# A Model Based Approach to Mine Detection and Classification in Sidescan Sonar

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***Abstract*-Developments in Autonomous Underwater Vehicle(AUV) technology has shifted the direction of Mine-Counter-measure(MCM) research towards more automated techniques. This paper presents an automated approach to the detection and classification of mine-like objects using Sidescan Sonar images. Mine-like objects(MLO) are first detected using a Markov Random Field(MRF) model. The highlight and shadow regions of these MLO's are then extracted using a Co-operating Statistical Snake model. Objects which are not identified as false alarms are then considered in a third classification phase. A sonar simulator model considers different possible object shapes, measuring the plausibility of each match. A final classification decision is carried out using Dempster-Shafer theory which allows both mono-image and multi-image classification. Results for all phases are shown on real data.**

## I. INTRODUCTION

Autonomous Underwater Vehicle (AUV) technology now enables large areas of the seafloor to be surveyed quickly. This has altered the direction of mine-counter measures (MCM) research towards more automated techniques [1][2][3]. However, the majority of these systems require training. The approach detailed in this paper is an automated alternative to the more traditional supervised model and is shown in Fig 1.

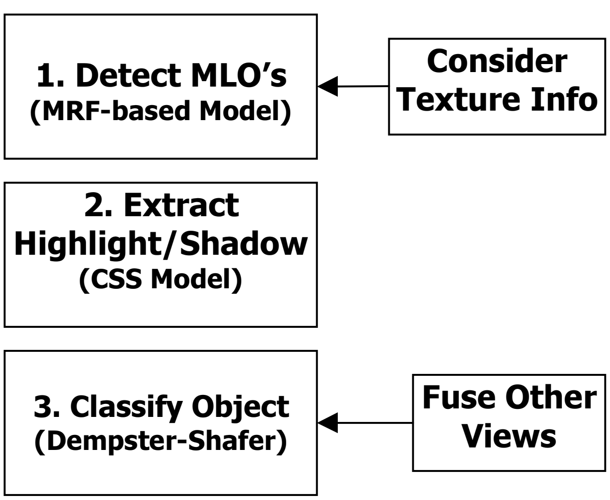


Fig. 1. Proposed 3-phase approach used for automated detection and classification of mine-like objects.

The first phase uses a MRF model to segment the image into regions of object-highlight, shadow and background, identifying possible MLO regions. The second phase uses a Co-operating Statistical Snake (CSS) model to extract the highlight and shadow region from each detected MLO. This model was developed to ensure an accurate segmentation could be achieved on complex seafloors [4]. The final phase uses a sonar simulator model to classify the object. The simulator allows possible shapes to be viewed under the same sonar conditions as the unknown MLO was detected. A classification decision is carried out using Dempster-Shafer theory, which allows the possibility of both mono and multi-view classification.

Section II will summarize the detection and feature extraction models. Section III will present results for these models. Section IV will present the classification model while Section V will detail current work regarding the incorporation of texture information (see Fig.1).

## II. DETECTION AND FEATURE EXTRACTION

### A. *Detection of the MLO's*

MRF models have been used to segment noisy images in a variety of applications [5]. This success is due to their ability to consider spatial information within the image as well as their ability to model a priori information [6]. The model described here segments the raw sonar image into regions of object-highlight, shadow and background. Priors were added to the MRF framework which modeled the characteristic mine signature in Sidescan sonar. These priors ensured that any object-highlight regions were therefore of the correct size and that they were accompanied by a shadow region (objects in sidescan imagery generally appear as a highlight/shadow pair).

Once segmentation was complete [4], a post-processing stage used the available navigation and size information to remove obvious alarms.

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### B. Extraction of the MLO's Highlight and Shadow Regions

Man-made objects such as mines leave regular-shaped recognizable shadow regions in Sidescan imagery. These shadow regions allow the object to be classified. Shadow extraction techniques have been developed that work well on simple seafloors but provide poor results on more complex backgrounds. The CSS model [4] overcomes these limitations by extracting both the object-highlight and shadow regions which are strongly related [7].

The CSS model considers a mugshot of each detected MLO and assumes the image to be composed of an object-highlight, object-shadow and background region. A fast, multi-scale segmentation technique is used [8] which segments by considering the image statistics. To ensure accurate segmentation on complex seafloors, priors were added modeling the relationship between the object-highlight and object-shadow regions [4].

