to as joint compatibility [21]. The Mahalanobis distance calculation is Equation 4.1, which is the same that is used in the nearest neighbor approach. The major difference is that \( S \) is calculated by:

\[
S = H_H P H_H^T + R_H
\] (4.3)

In this case, the \( H \) denotes the measurement Jacobian or measurement covariance for a given hypothesis. Also, since the most or all of the measurements obtained in one time step are considered jointly, then \( H_H \) and \( R_H \) will be the same or higher dimension than in the nearest neighbor approach.

It is important that the Mahalanobis threshold is properly chosen. For this application, a threshold based on a chi-squared test was chosen to qualify data. A chi-squared distribution is given in Equation 4.4. Note that \( n \) in this equation represents the degrees of freedom. An example of Chi-square tables is given by [36].

\[
\chi^2 = \sum_{i=1}^{n} \frac{(x_i - \mu)^2}{\sigma^2}
\] (4.4)

The primary navigation filter calculates the Mahalanobis distance for all observa-
<table>
<thead>
<tr>
<th>No. Observations</th>
<th>Threshold</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>6.64</td>
</tr>
<tr>
<td>2</td>
<td>9.21</td>
</tr>
<tr>
<td>3</td>
<td>11.35</td>
</tr>
<tr>
<td>4</td>
<td>13.28</td>
</tr>
<tr>
<td>5</td>
<td>15.09</td>
</tr>
<tr>
<td>6</td>
<td>16.81</td>
</tr>
<tr>
<td>7</td>
<td>18.48</td>
</tr>
<tr>
<td>8</td>
<td>20.09</td>
</tr>
</tbody>
</table>

Table 4.1: Outlier Rejection Threshold for 99% Confidence Region [36]

...tions in each time step. A lookup table is then used indexed by the degrees of freedom (or number of observations) to determine if the threshold has been exceeded. Table 4.1 shows the values that were used for the primary navigation filter. A confidence region of %99 is assumed.

One aspect of joint compatibility is the number of hypotheses should be considered. Given a set of $n$ measurements where each measurement can be considered to be good or bad (outlier), there are $2^n$ possible combinations of data that could be considered. In this case, a hypothesis assumes that one of the measurements is an outlier and it will be excluded when applying Equation 4.1. The idea of tracking multiple hypotheses to increase reliability is discussed by Reed [24] and Leonard and Cox [8]. These methods maintain multiple hypotheses over several time steps to provide more reliable data association. The method for the navigation filter described here evaluates several hypotheses over a single time step. The goal is to select the hypothesis with the highest probability conditioned on the current measurements. This is accomplished by selecting the hypothesis that results in the smallest Mahalanobis distance.

This becomes computationally burdensome as the number of measurements grows, so a constrained version of hypothesis testing is used to reduce computational complexity. The first step is to calculate the Mahalanobis distance considering the entire measurement vector. If this calculation achieves a result that is less than the threshold, it is assumed that there are no outliers and the original observation vector is accepted. However, if this threshold is exceeded, additional hypotheses are tested.
This set of hypotheses that assumes that one of the measurements is an outlier. To test this hypothesis, one measurement is excluded and the joint compatibility threshold test is repeated. A new threshold value is also determined because there is one less degree of freedom. If the test succeeds, the new measurement vector is accepted, and the filter terms are updated appropriately.

While this system is easy to implement, it has several drawbacks. The most severe problem is that this system will not reject outliers if more than one exists in the same time step. This occurs because each hypothesis only tests for the removal of one observation at a time. In addition, this method can be computationally time consuming. It is possible to test more hypotheses that consider different permutations of bad observations to overcome the first problem, but this only increases the computational complexity. It is unacceptable to allow an observation vector to contain two or more known outliers. If the second set of hypotheses fails the threshold test, the entire observation vector is deleted. This compromise is utilized to protect the filter from known bad data by accepting a loss of some useful data while minimizing the computational complexity of the algorithm.

Joint compatibility is a more thorough check of data validity compared to nearest neighbor gating, but it still suffers some of the same drawbacks. Like the nearest neighbor approach, joint compatibility also relies on a previous state estimate. Compared to the nearest neighbor gating approach, it is also much more computationally intensive because of the associated hypothesis testing. There is an advantage, however, in being able to compare different types of sensors simultaneously. This process should lead to an overall improvement in reliability.

4.4 Least Squares Discrimination

The two outlier rejection methods mentioned above share a common weakness since they both rely on previous estimates of the vehicle state. This can lead to a situation in which good information from a positioning system is incorrectly rejected. Another problem is that these methods can not be applied when first initializing
the vehicle position. Arguably, this is when the vehicle navigation system is most vulnerable to errors because future rejection techniques are based on this position estimate. For these reasons, the nearest neighbor and joint compatibility methods of outlier rejection are not adequate for validating data for the PM.

It is very important that fixes for the PM are as accurate as possible. An outlier in the PM fix could cause the PM position to disagree with the primary navigation filter (which may still be accurate). If the PM is used to reset the primary filter, an error could be inserted into the primary filter, which may be performing correctly.

