Harbor Threat Detection, Classification, and Identification

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LONG-TERM GOALS

There is a critical need for reliably and rapidly detecting, identifying, and tracking submerged low observable targets in port environments, which would allow for rapid and effective neutralization of such threats. Without this capability, personnel, naval platforms and targets of opportunity are exposed to a cheap kill by an opportunistic threat. The goal of this effort is to exploit for the first time detailed active and passive acoustic signature information associated with harbor threats together with advanced Bayesian classifier techniques. In this effort the intent is to leverage the highly successful science and technology carried out in the broadband mine identification program [Ref. 1 and EOY reports for Award Numbers: N0001406WX20052 and N0001406WX20679].

OBJECTIVES

The objective of the Harbor Threat Detection, Classification, and Identification Program is to exploit passive and active acoustic signal information associated with submerged threats in harbors and ports in order to monitor their presence in real time. There is no known capability for reliably detecting, identifying, and tracking low observable targets in such environments, particularly at ranges ~ 1km. Submerged threats include a variety of both man-made and human targets, and this project emphasizes both swimmer and non-swimmer threats. The effort will lead to a significantly improved detection and identification capability and to demonstration through experimentation and simulation.

APPROACH

The acoustic work is broken into the following two components. The first involves comprehensive, highly controlled broadband, multi-aspect measurements of swimmer- related acoustic signals (both passively generated and in response to active acoustic insonification). The second area involves the development of suitable signal processing techniques including both tracking and identification algorithms that can operate effectively on the environmentally corrupted threat target signals. These include, among others, those based on kernel matching pursuits [1], relevance vector machines [2-5], and time reversal mirrors recently developed at NRL [6,7]. The studies include the full range of broadband frequencies. The spectrum is limited at the extremes due to practical deployment issues, but

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14. ABSTRACT

There is a critical need for reliably and rapidly detecting, identifying, and tracking submerged low observable targets in port environments, which would allow for rapid and effective neutralization of such threats. Without this capability, personnel, naval platforms and targets of opportunity are exposed to a cheap kill by an opportunistic threat. The goal of this effort is to exploit for the first time detailed active and passive acoustic signature information associated with harbor threats together with advanced Bayesian classifier techniques. In this effort the intent is to leverage the highly successful science and technology carried out in the broadband mine identification program [Ref. 1 and EOY reports for Award Numbers: N0001406WX20052 and N0001406WX20679].

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the frequency range is sufficiently broad to capitalize on potential discoveries of target/false target signal features useful for identification.

The two task areas are detailed as follows:

Task 1: Database Generation: NRL will provide measurements and analysis of the broadband, multi-aspect signatures from a number of additional threats using its Laboratory for Structural Acoustics (Fig. 1). The priority ranking of threats to be studied is (1) diver with commercial rebreathers, (2) diver with diver assisted propulsors, and (3) small UUVs. The measurement band is (1 – 200 kHz), and the angular resolution of the diver rotation is 5 degrees (Fig. 2). Note that the system resolution is much higher (i.e. 1/10,000 of a degree), and the larger 5 degree resolution associated with diver measurements is due to the practical issue of dealing with a human target. The data bases will be examined with a view toward exploiting the structural acoustic features associated with the broadband diver and other threat target returns for potential classification.

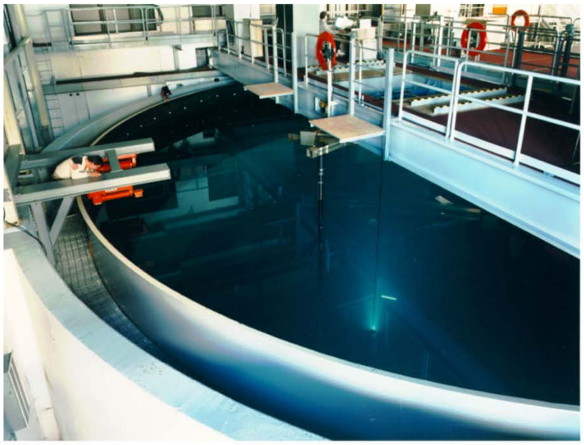

Fig. 1 The Large Acoustic Tank at NRL used to acquire the broadband active and passive signature data.

