The Even Higher Performance Plongeur - v3.0 GTMR RoboSub 2020

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***Abstract*—GTMR's goal for Robosub 2020 was to increase the reliability and robustness of hardware systems while also building additional capabilities in navigation and perception to allow for more tasks to be attempted successfully. On the hardware front, a new pressure vessel was designed and prototyped to create a more robust and modular sub. To improve both perception and navigation systems, a new Intel RealSense Stereo camera was installed to allow for visual odometry and SLAM, and a hydrophone system was designed to allow for acoustic navigation. To improve the machine-learning side of the perception system, a genetic algorithm was used to improve hyper-parameter tuning, and a water-clearing filter was used to improve training data. Due to COVID-19, there was not much time to quantify performance gains in real world scenarios; however, results from simulation and unit tests are promising.**

I. Competition Strategy

Observing the performance from last year, aspects of the sub's design that GTMR excelled in include perception, depth and heading control, mission/task planning, and software architecture, while areas of improvement consisted of the following: hardware reliability, simulation, hydrophone systems, and visual odometry. This year's competition strategy was to develop and implement additional features, both on the software front and hardware front that would allow for achieving reliability for hardware systems, expanding capacity for testing through simulation, and improving navigation systems, specifically for the transitions between tasks, using both visual odometry and hydrophone systems.

GTMR's team structure this year has been massively revamped from last year. Rather than have a small team that's familiar with most aspects of the sub, sub-teams have been formed that are familiar only with the area of interest for that particular sub-team. This allows for specialization in teams and diversification in the features that could be concurrently worked on. There are dedicated teams for each aspect of Robosub varying from perception to hardware to even outreach. This new structure proved pivotal in the breadth of improvements that could be started this year. It allowed for a lower barrier to entry for recruitment and as a result, the team grew massively from the previous year.

When deciding which issues to tackle first for the sub, a simple priority queue was used, with the priority being overall benefit towards completing the competition graded against the time it would take to complete the issue. Last year, only a few tasks were selectively targeted to streamline development and maximize points. With the improvements completed since then, new areas can be comfortably tackled without compromising competition points.

Complexity this year was a big issue. With the addition of new hardware systems, integrating everything in the existing sub architecture turned out to be a daunting endeavor. Hydrophones turned out to be much more complicated to implement than anticipated, and setting up a 3-D depth camera that could natively run S.L.A.M wasn't as simple as just swapping cameras. However, when given the option between sacrificing system reliability for a more complex system, system reliability should be chosen every time. The year started with a robust system that could already handle many of the tasks for RoboSub without major alterations. With this knowledge, the pursuit of adding new complex systems was possible knowing that a reliable system was there to fall back on.

II. Vehicle Design

This year's vehicle design decisions were selected to match the competition strategy. To improve hardware reliability, the mission was to design and implement a new pressure vessel to house sensors, power systems, and computers. The current pressure vessel design is prone to leaks and does not properly optimize space for mounting electronics. After that was done, creating a simulation was the next hurdle. Having a robust simulation is helpful for a variety of reasons namely the ability to test mission logic, control algorithms, and perception algorithms without having to be physically present at a pool. Additionally, to avoid the issue of having to estimate distances between tasks and hard coding commands for navigation, visual odometry was investigated to allow the sub to have an accurate state estimator that could aid in navigation. In a similar vein, hydrophones were explored as a means of estimating heading towards tasks that involved pingers. Lastly, improvements were made to the previous year's machine learning framework for perception that could improve training efficiency and object detection performance.

A. Hardware

When designing the new pressure vessel, considerations were made to address the two main problems with the current pressure vessel. These two issues are the aging characteristics of the hull and a general lack of user-friendliness. Figure 1 shows the exterior and interior of the current pressure vessel design. From these images it is clear that the the exterior of

