



Optimization of Side Scan Sonar Images for the Identification of Bottom-Mounted Objects in Shallow Coastal Marine Waters



Midshipman 1/C Candace Gordon, Midshipman 1/C James K. Kirby, and Midshipman 1/C Connor Knowles, USN, Class of 2020

Advisor(s): Dr. Joseph P. Smith, Instructor Alex Davies, Instructor Brianna Tracy

Abstract

Side scan sonar (SSS) is an established technology that can be used to collect high-resolution imagery of the seafloor for military and maritime applications. Higher-frequency SSS systems can be effective at detecting even small objects on the seafloor but detection probability is highly dependent on water column conditions, target aspect, and bottom type. Object identification is even more difficult, especially in coastal marine systems with heterogeneous bottom-types. Recent developments in artificial neural networks present a capacity to better detect and identify underwater, bottom-mounted objects but these models must be trained to recognize objects through the processing of thousands of images. This requires pre-processing of SSS imagery to enhance image appearance and resolution (i.e. gain and saturation) for the specific water column conditions at the time of the survey and against the specific bottom-type. In this study, an EchoBoat autonomous surface vehicle (ASV) equipped with a Humminbird Solix 10 CHIRP MEGA SI+ G2 fish finder was used to collect SSS imagery of small targets deployed on mud, sand, and rocky bottom-types in the coastal waters near Lewes, DE. Images were pre-processed using commercial software by applying fixed gain and saturation settings optimized for each bottom-type. Results suggest that the automated application of optimized pre-set gain and saturation settings based on the specific bottom type during SSS image pre-processing has the potential to improve the application of neural networks in the detection and identification of bottom-mounted objects in coastal systems. An integrated neural network model for the detection and identification of bottom-mounted objects that includes automated SSS image optimization based on bottom-type is proposed.

Study Area and Methods

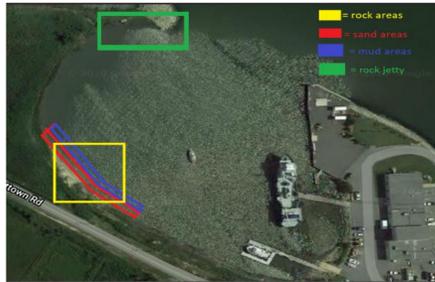


Figure 1. Map of SSS survey areas in Lewes Bay near the marine operations landing at the University of Delaware, School of Marine Science and Policy, College of Earth, Ocean, and Environment (CEOE), Lewes, DE. The four different survey locations had different known bottom-types and are represented by different colors: mud (blue); sand (red), rock (yellow) and rock jetty (green). At each site, prior to SSS surveys, a string of 5 custom targets was deployed on the bottom by wading or from a kayak. Surveys were performed between 26-29 February 2020 during wintertime conditions.

In collaboration with the Robotic Discovery Laboratories (RDL), School of Marine Science and Policy, College of Earth, Ocean, and Environment (CEOE), University of Delaware, 5 (6" to 12") targets were created (2 floating submerged buoys wrapped with (Al) HVAC tape and 3 steel pipes; **Fig. 2A-C**) and deployed in a target string parallel to the shoreline at four different survey locations in Lewes Bay representing different known bottom types (**Fig. 1**): mud; sand; rock; and rock jetty. Pre-planned autonomous SSS surveys consisting of multiple passes over the deployed target strings were performed with an RDL EchoBoat ASV equipped with a Humminbird Solix 10 CHIRP GPS combo fish finder with down-imaging and side-imaging sonar (50/83/200/455/800 kHz & 1.2 MHz) (**Fig. 2D&E**). Images were downloaded and pre-processed using SAR HAWK® Humminbird® Sonar Target Acquisition Software (Black Laser Learning) with gain (brightness) and saturation (contrast) settings optimized for each specific bottom-type. Optimal gain and saturation values for each bottom type were chosen by visual comparison then manually adjusted and applied equally across all bottom-types to create a comparative matrix of gain and saturation settings vs. bottom type.

Figure 2. (A) Midshipman 1/C Kent Kirby, Midshipman 1/C Connor Knowles, and Midshipman 1/C Candace Gordon with Grant Otto (RDL) constructing reflective objects to be deployed as (B) target for SSS surveys; (C) Midshipman 1/C Knowles and Midshipman 1/C Kirby deploying target strings; (D) the USNA Capstone team with Mark Lundine, Jack Bruno, Hunter Tipton, & Grant Otto from RDL.



References: Federal Guidelines Digital Guidelines Initiative (FAGDI), 2012: www.digitizationguidelines.gov, accessed 22 April 2020; Song et al., 2017, IEEE OCEANS 2017., pp. 1-4; Ye et al., 2019, Remote Sens. 11: 1281.

Results and Discussion

Table 1. Comparative matrix of SSS images of test target strings deployed on different bottom-types (muddy, sandy, rocky, and rocky jetty) with bottom-type specific optimal gain and saturation settings applied. Gain and saturation settings were selected based on what the levels that made the targets stand out the most against each bottom type and the other features on the seafloor. Red triangles indicate the SSS image with gain and saturation optimized for the actual bottom-type. For other images, non-optimal gain and saturation settings for a different bottom-type were applied. Target strings are outlined by a grey oval.

