Real-time Classification of Buried Targets with Teams of Unmanned Vehicles

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Abstract— **Recent rapid developments in autonomous underwater vehicle (AUV) technology have provided the opportunity to explore new approaches for detecting and classifying mine-like objects. In particular, the mobility of the vehicles allows the implementation of deformable sonar geometries that can be adaptively controlled based on the local acoustic scattering statistics. In addition, distributing teams of receiver vehicles provides the potential to exploit the spatial diversity of the target scattering, which may contain important classification clues that are not apparent with monostatic or towed array sonar geometries. Preferred target scattering directions for both specular and, more importantly, elastic scattering returns can be interrogated by the adaptively controlled receiver platforms. The multi-platform approach can also lead to detection and classification algorithms that require significantly less computation than these traditional sonar techniques, and as such these algorithms are more readily implementable in real-time onboard the vehicles. In this work, a method of target classification is shown in which the 3-D scattered field is sampled by several receiver vehicles and information is extracted about the targets that clearly distinguish mines from rocks and rounded objects from oblong objects. The method is applicable to both buried and proud targets, and does not require the sub-wavelength accuracy navigation that is necessary for synthetic aperture sonar (SAS) imaging. The relaxation of the navigation accuracy requirement is critically important for two reasons. Firstly, the SAS micronavigation methods, while very effective in benign environments, are subject to catastrophic failure in strong currents or complex topological environments. Secondly, the micronavigation methods restrict the area search rate due to the need for significant aperture overlap between consecutive receptions. The proposed classification method is shown to be easily implementable in real-time, as is demonstrated both in simulations and in post-processing experimental data from the GOATS'98 experiment. The AUV onboard implementation is planned to be demonstrated in the GOATS 2002 experiment off the coast of Italy in June 2002. [Work supported by ONR and SACLANTCEN]**

I. Introduction

The autonomous underwater vehicle (AUV) has become a useful tool in many fields of undersea research, including environmental observation [1], archaeology [2], ocean exploration [3] and littoral minehunting [4], [5]. While all of these fields are already benefitting from, and in turn driving, the rapid development of AUV technology, the full potential of these vehicles is far from being achieved. In particular, the capability of the vehicles to behave autonomously to achieve a mission goal has yet to be demonstrated in nontrivial circumstances. Further in the future is multi-vehicle cooperative behavior, which also remains a difficult challenge for land robots [6]. Undersea vehicles face the added challenge of a limited navigational capability, which includes both positional uncertainty [7] and motion control [8] challenges. For this reason, signal processing algorithms that are designed to exploit AUV maneuverability and adaptivity are required to be extremely robust to positional uncertainty and navigation errors.

One research project that has as a primary goal utilizing both vehicle autonomy and cooperative behavior is the ONR/SACLANTCEN/MIT Generic Oceanographic Array Technology Sonar (GOATS) project. This project is generally focused on littoral minehunting using one or several AUVs. Data analysis from the GOATS'98 and 2000 experiments have proven that the AUV is a viable platform for multi-static detection of both buried and proud targets, and that some interesting target features are detectable with favorable source/receiver geometries [9]. In this previous work, however, the vehicle was used in essentially the same manner as a towed array, and so the only AUV advantage that was exploited was the size, i.e., that it requires a very small vessel to maneuver in very shallow water. The reason for utilizing the AUV as an untethered array was simply to use known signal processing tools for feasibility testing of the AUV sonar platform. The signal processing work leading up to the 2002 experiment, on the other hand, primarily sought to provide a means to exploit some of the more powerful features of AUVs. One challenge to exploiting AUV maneuverability and adapability lies in the fact that the sonar receptions and resulting adaptive behavior are functions of the unknown environment, so it is nearly impossible to forecast the mission prior to launch in a realistic situation. For this reason, a highly realistic simulation suite was developed to aid in the evaluation of on-line sonar processing algorithms prior to sending an expensive robot or fleet of robots on a mission with unpredictable results.

II. Simulation Tools

The simulation suite was developed by combining high fidelity acoustic models with real-time AUV operating system software in a two-step process. The reason for making a two-step process is because the acoustic simulation of a complex reverberant field cannot be implemented in real-time, whereas the adaptive signal processing algorithms must be tested in real-time prior to implementation. In the acoustic simulation phase, the target field is created with buried or proud cylinders and spheres, along with a rough seabed, prior to execution. The simulation is performed using the full wavenumber integration code OASES, which includes complex acoustical processes such as evanescent waves, rough surface scattering, volume inhomogeneities, elastic seabeds and resonant targets. The source and receiver vehicle initial positions and velocities are given, and the field is simulated at the receiver. The system waits for the acoustic simulation, and then the adaptive signal processing algorithm is executed and the source and receiver are moved according to the recommendation of the particular algorithm. The whole process is repeated for a complete mission. Given a successful algorithm the vehicle will travel along its pre-programmed path until detecting the target, and then deviate from that path in order to optimize the detection or classification statistic as appropriate.

