Efficient Online Beacon Surveying

Chien-Wen Research Award – Summer ’13

Prepared by Vittorio Bichucher

Acknowledgments

When I started my undergraduate career at University of Michigan, I never thought I would be flirting with Graduate School. I must thank copious amounts of people for their inspiration and help:

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Lastly, my family and friends. Parents, without you I would be in Fortaleza – Brazil dreaming about how to expand my boundaries. I am at the University of Michigan thanks to you. Friends, thank you for making my head not go crazy with all the pressure I put on myself.

Table of contents

Table of Figures

Abstract

Autonomous Underwater Vehicles (AUVs) have expanded scientists' knowledge in a range of different scientific communities due to intensive research [6] [7]. Precision navigation relies heavily on acoustic signals sent by several beacons that are deployed in separate locations underwater. In order to be used for real-time navigation, we must know the exact location of the beacons. A surveyor with exact position is able to measure a two-way travel time to each of the beacons. The time recorded, together with the speed of sound in water, can be used as the radius of a circle that has the surveyor's location as its center. Multiple measurements will create multiple circles that intersect at a single point: the beacon location.

Underwater research is frequently limited by monetary expense. Hardware costs are approximately double when used underwater. Ship time can cost upwards of one hundred thousand dollars daily for each research cruise. Time efficiency is therefore a priority.

My research project involved developing an algorithm that could reduce the time spent surveying long baseline (LBL) beacons after deployment to find their true GPS location. The goals of my research project included the creation of an algorithm for real-time beacon surveying based on non-linear least-squares optimization. Matrices that contain mutual information of possible future paths are published in the graphical user interface PeRL's viewer. These matrices enable the user to rapidly reduce the uncertainty of the beacon position.

The algorithm was tested with the PeRL laboratory at the University of Michigan Biological Station on Douglas Lake in Pellston, Michigan. The algorithm provides the laboratory with a tool that will decrease their time on the water, and acquire more accurate beacon positions.

Executive Summary

Introduction

Scientific exploration of the seas, driven by a range of sectors, were normally conducted by inhabited submersibles, towed vehicles, and tethered remotely operated vehicles (ROVs). Since, the momentum has changed gear and Autonomous Underwater Vehicles (AUVs) have been proving to have a more practical use. AUVs complement the capabilities of these existing systems, offering superior mapping capabilities, improved logistics, and improved utilization of the surface support vessel [1].

The range of work where AUVs are used is broad, and their usage has proven to be reliable and robust. The Deep Submergence Laboratory, at Woods Hole Oceanographic Institution for example, has provided scientific work in bathymetric maps, magnetic maps, digital photos, and hydrographic maps. The Perceptual Robotics Laboratory at the University of Michigan, led by Professor Ryan Eustice, has used two Iver AUVs (Figure 1) to provide tools in which students can conduct research experiments. As the Iver-AUV vehicles mature (as their dive number increases), the abilities of the vehicle increase. A 3D-reconstruction of all the shipwrecks in the great lakes could be a good starting point.

Critical for any autonomous operation, navigation becomes more complex in the ocean environment due to the lack of Global Positioning System (GPS) underwater and the small rate of communication between the operator and the vehicle. The lack of GPS hardens navigation as errors grow unbounded with time. A few different kinds of navigation are present; many have studied their efficiency and accuracy. Narrowband long-baseline positioning refers to the determination of position via interrogation of two or more fixed transponders separated by long baselines, as seen in Figure 2, and it is used to constrain error growth.

The work presented in this paper provides PeRL laboratory with an algorithm that decreases cost by reducing the time in-water using a faster LBL beacon surveying approach.

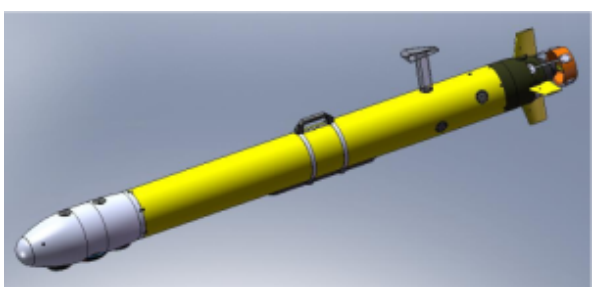

Figure 1 - Computer Aided Drawing of PeRL's Iver

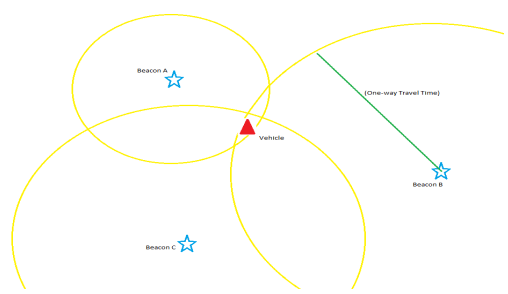

Figure 2 - Long baseline acoustic navigation.