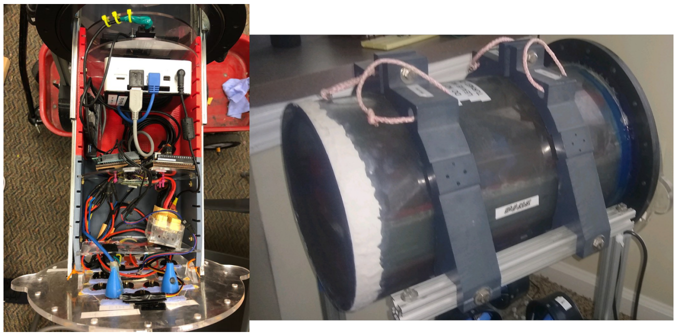

Figure 1: Current Pressure Vessel

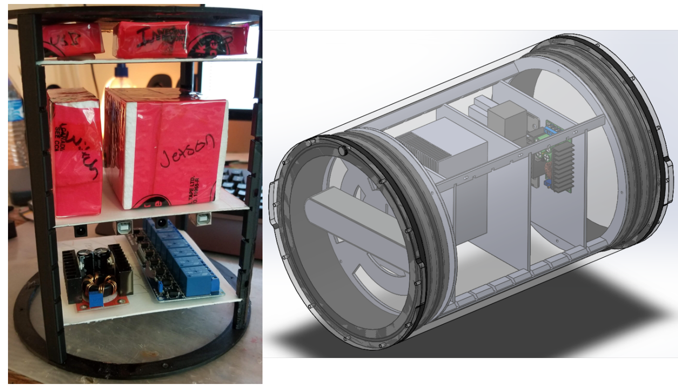

Figure 2: New Pressure Vessel

the hull has epoxy in multiple locations to alleviate leaks that have surfaced over the years, and the interior of the hull does not efficiently use all of the space to mount electronics.

The first issue was the aging of the current hull. By using a newly purchased acrylic hull and aluminum flanges, the entirety of the existing hull will be replaced. This will offer a fresh start for the hull itself, eliminating any aging characteristics. The new hull and flanges are also of a different design as the new hull flanges rely on a more robust mechanical seal of dual O-rings interfacing with the inside of the acrylic hull cylinder. The current hull design relies on adhesive sealant holding the flanges to the ends of the hull cylinder. However, the O-ring seal of the new hull makes removing the flanges more difficult, and therefore makes removing the end-caps to gain access to the hull more difficult. However, to combat this, a new user friendly non-damaging tool designed specifically for prying the flanges form the cylinder has been discussed. On top of that, the task of removing the flanges becomes easier with more practice.

Independent of the new hull, there have been design iterations and planning focused on the system electronics. The goal is to increase the organization, modularity, user friendliness, mechanical and electrical noise reduction, and broader capabilities. This will be done using a card-slot style layout where a metal frame extending from one of the hull flanges will house “cards” which contain various system components/electronics. Early in new design iterations, these cards will serve more as a mounting board for the electronic components such as ESCs, Arduinos, Jetson, TMU, camera etc. and allow for wiring up the system. Later in the design iterations, the goal is to have a more fully integrated system where the cards will act as daughter boards to a backbone board, all supported by a metal frame attached to the hull flange. This will allow for the design of more integrated and personalized circuitry which simply slots in and interfaces with whole system. Ultimately this would then allow for a more user friendly, customized, and capable system. Figure 2 shows a CAD model of the new pressure vessel along-side an initial rapid prototype.

B. *Simulation*

For the simulation environment, UUV simulator framework was used as a starting point [6]. This choice was made because it was implemented in Gazebo and had many default models for vehicles and sensors that could easily tweaked and customized to match GTMR’s configuration. It being a Gazebo simulation made it natural to interface with the GTMR software architecture, which uses ROS. Currently, the default REXROV submarine was modified to match GTMR’s submarine’s motor configuration and camera configuration. With a similar motor configuration and camera configuration, it became possible to tune controller gains and test out object detection algorithms in simulation and then easily apply them to the real sub.

C. *Visual Odometry*

The sub’s previous front facing camera was replaced by an Intel Real Sense Tracking camera. With the new tracking camera, the sub can perform distance calculations and S.L.A.M. algorithm to boost performance. The Intel RealSense camera uses stereoscopic depth sensing to determine the distance to an object by using its two infrared cameras and triangulation, allowing for an accurate depth measurement. A depth sensor enables the use of visual odometry to estimate change in position.

The real sense camera has the ability to natively run S.L.A.M, which both saves time that would be spent writing the algorithm and more importantly, doesn’t detract from the performance of the sub. S.L.A.M enables accurate state estimation that doesn’t solely rely on dead reckoning, which is what was used in prior years. To get this working, the intrinsics of the camera have to be set through calibration. This was done though running the perception stack on the sub during pool tests and using the real-sense ROS libraries. Unfortunately, S.L.A.M was not fully implemented; However, there still exist benefits from the increased visual clarity and stereo vision from the camera upgrade.

