AUV-Based Seabed Target Detection and Tracking

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 GOATS (Generic Oceanographic Array Technology Systems) Joint Research Program explores the development of environmentally adaptive autonomous underwater vehicles (AUV) specifically directed toward Rapid Environment Assessment and Mine Counter Measurement (MCM) in coastal environments. As part of the effort, MIT is developing the GOATS multi-static sonar concept which uses a low-frequency source on one AUV to sub-critically insonify the seabed over a wide area, while a formation of multiple AUVs are used for mapping the associated 3D scattered acoustic field in the water column. Based on the significantly different characteristics of the scattered field of various buried targets, an online algorithm has been developed for concurrent detection and tracking the buried seabed targets. The use of subcritical angle isonification essentially results in the measurement of the reception of weak signals from the buried targets. Tracking these targets in such a scenario encounters the difficulties of detecting the targets in the presence of extremely low signal-to-noise ratio. Furthermore, combining with the uncertainties of navigation of AUVs presents another challenge for detection and tracking the targets. The method proposed in this work applies the techniques of Track-Before-Detection (TBD) to solve this problem. This technique tracks the targets first using the slowly changing environment information, and then the weak signal detection is declared after confidence of the track estimation is established. However, enormous possible trajectories of AUVs 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 new algorithm has been applied on the GOATS 2000 bistatic data. The result shows successful detection of three buried targets where two of those are relatively weak targets. The result also shows the satisfactory performance of the algorithm in simultaneously detecting multiple, mixed strong and weak targets online.**

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 very shallow water 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.

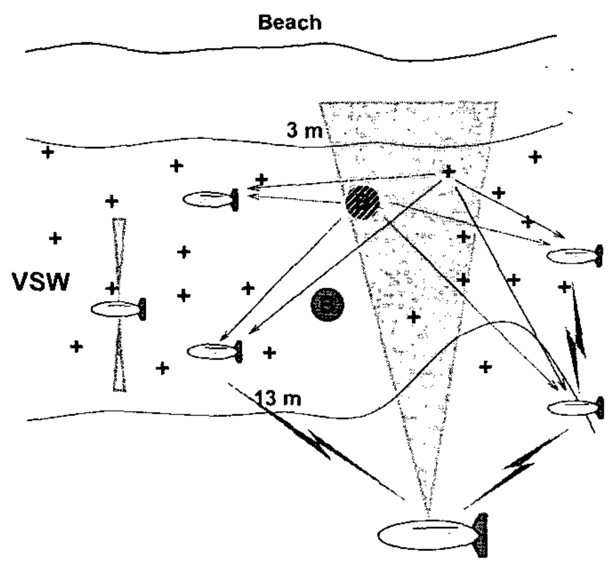

Fig. 1 GOATS: Generic Ocean Array Technology Sonar concept for coastal MCM. A fleet of AUV's connected by an underwater communication network, and equipped with acoustic receiver arrays is used to measure the 3-D scattering from proud and buried targets insonified by a dedicated master AUV.

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 continuing analysis of this data is exploring the fundamental physics of 3-D acoustic scattering by buried targets and the feasibility of the GOATS concept. 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 moving with constant velocity is modeled to be linear across the x-y image plane which is form by the real-time beamformer [2] 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 frames. The frame formed by the data recorded by the linear array is transferred to a matrix composed by square resolution cells. At each time k a measurement is recorded in each cell. The measurement matrix is given by

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

where $-N/2 \le \theta \le N/2$ and $1 \le i,j \le M$ and $\tilde{z}_{ij\theta}(k)$ is the measurement given by

$$\tilde{z}_{ij\theta}(k) = -\left[\frac{1}{M^2}\sum_{i=1}^{M}\sum_{j=1}^{M}\left\{z_{ij\theta}(k) - z_{i\cdot\cos\theta - j\cdot\sin\theta + i,\, i\cdot\sin\theta + j\cdot\cos\theta + j,\, \theta}(k-1)\right\}^2\right]^{\frac{1}{2}} \tag{4}$$