As explained in Chapter 2, the PM utilizes a least squares filter to calculate a vehicle fix based on positioning system data such as LBL. The least squares filter does not utilize past information. Once the filter calculates an estimated position, an observation estimate is calculated based on this new estimated position. This estimate can be compared with the actual timing measurement to each transponder. If the position estimate is accurate, each of the measured travel times between the vehicle and transponder will agree within some limit to the distance between the estimate and the known location of the transponder. The least squares filter will also produce a position estimate even if one of the measurements is corrupted. However, it is unlikely that the predicted measurements from this estimated position will be similar to the actual observation.

To determine the estimated measurement $\hat{z}$, the estimated range between the vehicle and transponder is calculated and converted into a time so that it can be compared to the measured travel time. In Equation 4.5 for the observation estimate, $x_{ls}$ and $y_{ls}$ are determined from the least squares filter. Also, note that $\hat{z}$ is determined directly from the depth sensor:

$$
\hat{z} = \frac{2\sqrt{(x_{ls} - X)^2 + (y_{ls} - Y)^2 + (\hat{z} - Z)^2}}{c_{sw}} + T_{lat}
$$ (4.5)

The original attempt to apply outlier rejection to the least squares solution was marginally successful. The main idea was to determine the difference between the measurement $z$ and estimate $\hat{z}$. This residual is normalized by the estimated mea-
measurement covariance for each measurement. These measurements are assumed to be independent. Therefore, for a situation with three measurements, the resulting calculation is:

\[
\gamma = \frac{(z_1 - \hat{z}_1)^2}{\sigma_1^2} + \frac{(z_2 - \hat{z}_2)^2}{\sigma_2^2} + \frac{(z_3 - \hat{z}_3)^2}{\sigma_3^2}
\] (4.6)

The result is then compared to a threshold to determine if the fix is acceptable. While it feasible that only one measurement is responsible for causing the threshold test to fail, further testing of the subsets of the entire observation is not done. Perhaps the biggest weakness of this method is that it is incorrect to assume that all of the innovations are independent and can be summed. Since the innovation depends on an estimated position of the vehicle calculated from all measurements, the estimated range estimates are correlated. Therefore, the innovation covariance matrix \( \Sigma \) is normally not a diagonal matrix.

A better estimate of the innovation covariance matrix is desired so that a typical Mahalanobis distance test can be applied. From Bar-Shalom and Li [3] the covariance matrix of a least squares solution is given by:

\[
P = (H^T R^{-1} H)^{-1}
\] (4.7)

Note that \( h \) is the measurement model, which is given by equation 4.5. The following relationships have been assumed:

\[
H = \frac{\partial h}{\partial x}
\] (4.8)

\[
\hat{x} = Hx
\] (4.9)

\[
E(zz^T) = R
\] (4.10)

\[
E(xx^T) = (H^T R^{-1} H)^{-1} = P
\] (4.11)
\[ E(xz^T) = (H^T R^{-1} H)^{-1} H^T = PH^T R^{-1} R = PH^T \] (4.12)

\[ E(zx^T) = HP \] (4.13)

The goal is to find the innovation covariance matrix \( S \), which is given by:

\[ S = E(z - Hx)(z - Hx)^T = E(zz^T) + HE(xx^T)H^T - E(z(Hx)^T) - E(Hxz^T) \] (4.14)

which reduces to:

\[ S = R + HPH^T - E(zx^T)H^T - HE(xz^T) = R - HPH^T \] (4.15)

The innovation of the range measurement and estimated measurement can be determined by:

\[ \nu = (z - \hat{z}) \] (4.16)

It is not normally possible to use the inverse of the covariance matrix \( S \) directly in the Mahalanobis distance calculation because \( S \) contains two or more zero eigenvalues, and the matrix is singular. The reason for this is that the number of beacons constrains the problem. For example, if there are three beacons, there is only one degree of freedom in the solution. In this case, \( S \) will be a three by three matrix with two zero eigenvalues. If four beacons are used, it is a two-degree of freedom problem, and \( S \) will have two zero and two non-zero eigenvalues. Therefore, instead of calculating the inverse of \( S \), the Pseudoinverse is calculated (\( S_{inv} \)) by using singular value decomposition as given by:

\[ S_{inv} = v s^{-1} v^T \] (4.17)

Where \( s \) is a diagonal vector of the non-zero eigenvalues and \( v \) is a unitary matrix.
from singular value decomposition. Further information on singular value decomposition is shown by Press [22] and Strang [28]. The new Mahalanobis distance calculation is given by:

\[ \gamma = \nu S_{\text{inv}}^{-1} \]  
(4.18)

This value can be compared with a threshold determined from the chi-square distribution. It is important that the correct value is found from the look-up table because the degrees of freedom are given by \( n - 2 \), where \( n \) is the number of beacons. Just as in the case of the joint compatibility test, it is possible to consider subsets of the observation vector if the initial test fails. Usually, further hypotheses are not considered due to the conservative nature of the PM.

With no prior position estimate, the geometry of the transponder field and especially, the number of transponders becomes more important to the robustness of the solution. For example, consider the case shown in Figure 4-1. In this case, normal direct path returns are received from beacons one and two. However, there is no way to determine that the multi-path return from beacon three is not a valid measurement because of how the range arcs converge. It looks like a good solution. While this is not a likely situation, it does show the possibility for computing an incorrect solution based on the method described above. This situation is not likely if four beacons are used. Ambiguous situations like this example demonstrate why the PM does not consider smaller sets of beacon measurements if the initial threshold test fails. This example also demonstrates how the number of beacons relates to the reliability of the AUV navigation solution. If a high multi-path environment is expected, it is prudent to use more than three transponders.

