Concurrent Navigation and Sea-bottom Targets Detection Using Acoustic Sensors on AUV

Te-Chih Liu and Henrik Schmidt

Massachusetts Institute of Technology
77 Mass. Ave.
Cambridge, MA 02139 , USA
tcliu@mit.edu,henrik@keel.mit.edu

***Abstract*-The detection of sea-bottom targets has encountered the problems using acoustic arrays with lower resolution on board. Moreover, The uncertainty of moving receivers and sources, the extremely low signal-to-noise ratio due to the weak signals from the buried targets, and the computational efficiency requirement of real-time processing present challenges to detection of the targets. For low signal-to-noise-ratio, the traditional scenario, detection then tracking, is not suitable for this kind of problem. The detection can't be declared unless the signal-to-noise ratio is greater than a reasonable threshold while more information is gathered. Enormous array signal processing methods could enhanced the signal-to-noise ratio while the information is gather spatially. However, the positions of the sensors are not known precisely due to the limitation of underwater navigation technique. Without knowing the spatial distribution of receivers, the results of detection results by means of array signal processing cannot be accurate. In contrast, the solution to this problem becomes reverse to traditional detection procedure. A Track-Before-Detection (TBD) algorithm is introduced. Unlike the traditional approaches, the TBD detections are not declared at each ping. Instead, a number of pings of data are processed. This technique integrates the measurements along the possible AUV trajectories. Using the slowly changing environment information or the fixed but unknown target fields, the states of AUV are tracked first. Then, the weak signal detection is declared after confidence of the trajectories estimation is established. However, enormous possible trajectories of AUV needed to be searched while the TBD algorithm is applied, which makes direct online implementation of this technique impossible. A dynamic programming (DP) algorithm is introduced to solve the highly interconnected stochastic network which TBD creates in a much more efficient way. Therefore, together with the DP algorithm, the TBD algorithm is feasible to implement online. This algorithm has been applied in GOATS (Generic Oceanographic Array Technology Sonar) project. Both mono-static and bi-static detection results will be demonstrated.**

I. INTRODUCTION

Recent progress in underwater robotics and acoustic communication has led to the development of a new paradigm in ocean science and technology, the Autonomous Ocean Sampling Network (AOSN)[1]. AOSN consists of a network of fixed moorings and/or autonomous underwater vehicles (AUV) tied together by state-of-the-art acoustic communication technology. This new technology is being rapidly transitioned into the operational Navy as platforms for small mine countermeasures sensors, e.g. side-scan sonars. Eliminating the need for divers and being independent on vulnerable surface platforms the AOSN has the potential for revolutionizing mine countermeasures in

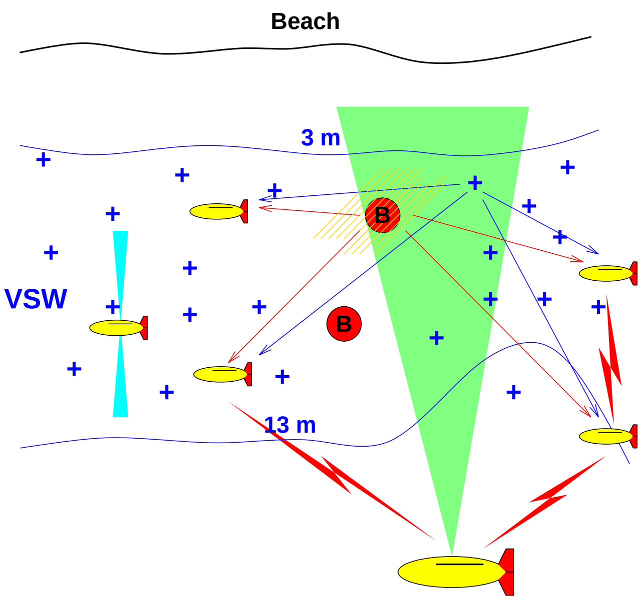

Fig. 1 GOATS: Generic Ocean Array Technology Sonar concept for coastal MCM. A fleet of AUV's connected by an underwater communication network, and equipped with acoustic receiver arrays is used to measure the 3-D scattering from proud and buried targets insonified by a dedicated master AUV.