where $z_{ij\theta}(k)$ is sonar return of possibly time-varying amplitude with additive noise recorded in resolution cell (i, j , θ). At the time K; given the measurement sequence $\mathbf{Z}_K$, where

$$\mathbf{Z}_K = \{\mathbf{z}_1, \ldots\ldots, \mathbf{z}_K\} \tag{5}$$

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

$$\mathbf{X}_K = \{\mathbf{x}_1, \ldots\ldots, \mathbf{x}_K\} \tag{6}$$

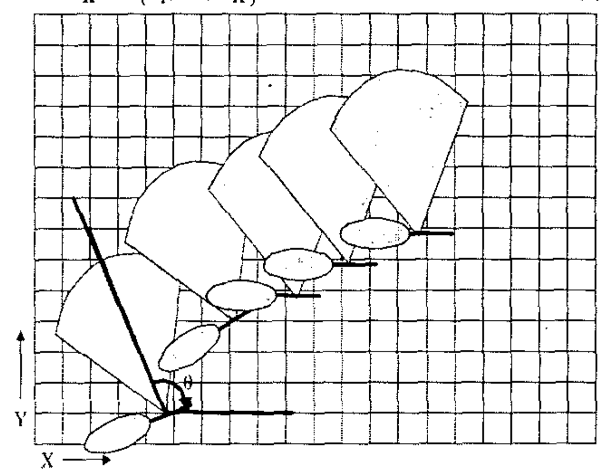

Fig. 2 Illustration of state space of AUV trajectory.

III. TRACK-BEFORE-DETECT ALGORITHM

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

$$\{\hat{\mathbf{X}}_K\} = \{\mathbf{X}_K : \sum_{k=1}^{K} \tilde{z}_{ij\theta}(k) > V_T\} \tag{7}$$

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 $\underline{\mathbf{x}}_k = [\underline{x}(k)\ \underline{\dot{x}}(k)\ \underline{y}(k)\ \underline{\dot{y}}(k)\ \underline{\theta}(k)\ \underline{\dot{\theta}}(k)]^T$, 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

$$
\begin{array}{ll}
x(k) \in [(\underline{x}-1)\Delta, \underline{x}\Delta) & x(k+1) \in [(\underline{x}+\underline{\dot{x}}-2)\Delta, (\underline{x}+\underline{\dot{x}})\Delta) \\
\dot{x}(k) \in [(\underline{\dot{x}}-1)\Delta, \underline{\dot{x}}\Delta v) & \underline{\dot{x}}(k+1) \in [(\underline{\dot{x}}-1)\Delta v, \underline{\dot{x}}\Delta v) \\
y(k) \in [(\underline{y}-1)\Delta, \underline{y}\Delta) & y(k+1) \in [(\underline{y}+\underline{\dot{y}}-2)\Delta, (\underline{y}+\underline{\dot{y}})\Delta) \\
\dot{y}(k) \in [(\underline{\dot{y}}-1)\Delta, \underline{\dot{y}}\Delta v) & \underline{y}(k+1) \in [(\underline{\dot{y}}-1)\Delta v, \underline{\dot{y}}\Delta v) \\
\theta(k) \in [(\underline{\theta}-1)\Delta, \underline{\theta}\Delta) & \theta(k+1) \in [(\underline{\theta}+\underline{\dot{\theta}}-2)\Delta', (\underline{\theta}+\underline{\dot{\theta}})\Delta') \\
\dot{\theta}(k) \in [(\underline{\dot{\theta}}-1)\Delta, \underline{\dot{\theta}}\Delta v) & \dot{\theta}(k+1) \in [(\underline{\dot{\theta}}-1)\Delta v', \underline{\dot{\theta}}\Delta v')
\end{array}
\tag{8}
$$

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

$$s(\mathbf{x}_n, \mathbf{x}_{n-1}, \ldots\ldots \mathbf{x}_1) = s_n(\mathbf{x}_n, \mathbf{x}_{n-1}) + s_{n-1}(\mathbf{x}_{n-1}, \mathbf{x}_{n-2}) \ldots\ldots s_1(\mathbf{x}_2, \mathbf{x}_1) \tag{9}$$