The second stage of the simulation suite is to test the algorithm inside a real-time system. In this stage, the approximate source and receiver paths are known from the first stage, and so the data files generated in the first stage can be streamed into the system as received data. The algorithms are then tested in real-time inside the actual vehicle mission oriented operating system (MOOS) [10] , in which all of the other vehicle processes are running, including navigation and dynamic control systems. This stage of simulation can also be used with experimental data, although such a procedure is limited to real-time detection, since the AUV trajectory obviously cannot be altered after the fact. For example, the AUV trajectory shown in 1 (b) is from the GOATS 2002 experiment.

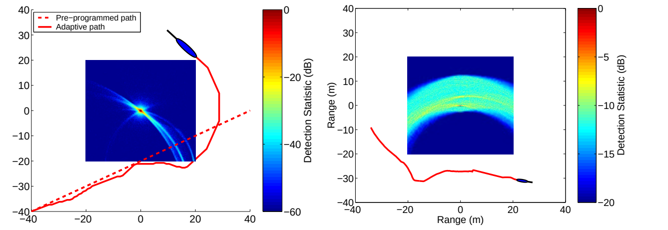

Fig. 1. (a) Simulated adaptive AUV missions. The planned path is shown by the dotted line, and a buried sphere lies at the origin. The vehicle follows the planned mission closely until it detects a target with high probability, then deviates from the path to investigate further. The color plot shows the detection statistic developed over the full path. (b) On-line algorithm applied to experimental data from the GOATS 2002 experiment. The vehicle trajectory is shown as it flies near the target field, and the detection statistic is shown by the color image.

III. Vehicle Adaptation

There are two fundamental approaches to mine hunting with AUVs. The first is the current state of the art, which consists of systematic sweeping in a lawnmower fashion while performing a standard imaging algorithm (generally post-processing). This type of approach requires a high level of precision, as the vehicle needs to maintain is preprogrammed path over a long period of time. It also requires either *a priori* knowledge of the target field or good luck to avoid sweeping the field multiple times to acquire necessary information about targets that may be found. The second approach, which is rapidly becoming feasible, is to adapt the vehicle behavior based on on-line processing of the sonar receptions. Figure **??** shows the realization of an on-line processing algorithm (a) in simulation and (b) in at-sea experiment for a monostatically operating AUV. The simulation result illustrates the envisioned full adaptive capability of the vehicle, as the vehicle begins following a prescribed path, and then deviates from the prescribed path once it detects a target. In this case, the vehicle executes a path to maximize detection and localization results. In (b), there are the results of the same on-line detection and localization algorithm as it was executed onboard the vehicle in the GOATS 2002 experiment. In the experiment, however, the detection algorithm ran on the host machine of the AUV and was not given control of the vehicle and thus could not adapt its behavior. The at-sea realization of adaptation based on the detection algorithm will be the subject of a future experiment. A variety of advanced online detection algorithms have also been tested with the simulation system as well as with experimental data from GOATS 2000 and 2002 [11], [12].

IV. Multi-Vehicle Classification

The definitions of the terms *detection* and *classification* generally vary depending on the application. In this paper, detection means to establish the existence of a compact object on or below the seabed, while classification means to distinguish some feature of the detected target. Algorithms are presented to use multiple vehicles for classifying the shape and the composition of the target.

A. Shape Classification

Shape classification is the primary goal of high-resolution sonar imaging, whether using side scan or synthetic aperture techniques. In buried target imaging, the AUV is is required to perform synthetic aperture imaging to achieve sufficient resolution due to the relative length scales of the AUV and the acoustic wavelength required for subbottom penetration. A great deal of progress has been made in overcoming the sub-wavelength navigation accuracy requirements imposed by synthetic aperture imaging, but it remains a difficult challenge, particularly to run on-line. A rough idea of the shape can be determined from its radiation beampattern, which gives an indication of the aspect ratio of the target as well as its overall size. For example, a sphere has a fairly omnidirectional scattered field at low frequency, while a high aspect ratio target such as a cylinder exhibits several lobes in its scattered field. Figure 2 illustrates the radiated field from a 2 m long, 0.5 m diameter cylinder both in simulation and in at-sea experiment. In both plots, the source comes from the bottom of the paper. Two AUVs fly by the target and simply map the amplitude of the scattered field to the angle of scattering. A strong lobe is clearly shown in both figures, which is consistent with the specular reflection from a cylinder of this size and shape. The slight alteration in direction is due to misalignment of the source and target during the at-sea experiment. Because the vehicles are approximately 50 m away from the target, this method is robust to navigation error, as an error of several meters (or wavelengths) will result in a very small angular error. In addition, the linear paths of the AUV minimize the navigation error and maximize the area search rate.