very shallow water (VSW) and even the surf zone. However, the full potential of this new technology goes far beyond serving as improved and safer platforms for existing sonar technology. Thus, the unmatched platform stability may rapidly advance the use of Synthetic Aperture Sonars (SAS), and the potential of deploying a network of AUVs, accurately navigated and linked by an acoustic communication network provides the basis for the development of entirely new multi-platform sonar concepts and operational paradigms. Thus, for example, the flexibility, mobility and the adaptive, coordinated behavior capability of such networks can be explored for new bi- and multi-static sonar concepts for littoral MCM. GOATS is a multi-disciplinary international research program, initiated and lead by MIT and SACLANTCEN, exploring the potential of such new technology for dramatically increasing the coverage rate of shallow water mine countermeasures. The MIT component specifically explores the feasibility of a low-frequency, bi-static sonar concept for concurrent detection and classification of buried targets in VSW.

The GOATS'2000 experiments provided extraordinarily rich bi-static acoustic data sets using a parametric source for insonification, and a suite of fixed arrays and an AUV as a mobile bi-static receiving platform. The successive GOATS'2002 experiment provided another excellent data set for mono-static acoustic analysis, by setting both source and receivers on the same AUV. This work includes a unique demonstration of sub-critical detection of buried targets by bi-static configuration of acoustic reception using an AUV. The autonomous detection and concurrent tracking of aspect-dependent targets are also investigated by means of TBD together with DP algorithm in this work.

II. PROBLEM DESCRIPTION

The motion of the AUV is modeled to be linear across the *x-y* plane as shown in Fig. 2. The state update equation is defined as

$$\mathbf{x}_{k+1} = \mathbf{F}\mathbf{x}_k \tag{1}$$

where

$$\mathbf{x}_k = \begin{bmatrix} x(k) \\ \dot{x}(k) \\ y(k) \\ \dot{y}(k) \\ \theta(k) \\ \dot{\theta}(k) \end{bmatrix}, \quad \mathbf{F} = \begin{bmatrix} 1 & T & 0 & 0 & 0 & 0 \\ 0 & 1 & 0 & 0 & 0 & 0 \\ 0 & 0 & 1 & T & 0 & 0 \\ 0 & 0 & 0 & 1 & 0 & 0 \\ 0 & 0 & 0 & 0 & 1 & T \\ 0 & 0 & 0 & 0 & 0 & 1 \end{bmatrix} \tag{2}$$

θ is the heading angle and T is the sampling interval between successive pings.

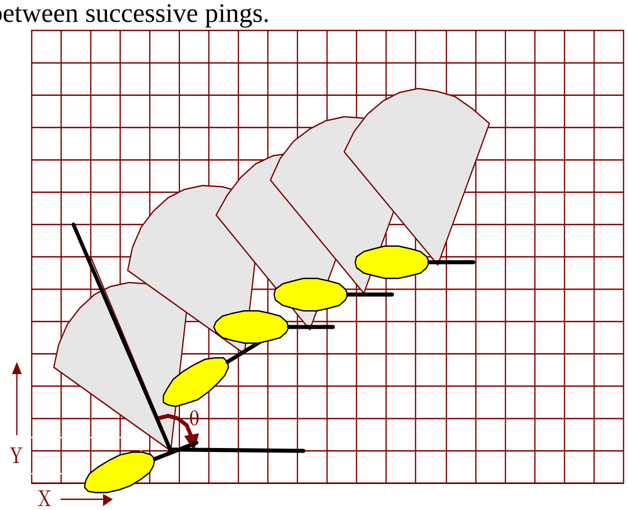

Fig. 2 Illustration of state space of AUV trajectory.