Real-time LBL Surveying

It is logical to think that accurate beacon locations must be known before sending the autonomous vehicle into a mission. My research involved creating an efficient and real-time method to survey *n* beacons.

Previously, a surveyor ship (topside ship) with access to GPS would request signals from each beacon. The data acquired would be post-processed, and the location of each beacon would be found. Over the summer, an algorithm that outputs each beacon location and its covariance matrix in real-time was developed.

A block diagram of the algorithm is expressed at Figure 3

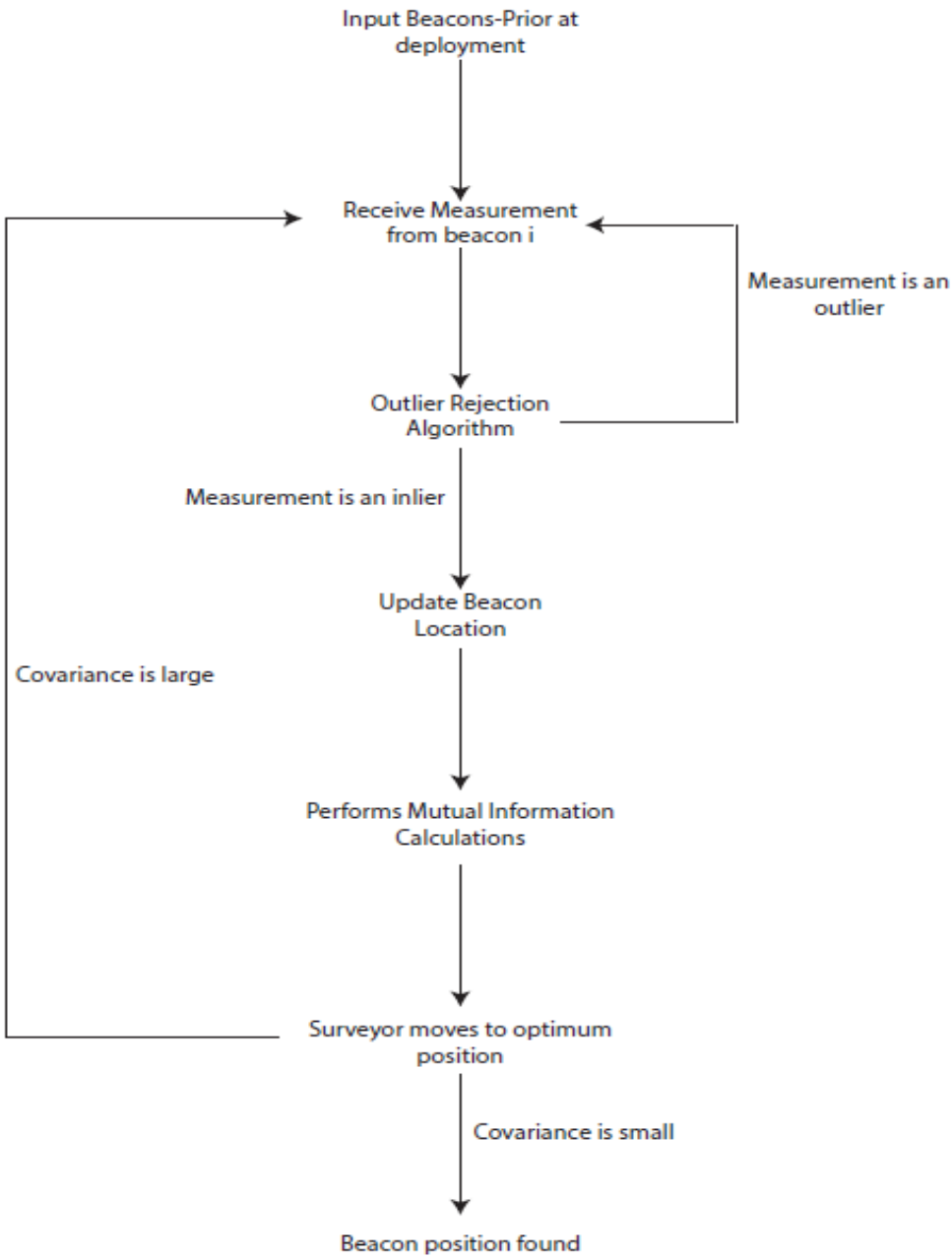

Figure 3 - Algorithm Diagram

As signals are requested to each transponder by the topside boat, a response is sent. The response time, referred to as two-way travel time (TWTT), is assumed to have a homogeneous path (time to go to the beacon is the same as the time to arrive back from the beacon), and that the topside ship is stationary during that period. A one-way travel time (OWTT) is found by halving the TWTT. The OWTT and linearized topside ship position data are stacked as a measurement if it passes an outlier rejection algorithm, explained at the Outlier Rejection Section.

