MAP-PF Detection and Tracking of Underwater Acoustic Targets

Grant Number: N00014-08-1-0225

Final Technical Report
September 30, 2009

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LONG-TERM GOALS

The goal of this project was to develop an automated detection and tracking algorithm for broadband targets using complex hydrophone data from a passive acoustic array. The algorithm is an integral part of a larger Coherent Automated Multi-Target Tracker (CAMTT) system under development by Metron, Inc. [1] for Detection, Classification, and Localization (DCL) for passive Anti-Submarine Warfare (ASW). The algorithm integrates the Maximum a Posteriori Penalty Function (MAP-PF) tracking algorithm [2]-[4] with the Likelihood Ratio Detection and Tracking (LRDT) methodology [5],[6], and spectral tracking approach of [7]. The detection and tracking problem is treated as a joint detection and estimation problem and the combined system automatically (1) detects and drops targets, (2) jointly estimates bearing vs. time tracks for all targets, and (3) jointly estimates the received spectrum of these targets. The spectral estimates improve the detection and tracking capability and will be used to aid the classification component of the CAMTT system.

OBJECTIVES

The technical objective of this project was to develop an automated detection and tracking algorithm for broadband targets using complex hydrophone data from a passive acoustic array. The detection and tracking problem was treated as a joint detection and estimation problem and the combined system automatically (1) detects and drops targets, (2) jointly estimates bearing vs. time tracks for all targets, and (3) jointly estimates the received spectrum of these targets. The goal was to develop an algorithm that outperforms existing techniques in terms of the mean square error (MSE) in tracking detected targets, increased and earlier detection of quiet targets, and reduction in false detections.

APPROACH

The detection and tracking problem was treated as a joint detection and estimation problem operating directly on the complex hydrophone data. The joint detection and estimation approach is theoretically difficult. An optimal solution is intractable to derive and would be computationally complex to implement. Traditional multitarget detection and tracking techniques therefore partition the process into two isolated processes: broadband target detection and bearing estimation from array snapshot data, followed by track estimation from the bearing estimates. This partitioning results in procedures which are suboptimal and require data association to match bearing estimates to targets. More sophisticated approaches first process the complex hydrophone data to provide estimates of spectral content across frequency and beams (frequency azimuth (FRAZ) data) and use the beamformed data as input to the tracker. The approach is still partitioned into two processes and must still incorporate a data association component, although the partition occurs closer to the original data. In order to improve performance, a new approach that operates directly on the array data is required.

The proposed algorithm integrates the MAP-PF tracking algorithm [2]-[4] with the LRDT methodology [5],[6], and spectral tracking approach of [7]. The algorithm operates directly on the complex hydrophone data.

The approach of MAP-PF is to develop a likelihood function for the complex hydrophone data as a function of the joint target state of all detected targets and then to find the joint target state that maximizes the likelihood function. This method requires knowledge of the number of targets and an initial estimate of the bearing and spectrum of each target. A key feature of the MAP-PF approach is the use of the penalty function method of nonlinear programming in conjunction with an alternating maximization procedure to obtain a tractable solution. Penalized maximum likelihood estimates of the target bearings and power spectra are found, which then act as a synthetic "measurements" in a Kalman filter update of the state. The two-step estimation process is similar to traditional methods, except the processes are coupled via the penalty function. In the bearing/power spectrum estimation step, the current target state is used to guide the estimation process and help eliminate ambiguous or spurious estimates, and to eliminate the data association step of traditional multitarget tracking approaches. In the track estimation step, the penalty function parameters act like the measurement error variance to control the influence of the bearing and power spectrum estimates on the final track estimate.

The LRDT approach is used to determine the presence or absence of targets and provide an initial state estimate of newly detected targets to the MAP-PF tracker. The LRDT methodology develops a likelihood ratio between the density of the complex hydrophone data given the joint target state of all detected targets and the density assuming an additional hypothesized target. When the likelihood ratio surpasses a threshold, a new target is declared present. A similar procedure is used to determine when an existing target should be declared absent.

Combining the MAP-PF and LRDT algorithms is straightforward and natural since they both compute the same joint likelihood functions. This approach provides a complete automated algorithm for detecting and tracking targets directly from complex hydrophone data, avoiding inefficiencies inherent in partitioned methods.