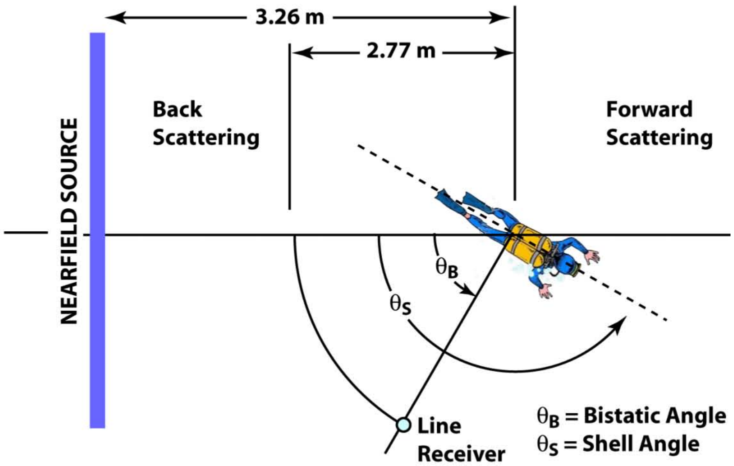

Fig. 2 The acoustic range used in the NRL laboratory measurements wherein both radiated noise and broadband active measurements are taken. For the active measurements, a horizontally oriented line array is used as a source.

Task 2: Detection, Tracking and Identification: NRL and SIG will evaluate the application to the diver detection problem of advanced techniques developed for the underwater mine problem. This task will focus on both existing threat databases generated with conventional harbor protection sonars as well as the new data acquired in Task 1. The intent is to apply highly successful techniques developed for the ONR (Robert Manning) Low Frequency Broadband Mine Program (LFBB) to the detection, tracking, and identification phases of the diver related problem.

WORK COMPLETED

In Task 1 for FY07, NRL successfully extended the laboratory database to include additional rebreather types and conditions, adding to the database originating in FY06. The FY06/07 active acoustic activities focused on the lower end of the band (0.7 – 35 kHz), and the FY08 laboratory active activities will now include the higher end (20 – 150 kHz). NRL's overall database is now substantial including broadband data on conventional scuba systems, the MK16, the Optima, and the Inspiration rebreathers. NRL has also collected significant data on passive signatures. Below is a summary:

<u>Passive Signature Data (300 Hz – 200 kHz):</u>
1) M-16 Rebreather
2) Optima Rebreather
3) Inspiration Rebreather
4) Conventional Scuba
5) Diver Assisited Propulsor

<u>Active signature Data (0.7 – 35 kHz):</u>
1) M-16 Rebreather
2) Optima Rebreather
3) Inspiration Rebreather
4) Conventional Scuba
5) Diver Assisited Propulsor
6) 21 inch BPAUV Class Autonomous Underwater Vehicle (AUV)

<u>Active Signature Data (20 kHz – 150 kHz):</u>
1) M-16 Rebreather
2) Optima Rebreather
3) Inspiration Rebreather

In Task 2, two areas have been addressed for processing the acoustic-scattering data from the diver and surrounding clutter. First, state-of-the-art tracking algorithms have been developed based on the particle filter. Unlike the Kalman filter which assumes a Gaussian distribution and linear tracks, the particle filter is applicable to general motion models (*e.g.*, for the diver) and for a non-Gaussian posterior density function on the target position. Moreover, the particle filter is applicable to arbitrary feature vectors, where here we are employing the features extracted by ARL-UT. Note that as a consequence, the particle-filter tracking software is now directly transferable to ARL-UT upon request. The algorithm has been tested on the measured data from ARL-UT, and we have demonstrated that the particle filter accurately sustains the actual diver track, while for false targets (clutter) tracks are started but not sustained. Second, we have begun investigating the hidden Markov model (HMM), a natural statistical algorithm for modeling and classifying time-evolving data.

RESULTS

The target scattering data has been analyzed from the perspective of potential exploitation of the target signature response to improve detection and classification at long range (700m to 1 km). The scattering data collected thus far generally show that the structural acoustic features associated with diver scattering cross-sections can be used to help distinguish the individual systems (divers with scuba, MK-16, Optima, Inspiration, etc.) from one another. This is an important result in that we believe this to be more difficult than the ultimate requirement of separating the threat signals from the clutter background existing in the various harbors. What is very promising thus far is not only that the laboratory data show robust structural acoustic features, but also that these features should be exploitable by either current operational systems or by future systems designed to exploit them.