If the information is accepted as an inlier, the algorithm updates the beacon position and covariance with the new information. Once updated, the algorithm computes a Mutual Information calculation among different possible paths. The Mutual Information (MI) is further explained in the Mutual Information Section; in simpler terms, the algorithm assumes the surveyor will move at a direction θ from the x-axis for the next *d* meters and take *n* measurements at every d/n meters and it computes the information gain among that path. The algorithm re-calculates the same information for all 360 degrees, giving an optimum location for the surveyor to move.

After performing these calculation multiple times, the covariance matrix achieves values that are too small to have a significant physical interpretation. The survey will stop and the optimum beacon location is presented in the screen.

Initialization and Non-linear Least-squares Optimization

For initialization, the surveyor uses PeRL's Viewer to specify the beacon of ID *i* that is being deployed. The algorithm uses the topside ship GPS location and approximate depth for the beacon initialization points. While deploying the beacon, the ship drifts with wind and surface current, and the beacon drifts due to underwater current. Therefore, the initial covariance assumes a 30 meters error for the linearized latitude and longitude, and 10 meters error for depth. The errors are associated with beacon deployment system. Beacons are attached to a buoy and stay near the bottom-surface (approximately 2 meters above the buoy's anchor). See Figure 4.

As measurements are received and accepted as an inlier, a matrix of the following form is stacked:

$$A = \begin{bmatrix} id_1 & x_i(m) & y_1(m) & z_1(m) & owtt_1(\text{sec}) \\ & & & \vdots & \\ id_i & x_i(m) & y_i(m) & z_i(m) & owtt_i(\text{sec}) \end{bmatrix}$$

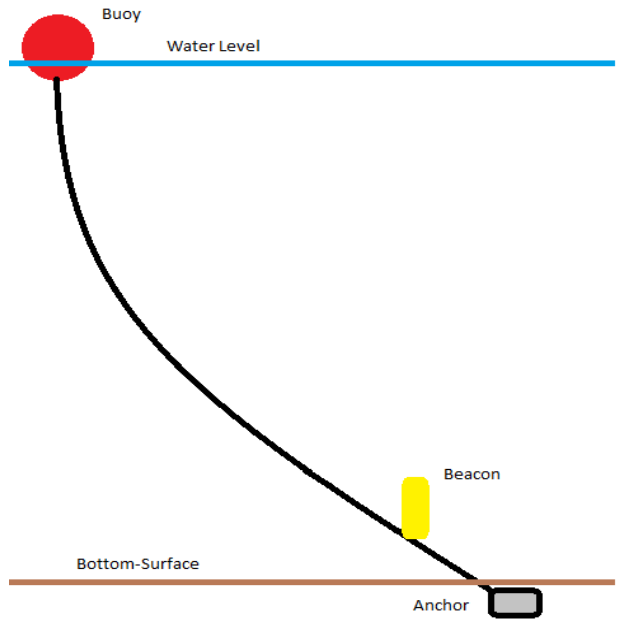

Figure 4 - Underwater Beacon Diagram

Where id_i is the beacon ID of the signal received, x_i is the linearized latitude location of the surveyor at the *ith* measurement, y_i is the linearized longitude location of the surveyor at the *ith* measurement, z_i is the depth at which the surveyor is requesting signals, and $owtt_i$ is the one-way travel time between surveyor and beacon of ID *i*.

As measurements are stacked, circles are being plotted in PeRL's viewer, see Figure 5 and Figure 6. The location of the beacon *i* will be at the intersection point of the circles that correspond to beacon *i*. To find the solution of that intersection point, a non-linear least square approximation is used.

Non-linear least square is a probabilistic analysis that compares *m* observations that are non-linear to *n* variables, where $m>n$. In simple words, it is an iterative process that finds the *n* unknowns that bring the system of equation closer to its final solution.

At every new measurement, independently of the ID *i*, a non-linear least square solution optimizes the location of the beacons, updates its belief in the beacons' positions, and computes the future path to which the error matrix will decrease the fastest.