WORK COMPLETED

In the first project year, we had the following technical accomplishments:

(1) Developed a broadband MAP-PF tracker for multiple targets and a maneuvering platform. The target state is the bearing, bearing rate, and spectrum. The noise background is assumed known and white.

(2) Developed an algorithm for computing a whitened likelihood function required for the LRDT detector. The algorithm effectively removes known targets by modeling them as slightly spatially spread targets rather than point sources.

In the second project year, we had the following technical accomplishments:

(3) Extended the MAP-PF tracker to model colored noise and include unknown noise parameters in the state vector.

(4) Developed a version of the algorithm that operates on beamformed data. This provides an intermediate algorithm that separates two key features of the MAP-PF algorithm underdevelopment: the MAP-PF methodology itself, and the use of element data.

In both project years, we also:

(5) Tested the algorithms on simulated data in a realistic moving target, maneuvering platform scenario.

(6) Assisted Metron in integrating the algorithms into their CAMTT system and initial testing on real data.

RESULTS

An effective multi-target tracker for broadband targets in unknown colored noise was developed and tested on simulated data in a realistic scenario involving moving surface and submerged targets and a maneuvering platform. The full state vector consists of the noise parameters and a target state vector for each target. The target state includes the bearing, bearing rate, and spectral parameters. Including the noise and target spectral parameters allows the tracker to discriminate between targets that are close spatially and provides a significant performance improvement for tracking "crossing" targets.

The algorithms were tested on a realistic scenario as shown in Figure 1. There are three targets: two loud surface ships and one quiet submarine. The platform is a surface ship towing a 48-element linear array with design frequency 667 Hz. The targets move in linear, constant velocity tracks in 3D-space, however, tracking is done in bearing space, so the target tracks cross and appear nonlinear. The bearing, bearing rate, and total target power as seen at the array are shown in Figure 2. The target spectra vary across the frequency band and are shown in Figure 3. The noise consists of spatially isotropic environmental noise that decreases in power across frequency plus spatially white sensor noise that is constant across frequency. The noise spectra are shown in Figure 3. The array collects broadband acoustic data in 41 frequency bins from 200-600 Hz.

During the bearing estimation step, the bearing of each target is found separately by maximizing a penalized, whitened likelihood function, where the other targets are considered to be interference and whitening is performed with respect to the combined noise and interference. To analyze the effect of proper noise modeling, we pre-whitened the data using a white noise model fitted to the data, and a combined white/isotropic model fitted to the data, followed by conventional beamforming (CBF). The result is shown in Figure 4. The thin lines are the CBF output in each frequency bin and the thick lines are the CBF outputs combined across frequency. It can be seen that in the colored noise case, the higher frequency likelihood functions contribute more to the combined likelihood function because they have less noise. Also, proper colored noise modeling allows the targets to stand out better above the noise floor.

The whitened likelihood functions for each target used in the MAP-PF tracker , as well as the whitened likelihood function with all targets removed is shown in Figure 5. The thin lines are the likelihood functions in each frequency bin. The thick line is the frequency-combined likelihood function, and the thick dashed line is the peanlized likelihood function. In each likelihood function, other targets are effectively suppressed, allowing for good tracking results. The final whitened likelihood function, which will be passed to the LRDT for new target detection, also shows effective suppression of known targets. The target tracks in bearing, bearing rate, and total power are shown in Figure 6, with excellent results comparable to the results obtained last year with white noise only.

A detailed description of the algorithm will be published at the *IEEE International Conference on Acoustics, Speech, and Signal Processing* in March 2010 and is included at the end of this report.

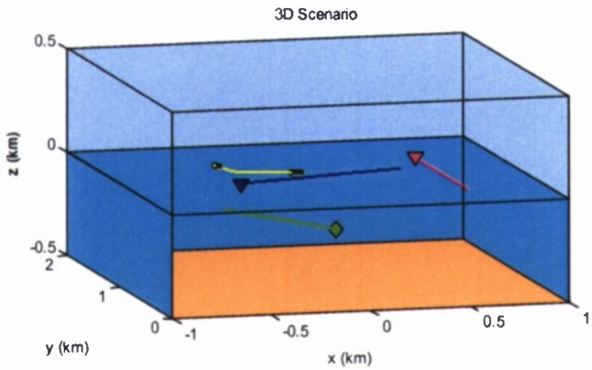

Figure 1. 3D scenario with three moving targets and a maneuvering platform.