Another use of the multiple hypothesis testing of least squares data is to provide a better interpretation of the data during post-processing. A better understanding of the quality of acoustic returns can lead to improved filter settings and more reliable navigation on future missions. One such application is to model the occurrence of multi-path returns as a possible hypothesis. A rudimentary measurement model can
Figure 4-1: LBL Data Association Problem: The LBL signal from transponder 3 arrives as a multi-path return, which appears as a valid fix to the least squares routine. This is a good example of how the system geometry and number of beacons can affect reliability.
interpret multi-path signals as having an range offset ($\Delta r$) from the direct path model as shown by:

$$r_{MP} = r_{DP} + \Delta r = \sqrt{(x_{ls} - X)^2 + (y_{ls} - Y)^2 + (z - Z)^2} + \Delta r$$  \hspace{1cm} (4.19)

The range offset will have to be determined by examining the data and determining the best average value. It is true, that $\Delta r$ is not a constant, and more accurate methods should be developed to model the multi-path effect. Another consideration is that multi-path returns tend to be more diffuse than direct path returns so $\sigma_{DP} < \sigma_{MP}$. This model can be applied to determine when multi-path returns are received. These can be plotted to help determine how geography of the region affects the number of multi-path returns.
Chapter 5

Simulation Results

5.1 Description of the Simulation

A computer simulation was created to help test the AUV navigation filter. Since it is almost impossible to accurately simulate the complex underwater environment, any simulation of this type should be regarded as a tool that can be used to investigate the filter performance. However, it is not proof that the filter will work in the real world. The object of this chapter is to show some of the results that were obtained with the simulation.

The simulator is written in MATLAB® and produces data from an AUV moving in a three-dimensional underwater environment. The simulated vehicle moves in a random or pre-determined path. Environmental factors such as current velocity and direction can be specified. Compass and speed measurements are recorded during each time step. At specified times, the vehicle emits an interrogation signal for the LBL transponders. The transit time of the acoustic signal is modelled, and the vehicle moves between the initial ping and receipt of the signal. A random error with a Gaussian distribution is applied to all of the measurements (compass, speed and LBL). An intermittent random factor is multiplied to some LBL signals to represent an outlier. For all of the experiments, the transponders are in the same location as shown by Table 5.1. Unless specifically mentioned, the same filter design parameters are used for all of the simulations.
<table>
<thead>
<tr>
<th>Transponder</th>
<th>x-coord (m)</th>
<th>y-coord (m)</th>
<th>z-coord (m)</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>0</td>
<td>600</td>
<td>80</td>
</tr>
<tr>
<td>2</td>
<td>-600</td>
<td>0</td>
<td>100</td>
</tr>
<tr>
<td>3</td>
<td>600</td>
<td>0</td>
<td>50</td>
</tr>
<tr>
<td>4</td>
<td>0</td>
<td>-600</td>
<td>75</td>
</tr>
</tbody>
</table>

Table 5.1: Simulated Transponder Positions

<table>
<thead>
<tr>
<th>Design Factor</th>
<th>Value</th>
</tr>
</thead>
<tbody>
<tr>
<td>System Noise Variance</td>
<td>$10 , m^2/s^4$</td>
</tr>
<tr>
<td>Heading Variance</td>
<td>$0.04 , \text{rad}^2$</td>
</tr>
<tr>
<td>Speed Variance</td>
<td>$0.09 , m^2/s^2$</td>
</tr>
<tr>
<td>LBL Variance</td>
<td>$1.0 \times 10^{-6} , \text{sec}^2$</td>
</tr>
</tbody>
</table>

Table 5.2: Simulation Filter Design Parameters

There are some important aspects of the real world that the simulation does not model. There is no refraction or ray bending of the acoustic signal. In addition, LBL transponder locations are assumed to be exactly known. As discussed before, it is unrealistic that a Gaussian pdf accurately describes the LBL signal errors. The fact that this type of corruption is applied to the simulated data implies that the filter should perform much better than with real data.

5.2 Analysis of a Typical Search Pattern

Several different AUV behaviors and course selections were tested with the simulator. One of these patterns represents a typical search pattern that is commonly used by underwater vehicles. This pattern is sometimes called “mowing the lawn” shown in Figure 5-1. This figure shows the estimated vehicle track is so close to the actual track that they are indistinguishable. The crosses show the fix locations using least squares.