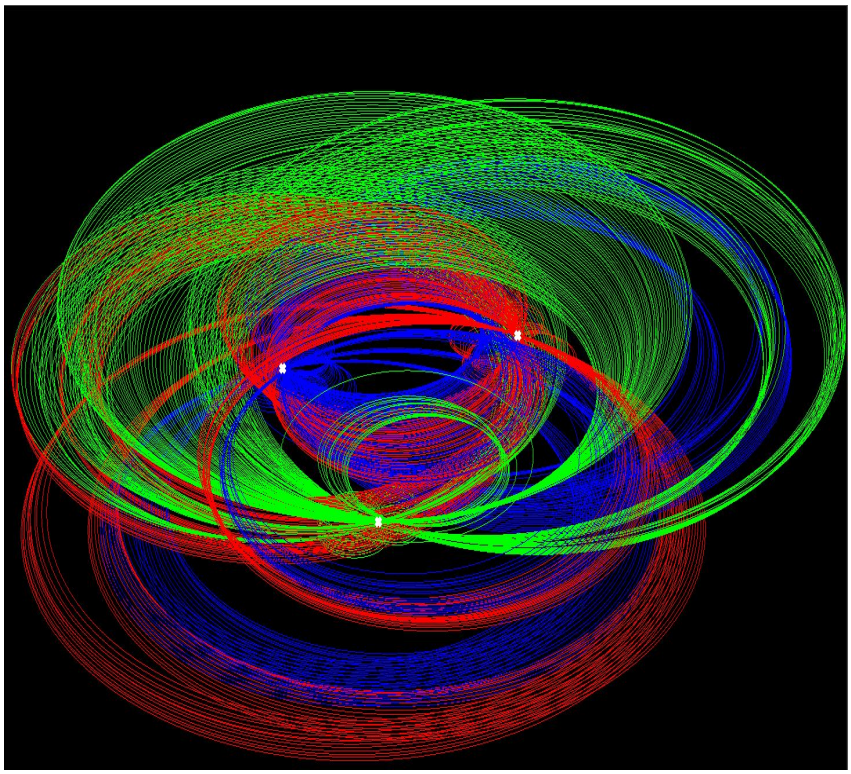

Figure 5 - Beacon Survey

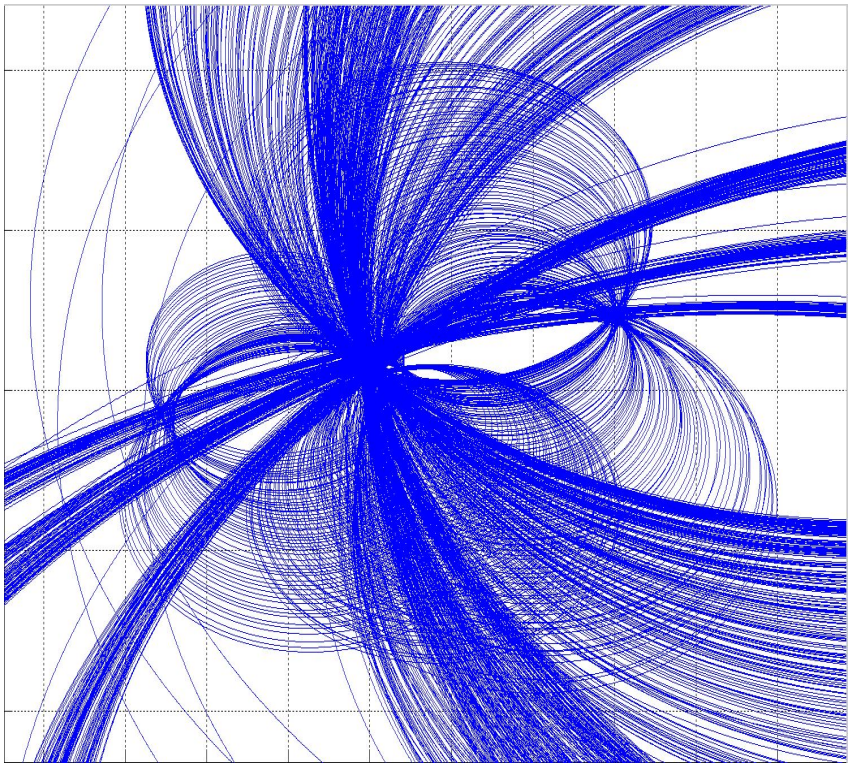

Figure 6 - Closer Look at Beacon B

Outlier Rejection

Data received, as seen in Figure 7, is not clean. Some returns do not correspond to the direct round-trip path between transponder and vehicle, and are considered outliers, see Figure 7. These bad returns could have originated from systematic or random characteristics, and they are easily identifiable when analyzing the data at Figure 7.

Systematic errors are primarily caused by multi-path. The signal leaves the transponders omnidirectionally, therefore parts of the signal can reflect on the surface, or bottom, and return to the vehicle. It is crucial to discard these measurements.