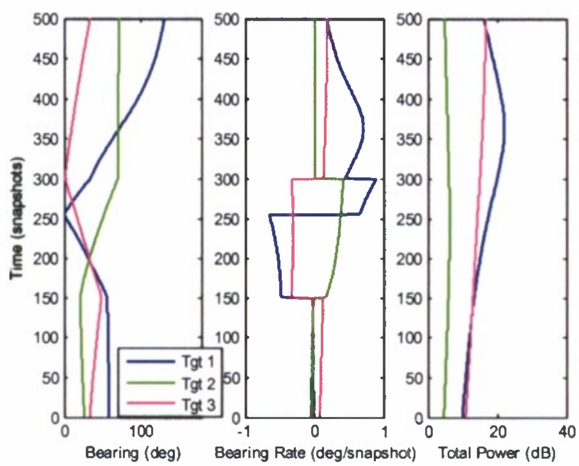

Figure 2. Bearing, bearing rate, and total power of targets as seen at the array.

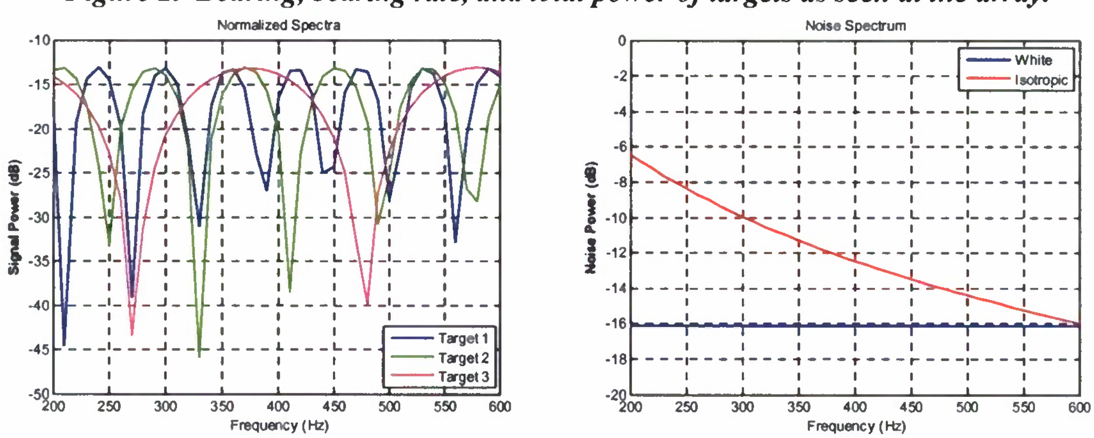

Figure 3. Target spectra (normalized) and noise spectra.

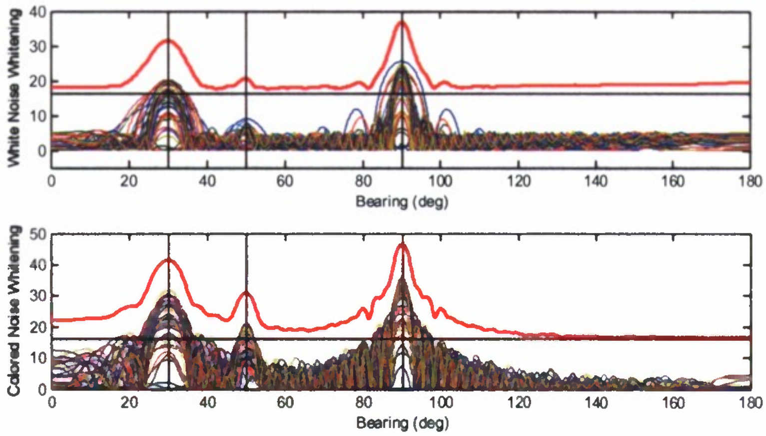

Figure 4. CBF output with (mismatched) white noise whitening and colored noise whitening.