The signals received from the insonified area can be divided into two parts. The first part is from the targets which we are interested in, and the second part is from the seabed roughness. These two parts owns major differences in scattering physics, i.e. the scattering signals from targets and roughness have different characteristics in both time and frequency content. We model the total area as virtual sources placed on a discrete grid as shown in Fig 3.These virtual sources are treated as stationary points in space.The data recorded by the linear array is transferred to beam space by a real-time beamformer [2]. At each time k a measurement is recorded in each cell. The measurement matrix is given by

$$\mathbf{z}_k = \{\tilde{z}_{R,\beta}(k)\} \quad \text{for } k = 1,2,\ldots K \tag{3}$$

where R is the range from possible virtual sources to AUV, and ,β is the bearing angle. The resolution of (ΔR, $\Delta\beta$) depends on sampling frequency and the length of linear array respectively, and where $\tilde{z}_{R,\beta}(k)$ is beamformed results from a virtual source of possibly time-varying amplitude with additive noise recorded in beam space image cell (R,β). At the time K, given the measurement sequence $\mathbf{Z}_K$, where

$$\mathbf{Z}_K = \{\mathbf{z}_1, \ldots\ldots, \mathbf{z}_K\} \tag{4}$$

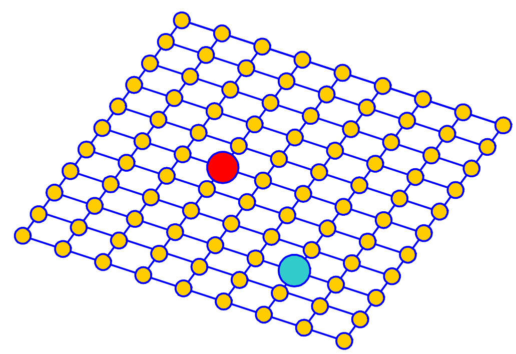

Fig. 3 Illustration of a grid of virtual sources: The small solid circle indicates the seabed roughness patches and large circle indicates the potential targets located at certain place

The beam space parameters, (R,β), link with $\mathbf{x}_k$ illustrated in Fig 4.

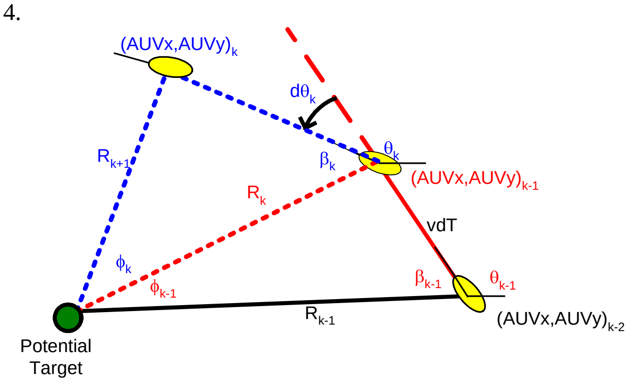

Fig 4. Illustration of the relationship between state space of AUV and the beam space image: The fixed potential target shown in the figure are linked with AUV with the *R* and β in difference stage k.

We wish to estimate the most likely trajectories of the AUV, where the track at the time K of the AUV is defined as a sequence of successive states by

$$\mathbf{X}_{\boldsymbol{K}} = \{\mathbf{x}_1,\ldots\ldots,\mathbf{x}_K\} \tag{5}$$

III. TRACK-BEFORE-DETECT ALGORITHM

We estimate the track trajectories using the track-before-detect algorithm [3] defined as

$$\{\hat{\mathrm{X}}_K\} = \{\mathrm{X}_K : \sum_{k=1}^{K} \tilde{z}_{ij\theta}(k) > V_T\} \tag{6}$$