As well as being capable of obtaining accurate extraction results on complex seafloors, the CSS model was also capable of identifying and removing false alarms. Detected MLO regions which did not have a highlight and shadow pair would often result in the CSS snakes expanding past mine-like dimensions. When this occurred, the false alarm could be removed from the result.

## III. DETECTION/EXTRACTION RESULTS

The combined Detection and CSS model was tested on over 200 Sidescan images provided by the NATO Saclant Centre, La Spezia, Italy. The models are demonstrated on 2 of these images.

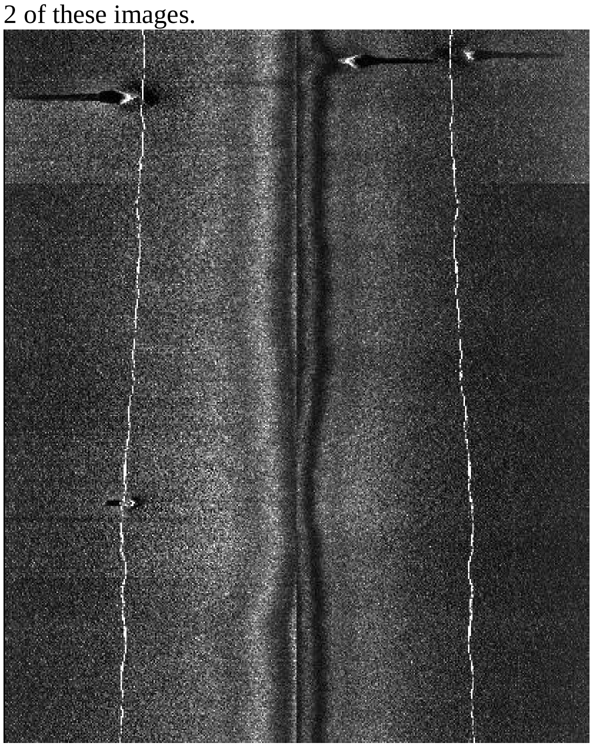

Fig 2. Raw Sidescan Image containing 4 objects.

Fig 2 shows a Sidescan Sonar Image containing 4 objects. The final detection result along with the extracted object features are shown in Fig 3.