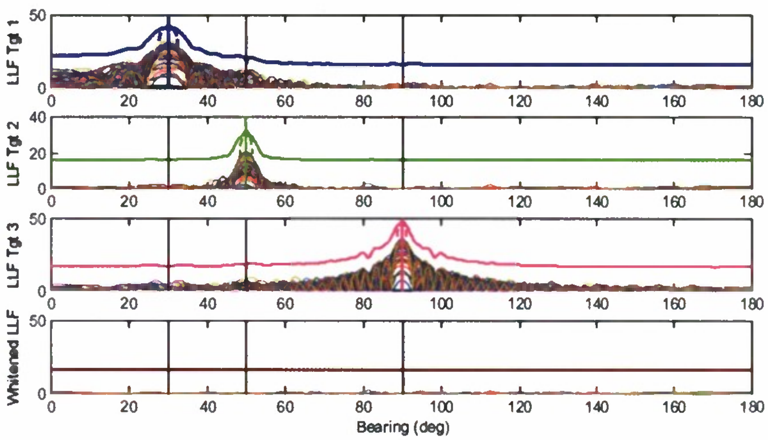

Figure 5. Likelihood functions for each target and LRDT.

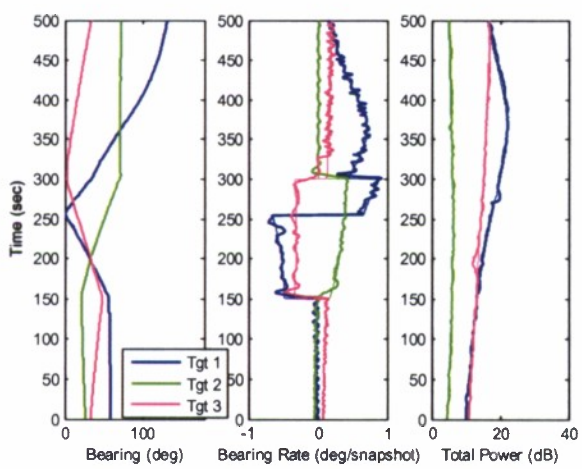

Figure 6. Bearing, bearing rate, and total power tracks overlaid on true values.

Preliminary results for MAP-PF using beamformed data show that it does not perform as well as MAP-PF using element data during target crossings. The beamforming operation removes phase information that is critical for effective whitening of other targets when the targets are close together.

IMPACT/APPLICATIONS

The work is directly aimed at improving the performance of Navy ASW systems. By using a joint detection and estimation approach operating directly on the complex hydrophone data, inefficiencies inherent in currently used partitioned methods can be avoided, resulting in improved tracking of detected targets, earlier detection of quiet targets, and a reduction in false detections. The algorithm is being integrated into Metron's CAMTT system, which will have transition capability into the Integrated Undersea Surveillance System (IUSS) Integrated Common Processor (ICP) as well as other systems discussed in [1].

TRANSITIONS

The MAP-PF tracking methodology is currently being implemented for tracking frequency in the LandSafe system, a laser radar system for determining the ground speed and landing distance of a helicopter, which is under development by Optical Air Data Systems (OADS), under an SBIR project sponsored by ONR.

RELATED PROJECTS

GMU is not currently involved in any related projects.

Dr. Bell was acting as a consultant to Optical Air Data Systems via Signal Processing Consultants, Inc. to implement the MAP-PF tracking methodology to track frequency in a laser radar system for estimating helicopter height and ground speed.

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PUBLICATIONS

K. L. Bell, R. E. Zarnich, and R. Wasyk, "MAP-PF Wideband Multitarget and Colored Noise Tracking," *2010 IEEE Intl. Conf. on Acoust., Speech, Sig. Proc. (ICASSP 2010),* Dallas, TX, March 2010. [submitted, refereed] *Included at end of report.*

HONORS/AWARDS/PRIZES

Kristine L. Bell, George Mason University, received the 2009 Outstanding Alumnus Award from the Volgenau School of IT & Engineering, George Mason University.

MAP-PF WIDEBAND MULTITARGET AND COLORED NOISE TRACKING

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ABSTRACT

The maximum a posteriori penalty function (MAP-PF) approach is applied to tracking the bearing and bearing rate of multiple wideband sources in unknown colored noise. The track estimation problem is formulated directly from the array data using the maximum a posteriori (MAP) estimation criterion. The penalty function (PF) method of nonlinear programming is used to obtain a tractable solution. A sequential update procedure is developed in which penalized maximum likelihood estimates of target bearings, spectra, and noise parameters are computed and then used as synthetic measurements in a set of Kalman filter trackers. The two steps are coupled via the penalty function. During parameter estimation, the penalty function prevents erroneous outlier estimates which can cause the tracker to lose track. During the tracking step, it determines the influence of the parameter estimates on the final track estimates by adaptively adjusting the measurement error variance. Performance is demonstrated on a typical sonar scenario.