Figure 5-2 shows the LBL data for a simulated search pattern run. Ten outliers occur in this data set. An interesting pair of outliers occur at the same time near step 4200. In this case, the filter rejected the entire observation vector as described in Section 4.3. There are no obvious ill effects to the filter since the filter output closely matches the actual vehicle track.
Figure 5-1: Typical AUV Search Pattern (Simulated): The AUV is engaged in a standard search pattern while obtaining positioning information from the LBL system. The green dots represent least squares fixes, while the blue track is the estimated position determined by the primary filter.
Figure 5-2: Simulated LBL Travel Times: The LBL time of flight measurements are shown for all four transponders. The time of flight measures the time from when the interrogation signal is sent until the reply is received from the transponder. There is a 2% chance that each measurement will be an outlier that is corrupted by a uniform distribution.
The simulation of this search pattern was useful for showing the effect of vehicle motion on LBL measurements. Figures 5-3 and 5-4 both show how the estimated $x$ and $y$ position of a simulated vehicle compares with its actual position. Both of these figures show the 1-$\sigma$ and 3-$\sigma$ bounds for the filter. These imply that approximately 67% of the points should fall within the first bound, and 99% of the points should fall within the second bound. The difference between these figures is that the navigation filter in Figure 5-4 uses the method described in Section 3.2 to adjust the LBL times. Note how the difference in the $x$-coordinate appears to have a bias in Figure 5-3. A majority of the points do not fall within the 1-sigma bounds as expected. This occurs because most of the vehicle movement is along the $x$-axis directly toward and away from two of the transponders. Figure 5-4 shows how this bias is mitigated when the correction method in Section 3.2 is applied.

5.3 Outlier Rejection Performance

To compare the outlier rejection performance between joint compatibility and nearest neighbor gating methods, both methods are tested with the same data generated from a simulated run. The measure of effectiveness is the actual $x$ and $y$ error and standard deviation. The results of these trials are summarized below along with the important simulation parameters. Two Monte Carlo runs were conducted. Each run was composed of 20 simulations of an AUV conducting a search pattern as described above. The same set of data was applied to a filter with joint compatibility and one using nearest neighbor gating. Statistics on estimation performance are collected for each run. The LBL time of flight measurements have a 2% chance of being a spurious outlier in Run 1 and 20% in Run 2. All of the measurements were corrupted by a Gaussian noise term. These results are shown in Figures 5-5 and 5-6. The bottom plot shows the difference between the number of outlier rejections conducted by the algorithm minus the actual number of outliers produced in the simulation. A positive number indicates that "good" data was rejected. It is possible that some of these measurements were normal direct path measurements with a Gaussian error that was
Figure 5-3: Unadjusted LBL Travel Times (Simulation): The differences between the x and y estimated positions and the actual position of the vehicle are shown. The 1-σ and 3-σ bounds are also depicted. The estimated measurements were not compensated to adjust for AUV movement between transmitting and receiving the LBL signal. A large bias is evident in the x-direction because the AUV spent most of its time travelling parallel to the x-axis.
Figure 5-4: Adjusted LBL Travel Times (Simulation): The difference between the estimated x and y position are shown along with the 1-σ and 3-σ bounds. This time, the estimated LBL time of flight has been adjusted to account for AUV motion. This results in a reduced bias in the position estimate.
### Table 5.3: Outlier Rejection Comparison Run 1

<table>
<thead>
<tr>
<th>Method</th>
<th>Joint Compatibility</th>
<th>Nearest Neighbor</th>
</tr>
</thead>
<tbody>
<tr>
<td>$X_{\text{err}}$ mean (m)</td>
<td>-0.357</td>
<td>-0.341</td>
</tr>
<tr>
<td>$Y_{\text{err}}$ mean (m)</td>
<td>0.030</td>
<td>-0.227</td>
</tr>
<tr>
<td>$X_{\text{err}}$ STD (m)</td>
<td>0.375</td>
<td>0.3807</td>
</tr>
<tr>
<td>$Y_{\text{err}}$ STD (m)</td>
<td>0.502</td>
<td>0.507</td>
</tr>
<tr>
<td>$OR_{\text{count}}$</td>
<td>3.05</td>
<td>3.45</td>
</tr>
</tbody>
</table>

### Table 5.4: Outlier Rejection Comparison Run 2

<table>
<thead>
<tr>
<th>Method</th>
<th>Joint Compatibility</th>
<th>Nearest Neighbor</th>
</tr>
</thead>
<tbody>
<tr>
<td>$X_{\text{err}}$ mean (m)</td>
<td>0.420</td>
<td>0.418</td>
</tr>
<tr>
<td>$Y_{\text{err}}$ mean (m)</td>
<td>-0.873</td>
<td>-0.875</td>
</tr>
<tr>
<td>$X_{\text{err}}$ STD (m)</td>
<td>5.77</td>
<td>5.77</td>
</tr>
<tr>
<td>$Y_{\text{err}}$ STD (m)</td>
<td>5.508</td>
<td>5.515</td>
</tr>
<tr>
<td>$OR_{\text{count}}$</td>
<td>4.35</td>
<td>2.95</td>
</tr>
</tbody>
</table>

too large for the outlier rejection method. The averages for all of the trials in each run are summarized in Tables 5.3 and 5.4.

These results show that there is not much performance difference between the two methods in simulation. In Run 2, the difference between the x-error and y-error is so small that it is indistinguishable on the figure.