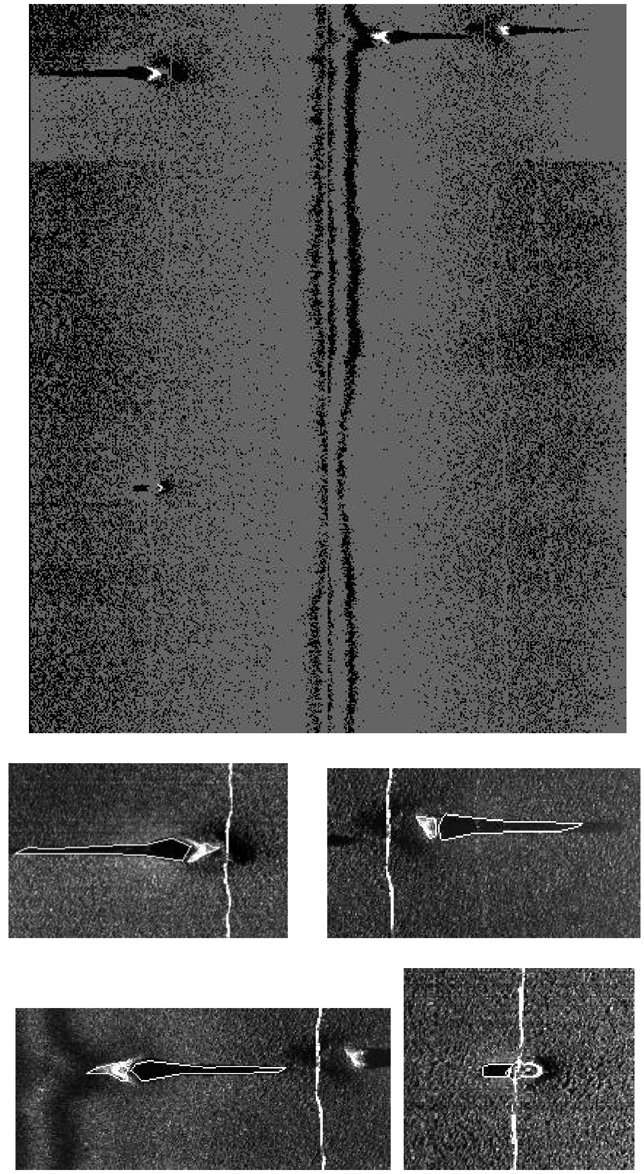

Fig 3. The final detection and feature extraction results for the raw image contained in Fig 2.

As Fig. 3 shows, all the MLO were successfully detected and the relevant features correctly extracted. No false alarms were observed.

The second considered image is shown in Fig 4. This shows objects lying on a sand ripple seafloor which ensures that an accurate shadow extraction is difficult. The results are shown in Fig 5.

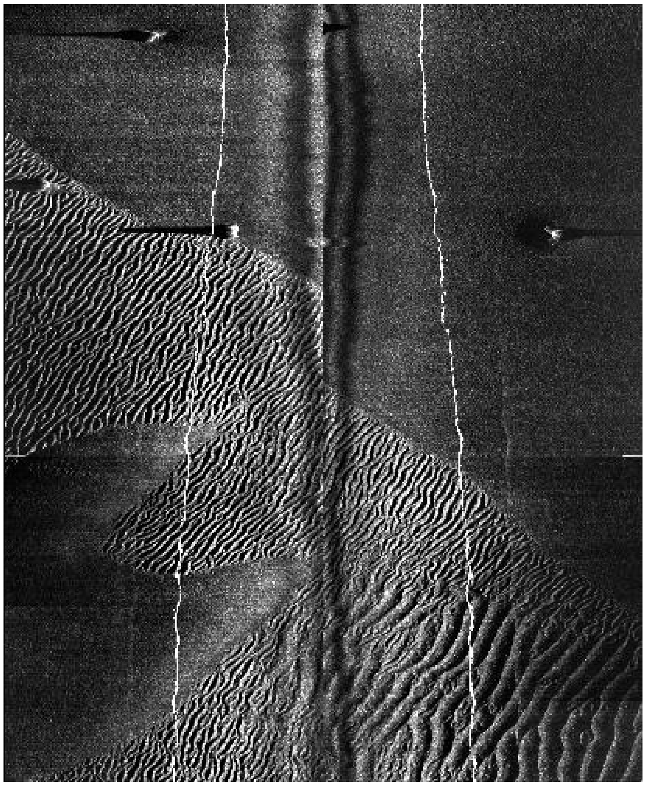

Fig 4. Raw Sidescan Image containing 4 objects. Some of the objects lie on a sand ripple seafloor making detection and feature extraction difficult.

As Fig 5 shows, all the objects have been detected and their features extracted well. These results demonstrate how the Detection and CSS models are able to operate well on complex sonar images. On the complete 200 image data set, 70 objects were identified as possible MLO's. The model was able to detect and extract the features from over 80% of these. Of the objects that were not detected, most were due to the presence of the surface return seen in Fig 2 and 4. Removal of this line would result in a result of around 91%. It should also be noted that many of the 70 MLO's are actually the same object seen under a different view since the area was surveyed in a lawnmower type pattern. An even higher detection result would be obtained if each object need be detected in only one of the images it appears in.