An example of the rich structural acoustic features associated broadband low frequency acoustic scattering from diver equipment is shown in Fig. 3. The axes of the mosaic are frequency (ordinate) and target aspect (abscissa). Target Strength levels are displayed with the indicated color scale. Because this particular piece of diver equipment (scuba air bottle) is a relatively simple cylindrical shell, this target produces a broad angular elastic TS response below ~ 7 kHz that is directly related to the vibrational modes known to exist for a simple, fluid-loaded shell. Above approximately 10 kHz, the re-radiation from membrane waves excited in the tank shell is observed over an angular sector of approximately ± 30° about beam (90°) aspect. Similarly, re-radiation from supersonic flexural waves also excited in the shell is observed near bow (0°) incidence (the valve end of the bottle) above approximately 15 kHz. Above 10 kHz, the geometric, specular responses from the beam (90°) and flat-end stern (180°) aspects produce the very large, persistent, standout features clearly evident in the figure. Further understanding of the detail in the response at beam and end-on incidence can be obtained from the more detailed analysis in ref. [8].

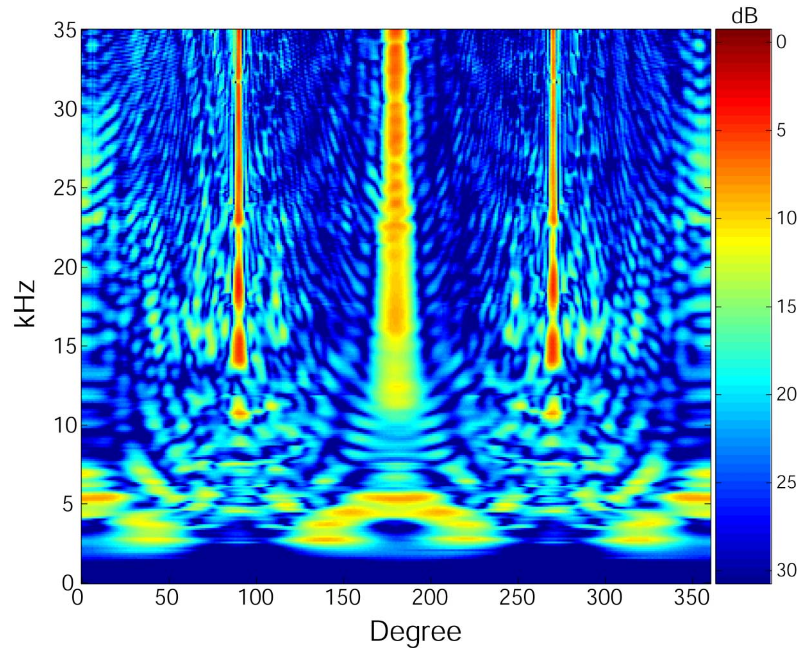

Fig. 3 A mosaic plot of the measured monostatic TS vs frequency and angle for the scuba bottle alone over a full 360° in 1° increments.

We have successfully applied the tracking algorithm based on the particle filter to the ARL-UT data. The measurement configuration is shown in Fig. 4 and the results for the diver path depicted in the figure are shown in Fig. 5. The software used in this demonstration is available for transition upon request (it directly takes as input ARL-UT generated features, and therefore is applicable to that system).

The mechanics of the particle filter may be summarized as follows. A “starter” distribution is assumed for the location of the target; this distribution need not be Gaussian, and it has only the requirement that sampling from it be simple. Using the (general) motion model for the target of interest together with the observed data, the points sampled from the distribution are weighted to reflect how well they match the data and model, with the distribution of weighted particles (distributed spatially) defining an approximate distribution for the target position. As new data come in, some particles are pruned, as they no longer match the data and target model, and new particles are spawned. As the data evolves, the particle filter yields a time evolving distribution of weighted points quantifying the statistical representation for the target location. The "filtering" process occurs over time, with evolving data, as samples (particles) are added and subtracted with new observations. Since in practice we need to compute only a relatively small number of weighted particles and particles are added and pruned over time, the technique is computationally tractable.