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

$$
\begin{aligned}
& s^*(\mathbf{x}^*_n, \mathbf{x}^*_{n-1}, \ldots\ldots, \mathbf{x}^*_1) \\
&= \max_{\mathbf{x}_n}[\max_{\mathbf{x}_{n-1}}[s_n(\mathbf{x}_n, \mathbf{x}_{n-1}) + \max_{\mathbf{x}_{n-2}}[s_{n-1}(\mathbf{x}_{n-1}, \mathbf{x}_{n-2}) + \\
&\qquad \ldots\ldots\ldots + \max_{\mathbf{x}_1}[s_1(\mathbf{x}_2, \mathbf{x}_1)]]]] \\
&= \max_{\mathbf{x}_n}[h_{n-1}(\mathbf{x}_n)]
\end{aligned}
\tag{10}
$$

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

$$
\begin{aligned}
h_{K-1}(\mathbf{x}_k) &= \max_{\mathbf{x}_{k-1}}[h_{k-2}(\mathbf{x}_{k-1}) + s_k(\mathbf{x}_k, \mathbf{x}_{k-1})] \\
h_1(\mathbf{x}_2) &= \max_{\mathbf{x}_1}[s_1(\mathbf{x}_2, \mathbf{x}_1)]
\end{aligned}
\tag{11}
$$

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

$$s(\mathbf{X}_k) = \log\left[\frac{P_{k|k}(\mathbf{X}_k|\mathbf{Z}_k)}{P_{k|k}(H_0|\mathbf{Z}_k)}\right] \tag{12}$$

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 (11), the Bayes Theorem and the first-order random walk model are applied to the term in the bracket in (12).

$$
\begin{aligned}
\frac{P_{k|k}(\mathbf{X}_k|\mathbf{Z}_k)}{P_{k|k}(H_0|\mathbf{Z}_k)} &= \frac{P(\mathbf{z}_k|\mathbf{x}_k)}{P(\mathbf{z}_k|H_0)} \cdot \frac{P_{k|k-1}(\mathbf{X}_k|\mathbf{Z}_{k-1})}{P_{k|k-1}(H_0|\mathbf{Z}_{k-1})} \\
&= \frac{P(\mathbf{z}_k|\mathbf{x}_k)}{p(\mathbf{z}_k|H_0)} \cdot P(\mathbf{x}_k|\mathbf{x}_{k-1}) \cdot \frac{P_{k-1|k-1}(\mathbf{X}_{k-1}|\mathbf{Z}_{k-1})}{P_{k-1|k-1}(H_0|\mathbf{Z}_{k-1})}
\end{aligned}
\tag{13}
$$

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

$$h_{k-1}(\mathbf{x}_k) = \log\left(\frac{P(\mathbf{z}_k \mid \mathbf{x}_k)}{P(\mathbf{z}_k \mid H_0)}\right) + \max_{\mathbf{x}_{k-1}}\{\log P(\mathbf{x}_k \mid \mathbf{x}_{k-1}) + h_{k-2}(\mathbf{x}_{k-1})\} \tag{14}$$

The recursion is a filter, providing state estimates based on system dynamics and observations. The system model is represented by the conditional probability densities $P(\mathbf{x}_{k+1}|\mathbf{x}_k)$ and $P(\mathbf{z}_k|\mathbf{x}_k)$, 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 (7)

$$P(\mathbf{z}_k \mid \mathbf{x}_k) \approx \tilde{\mathbf{Z}}_k = \frac{\mathbf{z}_k}{\max(\mathbf{z}_k)} \tag{15}$$

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

$$P(\mathbf{z}_k \mid H_0) \approx 1 - \tilde{\tilde{\mathbf{Z}}}_k \tag{16}$$

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

$$\log P(\mathbf{x}_k \mid \mathbf{x}_{k-1}) = -\log(|\underline{\mathbf{x}}(k) - F\underline{\mathbf{x}}(k-1)|) \tag{17}$$

IV EXPERIMENTAL RESULTS

In the GOATS'2000 experiment an Odyssey II class autonomous underwater vehicle, shown in Fig. 3, 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.