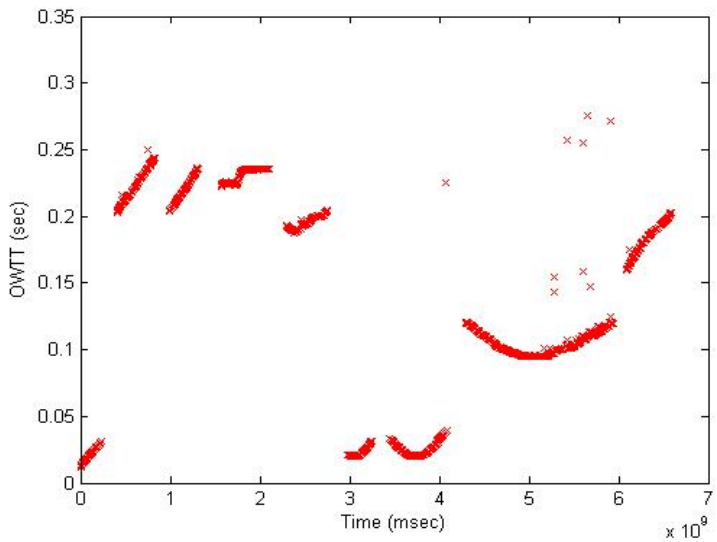

Figure 7 - OWTT Data for Beacon C

Three different methods were tested with previous data: Residual Testing, Median Filter, and Spectral Cluster Graph Partitioning (SCGP).

Residual testing is an outlier rejection algorithm that rejects a measurement if its non-linear least square residual is below a tolerance level. The benefit of this algorithm is its simplicity: it requires little computing power. The downside is its non-robustness characteristic: It is important that an algorithm runs autonomously, without the need of modifying it every time a new experiment is performed. This method requires the user to change a tolerance at a new experiment.

Yorger, *et al* [1] presented the Median Filter rejection. This algorithm creates a sliding window of size *N* that compares the new measurement to the median value of the set of numbers inside the window. If the newly acquired data is above the median value of the sliding window by a certain tolerance amount, the measurement is rejected. Otherwise, the measurement is considered an inlier.

A sample algorithm, presented by Yoerger, et al [1]:

Variable Definition:

- r_k measured ranges r, $r = \{r_k\}, k \in \{1, \ldots, K\}$
- N median filter window
- TOL maximum tolerance that selects an outlier
- t discrete time index, $(\ )^t$ denotes a variable's value at time t

Function Definition:

bool median_filter(r_k)

if $\left|r_k^t - median\left(t_k^{t-1,\ldots,t-N}\right)\right| > TOL$

return *false*

else *return true*

Pictorially, this algorithm can be explained in Figure 8.

The downside of this outlier rejection algorithm occurs when the one-way travel time data is not continuous. As the beacons survey occurs, it is often common to pause the data acquisition, change the location of the topside boat to receive different measurements, and restart the data acquisition. Therefore, when data acquisition restarts, the distance to the beacons will drastically change, as seen in the discontinuity of the data in parts of Figure 7. This jump will cause the algorithm to reject the first N measurements after the discontinuity, N being the size of the sliding window. This algorithm, however, is still easy to implement and it does not require much computing power.

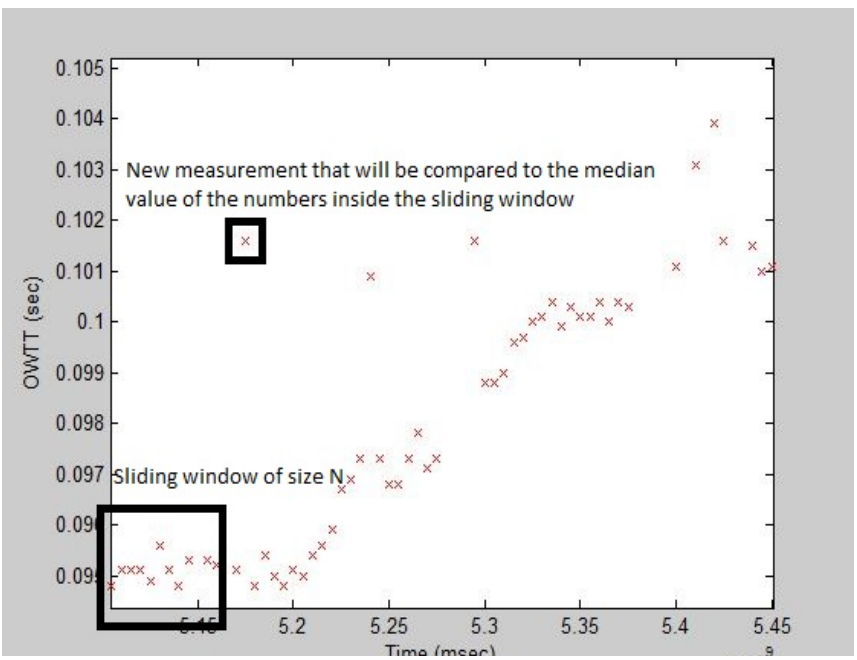

Figure 8 - Median Filter

The last outlier rejection algorithm, the Spectral Cluster Graph Partitioning (SCGP), was first presented by Olson [2]. SCGP measures the quality of the newly acquired data by comparing it to the previous data. Every new measurement received by the topside boat can be understood as a circle centered at the topside boat's location and the one-way travel multiplied by the speed of sound as the radius. As the amount of data increases, different circles are plotted, and the intersection of the circle is the optimum location of the beacon.