### 5.4 Filter Correction

Another simulation is shown to demonstrate how the PM can be used to reset the primary filter. In this example, an artificial “problem” was created after time step 200. A constant offset of 1.0 radians was added to the heading measurement so that it is not removed by the outlier rejection process. Figure 5-7 shows the results of this simulation. A large measurement error that was intentionally not rejected was used to show how the PM would work independently from the outlier rejection technique. In the top plot of the figure, the PM is allowed to reset the primary filter. A total of 21 resets occurred during this run. The plot on the bottom demonstrates what would happen if the PM is not allowed to reset the primary filter.
Figure 5-5: Monte Carlo Testing of Outlier Rejection Methods (Run 1): A performance comparison is shown between the joint compatibility and nearest neighbor outlier rejection methods. This run simulated measurements with a 2% chance of being an outlier. The top two plots show the average x and y errors for each trial, and the bottom plot shows the difference between the measurements that are rejected and the total number of outliers present in the sample.
Figure 5-6: Monte Carlo Testing of Outlier Rejection Methods (Run 2): A performance comparison is shown between the joint compatibility and nearest neighbor outlier rejection methods. This run simulated measurements with a 20% chance of being an outlier. The top two plots show the average x and y errors for each trial, and the bottom plot shows the difference between the measurements that are rejected and the total number of outliers present in the sample.
Figure 5-7: Example of Pessimistic Model Filter Correction: In this simulation, the heading measurements were perturbed in such a way that they would not be cancelled by the outlier rejection routine. The plot shows the position of the vehicle along one leg of the search pattern. In the top figure, the PM is allowed to reset the filter. However, the filter on the lower vehicle is not reset, and the error between the estimated and actual location grows.
5.5 Simulation Drawbacks

The simulation is a useful tool for testing the capabilities of the filter. However, there are several drawbacks associated with using a simulation. It models errors as Gaussian, which is an acceptable approximation, but may not reflect what is happening in the real world. This causes the simulation to appear to be more effective than its actual performance. Additionally, the physics of acoustics are much more complex than what is being simulated.
Chapter 6

Experimental Results

6.1 Experiment Process

It is desirable to achieve good results in simulation, but the true test of the algorithm is how well it performs with actual data. To test this navigation algorithm, several different data sets are examined from actual AUV missions. One of the goals of this thesis is to design a generic algorithm that can work in many different situations.

6.2 GOATS 98 Results

GOATS 98 is one set of a series of experiments designed to test applications of AUVs in a mine hunting role. In 1998, these experiments were conducted near Elba, Italy, using an Odyssey II AUV equipped with a 10 hz LBL system. The LBL transponder net was carefully surveyed to determine accurate beacon locations. More information about the experiment can be found in the GOATS Mission Report [25].

One data set from the experiment (x9814501) is selected for investigation. In this run, the AUV's task was to travel to a selected area and conduct a survey pattern that is similar to the pattern used in the simulated experiments. One problem with testing the algorithm on this type of data is that there is no ground truth, which makes it difficult to evaluate the true performance of the navigation system. However, it is a useful tool as a consistency check and to examine how the filter handles "real world
Figure 6-1: Overall View of GOATS 98 Results (With Filter Reset): The estimated position of the vehicle from the primary filter is shown in red along with the least squares fixes (crosses) and the estimated position calculated by the filter on the vehicle at the time of the experiment in black. During this run, the PM is used to reset the primary filter. The numbers refer to locations of the transponders.

Figure 6-1 and Figure 6-2 show the navigation algorithm results with the GOATS 98 data. The “old position” track shows the position estimate that was calculated by the vehicle using a filter designed by Moran [25]. The PM is allowed to reset the primary filter if it exceeded the PM COU since LBL reception was so poor in the beginning of the mission. Since the nearest neighbor and joint compatibility outlier rejection methods rely on an estimate of the vehicle state to determine a residual, they can reject good data if the position estimate is poor. Figure 6-3 shows how the
Figure 6-2: Close View of GOATS 98 Results (With Filter Reset): A close-up portion of the vehicle track in the vicinity of the survey lines is shown.
Figure 6-3: Overall View of GOATS 98 Results (No Filter Reset): This run is similar to Figure 6-1 except that the primary filter is not reset by the PM. Due to initial errors in dead reckoning, the difference between the estimated and actual position of the vehicle causes the outlier rejection method to reject the LBL information. Therefore, the entire track is based on dead reckoning measurements.

The filter performs when the PM is not used to bound the primary filter. The filter has rejected all of the LBL returns because of a large difference between the predicted and actual measurement. This occurs because the dead reckoning information is not accurate enough to estimate a good vehicle position. This is probably the result of an unknown bias or more likely an ocean current that was not sensed by the vehicle.

Figure 6-4 shows the travel times for the LBL system. The circled points have been removed by the joint compatibility outlier rejection method. Similar results are achieved using nearest neighbor gating. The filter design factors that are used are shown in Table 6.1. There is a discussion at the end of this chapter about the process used to determine the filter parameters.
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<td>LBL Variance</td>
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Table 6.1: GOATS 98 Filter Design Parameters

Finally, the GOATS data was run through the fixed-lag smoother version of the filter. The results for a portion of the run are shown in figure 6-5. The result is a vehicle track that appears more realistic than the original EKF version of the filter.

### 6.3 Florida Trial Results

In March 2002, the AUV Lab at MIT SeaGrant conducted tests of a new vehicle operating system on an Odyssey II class AUV near Key West, Florida. The primary goal of the trials was to test vehicle functionality and software operability, but important navigation information was also collected. During the trials, the vehicle used a Sonardyne AVTRAK LBL system (20 hz) within a four beacon transponder field. In several cases, the vehicle operated on the surface which allowed simultaneous tracking with GPS and LBL. One problem that did affect the LBL results is that the transponders were not accurately calibrated. They were deployed, and their positions were marked by taking a single GPS fix. Unfortunately, this produces some disparity between the GPS and LBL estimated positions.

