

Identification of Underwater Mines from Electro-Optical Imagery

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Objectives:

A critical need of the U.S. Navy is the development of Unmanned Undersea Vehicles (UUVs) equipped with sensory technology to detect targets such as underwater mines. UUVs must have the ability to capture sensory data of targets, as well as detect and classify the target. This research focuses on algorithm development for underwater mine detection, classification, and identification using Electro-Optical (EO) imagery data. The objective of this research is to design a robust EO target detection method which has the ability to detect underwater objects and extract their silhouettes for subsequent classification into targets or non-targets and the identification of target types.

Challenges arise when considering the wide statistical variability of EO imagery data. Moreover, targets have diverse sizes, shapes and reflectivity properties. Target features can change significantly with variations in water conditions, and target range. Surface and bottom characteristics and reflectivity are highly variable, thus impacting the quality of the data. Variations in environmental conditions, e.g. turbidity, can also substantially change the fidelity of the collected data. Finally, natural and man-made clutter can increase the occurrence of false alarm while target obscuration caused by vegetations and other bottom features increases the misdetection rate.

Results:

For this research algorithms have been designed utilizing the data from a high resolution EO sensor by Applied Signal Technologies (AST). The sensor is shown in Figure 1. The EO sensor consists of a 12-bit CCD Camera, PC104 Stack, storage, software control, and changeable LED illuminators. The EO data is collected by towing the vehicle that carries the sensor while acquiring successive snapshots of the ocean floor. A block detection scheme has been designed to estimate the log-likelihood ratio for an object within a region of a test image. Each acquired image is sized to 512 x 512 pixels – then partitioned into 8 x 8 pixel blocks for log-likelihood ratio estimation. The detector is trained using 328 test blocks. From each image the detector calculates a ‘likelihood map’ used for detection, and segmentation of targets. If the likelihood of a particular block is above or below a derived threshold it will be considered a target or non-target block, respectively. Also size and shape constraints are imposed on the detected object in order to reduce the number of false alarms (for example Area and Solidity of the segmented object are constrained). An example of a target image, and likelihood map are shown in Figures 2 and 3, respectively.

Detection, segmentation and feature extraction can be achieved using only the generated likelihood map. This is because the likelihood map gives size, and shape data of the object. An example of the segmented target is shown in Figure 4. The detector was tested using 6 data runs containing 1454 total frames and 20 target frames. The overall receiver operating characteristics (ROC) curve in Figure 5 shows that for $P_d = 100\%$ the false alarm rate is $P_{fa} = 14\%$, which is certainly manageable. This performance is largely a function of the training set used in the block detector, and is a work in progress.

After the target is segmented, features can subsequently be extracted and passed to a classifier for classification into the Target or Non-target classes. Fourier descriptor coefficients that represent contour-based features are being considered for features of the segmented targets.