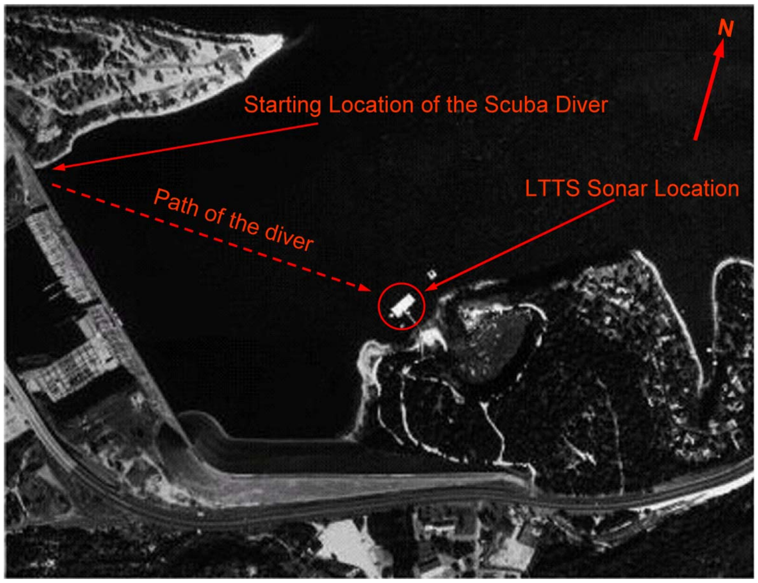

Fig. 4 View of the measurement configuration, with tracking results shown in Fig. 5 for the particular diver path depicted here.

As the second component of the work, SIG is currently moving beyond the idea of simply performing detection and tracking, and now investigating classification techniques. We are interested in developing statistical techniques appropriate for classifying time-evolving data. Toward this end we have begun investigating the hidden Markov model (HMM) for modeling and classifying time-evolving data. A key issue in developing HMM's concerns selection of an appropriate number of states for the underlying Markov process. To address this problem in a statistically principled manner, we have employed a Dirichlet process (DP) framework [9]. The DP represents a setting whereby one need not set *a priori* the number of states characteristic of the data; rather, the inference framework provides a posterior distribution on the number of states. (Therefore, in this sense, there is not a single HMM learned, but rather an ensemble of HMMs.) We have demonstrated that this framework typically yields a far better fit to general acoustic scattering data [9] compared to conventional maximum-likelihood-based HMMs with a fixed number of states. Two inference techniques have been considered: (i) Markov chain Monte Carlo (MCMC) sampling, which is a more-general form of the aforementioned particle filter; and (ii) variational Bayesian inference which is approximate but computational quite fast.

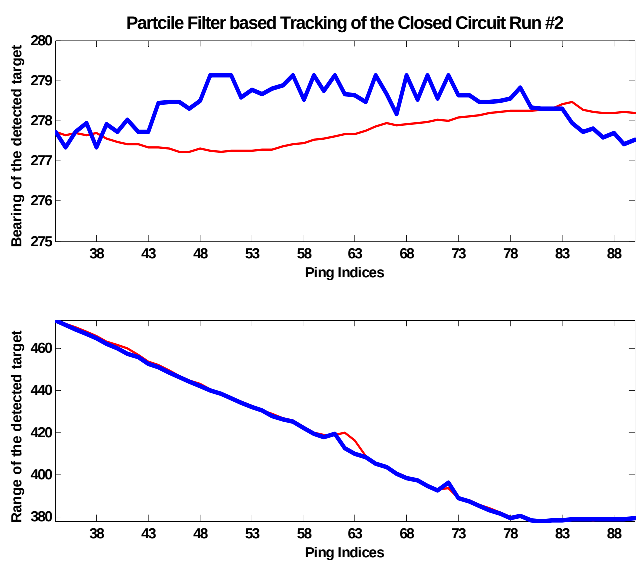

Fig. 5 Particle-filter estimated tracks (blue) and the estimated "truth" (red) based on characteristics of the test. Note that the particle filter estimates a full (time-evolving) distribution on the diver location, where here we plot the associated time-evolving maximum likelihood.

We are now examining design of this class of HMMs for modeling divers and (separately) for modeling clutter. The idea is that the available set of data for divers is limited, and it is unclear as to how representative these data are of the actual threat. However, there is a large quantity of variable, time-evolving clutter data, from which the HMM may be trained and time-evolved (as new data are observed). We are considering design of HMMs for clutter, and the goal is to demonstrate that the diver data yields signatures that have a low likelihood of being generated by such (clutter) HMM models. In this context the detection of a diver will be performed by sensing something that is anomalous with respect to typical observed data. The HMM may be learned and refined continuously, as the "typical" data changes with time, for example with changing weather and sea state. In this sense the algorithm is also less dependent on requiring a large set of training data for divers covering the full range of possible threats.

IMPACT/APPLICATIONS

Success will enable advanced detection and identification technology against covert terrorist swimmers and other asymmetric threats that constitute a serious problem and challenge to harbor/port security.

RELATED PROJECTS

This program is leveraging the following efforts: (1) Harbor Protection (NRL Base Effort) and (2) ONR funded efforts in Low Frequency Broadband Mine Identification (LFBB), Award Numbers: Award Numbers: N0001407WX20246, N0001407WX20058, N0001407WX20664, N0001407WX20953.

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