An example of one of these missions is run.13.3.2002.14.21. For simplicity, this will be referred to as FL.Run 1. During this test, the vehicle was on the surface, and being tracked by GPS. There are two problems with this data set that make it hard to test the full capabilities of the navigation algorithm. There is no speed information available directly from the vehicle and because of an incorrectly placed piece of metal near the gyro, the heading information is not accurate. However, this is still an interesting data set that shows some important characteristics of the navigation filter.

Figure 6-6 shows the LBL travel times for Run 1. Note that the signal from
Figure 6-4: GOATS 98 LBL Travel Times: The time of flight measurements for all of the transponders are shown. When the vehicle moves toward one of the transponders, the time of flight will decrease. The circled times are measurements that are rejected by the outlier rejection method.

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Table 6.2: Florida Trials Design Parameters
Figure 6-5: GOATS 98 Fixed Lag Smoothing Result: Applying a Kalman smoother to the GOATS data provides a more realistic vehicle track compared to the position estimates calculated on the vehicle at the time of the experiment.
Figure 6-6: Florida FL Run 1 LBL Travel Times: The LBL time of flight measurements for all of the transponders is shown. The transponders used in this experiment have a much longer turn around time compared to those used in the GOATS experiment.
transponder 4 is erratic in the beginning of the run, and the signal from transponder 3 does not record many returns toward the end of the run. Figure 6-7 shows the results of running the least squares portion of the navigation filter on this data without the outlier rejection portion. In this plot, some of the distortion caused by transponder 4 is visible in the beginning of the run, which occurs in the upper right portion of the plot. Next, the outlier rejection method is enabled, but is set to discard the entire fix if the first full measurement does not pass the threshold test. These results are shown in figure 6-8. Finally, the outlier rejection method is modified so that it considers more than one hypothesis. If four measurements are evaluated and do not pass the threshold test, subsets of three measurements are tested to see if they fall within the required threshold. If this occurs, the group of measurements with the smallest Mahalanobis distance is used to compute the least squares position estimate. The results of this method are shown in Figure 6-9. This data set provides a good example of when this hypothesis testing may be useful. Earlier, it was stressed that hypothesis testing was not normally done for the PM because it could be prone to multi-path errors. However, this data set demonstrates an example where multi-path is not really apparent, but transponder drop-out is. Therefore, to capitalize on available data, it may be necessary to implement a more elaborate hypothesis testing method.

Since the dead reckoning data for this run is not reliable, it is difficult to show the entire filter running with multiple sensor inputs. However, a test is conducted to see how speed and heading data derived from the GPS information can be used. The results of this test are shown in Figure 6-10. The filter estimated position does not correspond directly with the GPS information. The best explanation of this occurrence is due to the inaccuracy of the initial positions of the transponders. Even though speed and heading are derived from GPS, direct positioning information is not available to the filter. As mentioned in Chapter 3, the navigation filter is capable of accepting other positioning data. In Figure 6-11, the results are shown when the navigation filter also incorporates GPS positioning information.
Figure 6-7: Florida FL Run 1 Least Square Solution (No Outlier Rejection): The least squares estimated positions are shown along with the vehicle track recorded by GPS. Outlier rejection was not applied to any of the data. The numbers indicate the locations of the transponders.
Figure 6-8: Florida FL Run 1 Least Square Solution (Outlier Rejection): The same data used in Figure 6-7 was processed with a conservative outlier rejection process that only considers four measurements. In this instance, the fix is rejected if any of the measurements do not fall within the accepted bounds.
Figure 6-9: Florida FL-Run 1 Least Square Solution (Outlier Rejection with Hypothesis Testing): In this trial, the LBL data was processed using a hypothesis testing routine that considers subsets of three measurements if the four measurement case fails the threshold test.
Figure 6-10: Florida FL_Run 1 Using Derived Heading and Speed Input: The primary filter was used to process information using heading and speed information derived from GPS. The PM was used to reset the primary filter.
Figure 6-11: Florida FL Run 1 Using Derived Heading and Speed Input With GPS Correction: The same measurements used in Figure 6-10 were combined with GPS position information in the primary filter.
<table>
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<tr>
<td>Heading Variance</td>
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<tr>
<td>LBL Variance</td>
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Table 6.3: Charles River Trials Design Parameters

6.4 Charles River Results

In April 2002, another set of trials were conducted with the Odyssey II AUV in the Charles River near MIT. During this deployment, the vehicle remained on the surface and was able to receive GPS information. The LBL transponders were surveyed using the same method as the Florida tests. Therefore, their actual positions are questionable. Instead, their location was marked by taking a GPS reading at the time of deployment. Additionally, the configuration of the transponders is not ideal. Three of the transponders were attached to a pier in a straight line. This introduces more errors due to non-linear effects when the AUV travels near this baseline. This line of transponders on the pier includes transponders 1, 2, and 4. An environmental parameter that was modified for these trials is the estimated sound velocity. All of the AUV runs described above occurred in warm salt water. For these runs, a sound velocity of 1500 m/s was used. In contrast, the Charles River experiments took place in relatively cool brackish water and a sound speed velocity of 1420 m/s was used.