D. *Hydrophones*

Although not currently complete, the proposed hydrophone system was designed to be self-contained and use all 3 of the team’s existing hydrophones. By creating a self-contained system, it could easily be moved around the body of the sub for better placement, and reused on other platforms, such as the Roboboat and the WAM-V catamaran. Such a self-contained system is well suited for adapting electrical isolation via an

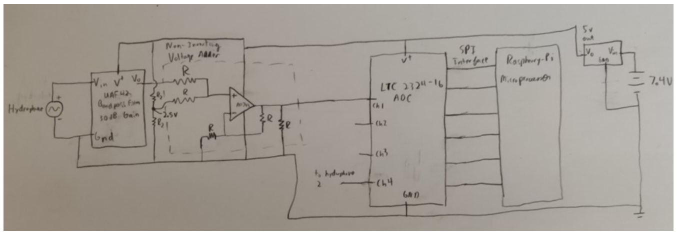

Figure 3: Hydrophone Array

independent low-ripple power supply, a necessity for low-noise ADC measurements.

In a past attempt at creating hydrophones, the team discovered that using the voltage regulated output of an arduino while the arduino was generating PWM outputs resulted in significant voltage level transients from the onboard regulator, necessitating the need for an external reference voltage regulator for the hydrophones. Similar to other designs from other competitors [2], [5], [1], the hydrophone array was designed to have a hardware pre-filtering and amplification step, which would magnify the weak, piezoelectric pulses of each hydrophone and perform band-pass filtering around the known pinger frequency of 25 to 40 Khz. The removal of spurious frequencies, particularly high frequency elements, is necessary to reduce signal distortion and aliasing that would skew frequency-domain analyses.

Although many hardware-based filters exist, the Butterworth filter is one of the easiest to implement [4], leaving less opportunity for error over more complex filters while attenuating unwanted frequencies well. For this reason, a Butterworth filter was chosen for the bandpass filter. Although theoretically an 80 Khz sampling rate was the minimum rate necessary to avoid aliasing, previous sampling at 110Khz proved inadequate and from the reports of other teams [2], a minimum of 500Khz is required to sample data well enough for signal detection.

Further signal processing would use an op-amp to multiply the transient signal voltage by a factor of 1000 and bias the signal such that at rest the voltage was mid-range for the sampling ADC. This preprocessing step would allow the ADC to sample the signal over its full range. The LTC2324-16, a 16 bit resolution with a 2 Msps sampling rate over 4 channels was chosen for its ability to sample all 3 channels near synchronously with high accuracy.

Data collection would be offloaded to an onboard compute unit, most likely a Raspberry pi or a Xilinx signal processing board figure 3 where the streaming data would be checked against a noise floor threshold to see if a pulse had arrived. If the streamed data exceeded the threshold, the data would be retained in memory for further processing, being discarded otherwise. The beacon-locating algorithm utilizing this data is undecided and depends on the reliability and sensitivity of the hardware when assembled.

E. Machine Learning

For the sub's perception system, a machine learning framework was developed last year in which object detection is accomplished using the YOLO object detection algorithm [7].

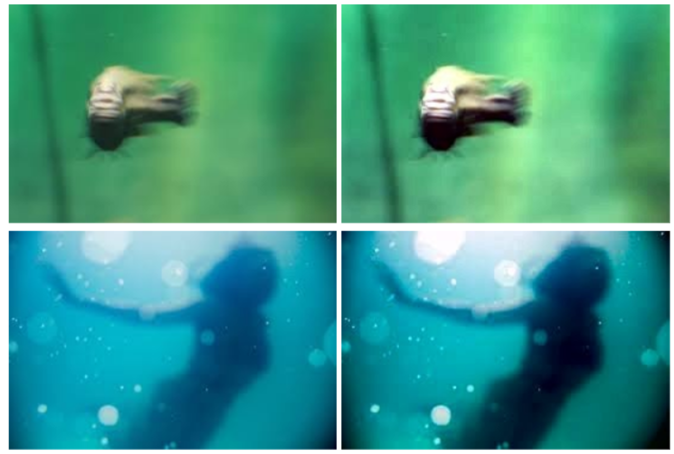

Figure 4: Water Clearing Filter [3]

This year time was spent to improve the performance and efficiency of last year's object detection system. This was done in two ways: smarter hyper-parameter tuning and an improved data collection method.