1. INTRODUCTION

Traditional target tracking techniques using sensor array data partition the track estimation problem into two isolated processes: bearing estimation based on data collected at the array, followed by target tracking using the bearing estimates as measurements [1]. The maximum a posteriori penalty function (MAP-PF) approach [2]-[4] formulates the track estimation problem directly from the array data using the maximum a posteriori (MAP) estimation criterion and the penalty function (PF) method of nonlinear programming to obtain a tractable solution. The result is a two-step estimation process is similar to traditional methods, except the processes are coupled via the penalty function and the data association step of traditional approaches is eliminated. In the bearing estimation process, the penalty function uses the current target states to guide the estimator. In the track estimation process, the penalty function determines the influence of the bearing estimates on the final track estimates by adaptively adjusting the measurement error variance.

The MAP-PF tracking techniques in [2]-[4] were developed under the assumption that the noise was spatially white with a known frequency spectrum. In this paper, we extend the technique to handle the case of unknown, spatially colored noise. In order to focus on the noise estimation, we assume a single array and track the bearing and bearing rate of each target. Extension to tracking target position in three-dimensional space using multiple sensor arrays is straightforward. As in [4], we consider wideband sources and include the target spectrum in the target state.

This work was supported by the Office of Naval Research under Grant N00014-08-1-0225.

The statistical model is presented in Section II, the MAP-PF technique for unknown colored noise is developed in Section III, simulation results are presented in Section IV, and conclusions are given in Section V.

2. STATISTICAL MODEL AND ASSUMPTIONS

The model consists of M moving targets radiating broadband signals that are received by a linear array of N sensors. The number of targets M is assumed known and $M < N$. Let θ denote the target bearing and $\dot{\theta}$ the bearing rate.

At the array, the received broadband signal is sampled and transformed into the frequency domain. We assume that there are L frequency bins of interest. Let $\gamma_{klm}, l = 1, \ldots, L$ denote the received power spectrum of the mth target at time k. The $(L+2)$-dimensional state vector of the mth target at time k is

$$\mathbf{s}_{km} = \left[\theta_{km}\ \dot{\theta}_{km}\ \gamma_{k1m} \cdots \gamma_{kLm}\right]^T. \tag{1}$$

We assume the target states are independent of each other and the motion of the targets is described by a first order Gauss-Markov process, i.e.,

$$\mathbf{s}_{km} = \mathbf{F}\mathbf{s}_{k-1,m} + \mathbf{w}_{km}, \tag{2}$$

where $\mathbf{w}_{km}$ is a zero-mean, white Gaussian noise process with covariance matrix $\mathbf{Q}_s$, and $\mathbf{F}$ is the block diagonal matrix

$$\mathbf{F} = \text{block diag}\left[\mathbf{F}_1, \mathbf{I}_L\right], \tag{3}$$

where $\mathbf{I}_L$ is $L \times L$ identity matrix and

$$\mathbf{F}_1 = \begin{bmatrix} 1 & \Delta t \\ 0 & 1 \end{bmatrix}, \tag{4}$$

where Δt is the time interval from $k-1$ to k. Therefore, the probability density function (pdf) of $\mathbf{s}_{km}$ given $\mathbf{s}_{k-1,m}$ is

$$p(\mathbf{s}_{km}|\mathbf{s}_{k-1,m}) \sim \mathcal{N}\left(\mathbf{F}\mathbf{s}_{k-1,m}, \mathbf{Q}_s\right) \tag{5}$$

with

$$p(\mathbf{s}_{0m}) \sim \mathcal{N}\left(\bar{\mathbf{s}}_{0m}, \mathbf{\Omega}^s_{0m}\right). \tag{6}$$