An outlier, based on SCGP, is a portion of the data acquired that does not intersect with a significant amount of past data. In more details, a matrix A is formed with the following properties:

$$A_{ij} = \begin{cases} 1 \; if \; circle \; i \; and \; j \; intersect; \\ 0 \; otherwise \end{cases}$$

Then, a "cut" is created. A cut is a vector u that identifies the outliers:

$$\vec{u}_i = \begin{cases} 1 \; if \; measurement \; i \; is \; considered \; an \; inlier \\ 0 \; otherwise \end{cases}$$

In single-cluster graph partitioning [5], the quality of the cut is given by:

$$r(u) = \frac{(u^T A u)}{u^T u}$$

To optimize u:

$$\Delta r(u) = \frac{Auu^T u - u^T Auu}{(u^T u)^2} = \frac{Au - ru}{u^T u} = 0$$

The extreme of r is:

$$Au = ru$$

Which is a known eigenvalue/eigenvector problem. Therefore, the optimum cut is the eigenvector of A associated with the maximum eigenvalue.

Next, the row vector u is continuous-valued, but the outlier/inlier problem is discrete. To transform u into a discrete-value function:

$$v_i(t) = \begin{cases} 1 \; if \; u_i \geq t \\ 0 \; otherwise \end{cases}$$

The optimum threshold is:

$$t_{opt} = \max_{t \, \epsilon \, u} \frac{v(t)^T u}{v(t)^T v(t)}$$

The physical interpretation of a dot product is the similarities between two vectors. Therefore, maximizing the dot product of *v(t)* and u maximizes the relation between these two vectors. The denominator normalizes the expression.

Pictorially SCGP can be view in Figure 9. The red circles were considered outliers due to their low relation to the inner circles. Blue circles were considered inliers.

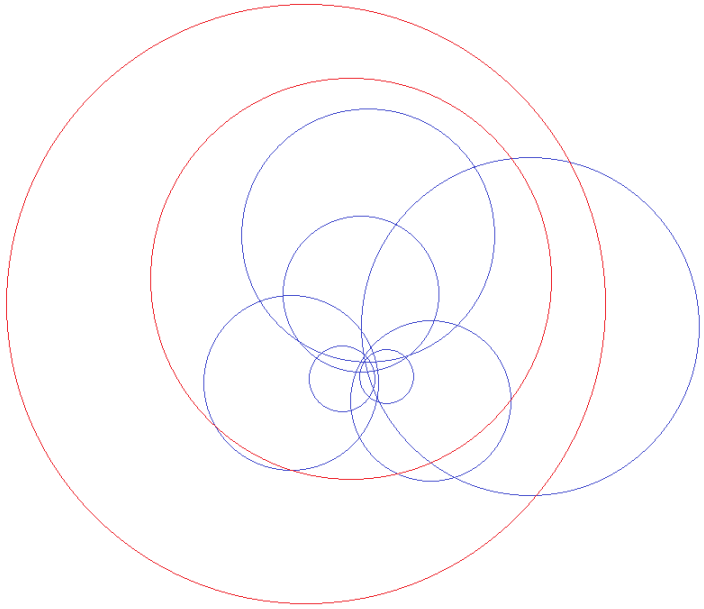

Figure 9 - SCGP Outlier Rejection

The benefits of this method are its robustness and quality. The downside is the algorithm's computational complexity as measurements increase, and its poor performance with high variance data. With broad ranges of data, an outlier at time t can have a strong relation to the data at a time t-t_0, turning the outlier into an inlier. The implemention of a sliding window SCGP into the algorithm developed during the summer is an interesting project for future work.

Median Filter was included in the real-time surveying algorithm. Results can be found at Figure 10, the size of the sliding window and tolerance used was 3 and 7 meters. The outlier rejection worked optimally at these values. Blue *x*'s signify inliers, red represents outliers.