The first run analyzed was run.10.4.2002.12.36, which will be referred to as River.Run 1. Since the travel times from one of the transponders was consistently noisy, it was turned off for this run. That is why there are only three sets of travel times shown in Figure 6-12. The resulting least squares solution is shown in Figure 6-13.

During this series of tests, there were no problems with the yaw sensor (a Crossbow gyro), but direct speed measurements were not available. Figure 6-14 shows an example of the filter output using only LBL information and heading measurements. The PM is being used to reset the primary filter. Another experiment was conducted to derive speed measurements from GPS data to evaluate its impact on the filter. These results are shown in figure 6-15. There is little difference between figures 6-14.
Figure 6-12: River_Run 1 LBL Times: The LBL time of flight measurements for all of the transponders is shown. Transponder 3 has been turned off because of poor measurements. An example of one of the outliers is circled.
Figure 6-13: River Run 1 Least Squares Solution: The least squares position estimate is shown along with the GPS track. The LBL measurements have been screened by the outlier rejection process.
The output of the primary filter is shown along with the least squares and GPS position estimates. Heading information from the gyro along with LBL times are used by the primary filter, and joint compatibility is used for outlier rejection. The PM is used to reset the primary filter.

The next Charles River trial that is analyzed is run.10.4.2002.10.56, referred to as River_Run 2. This is an example of data collected in the river from four transponders. The LBL travel times are shown in Figure 6-16. There are few times when all four LBL signals are received without one of them appearing erratic. The normal least squares fixes (3 or 4 beacons) is shown in Figure 6-17. In contrast, the least squares solution for four returns is shown in Figure 6-18. There are only a few times when all four beacons are received clearly, resulting in few fixes, but they appear to be much more accurate. The navigation filter solution is shown in Figure 6-19. Unlike
Figure 6-15: River_Run 1 Filter Solution (With Derived Speed): This trial is similar to Figure 6-14 except that derived speed from GPS is also used as an input.
Figure 6-16: River_Run 2 LBL Times: The LBL time of flight measurements for all of the transponders is shown. There are fewer instances when all four signals are received clearly compared to the other trials.

In the previous example, the PM is not used to reset the primary filter this time. To prevent the outlier rejection method from discarding all of the LBL measurements due to a large distance between the estimated and true measurement, the standard deviation for the LBL times was increased. This increase results in a larger number of LBL least square estimated positions. The filter uses actual heading measurements and derived speed measurements. Overall, this provides a smoother result than in Figure 6-14.
Figure 6-17: River_Run 2: 4-Beacon Least Squares Solution: The least square solution is shown for the case when all four measurements pass the outlier rejection criteria.
Figure 6-18: River Run 2: 3 or 4-Beacon Least Squares Solution: This is similar to Figure 6-17 except that solutions are also shown if only three travel times are present. This causes more errors because it is harder for the outlier rejection routine to evaluate three returns effectively.
Figure 6-19: River_Run Filter Performance (No Reset): The output of the primary is shown when it also considers heading and derived speed as an input. In this case, the filter was not reset based on the PM. To ensure that LBL times were not inadvertently rejected, the travel time error variance was increased. This explains the higher number of poor least square fixes.
6.5 Parameter Estimation for Real Data

Since a reference that provides exact uncertainty parameters for the sensors does not exist, a method must be used to approximate them. This section provides a brief explanation of some of the parameter estimation techniques used. For some parameters such as the gyro, operational experience provides an initial estimate for the variance of the sensor. The validity of this estimate is then checked by observing the filter innovation term for the sensor and comparing it to the square root of the diagonal term of the innovation covariance matrix ($S$) for the particular sensor. Figure 6-20 shows the innovation plots for the GOATS 98 data. Notice that in this case, the speed estimated variance is probably too high since almost all of the values fall within the 1-σ curve. The “jumps” in the standard deviation curves is caused by uneven time steps in the data set and periodic resetting of the filter by the PM.

Determining a good estimate for the LBL time of flight measurements was more difficult since the same system can produce varying results in different environments. It is helpful to create a vector of the Mahalanobis distance calculations for each step from the least squares solution. This data is then sorted and plotted to help visually estimate which data was an outlier. Finally, the points that are assumed to be direct path measurements are plotted in a histogram. Since it is assumed that the distribution of these points should follow a Chi-square distribution, it is possible to see if the measurement variance is over or under estimated. Finally, the innovation for the time of flight terms is compared to the error bounds. The results of this process are shown in Figure 6-21. The bottom plot shows that the error estimate appears to be acceptable.
Figure 6-20: GOATS Parameter Estimation (Heading and Speed): The heading and speed innovation along with the acceptable error bounds are shown. Approximately 67% of the innovation points should fall within the 1-σ bound, and 99% should fall within the 3-σ bound. The speed error covariance (lower plot) is over estimated in this example.
Figure 6-21: GOATS Parameter Estimation (LBL Timing): These plots summarize some of the techniques used to estimate the LBL timing error variance. The first plot shows the sorted group of Mahalanobis distance measurements for the timing signals. In the middle group, most of these terms are plotted in a histogram to compare with a chi-square distribution. The lower plot shows the resulting innovation plot with error bounds.
Chapter 7

Conclusions and Future Research

7.1 Contributions

The contributions of this thesis are summarized below:

- An EKF navigation algorithm is developed that utilizes a pessimistic model to protect against divergence.
- Several methods of rejecting outliers are investigated, including joint compatibility and nearest neighbor gating.
- Field experiment data are used to demonstrate filter performance.
- Hypothesis testing is investigated in conjunction with outlier rejection methods.
- Other methods of improving filter performance such as accounting for vehicle motion during LBL measurement are examined.