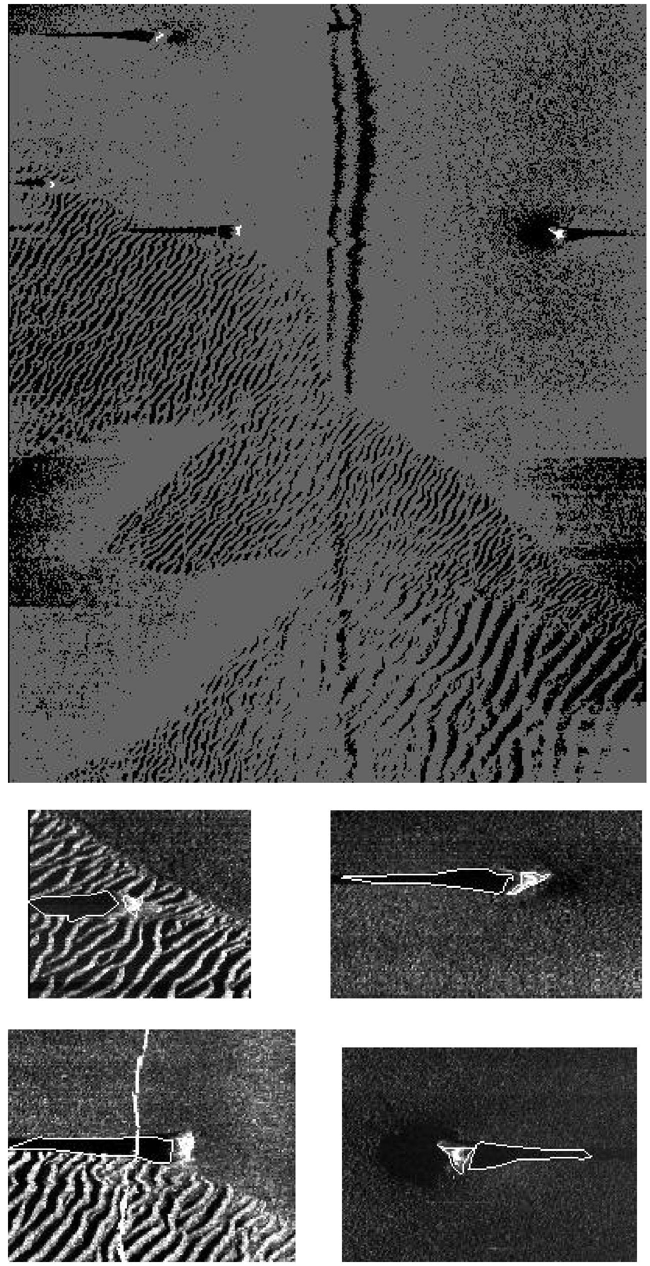

Fig 5. The detection and extraction results for Fig. 4.All the objects have been detected. The shadow regions have all been well extracted even when the object lies on a ripple seafloor.

## IV. THE CLASSIFICATION MODEL

### *A Introduction*

Many classification models extract a variety of features from the unknown object and classify using these. This is difficult when considering shadow regions in sonar imagery due to the non-linear nature of the shadow formation process. Using the available navigation information (sonar fish height, range etc), the model described here uses a sonar simulator model [9] to generate shadows from possible objects under the same conditions as the MLO was detected. The final classification decision is then carried out using Dempster-Shafer theory which allocates a *Belief* to each class. This is an attractive alternative to simply defining a 'classification threshold' which produces a hard, inflexible result. Dempster-Shafer is also useful in that it can fuse classification results from multiple images. This occurs a lot in MCM surveys where a lawnmower trajectory is generally used. In this paper, we consider that each object belongs either to the *cylinder*, *sphere*, *truncated-cone* or *clutter* class.

*B The Sonar Simulator*

Given the navigational information and a set of object parameters $\Phi$ (for example a sphere is completely described by its radius and depth into the seafloor), shadow regions from possible objects can be generated. Examples of synthetic shadows from the cylinder, sphere and truncated cone classes are shown in Fig 6.

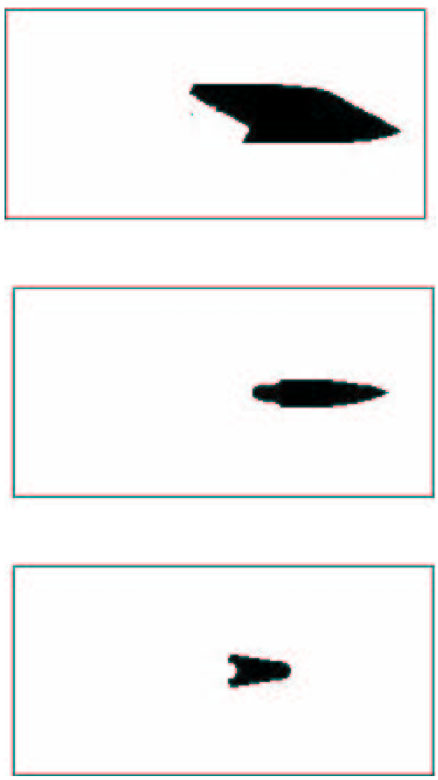

Fig 6 Examples of synthetic shadow regions from the cylinder, sphere and truncated cone classes using the line-of-sight sonar simulator.