The $N \times 1$ observed data vector in the lth frequency bin during the kth observation snapshot has the form

$$\mathbf{z}_{kl} = \sum_{m=1}^{M} b_{klm}\mathbf{v}_l(\theta_{km}) + \mathbf{n}_{kl}, \tag{7}$$

where b_{klm} is a random signal sample with $E[b_{klm}b^*_{klm}] = \gamma_{klm}$. The vector $\mathbf{v}_l(\theta_{km})$ is the $N \times 1$ array response vector for the lth frequency bin to a target whose bearing is θ_{km}. The vector $\mathbf{n}_{kl}$ is an $N \times 1$ vector of spatially colored noise samples with covariance matrix $E[\mathbf{n}_{kl}\mathbf{n}_{kl}^H] = \mathbf{R}(\mathbf{a}_{kl})$. The noise covariance matrix is parameterized by a p-dimensional parameter vector $\mathbf{a}_{kl}$, whose values vary across frequency and snapshots. The signals and noise are assumed to be sample functions of stationary, zero-mean, Gaussian random processes. It is assumed that the observations are collected and processed so that they are independent from snapshot to snapshot and frequency bin to frequency bin.

To handle the unknown colored noise, we define $\mathbf{a}_{kl}$ to be the p-dimensional noise state vector in the lth frequency bin at time k, i.e.

$$\mathbf{a}_{kl} = [a_{kl1} \cdots a_{klp}]^T . \tag{8}$$

We assume the noise states are independent across frequency and independent of the target states. The noise state equation is given by

$$\mathbf{a}_{kl} = \mathbf{a}_{k-1,l} + \boldsymbol{v}_{kl}, \tag{9}$$

where $\boldsymbol{v}_{kl}$ is a zero-mean, white Gaussian noise process with covariance matrix $\mathbf{Q}_a$. Therefore, the pdf of $\mathbf{a}_{kl}$ given $\mathbf{a}_{k-1,l}$ is

$$p(\mathbf{a}_{kl}|\mathbf{a}_{k-1,l}) \sim \mathcal{N}(\mathbf{a}_{k-1,l}, \mathbf{Q}_a) \tag{10}$$

with

$$p(\mathbf{a}_{0l}) \sim \mathcal{N}(\bar{\mathbf{a}}_{0l}, \boldsymbol{\Omega}_{0l}^a). \tag{11}$$

At time k, we denote the collection of target states across all targets as $\mathbf{s}_k$, and the collection of noise states across all frequency bins as $\mathbf{a}_k$. Given $\mathbf{s}_k$ and $\mathbf{a}_k$, the pdf of the array data $\mathbf{z}_{kl}$ is then jointly complex Gaussian,

$$p(\mathbf{z}_{kl}|\mathbf{s}_k, \mathbf{a}_k) \sim \mathcal{CN}(\mathbf{0}, \mathbf{K}_{kl}(\mathbf{s}_k, \mathbf{a}_k)), \tag{12}$$

where

$$\mathbf{K}_{kl}(\mathbf{s}_k, \mathbf{a}_k) = \sum_{m=1}^{M} \gamma_{klm} \mathbf{v}_l(\theta_{km}) \mathbf{v}_l(\theta_{km})^H + \mathbf{R}(\mathbf{a}_{kl}). \tag{13}$$

Let $\mathbf{Z}$, $\mathbf{S}$, and $\mathbf{A}$ denote the collections across snapshots of array data, target states, and noise states, respectively. Assuming there are $\mathcal{K}$ snapshots, the joint pdf of $\mathbf{Z}$, $\mathbf{S}$, and $\mathbf{A}$ is given by

$$\begin{aligned} p(\mathbf{Z}, \mathbf{S}, \mathbf{A}) &= p(\mathbf{Z}|\mathbf{S}, \mathbf{A}) p(\mathbf{S}, \mathbf{A}) \\ &= p(\mathbf{Z}|\mathbf{S}, \mathbf{A}) p(\mathbf{S}) p(\mathbf{A}) \\ &= \left(\prod_{k=1}^{\mathcal{K}} \prod_{l=1}^{L} p(\mathbf{z}_{kl}|\mathbf{s}_k, \mathbf{a}_k) \right) \bullet \\ &\quad \left[\prod_{m=1}^{M} \left(\prod_{k=1}^{\mathcal{K}} p(\mathbf{s}_{km}|\mathbf{s}_{k-1,m}) \right) p(\mathbf{s}_{0m}) \right] \bullet \\ &\quad \left[\prod_{l=1}^{L} \left(\prod_{k=1}^{\mathcal{K}} p(\mathbf{a}_{kl}|\mathbf{a}_{k-1,l}) \right) p(\mathbf{a}_{0l}) \right]. \end{aligned} \tag{14}$$