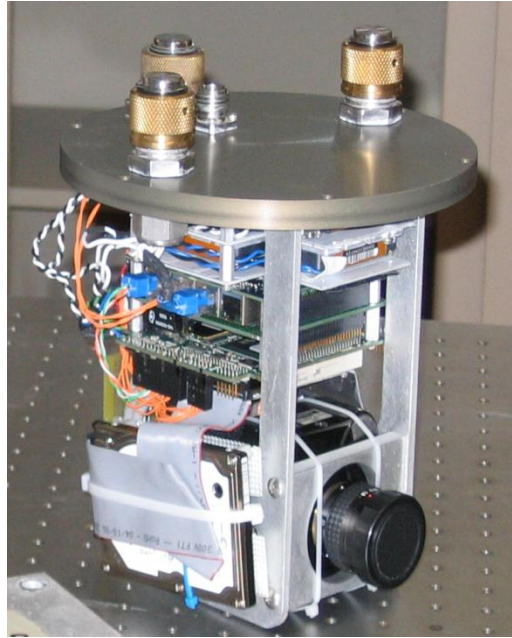


Figure 1. Electro-Optical sensor for underwater mine detection courtesy AST

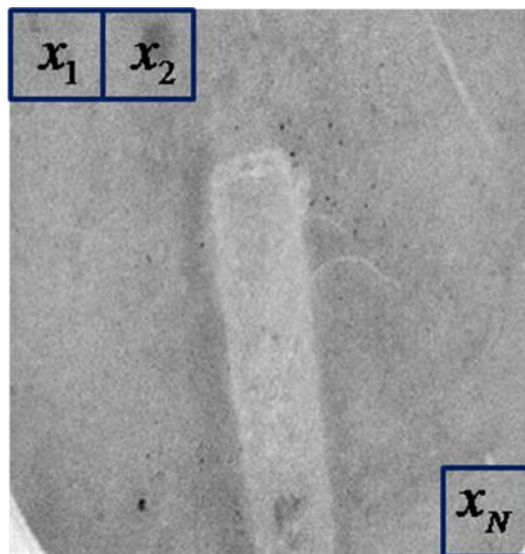


Figure 2 Example EO imagery data of an underwater mine.

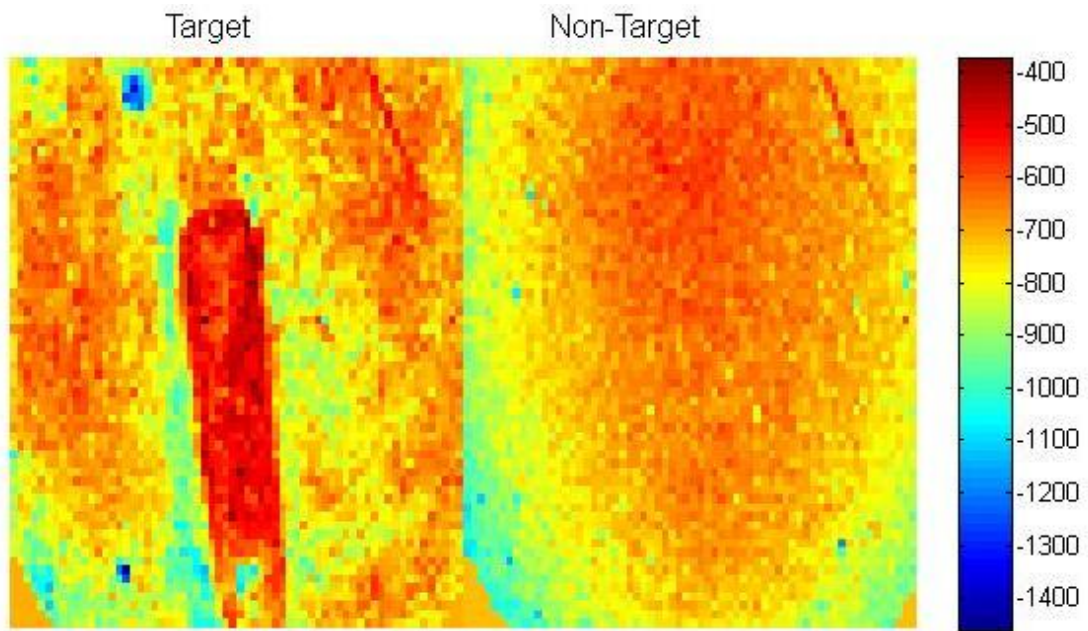


Figure 3 Example block log-likelihood for both Target (left) and Non-Target (right).