7.2 Summary of Results

7.2.1 Outlier Rejection Performance

There does not appear to be a noticeable improvement in outlier rejection performance between nearest neighbor and joint compatibility techniques. It is true that these are similar processes, and they both suffer some of the same problems, but the advantage described by Neira and Tardós [21] is not always apparent. One possible
explanation is data association errors that confuse which measurement is associated with which beacons are unlikely. Instead, most of these errors are most likely the result of multi-path or spurious detections that are likely to be rejected by either method. The joint compatibility method of outlier rejection has an advantage since it considers all of the measurements (even of different sensor types) simultaneously.

The outlier rejection method for the least squares solution performed well. The method used was definitely affected by the number of received LBL signals. There is a visible difference between using three or four transponder returns. The use of hypothesis testing for the least squares outlier rejection method is also shown to be effective in some circumstances.

7.2.2 Pessimistic Model Bounding

The pessimistic bounding approach is shown to be effective at preventing a diverging filter from causing the vehicle to become lost. In addition, it was shown that this model could be used to reset the primary filter, which can then continue with normal navigation. Even when it was not used to reset the filter directly, a disagreement between the PM and primary filter can be used by the primary AUV control program to determine if the mission is in jeopardy due to navigation problems.

7.2.3 Hypothesis Testing

There are several instances when hypothesis testing is used within this navigation algorithm. One application is using hypothesis testing to check subsets of the original measurement vector for the goodness of fit of the least square solution. This technique should be used carefully. In high multi-path environments, situations may occur where the process incorrectly assumes that the returns are direct-path and could then incorrectly reset the primary filter to a bad position. However, there are situations where some of the transponders consistently provide erroneous measurements that are hard to confuse with real returns. In this case, it is advantageous to use a hypothesis testing approach to maximize the use of available data. An efficient hypothesis testing
technique for joint compatibility is also demonstrated.

7.2.4 LBL Delay Times

Even when LBL information is not corrupted by multi-path or spurious outliers, it is not straightforward to use because the vehicle moves between transmitting an interrogation pulse and receiving a response from the transponders. A running fix technique is applied that shows a mitigation of the impact of the LBL delay on the filter.

7.3 Future Research

The area of underwater navigation is a rich field for study. The need for resources and the quest for exploration will require more effective means of locating a vehicle underwater. There are two areas that offer the most promise. One of these methods is feature based navigation, CML. In the short term, it is very plausible that un-surveyed transponders will be used as features. These methods still rely on accurate data association to be successful, and it is important to investigate methods of checking or bounding the primary navigation filter. Both of these concepts have been discussed in this thesis, but the methods should be advanced and refined. The other major area of research focuses on improvements to dead reckoning techniques. These improvements focus on building better sensors. A filter such as the one discussed in this thesis is still needed to fuse all of the available information together to form the best estimate of the vehicle position.

One area that should be investigated further is the benefit of keeping track of past states in the filter. This could lead to improvements in positioning based on LBL information (due to the delay time) and incorporating other positioning data such as GIB positioning information.

Another area that merits further research is determining the optimum method to implement filter bounding. The usefulness of a bounding method is demonstrated, but determining when to reset the filter is not explored in great depth.
The EKF used in the primary model is based on a fairly simplistic vehicle model. It is expected that further accuracy could be achieved with a more detailed model. A drawback of the model presented here is that it is primarily concerned with vehicle movement in two dimensions. An improvement would be to model the effect of pitch and movement in the z-direction. Prestero [23] provides a thorough description of modelling the dynamics of an AUV.

Another area that is not covered is modelling sensor error characteristics. For example, it is not uncommon for a compass to have a bias. It is possible to use a Kalman filter approach to estimate this error. In turn, this could lead to a more accurate navigation solution. It would also be useful to take information from the outlier rejection portion of the filter and use it to modify the measurement covariance. For example, if the yaw sensor is performing poorly, then it may be useful to increase the associated variance term in the measurement covariance $R$ matrix during the mission.

New technology should soon increase the capabilities of LBL systems [1], [35]. Some of these improvements include spread spectrum coding of acoustic pulses and beam steering for transponders. The effects of these improvements on outlier rejection techniques should be investigated.

7.4 Conclusion

This thesis demonstrates a robust navigation algorithm for AUV navigation. The applicability of the EKF as a tool to optimally combine measurements from several sensors is also shown. In particular, this thesis explores some of the issues involved with using an LBL navigation system with an AUV. The importance of having sound outlier rejection techniques is also shown, and several different methods of outlier rejection are successfully implemented. A process for compensating for the relatively long delay involved with LBL acoustic systems is used to improve performance. The importance of having an effective monitor for the primary filter is demonstrated with the PM. Finally, some of the issues that are not fully addressed are explained to fa-
cilitate continued research in this area. The ultimate goal is to increase our ability to remotely and autonomously explore and utilize the ocean. Some of the methods explained in this thesis will be implemented on the next GOATS experiments scheduled for the summer, 2002.
Bibliography


