University Defence Research Collaboration in Signal Processing

Edinburgh Consortium White Paper

Towards Accurate and Reliable Detection of Anomalous Objects in Synthetic Aperture Sonar (SAS) Imagery

Introduction

Autonomous detection and recognition of objects lying on the seabed is a task which has many applications, in both commercial and defence domains. A pressing challenge involves the ability to reliably identify known objects of interest, and also potentially anomalous or previously unseen objects. Here we describe the motivation and methodology for performing both tasks.

Detection is achieved via forming images from Synthetic Aperture Sonar (SAS) returns, and then using pattern recognition techniques to find objects in the resulting images. A problem of considerable interest is mine countermeasures (MCM), or finding mine-like objects in images; in Figure 1, a cone-shaped object is lying on the seabed near the top left corner of the image. Automated mine detection using one or more autonomous underwater vehicles (AUVs) is a long-term research goal.

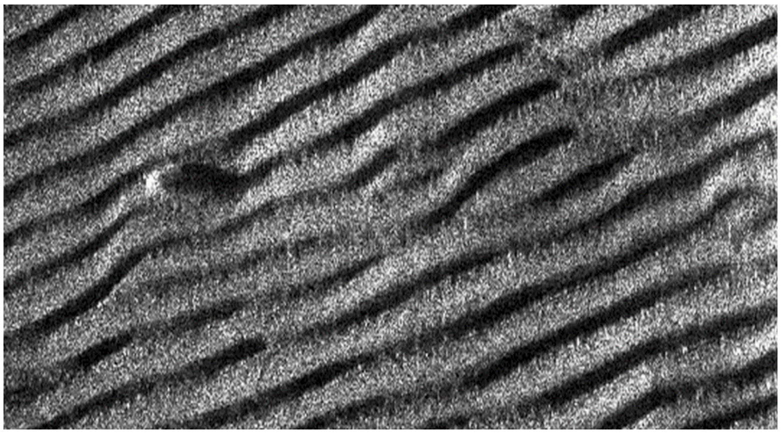

Figure 1: A cone-shaped object (top left of image) lying on a sandy seabed area.

Progress in this task is complicated by the difficulty of collecting data in underwater environments (as this is significantly more expensive than gathering video, audio, or radar data on land). This means that when trying to use machine learning techniques to learn a robust model of all objects of interest, not all algorithms are suitable due to the comparative lack of training data in this scenario.

Method

Our approach detects objects in two classes (cones and wedges) in the COLOSSUS2 and CATHARSIS datasets. These were supplied by NATO CMRE (Centre for Maritime Research and Experimentation) and DSTL (Defence Science and Technology Laboratory) [1]. By training on examples like this, cones and wedges can be detected in unfamiliar environments (such as situations where the characteristics of the background seabed of the testing data are different to those of the training data). We use support vector machines (SVMs) and Gaussian Process Classifiers (GPCs) as classification algorithms. In both cases a standard, sliding-window approach is used, with training images separated into ‘background’ and ‘object of interest’ classes. During testing, for all potential objects, we generate a confidence score and convert this to a probability score ranging from 0-100%.

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The detection of anomalous objects (those which may be of interest to human operators but which are different to the discrete classes which are already known) is also an important task which can ideally be automated. By using reliable classifiers which can indicate when they are uncertain about the classification they assign to an image region, regions of extremely high uncertainty are identified. This is highest when both classifiers are around 50% confident (i.e. extremely uncertain) about the sample they classify. By considering only regions of high uncertainty, a limited number of regions can be marked as uncertain or anomalous. To demonstrate this, the COLOSSUS dataset contains several cylinder objects which are different from the cones and wedges. By only attempting to classify these objects at test time, we are able to use them as proxies for anomalous objects which may require further inspection, either by a human operator or by processing more complex algorithms which would be too expensive to evaluate on the entire seabed region.

Results

The image on the right shows an "anomalous" cylinder object (unseen before testing) detected by an uncertainty detector (dark blue box); in our experiments we were able to detect 44% of cylinders using an RBF-SVM classifier [2]. However, the techniques described here are not limited to SAS imagery and can also be applied to other multi-class classification problems.

In conclusion, detection of unseen and potentially anomalous objects using conventional detectors is a challenging task, as they bear little similarity to any of the classes seen at training time. By using detectors which generate reliable detection scores and are thus able to indicate when they are unsure about object presence in a region, regions of extreme uncertainty can be flagged as anomalous.

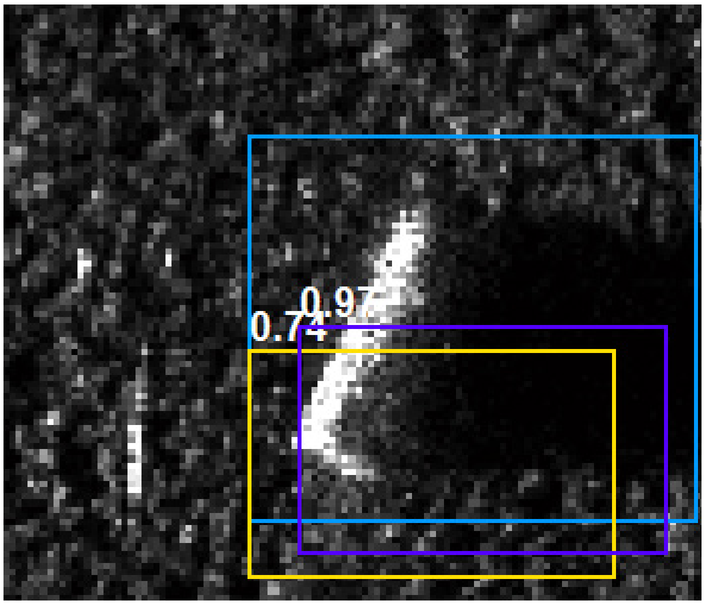

Figure 2: Figure 2 "Anomalous" cylinder object detected by uncertainty detector (dark blue box).

References:

[1] J. Groen, E. Coiras, and D. Williams, "Detection rate statistics in synthetic aperture sonar images," in Proceedings of the 3rd International Conference and Exhibition on Underwater Acoustic Measurements, 2009, no. June, pp. 21–26.

[2] C. G. Blair, J. Thompson, and N. M. Robertson, "Identifying Anomalous Objects in SAS Imagery Using Uncertainty," in Information Fusion, Proceedings of the International Conference on, 2015, p. 7.