The model parameters $\Phi$ were iteratively changed for each of the classes until the best match for each class was found. The parameter space searched through for each class was limited by using available information from the extracted highlight and shadow obtained using the CSS model [10]. The degree of similarity between the synthetic shadows and the real shadow was measured using the Hausdorff Distance [11]. Information such as the plausibility of the model features $\Phi$ used to generate each match was also considered (i.e was the synthetic object mine-like in dimension.) [10].

*B. The Classification Decision*

Dempster-Shafer theory is often used as an alternative to Bayesian and Fuzzy theory for fusion. It has several attractive properties such as its ability to consider union of classes and provides a well developed framework for fusing classification results from multiple images. The model was first tested on 66 mugshot images containing spherical, cylindrical and conical mine objects as well as clutter. Two of these objects are shown in Fig 7. The left image contains a cylinder while the right contains a truncated cone. The mono-image classification results can be seen in Table 1 and 2 respectively.

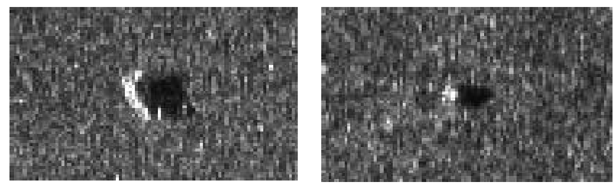

Fig 7. 2 images containing detected MLO's. The image on the left contains a cylindrical object while the object on the right contains a truncated cone object.

TABLE 1
DEMPSTER-SHAFER RESULT FOR CYLINDER (Fig 7a)

| Class | Belief |
|---|---|
| Cyl | 0.83 |
| Sph | 0.00 |
| Cone | 0.00 |
| Clutter | 0.08 |

TABLE 2
DEMPSTER-SHAFER RESULT FOR CONE (Fig 7b)

| Class | Belief |
|---|---|
| Cyl | 0.00 |
| Sph | 0.30 |
| Cone | 0.40 |
| Clutter | 0.05 |

As Table 1 and 2 show, both objects are classified correctly. The cylinder is classified correctly with a very high belief. The cone example shows that the model correctly classified the object as a cone but has also allocated the sphere class a high belief value. These 2 classes often produce similar shadow types under certain sonar conditions and it is therefore not unusual that they should often have similar results.

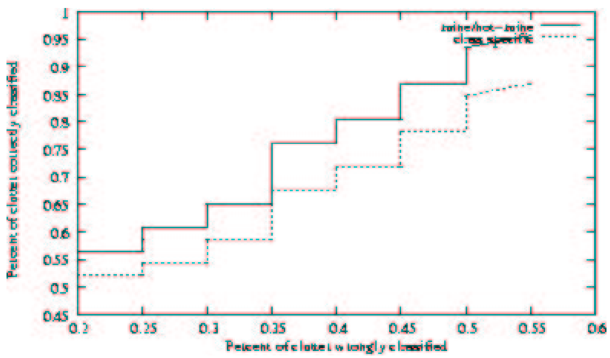


Fig 8. Classification Results of the model for mine-like objects against the Percent of clutter wrongly classified as an object.

Fig 8 shows how over 80% of the objects can be classified correctly by shape while identifying over 50% of the clutter as false alarms. This classification result provides shape and size information on the object and so could effect how a clearing mission is conducted. A classification rate of around 90% can be achieved if only a simple mine/not mine classification is required. The difference in these results occurs when the model cannot distinguish between the sphere and truncated-cone class under certain sonar conditions.

The same model can be applied for multi-image classification. Tables 3 and 4 show the classification results for a cylinder and truncated-cone object respectively that have been observed from 4 different views.