The AUV trajectory estimates are those state sequences for which the sum of measurements exceed a threshold V_T. This is equivalent to performing integration of sonar returns prior to the detection. This technique for target tracking provides improved efficiency over the standard tracking methods which declare detection at each frame. Instead, after sequences of frames are processed, the estimated trajectory is returned at the same time as the detection is declared. This is intended for the low signal-to noise ratio returns to avoid discarding information contained in each single frame of measurement. However, this technique requires an exhaustive search over the entire state space which is difficult to achieve for onboard computing capability of a resource-limited AUV. We substitute the exhaustive search as described above with a dynamic programming algorithm which is generally known to effectively perform the equivalent of an exhaustive search. To perform the search using dynamic programming algorithm, we first discretize the sonar state space. The discrete state space is denoted by $\underline{\mathrm{x}}_k = [\underline{x}(\mathrm{k})\ \underline{\dot{x}}(k)\ \underline{y}(k)\ \underline{\dot{y}}(k)\ \underline{\theta}(k)\ \underline{\dot{\theta}}(k)]^T$, where the resolution cell of the position space is of size $\Delta\times\Delta$. The velocity space is defined to be $\Delta V \times \Delta V$, and $T\Delta V = \Delta$. The angular resolution is of size Δ' and the resolution of angular velocity is defined as $\Delta v'$ such that $T\Delta v' = \Delta'$. The state and state transitions can be defined by

$$\begin{array}{ll}
x(k) \in [(\underline{x}-1)\Delta, \underline{x}\Delta) & x(k+1) \in [(\underline{x}+\underline{\dot{x}}-2)\Delta, (\underline{x}+\underline{\dot{x}})\Delta) \\
\dot{x}(k) \in [(\underline{\dot{x}}-1)\Delta, \underline{\dot{x}}\Delta v) & \underline{\dot{x}}(k+1) \in [(\underline{\dot{x}}-1)\Delta v, \underline{\dot{x}}\Delta v) \\
y(k) \in [(\underline{y}-1)\Delta, \underline{y}\Delta) & y(k+1) \in [(\underline{y}+\underline{\dot{y}}-2)\Delta, (\underline{y}+\underline{\dot{y}})\Delta) \\
\dot{y}(k) \in [(\underline{\dot{y}}-1)\Delta, \underline{\dot{y}}\Delta v) & \underline{y}(k+1) \in [(\underline{\dot{y}}-1)\Delta v, \underline{\dot{y}}\Delta v) \\
\theta(k) \in [(\underline{\theta}-1)\Delta, \underline{\theta}\Delta) & \theta(k+1) \in [(\underline{\theta}+\underline{\dot{\theta}}-2)\Delta', (\underline{\theta}+\underline{\dot{\theta}})\Delta') \\
\dot{\theta}(k) \in [(\underline{\dot{\theta}}-1)\Delta, \underline{\dot{\theta}}\Delta v) & \dot{\theta}(k+1) \in [(\underline{\dot{\theta}}-1)\Delta v', \underline{\dot{\theta}}\Delta v')
\end{array} \tag{7}$$

Sufficient state transitions should be hypothesized to anticipate reasonable maneuvering of the AUV. All state transitions are considered equally likely and no velocity transitions are assumed between consecutive frames. Here, for a given state at time k, we assumed 4 possible states at time $k+1$.

IV. DYNAMIC PROGRAMMING ALGORITHM

The approach adopted in this paper is suggested by [4]. Assuming that state transitions can be modeled as a first-order Markov random walk, then the cost function on selecting the trajectory X_n can be written as

$$s(\mathbf{x}_n,\mathbf{x}_{n-1},\ldots\ldots\mathbf{x}_1) = s_n(\mathbf{x}_n,\mathbf{x}_{n-1}) + s_{n-1}(\mathbf{x}_{n-1},\mathbf{x}_{n-2})\ldots\ldots\ldots s_1(\mathbf{x}_2,\mathbf{x}_1) \tag{8}$$