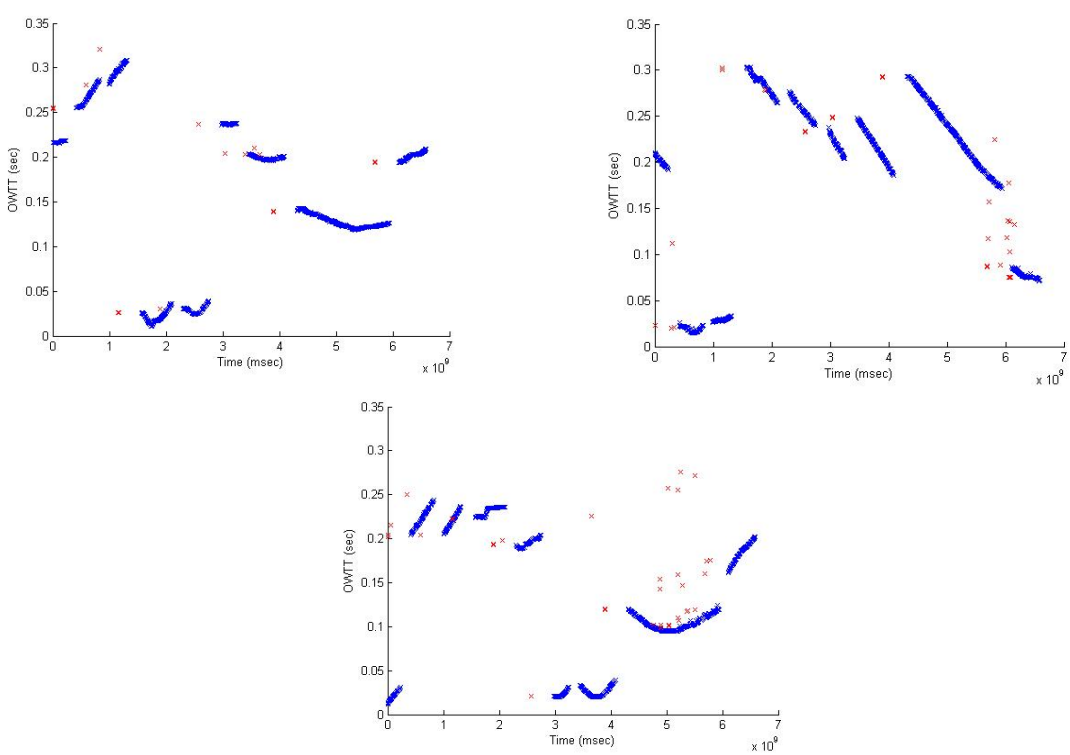

Figure 10 - Median Filter Results

Mutual Information

The Mutual Information was the last but most crucial part of the summer project. The idea is to create an algorithm that assumes the surveyor will move at a direction θ for the next l meters and take n measurements at every $\frac{l}{n}$ meters.

In detail, the information gain in θ direction is calculated by performing the maximum likelihood estimate (MLE) described in Charrow [4]:

$$MI[x,y] = \int_x \int_y p(x,y) * \log\left(\frac{p(x,y)}{p(x)p(y)}\right) dydx$$

Entropy H[x] is a measure of the uncertainty, and it can be evaluated as:

$$H[x] = -\int_{R^d} p(x) \log\big(p(x)\big)\, dx$$

For a d-dimensional Gaussian Random Variable where $\vec{x} \sim \mathrm{N}(\vec{\mu}, \Sigma)$, entropy becomes:

$$H[x] = \frac{1}{2}\log((2\pi e)^d |\Sigma|) = \frac{d}{2}\log(2\pi e) + \frac{1}{2}\log(\Sigma)$$

Mutual Information is therefore defined as:

$$MI[x,y] = H[x] + H[y] - H[x,y], x \in R^m \text{ and } y \in R^n$$

$$MI\,[x,y] = \frac{1}{2}\log\left(\frac{|\Sigma_{xx}||\Sigma_{yy}|}{\Sigma}\right)$$

$$\text{Where } \Sigma = \begin{bmatrix} \Sigma_{xx} & \Sigma_{xy} \\ \Sigma_{yx} & \Sigma_{yy} \end{bmatrix}$$

Assuming that beacon locations are Gaussian distributed, this property can be used for the problem of locating an optimal path c^* that provides the highest information gain.

$$c^* = argmax\, H[z(a)] - H[z(a)|x]$$

Where H is the entropy, *z(a)* is the set of future measurements, and *x* is the estimated state. Upon the reception of a measurement $z = h(x) + w$, where h is the theoretical value, and w is the noise, where w~N(0,R), the mutual information becomes:

$$MI\ [x,z] = \frac{1}{2}\log\left(\frac{|\Sigma||H\Sigma_{xx}H^T + R|}{\begin{vmatrix} \Sigma_{xx} & \Sigma_{xx}H^T \\ H\Sigma_{xx} & H\Sigma_{xx}H^T + R \end{vmatrix}}\right)$$

Using linear algebra properties of the determinant of block matrices, this expression can be simplified to:

$$MI\ [x,z] = \frac{1}{2}\log\left(\frac{|H\Sigma_{xx}H^T + R|}{|R|}\right)$$

This expression outputs the mutual information gain at a single direction θ for the next d meters and takes n measurements at every $\frac{d}{n}$ meters. The equation will compute the information in all 360 degrees of possibilities and follow the direction with the highest information gain. The Mutual Information gain was published at PeRL's Viewer using a color map. Red represents high information gain, and blue small.