3. MAP-PF TRACKING ALGORITHM

We wish to estimate the random variables $\mathbf{S}$ (the target tracks) and $\mathbf{A}$ (the noise parameter tracks) from the observations $\mathbf{Z}$. We find the MAP estimate [5] by maximizing $p(\mathbf{Z}, \mathbf{S}, \mathbf{A})$ with respect to $\mathbf{S}$ and $\mathbf{A}$. Following [2]-[4], we introduce a set of auxiliary variables $\boldsymbol{\mu}$ and $\boldsymbol{\alpha}$ and use the penalty method of nonlinear programming to make the problem tractable. The result is a sequential track state update procedure based on the Kalman filter (KF) [6]. After each observation, target and noise parameter estimates are obtained from the array data. First, the noise parameters are assumed known and penalized ML estimates of the source bearings and power spectra are obtained as in [4], except the colored noise covariance matrix is used in place of the white noise covariance matrix in the pre-whitening step. Next, noise parameter estimates are obtained for each frequency bin as in [7]. These estimates are then passed to the KFs as measurements, and the target and noise states are updated. An explicit pseudo-code description of the algorithm is provided in Table 1.

The two-step estimation process is similar to traditional methods, except the processes are coupled via the penalty function. In the parameter estimation step, the predicted target states from the KF are used in the penalty function to guide the estimation process as well as to eliminate the data association step [1] of traditional multitarget tracking approaches. In the track estimation step, penalty function parameters act like the measurement error variance to control the influence of the parameter estimates on the final track estimates.

The penalty function parameters are chosen to be equal to the Cramér-Rao Bound (CRB) for the bearing/power spectrum estimation problem in unknown colored noise. The CRB will be smaller for stronger targets than weaker targets, and will be larger when targets are close together. This provides a natural tightening or relaxation of the penalty function for the different target and noise parameters as the scenario evolves.

Narrow band (single frequency bin) Fisher Information (FI) terms can be obtained by combining the analysis in [8, pp. 961-962] with the analysis in [7] or [9] for colored noise. The bearing FI components are then summed over frequency as in [10], and the wideband CRB is found by inverting the resulting joint FI matrix. The CRB $\mathbf{C}(\mathbf{s}_k, \mathbf{a}_k)$ is a function of the actual target and noise states $\mathbf{s}_k$ and $\mathbf{a}_k$, which are the quantities being estimated. We evaluate the CRB at the predicted state estimates from the Kalman filter. The penalty parameters are then obtained from the appropriate diagonal elements of the estimated wideband CRB.

4. SIMULATION RESULTS

The algorithm was tested on a typical sonar scenario in which a moving platform is towing an $N = 48$-element linear array. The array collects broadband acoustic data in $L = 41$ frequency bins from 200-600 Hz. There are two high signal-to-noise ratio (SNR) targets and one low SNR target. The array platform and targets move in linear, constant velocity tracks in 3D-space, and the platform performs a maneuver and changes direction during the observation interval. A bird's eye view of the scenario in xy-space is shown in Figure 1. In bearing-space where the tracking is performed, the target tracks cross and appear nonlinear, and move across array endfire during the platform maneuver. The bearing, bearing rate, and total target power as seen at the array for each of the targets is shown in Figure 2. The target spectra vary across the frequency band and are shown in Figure 3. The noise is a combination of isotropic environmental noise and spatially and temporally white sensor noise. The noise covariance matrix in the lth frequency bin at time k has the form

$$\mathbf{R}(\mathbf{a}_{kl}) = \sigma_{i,kl}^2 \mathbf{R}_{i,l} + \sigma_{w,kl}^2 \mathbf{I}, \tag{15}$$

where $\mathbf{R}_{i,l}$ is the normalized, known isotropic noise covariance matrix in the lth frequency bin. The noise state has two parameters

$$\mathbf{a}_{kl} = \left[\sigma_{i,kl}^2 \; \sigma_{w,kl}^2\right]^T . \tag{16}$$

Table 1. Sequential MAP-PF algorithm pseudo code.