Because each functions $s_k(\mathrm{x}_k,\mathrm{x}_{k-1})$ depends only on consecutive state vectors, the optimization can be carried out in a nested expression

$$\begin{aligned}
& s^*(\mathbf{x}^*{}_n, \mathbf{x}^*{}_{n-1},\ldots\ldots\ldots, \mathbf{x}^*{}_1) \\
&= \max_{\mathbf{x}_n}[\max_{\mathbf{x}_{n-1}}[s_n(\mathbf{x}_n,\mathbf{x}_{n-1}) + \max_{\mathbf{x}_{n-2}}[\, s_{n-1}(\mathbf{x}_{n-1},\mathbf{x}_{n-2}) + \\
&\qquad \ldots\ldots\ldots\ldots + \max_{\mathbf{x}_1}[s_1(\mathbf{x}_2,\mathbf{x}_1)]]]]] \\
&= \max_{\mathbf{x}_n}[h_{n-1}(\mathrm{x}_n)]
\end{aligned} \tag{9}$$

where $h_{K-1}(\mathrm{x}_K)$ represents the maximum partial sum of $s_l(x_l, x_{l-1}),\ l = 2,3,\ldots k$

$$\begin{aligned}
h_{K-1}(\mathbf{x}_k) &= \max_{\mathbf{x}_{k-1}}[h_{k-2}(\mathbf{x}_{k-1}) + s_k(\mathbf{x}_k,\mathbf{x}_{k-1})] \\
h_1(\mathbf{x}_2) &= \max_{\mathbf{x}_1}[s_1(\mathbf{x}_2,\mathbf{x}_1)]
\end{aligned} \tag{10}$$

that is , a recursive equation is obtained by splitting the maximization on X_k into a partial maximization on the trajectory X_{k-1} and a maximization on the state x_k. The cost function s is defined as the logarithm of the ratio of posteriori event probabilities

$$s(\mathrm{X}_k) = \log\left[\frac{P_{k|k}(\mathrm{X}_k \mid \mathrm{Z}_k)}{P_{k|k}(H_0 \mid \mathrm{Z}_k)}\right] \tag{11}$$

where H_0 represents the null-state hypothesis. The cost function therefore takes into account both of evidences which supports and contradicts the sonar track hypothesis X_k conditioned on the observation Z_k.

To develop the recursive solution of (10), the Bayes Theorem and the first-order random walk model are applied to the term in the bracket in (11).

$$\begin{aligned}
\frac{P_{k|k}(\mathrm{X}_k \mid \mathrm{Z}_k)}{P_{k|k}(H_0 \mid \mathrm{Z}_k)} &= \frac{P(\mathrm{z}_k \mid \mathbf{x}_k)}{P(\mathrm{z}_k \mid H_0)} \cdot \frac{P_{k|k-1}(\mathrm{X}_k \mid \mathrm{Z}_{k-1})}{P_{k|k-1}(H_0 \mid \mathrm{Z}_{k-1})} \\
&= \frac{P(\mathrm{z}_k \mid \mathbf{x}_k)}{p(\mathrm{z}_k \mid H_0)} \cdot P(\mathbf{x}_k \mid \mathbf{x}_{k-1}) \cdot \frac{P_{k-1|k-1}(\mathrm{X}_{k-1} \mid \mathrm{Z}_{k-1})}{P_{k-1|k-1}(H_0 \mid \mathrm{Z}_{k-1})}
\end{aligned} \tag{12}$$

Finally, the maximum cost for the dynamic programming update equation can be computed recursively based on the above derivation

$$h_{k-1}(\mathbf{x}_k) = \log\left(\frac{P(z_k \mid \mathbf{x}_k)}{P(z_k \mid H_0)}\right) + \max_{\mathbf{x}_{k-1}}\left[\log P(\mathbf{x}_k \mid \mathbf{x}_{k-1}) + h_{k-2}(\mathbf{x}_{k-1})\right] \quad (13)$$