Gain Setting	Saturation	Bottom Type			
		Muddy	Sandy	Rocky	Rocky Jetty
-1	0.5				
	0.4				
-1	0.3				
	0.3				

The comparative matrix in **Table 1** shows SSS images of test target strings deployed on different bottom-types (muddy, sandy, rocky, and rocky jetty) with bottom-type specific optimal and non-optimal gain and saturation settings applied. Gain is the apparent brightness and apparent sensitivity to light of the image and saturation is the purity of color and the difference from gray in an image, or contrast (FADGI, 2020). Gain and saturation were adjusted manually by visual inspection then fixed for the each bottom-type based on which settings had the biggest impact on the detection of targets against a grainy and noisy SSS image background. Others have show that the ability to detect objects on the seafloor in SSS imagery is highly sensitive to bottom-type (among other factors like water column conditions, beam angle, and water depth or height above target) so gain and saturation setting should be adjusted based on the local bottom-type when (pre-)processing SSS images (Ye et al., 2019). Comparing the pre-processed SSS images of target strings in **Table 1** across different optimized and non-optimized gain and saturation settings it is clear that the ability to visually detect and resolve targets (targets can be identified by a bright return along with a shadow behind them) is affected by gain and saturation and, in most cases, is significantly degraded if a non-optimal setting for a different bottom-type is applied. Image processing starts with image segmentation, or partitioning a digital image into multiple sets of pixels, in order to highlight features for detailed analysis which in the case of underwater objects usually means object detection, identification and classification. Pre-processing imagery and image segmentation for underwater object detection and identification can be performed using a range of methods from fully manual techniques that require a skilled and experienced operator to advanced, fully-automated methods that apply deep machine learning algorithms such as neural networks (Song et al., 2017). Results of this study suggest a simple approach to image pre-processing of SSS images could improve automated methods to detect and identify underwater bottom-mounted objects in coastal waters.

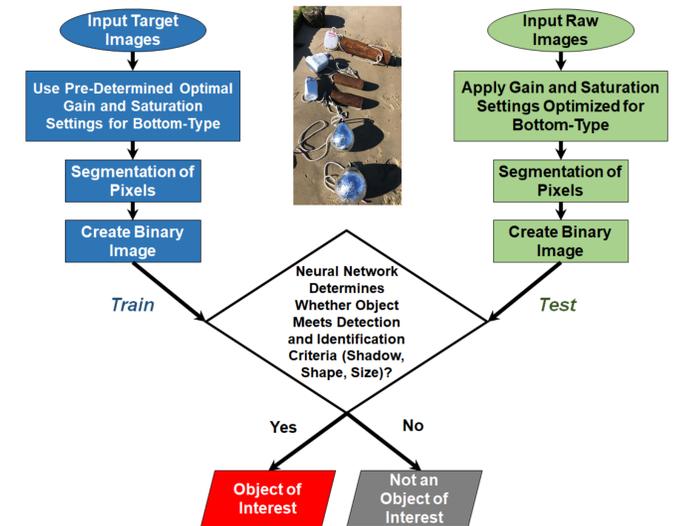


Figure 3. Conceptual diagram of an approach for integrated SSS image pre-processing using pre-set gain and saturation settings based on bottom type into a neural network for the detection and identification of underwater bottom-mounted objects. The approach involves controlled training surveys of known target strings like the ones performed in this study and live field test surveys.

An automated approach combining image pre-processing using pre-set gain and saturation settings based on bottom-type and a neural network model is proposed for the detection and identification of underwater bottom-mounted objects. **Figure 3** shows a conceptual diagram of the proposed approach adapted from current work being performed by the RDL at the University of Delaware. By applying pre-set gain and saturation settings for pre-processing SSS imagery prior to image segmentation based only on bottom-type, it might be possible to eliminate operator intervention and enhance the ability to train the neural network to detect and identify underwater bottom-mounted objects without significant bias. This approach would not solve all the challenges associated with automated detection and identification bottom-mounted underwater object in coastal waters but it does represent a potential way to streamline automation through the application of neural networks.

Conclusions

- *Gain and saturation are both adjustable settings during the pre-processing of SSS imagery prior to image segmentation. The ability to detect and identify underwater bottom-mounted objects can be significantly degraded if non-optimal settings for the local bottom-type are applied.*
- *An automated approach with image pre-processing using pre-set gain and saturation settings based on bottom-type could potentially enhance the ability to train neural networks to detect and identify underwater bottom-mounted objects without significant bias. If this approach was adopted the probability of automated object detection and identification would still be low in coastal systems because of other challenges (water clarity, beam angle, depth, object size & aspect, full or partial burial, and object material properties).*
- *Research efforts should continue to find ways to overcome these challenges to provide a means for reliable, automated identification and detection of underwater bottom-mounted objects in coastal systems for military and maritime industrial purposes.*

Acknowledgements: This work was made possible by the generous gift of funding by Volgenau family and supported by the U.S. Office of Naval Research through the USNA Summer Internship Program. Thanks to Dr. Ari Trembanis, Grant Otto, Hunter Tipton, Mark Lundine, Jack Bruno, and everyone at the Robotic Discoveries Laboratory (RDL), School of Marine Science and Policy, College of Earth, Ocean, and Environment (CEOE), University of Delaware. Special thanks to Vince Capone of Black Laser Learning for the use of SAR HAWK® Humminbird® Sonar Target Acquisition Software.