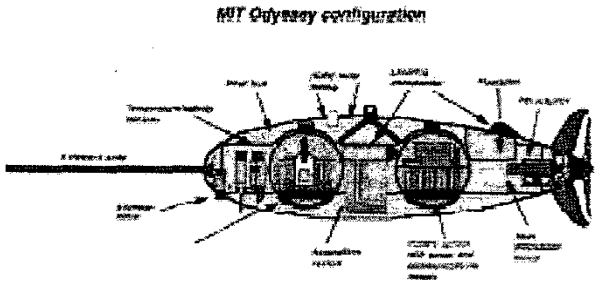

Fig. 3 Configuration of Odyssey II AUV 'Xanthos' for acoustic measurements in GOATS'2000. The AUV control electronics and batteries are located in two 17" Benthos glass spheres. An 8-element array is mounted in a 'swordfish' configuration, and connected to adedicated acquisition system in the center well of the vehicle.

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.

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. 5. On the left part of Fig. 5, the most possible track of AUV is established by means of TBD first. The track has the maximum cost value among those possible searching trajectories that exceed the preset threshold in (7). The DP algorithm in (12), (15), (16) and (17) provide the efficient computation structure for calculating the cost function of possible tracjectories While the track is determined, the multiple targets has been detected on the right part of Fig. 5 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 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.

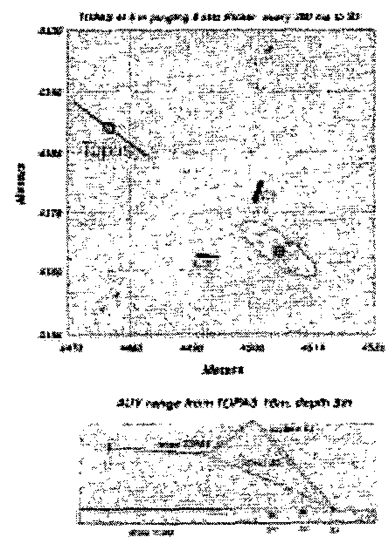

Fig. 4 Bistatic sonar geometry. The TOPAS parametric source isinsonifying the seabed with a footprint of approximately 5m by 10m, centered on the half-buried spherical target S3, and two cylinders C1 and C2 are flush buried

V. CONCLUSION

We have developed a method for detecting the seabed targets and tracking the corresponding AUV states 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.

Acknowledgments

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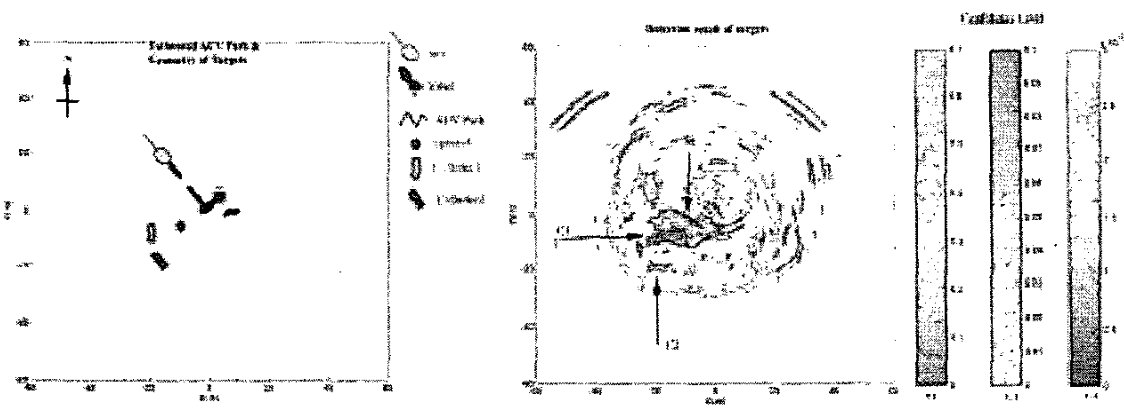

Fig. 5 Track and detection results, using 50 pings from the GOATS' 2000 experiment

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