The recursion is a filter, providing state estimates based on system dynamics and observations. The system model is represented by the conditional probability densities $P(\mathrm{x}_{k+1}|\mathrm{x}_k)$ and $P(\mathrm{z}_k|\mathrm{x}_k)$, which can embody nonlinear relationships in the state evolution and in the relationship between states and observations. The method we adopted to assign the conditional observation probability density is based on the definition of the track-before-detect algorithm (6)

$$P(\mathbf{z}_k \mid \mathbf{x}_k) \approx \tilde{\mathrm{Z}}_k = \frac{\mathrm{z}_k}{\max(\mathrm{z}_k)} \quad (14)$$

that is, the cost of selecting the trajectory x_k is represented by the observation z_k. For the same reason, we used the approximation

$$P(\mathbf{z}_k \mid H_0) \approx 1 - \tilde{\tilde{\mathrm{Z}}}_k \quad (15)$$

The value of the state transition probability density function is obtained by its definition

$$\log P(\mathbf{x}_k \mid \mathbf{x}_{k-1}) = -\log(|\underline{\mathbf{x}}(k) - F\,\underline{\mathbf{x}}(k-1)|) \quad (16)$$

IV EXPERIMENTAL RESULTS

In the GOATS'2000 experiment an Odyssey II class autonomous underwater vehicle, shown in Fig. 5, was used as a mobile platform for mapping the 3-D scattering from proud and buried targets and the associated seabed reverberation in VSW, and explore the potential of bistatic on-line detection processing. The core vehicle has a depth rating of 6,000 m, weighs 120 kg, and measures 2.2 m in length and 0.6 m in diameter. It cruises at approximately 1.5 m/s (3 knots) with endurance in the range of 3-12 hours, depending on the battery installed and the load. The AUV used in GOATS'2000 featured an 8-element acoustic array for bistatic reception, mounted in the vehicle's nose in a 'swordfish` configuration, and an autonomous data acquisition system, installed in a watertight canister in the vehicle's payload bay.

A. Bi-stiatic Case

Fig. 4 shows the bistatic sonar geometry of the Goats'2000 experiment. The TOPAS parametric source is insonifying the seabed with a footprint of approximately 5m by 10m , centered on the half-buried spherical target S3. The Odyssey AUV equipped with an 8-element array is passing over the targets receiving the scattered field along its track. The concurrent detection and tracking algorithm stated above has been applied to the data collected in this fashion.

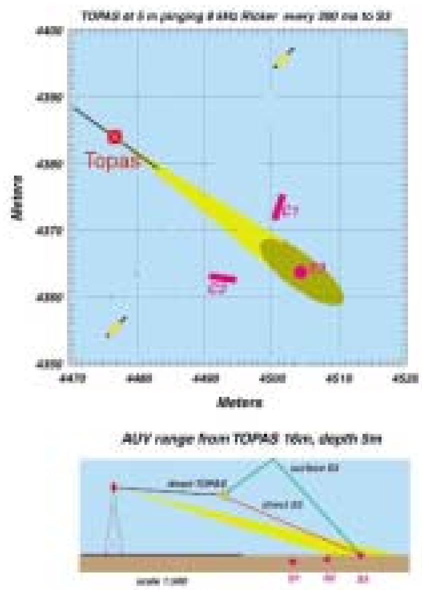

Fig.5 Bistatic sonar geometry. The TOPAS parametric source is insonifying the seabed with a footprint of approximately 5m by 10m, centered on the half-buried spherical target S3, and two cylinders C1 and C2 are flush buried