Hyper-parameter tuning was initially done through a simple grid search. Since this method exhaustively checks every possible set of parameters, it is guaranteed to return the optimal parameters given the search space. However, due to time and computing power constraints, the search space itself must be limited. This method also makes updating the model an inconvenient task. Because of this, genetic algorithms were also explored. Random chromosomes (sets of parameters) were generated and each were evaluated for accuracy. Using a tournament selection method, chromosomes were also chosen to generate the next generation of chromosomes via n-point crossover. Mutation was also included to prevent premature convergence. Initial results were promising in simulation; however, further evaluation is needed to determine its effectiveness in the real world.

Strides have also been made in data collection for perception. In last year's competition, to achieve good performance for object detection, the majority of training images had to be taken in the environment of operation. This year methods were considered to try and normalize images taken in different environments. The goal was to allow the object detector to be robust to different environments. One approach that was investigated is called Relative Global Histogram Stretching [3]. This method enhances the image, standardizes it to grayscale, performs RGHS, and then color corrects the image.

With this method light absorption inconsistencies and scattering can be avoided, thus improving the quality and robustness training data. This filter can help save a considerable amount time at competition that would be spent on collecting training data and training object detection models. This time would be saved because the filter would allow for models trained on training data from the Georgia Tech CRC pool to be usable in the Transdec. Figure 4 below shows how the water clearing filter works. The original images are on the left, and the filtered images are on the right.

III. EXPERIMENTAL RESULTS

Prior to the pandemic, most testing took place in the Georgia Tech pool. Most of the testing time was used to calibrate the stereo camera for visual odometry and to test out visual odometry performance. After the pandemic started, the addition of simulation capability allowed for testing tasks without pool access. More specific optimizations, such as those to the machine learning architecture were tested through unit tests and test data. For the new pressure vessel, a full CAD model was made, and an initial prototype was 3D printed. For the hydrophone system, a conceptual schematic was formulated and will be prototyped in the future.

To couple with the improvements to the machine learning architecture, a new camera, the Intel Real Sense tracking camera, was added to the sub which greatly expands the potential for visual odometry while also increasing overall camera quality and clarity. This was tested during pool tests where calibration was done for the intristic matrix for the camera and testing was done for the accuracy of the visual odometry. Accuracy was defined as the error between the predicted position of the sub and the actual position. The position measurements were initially very inaccurate in the pool prior to calibration though they became only mildly inaccurate afterwards. This is very far away from the performance of the camera on the surface, where it was very accurate in measuring position changes. Based on repeated tests of the position measurements underwater, it was concluded that the camera is decent for attaining an approximation of sub movement but shouldn't be the sole source of state estimation. In the future, this measurement will be combined with other measurements and a system model in a Kalman Filter to have a more precise form of state estimation.

The optimizations to the machine learning architecture were tested primarily though unit tests as there was not enough time to put the genetic algorithm on the sub to run real time. The procedure was fairly straight forward. The genetic algorithm was put into action to dictate hyper-parameters during training and the results of which were cross verified against the old set of parameters. The training data set was made from images collected from rosbags in the past. The genetic algorithm improved accuracy across the board for an MLP classifier. The sub, however, currently uses a CNN and YOLO darknet for object detection. To simplify the creation of the genetic algorithm, the starting point was an MLP (multi-layer perceptron) due to it having less parameters to alter, and while this was useful for getting started, it turned out to be less useful than intended for the sub as it is now. The next immediate step would be to broaden the scope of the genetic algorthm to accept the CNN and YOLO Machine Learning architectures so that hyper-parameters can be tuned optimally for maximum performance during object detection tasks.

Testing of the new pressure vessel involved partially recreating the sub in SolidWorks, namely the hull and card slot system. The design was inspired by the existing vessel layout with careful consideration into existing problems, such as leaks and user unfriendliness, the new hull cylinder, flange constraints, and other various features. A sample frame was created and then 3D-printed in order to first verify the fit. Doing this resulted in decent performance, however a few flaws were highlighted: tight-fitting components and difficulty in machining parts. Machinability is a concern due to the end vessel being machined from aluminium rather than 3D-printed. Next steps for the pressure vessel would involve reworking the 3D model for better fitting components through the experience gained from 3D printing the first time and restructuring parts for more machinability.