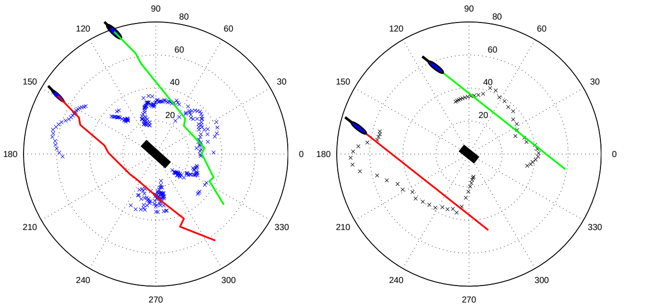

Fig. 2. (a) At-sea GOATS'98 experimental result. The AUVs move past the target along a line, mapping the target scattered amplitude on the angular map. The approximately 45° aspect angle of the cylinder is consistent with a strong specular return directly to the left. (b) Simulation of a similar experiment. The results closely match the experimental result, demonstrating the highly accurate modeling capability.

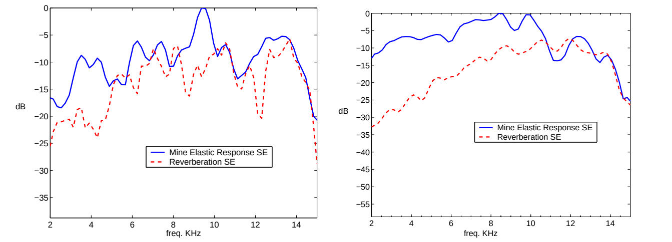

Fig. 3. (a) Simulated adaptive AUV missions. The planned path is shown by the dotted line, and a buried sphere lies at the origin. The vehicle follows the planned mission closely until it detects a target with high probability, then deviates from the path to investigate further. The color plot shows the detection statistic developed over the full path. (b) On-line algorithm applied to experimental data from the GOATS 2002 experiment. The vehicle trajectory is shown as it flies near the target field, and the detection statistic is shown by the color image.

B. Composition Classification

Classifying the composition of the target in littoral minehunting essentially consists of discriminating between man-made objects (possibly mines) and natural objects (probably rocks). Man-made objects are likely to contain characteristic dimensions and nonhomogeneous composition, while rocks are typically homogeneous in nature. The characteristics of man-made objects give rise to resonant responses from the targets, which are typically of low amplitude and do not constructively sum over a spatial aperture. In addition, the resonant behavior of the target is not in general directed back at the source, but rather in a direction that is characteristic of the target. The adaptability of the AUV sonar platform allows the vehicles to search for advantageous sonar geometries to detect these elastic target responses. Figure 3 shows a simple comparison of the received field from (a) experimental and (b) simulated resonant targets to the pure reverberation field in terms of power spectral density. In both results, the source insonifies a buried 1 m diameter sphere at subcritical grazing while the receiver remains within the supercritical cone in which the target reradiation is strongest and teh reverberation is relatively low. Although the overall signal power is low, the low frequency resonances are easily detectable over the reverberation. In fact, the reverberation tends to decrease with decreasing frequency, while target resonances tend to be stronger at lower frequency. This simple spectral analysis illustrates the possibility of detecting elastic returns from advantageous source/receiver geometries.

V. Conclusions

It has been shown that adaptive and cooperative AUV behaviors can be used to reduce the need for precise navigation and computationally intensive signal processing algorithms, while at the same time providing higher area search rates and effective detection and classification capabilities. A highly realistic acoustic simulation tool has been developed to provide adaptive path planning and multi-vehicle operation planning, as well as on-line algorithm testing. Results from past experiments demonstrated that the simulation tool is truly realistic. Robust and computationally simple shape classification and composition classification methods that utilize multi-vehicle and adaptive behavior were illustrated with at-sea experiments and simulations.

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