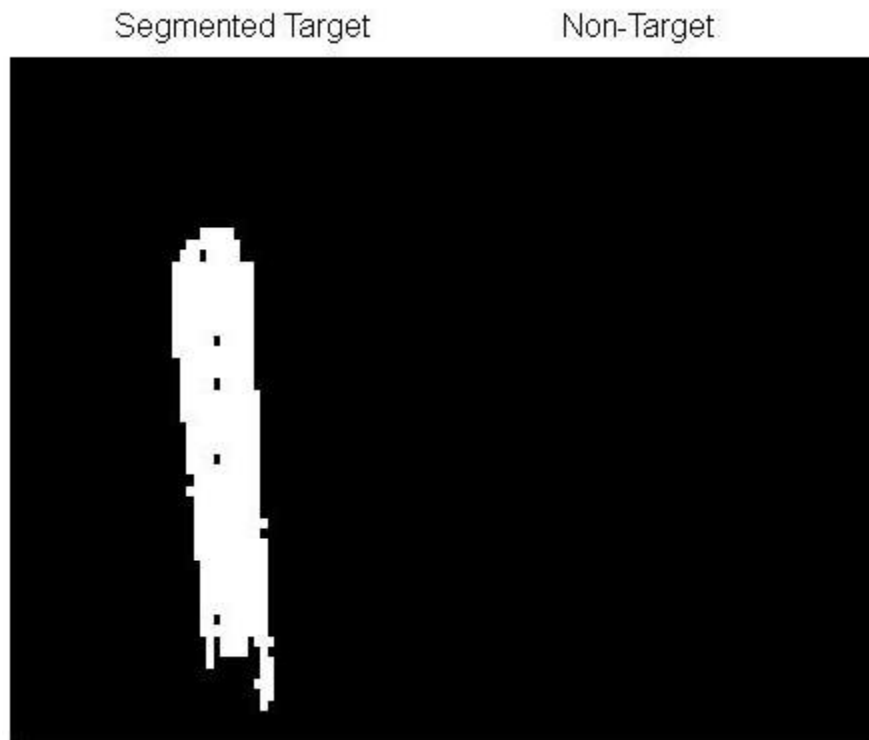


Figure 4 Example of Segmentation process of the Target (left), and the Non-Target (right)

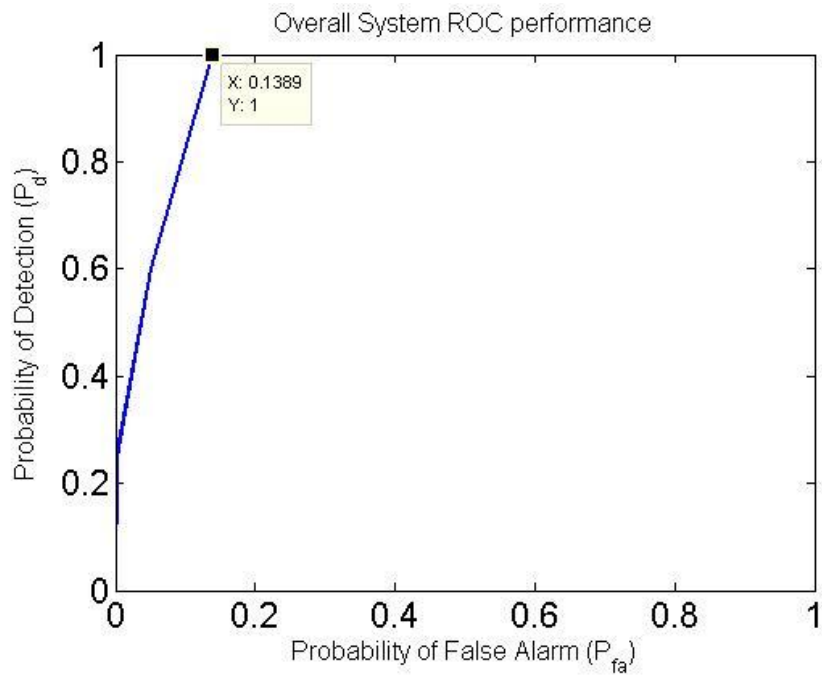


Figure 5 ROC for 6 run experiment of 1454 total frames containing 20 Target. For $P_d=100\%$ $P_{fa}=14\%$