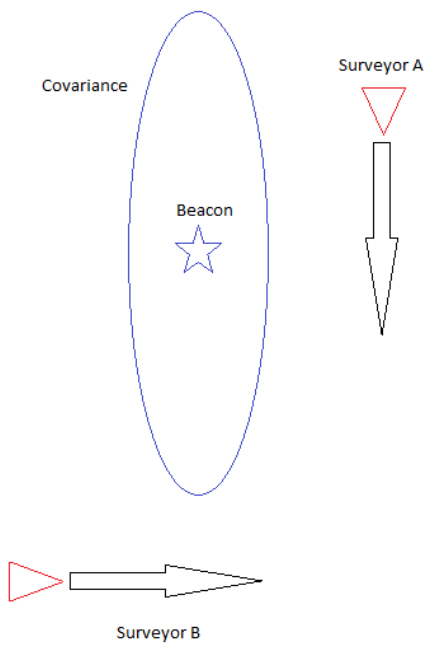

Figure 11 - Mutual Information Toy Example

In simpler terms, as seen in Figure 11, the result expressed that surveyor B would gain more information than surveyor A. The covariance ellipse, plotted around the beacon, has a higher range of possible values in the vertical direction. Surveyor A, by moving in the same direction, is increasing the information in the horizontal plane, where the covariance is already relatively smaller than the vertical direction value of the covariance.

Conclusion

The project helped the scientific community with an algorithm that decreases the time spent surveying beacons. The real-time beacon localization helps when making decision about where to deploy the beacons, while also providing relief to see that all beacons are working.

Although only two sets of data were tested, data acquisition and measurement did not vary much. The algorithm is robust and it will be useful for different situations.

Future Work

Robustness is an important characteristic of automation. Making the algorithm more robust would improve its functionality. For future work, the survey should be run by the AUVs while on the surface.

The first improvement to make this possible is to change the transducer location on the Iver. Currently, it is located above the water line, making the beacons above water when navigating on the surface. It is crucial that the transducer is moved to the bottom part of the vessel in order to the AUV to be able to communicate with the deployed transponders.

Secondly, a sliding window SCGP should be implemented in the algorithm. The current method, sliding median filter, involves modifying the size of the sliding window and tolerance. Which is not an ideal scenario for automation.

Thirdly, the mutual information calculations should be limited according to the the surveyor maneuverability. If the highest information gain is exactly to Port or Starboard (90 degrees), it is impossible to maneuver in that direction directly.

Lastly, a path-planning algorithm should be added to the program. Mutual Information outputs the direction of largest information gain. However, a complete path could be calculated by the AUV based on the initial covariance matrix, decreasing even further the surveying time. A good possibility would be implementing the Rapidly–exploring Random Trees algorithm as mentioned by Karaman and Frazzoli in their *Incremental Sampling-based Algorithms for Optimal Motion Planning [6].*

Personal Thoughts in Summer Projects

Unexpected is the word that best describes this past summer. It has been a unique and pleasant experience that will shape my future: I am truly thankful for Mr. Wang for providing the resources I needed to make the project possible.

As summer approached, my perspective was that this summer would be a lot like my previous internship experiences. But as the project started and I was instantaneously stunned. Stunned by the knowledge Ph.Ds. and professors had, how much I did not know, and also overwhelmed by the infinite amount of possibilities to tackle the same problem. I felt free with the opportunity to apply any knowledge I had to tackle the problem. Special thanks to Jeff Walls for letting me try different things and being so patient while helping me.

There was an exact moment that I realized I wanted to pursue my graduate studies. During the lab's first trip to the University of Michigan Biological Station (UMBS), one of the AUVs sank. The retrieval process was a lot less stressful than I suspected, and the investigation afterwards fascinated me. As the computer codes ran across screens, and the theories behind the failure were tested, I was impressed

by everyone's critical and logical thinking, and their skills of applying the ideas into code in a timely manner.

My experience was so rewarding and educational that I strongly believe every college student should be mandated to do research during at least one summer throughout his or her college career.

I left this summer feeling a lot more stupid than when I came in, but this summer has showed me what path I want to choose for the next 10 years of my life, and the path of exploration I want to lead. I am extremely thankful for Mr. Wang for providing this opportunity.

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