A robust and fast detection algorithm suitable for real-time autonomous operation has been developed in this work. It has been demonstrated that combining AUV dynamic data with the beamformed, bistatic acoustic signals real-time detection is feasible, provided accurate time synchronization is available. A detection result using the new algorithms on the GOATS 2000 bistatic data is shown in Fig. 6. On the left part of Fig. 6, the most possible navigation track of AUV is established by means of TBD first. The track has the maximum merit value among those possible searching trajectories that exceed the preset threshold in (6). The DP algorithm in (11), (14), (15) and (16) provide the efficient computation structure for calculating the cost function of possible trajectories While the track is determined, the multiple targets has been detected on the right part of Fig. 6 by simply integrating the image of each ping. The availability of time synchronization and strong returns makes the spherical target S1 detected at a high confidence level. Due to the fact that the detection algorithm uses multiple pings, the ambiguity of this target is eliminated, leading to a high probability of detection. The presence of the cylindrical targets C1 and C2 causes two main problems. The longer return path and the multi-path effect in the waveguide make the target multiples appear in different positions for each consecutive ping. In addition, the aspect dependence of these targets results in weak returns for most pings. As a result, C1 and C2 are detected

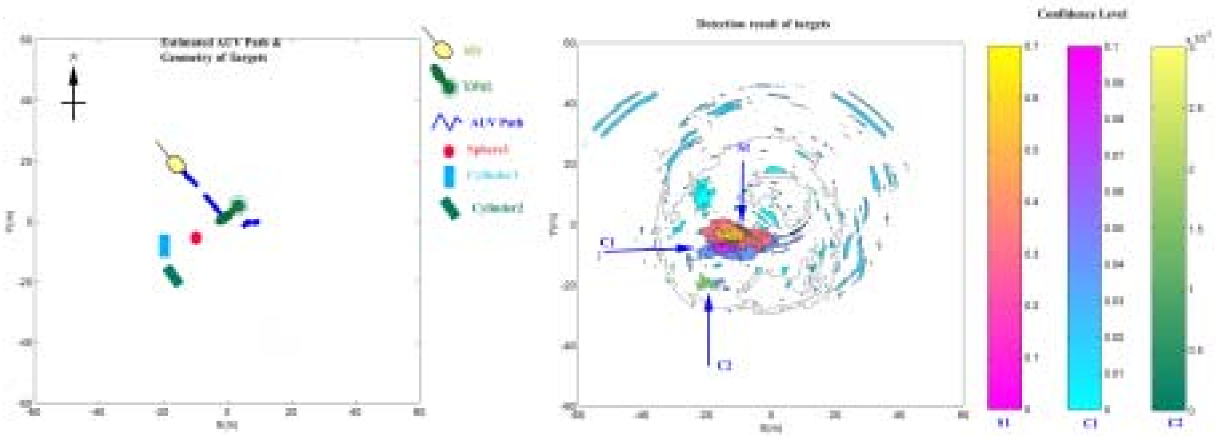

Fig. 6 Track and detection results, using 50 pings from the GOATS' 2000 experiment

at a relatively weak confidence level. However, the results suggest that autonomous detection of such aspect-dependent targets is indeed possible. The result also shows the satisfactory performance of the algorithm in simultaneously detecting multiple, mixed weak and strong targets.

B. Mono-Static Case

In GOATS' 2002 experiment, the AUV is equipped a seabottom profiler as a source together with the nose array. This configuration meets the need for searching a wider range of target field with mobility of the source. In order to simulate the real working scenario in this sonar concept, the targets field in GOATS 2002 are concrete blocks which scattered randomly in a 200m by 200 m area.

Fig 7. shows the navigation results of the AUV track. There are 16 targets detected concurrently. Moreover, some of the targets are detected twice while the targets are again shown inside the visible working area of the AUV when the AUV make a second attempt to approach the targets.