TABLE 3
FUSED CLASSIFICATION RESULT FOR A CYLINDERICAL OBJECT

| | Fused Belief Functions | | | |
|---|---|---|---|---|
| Views Fused | Cyl | Sph | Cone | Clutter |
| 1 | 0.70 | 0.00 | 0.00 | 0.21 |
| 1, 2 | 0.93 | 0.00 | 0.00 | 0.05 |
| 1, 2, 3 | 0.98 | 0.00 | 0.00 | 0.01 |
| 1, 2, 3, 4 | 0.96 | 0.00 | 0.00 | 0.03 |

TABLE 4
FUSED CLASSIFICATION RESULT FOR A TRUNCATED CONE OBJECT

| | Fused Belief Functions | | | |
|---|---|---|---|---|
| Views Fused | Cyl | Sph | Cone | Clutter |
| 1 | 0.00 | 0.17 | 0.23 | 0.45 |
| 1, 2 | 0.00 | 0.00 | 0.30 | 0.60 |
| 1, 2, 3, | 0.00 | 0.02 | 0.67 | 0.17 |
| 1, 2, 3, 4 | 0.00 | 0.01 | 0.62 | 0.20 |

Table 3 and 4 both show the correct multi-image classification result being obtained. The truncated cone example uses 3 mono-image classification results which wrongly classify the object as clutter. However, fusing the images together resulted in the correct classification result.

## V. CURRENT RESEARCH

The models detailed in sections II-IV detect and classify objects in Sidescan Sonar based on the knowledge that objects appear as a highlight/shadow pair. An object can also be described as a discrepancy in the surrounding texture field. Work has started which attempts to segment the seafloor into regions of flat, sand ripple and complex seafloors. Once the seabed regions has been segmented, it is possible to search for regions which do not match the surrounding texture field. The model being currently developed uses Dempster-Shafer theory and a MRF model to segment the image. Select features have been used which offer good separability between the different classes. An example of the segmentations achieved is shown in Fig 9 and 10. This work will allow the initialization process for the MRF detection model (see Fig 1) to be dependant on the type of seafloor the model is searching through.

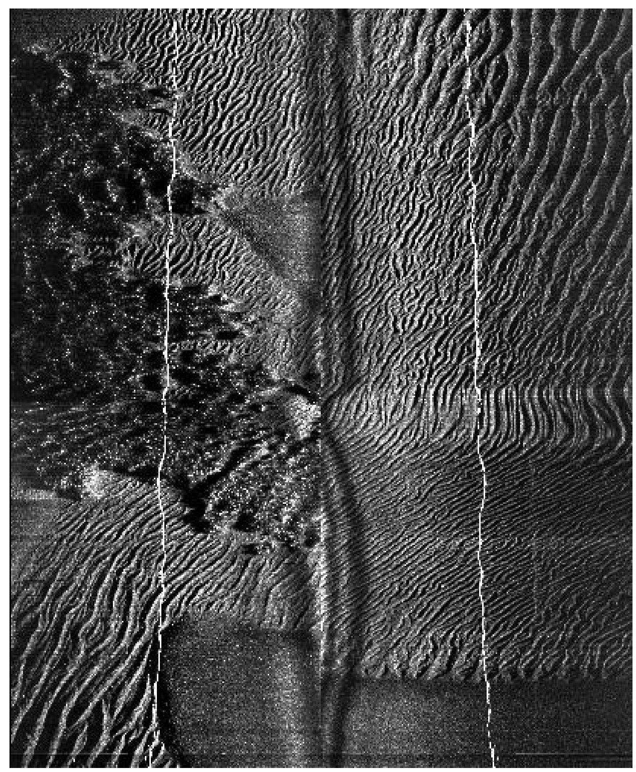

Fig 9 A raw Sidescan image containing regions of flat, rippled and complex seafloor.

Fig 10 Example of the texture segmentation model on an image shown in Fig 9.

VI. CONCLUSIONS

This paper has presented a model-based approach to the detection and classification of mines in Sidescan Sonar. A MRF/Co-operating Statistical Snake model was presented for detected and extracting the features of the MLO's within the image. A technique was also presented which classified the object offering shape and dimension information. This model iteratively compared the unknown MLO's shadow to those cast by objects imaged using a sonar simulator model. Current research into seafloor texture segmentation was also presented. This work will allow objects to be detected by searching for discrepancies in the local texture field.

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