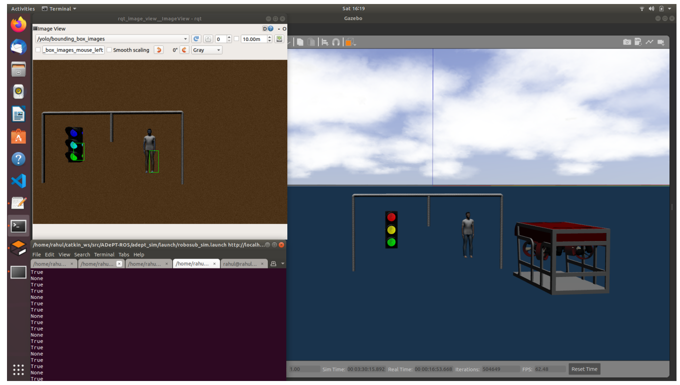

Figure 5: Simulated Gate Task

The simulation environment served to be useful for testing out task logic. Prior to the RoboSub cancellation announcement in early May, it was a priority to develop a robust simulation to test in due to the increased difficulty of finding pools to test the sub in. Using the simulation environment, the gate task was successfully simulated. This can be seen in the figure below.

In the above figure, a CAD model of the gate is placed in the simulation and the sub is using the YOLO object detection algorithm to navigate to the side with the traffic light. The sub is also running PID control logic to perform heading and depth control to navigate through the correct side of the gate while simultaneously performing object detection.

IV. CONCLUSION

The approach for this year's competition was to optimize the sub for performance while iteratively adding improvements and new features. This was accomplished through the many software optimizations in code that were created as well as the hardware improvements and additions. The software optimizations focused on reducing computational overhead while the system was in use while the hardware additions were focused on enhancing the ability to perceive underwater. A more reliable form of state estimation has been implemented in the new depth camera additions that will allow for the completion of tasks more consistently, without worry that the sub would get lost in between tasks. The perception stack, which debuted last year has been vastly improved upon with an array of new features and software optimizations. Although unforeseen circumstances caused a huge shift in plans, GTMR is confident about Robosub 2021!

ACKNOWLEDGMENTS

We would like to thank the GT Aerospace Systems Design Labs and GT Student Government Association for supporting our work on this project. Within ASDL, we would also like to thank the ADEPT Lab for continuing to allowing us to use the space and manufacturing tools. We would also like to give a special thanks to our sponsors: ConnectTech, for their generous donation of an Orbitty board for the Jetson TX2 and Fischer Connectors for their donation of waterproof connectors for the sub. We would also like to acknowledge the GT Campus Recreation Center for helping us schedule pools tests and allowing us to use the pool. Finally, we would like to thank all previous team members here at Georgia Tech, to without their prior dedication and experience, none of this would be possible.

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Appendix A
Component Specifications

Component	Vendor	Model/Type	Specs	Cost (if bought new)
Buoyancy Control	Sea Pearls	Vinyl Coated Lace Thru Weights	Miscellaneous sizes, 1-5 lbs.	Varies, up to $30 for a 5 lb. weight
Frame Rails	McMaster-Carr	T-Slotted Framing	Single	$17.68 per 5ft. section
Waterproof Housing	Custom Made	Clear PVC Tube	7” ID	N/A
Waterproof Connectors	Amazon	Generic IP68 Waterproof Connector	2-8 pin	Roughly $3 / connector
Thrusters	Blue Robotics	T200	No ESC	$169
Motor Control	Hobby King	Afro ESC	30 Amp	$11.36
Mid Level Control	Arduino	Mega	N/A	$38.50
Battery (Motors)	Hobby King	Turnigy Multistar 10000 mAh	4S, 10C	$47.64
Battery (Electronics)	Hobby King	Turnigy Multistar 5200 mAh	4S, 10C	$29.04
CPU	Intel	NUC, i7 (discontinued line)	N/A	From $212.83
External Comm Interface	Microhard	VIP2400	N/A	N/A
Programming Language (Navigation)	Python	3.7	N/A	N/A
Programming Language (Vision)	C++ / Python	11 / 3.7	N/A	N/A
Inertial Measurement Unit (IMU)	Lord Microstrain	3DM-GX3-25 (discontinued)	N/A	$1615.00
Camera (forward)	Intel	Real-Sense Tracking Camera	3-D Stereo Depth Camera	$149.99
Camera (downward)	ELP	Fisheye Lens 1080p Wide Angle		$45.00
Open source software	ROS	OpenCV	TensorFlow	
Team Size	15	AE/ME/ECE/CS	Rotated throughout year	Priceless?
HW/SW expertise ratio	1:2	N/A	All team members had basic HW proficiency	N/A
Testing time: simulation	20 hours			
Testing time: benchtop	15 hours			
Testing time: in-water	30 hours			