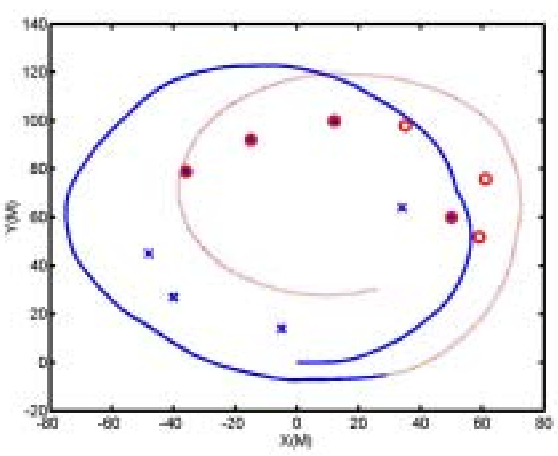

Fig 7. The navigation results of GOATS 2002: The blue solid line and red dot line show the track of AUV in xy plane. The corresponding detected targets are shown in blue crosses while AUV is in the track of blue line, and red circles while AUVis in red dot line

Unlike the GOATS' 2000 experiment, the moving platform results in a moving isonified area. In this case, this algorithm still shows its superior performance on the navigation and tracking.Fig 8. shows a comparison of the track of AUV by LBL navigation and by this method. The track matches at most segments inside 5 meters error circles. However, the track is biased at a large amount especially at corners or the sharply changed curve. On one hand, these features show the model assumptions of AUV states are not able to catch the highly maneuvering vehicle behavior. On the other hand, even the model doesn't quiet match the real state, this method still shows the robustness of this navigation method.

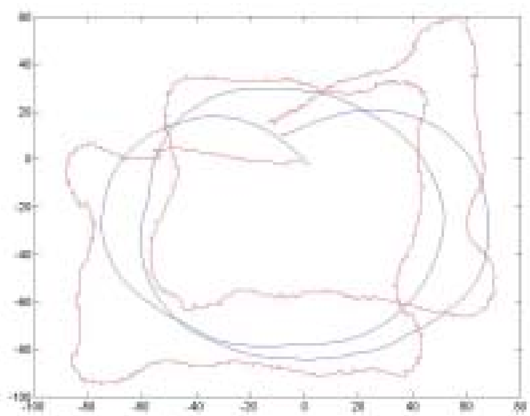

Fig 8. Comparison of navigation results in GOATS 2002: LBL navigation results are indicated by red line and the navigation results by this method are indicated by blue line.

V. CONCLUSION

We have developed a method for detecting the seabed targets and tracking the corresponding AUV tracks using acoustic sensors. The method has the following desirable properties:

1. The method does not rely on distinguishable features in the environment. Thus it avoids the difficulties of feature detection and feature correspondence.
2. The method does not require an a priori world model.
3. The method can handle sensor noise. It uses most of the sensed data therefore it does not discard useful information contained in the measurements.

However, the simplified model of AUV is not able to perform the tracking task of highly maneuvering vehicles. A more vivid model should be carefully investigated in the near future.

Acknowledgments

The authors are highly appreciative of the collaboration with a large group of scientists and engineers from SACLANTCEN and MIT and the crew of R/V alliance without whom the extremely rich GOATS data set would never have materialized. This work is supported by the Office of Naval Research and SACLANT.

REFERENCES

[1] T. Curtin, J.G Bellinghaam, J. Catipovic, and D. Webb. “Autonomous oceanographic sampling networks.”, *Oceanography*, 6(3):86-94, 1993

[2] W. Xu ,T. Liu and H. Schmidt, ”Beamforming based on spatial-wavelet decomposition”,*IEEE Sensor Array and Multichannel signal processing workshop*,2002

[3] Tonissen, R. J. Evans, “Performance of Dynamic Programming Techniques for Track-Before-Detect,” *IEEE Transactions on Aerospace And Electronics System*, Vol 32,No 4 Oct 1996

[4] Yair Barniv, Offer Kella, ”Dynamic Programming Solution for Detecting Dim Moving Targets part II: analysis,” *IEEE Transactions on Aerospace And Electronics System*, Vol aes23, No 6, Nov 1987

.