Initialize $\hat{\mathbf{s}}_{0m} = \bar{\mathbf{s}}_{0m}, \mathbf{P}^{s}_{0|0,m} = \mathbf{\Omega}^{s}_{0m}$; $\hat{\mathbf{a}}_{0l} = \bar{\mathbf{a}}_{0l}, \mathbf{P}^{a}_{0|0,l} = \mathbf{\Omega}^{a}_{0l}$
for $k = 1, \ldots, \mathcal{K}$
  Predict current state
  for $m = 1, \ldots, M$
    $\hat{\mathbf{s}}_{k|k-1,m} = \mathbf{F}\hat{\mathbf{s}}_{k-1,m}$
  end $\{m\}$
  for $l = 1, \ldots, L$
    $\hat{\mathbf{a}}_{k|k-1,l} = \hat{\mathbf{a}}_{k-1,l}$
  end $\{l\}$
  Calculate CRB and update penalty parameters
   $\mathbf{C}_k = \mathbf{C}(\hat{\mathbf{s}}_{k|k-1}, \hat{\mathbf{a}}_{k|k-1})$
   $\xi^{u}_{km} = [\mathbf{C}^{u}_{k}]_{m,m}$
   $\xi^{\gamma l}_{km} = \left[[\mathbf{C}^{\gamma}_{k}]_{m,m}\right]_{l,l}$
   $\mathbf{\Sigma}^{a}_{kl} = [\mathbf{C}^{a}_{k}]_{l,l}$
  for $m = 1, \ldots, M$
   Pre-whiten data
   for $l = 1, \ldots, L$
    $$\mathbf{\Gamma}_{klm} = \sum_{m' \neq m} \left\{ \hat{\gamma}_{k|k-1,l,m'} \mathbf{v}_l(\hat{\theta}_{k|k-1,m'}) \cdot \mathbf{v}^{H}_{l}(\hat{\theta}_{k|k-1,m'}) + \mathbf{R}(\hat{\mathbf{a}}_{k|k-1,l}) \right\}$$
    $\tilde{\mathbf{z}}_{kl} = \mathbf{\Gamma}^{-1/2}_{klm}\mathbf{z}_{kl}$
   end $\{l\}$
   Estimate bearing and power spectrum
   $$\hat{\mu}_{km} = \underset{\mu}{\operatorname{argmax}} \sum_{l=1}^{L} \{\eta_{klm}(\mu) - \ln \eta_{klm}(\mu) - \tfrac{1}{2}(\mu - \hat{\theta}_{k|k-1,m})^T (\xi^{u}_{km})^{-1} (\mu - \hat{\theta}_{k|k-1,m})\}$$
    where $\eta_{klm}(\mu) = \max\left[1, \left|\tilde{\mathbf{z}}^{H}_{kl}\tilde{\mathbf{v}}_l(\mu)\right|^2 / |\tilde{\mathbf{v}}_l(\mu)|^2\right]$
    and $\tilde{\mathbf{v}}_l(\mu) = \mathbf{\Sigma}^{-1/2}_{klm}\mathbf{v}_l(\mu)$
   for $l = 1, \ldots, L$
    $\hat{\rho}_{klm} = (\eta_{klm}(\hat{\mu}_{km}) - 1) / |\tilde{\mathbf{v}}_l(\hat{\mu}_{km})|^2$
   end $\{l\}$
   $\hat{\boldsymbol{\mu}}_{km} = [\hat{\mu}_{km}\ \hat{\rho}_{k1m} \cdots \hat{\rho}_{kLm}]^T$
  end $\{m\}$
  Estimate noise parameters
  for $l = 1, \ldots, L$
   $\hat{\boldsymbol{\alpha}}_{kl} = \underset{\boldsymbol{\alpha}}{\operatorname{argmax}}\ \bar{L}(\boldsymbol{\alpha}, \hat{\boldsymbol{\mu}}_{k1}, \cdots, \hat{\boldsymbol{\mu}}_{kM})$ (from [7])
  end $\{l\}$
  KF target and noise state updates
  $\mathbf{H} = [1\ 0\ 1 \cdots 1]^T$
  for $m = 1, \ldots, M$
   $\mathbf{R}^{s}_{km} = \operatorname{diag}\left(\left[\xi^{u}_{km}\ \xi^{\gamma 1}_{km} \cdots \xi^{\gamma L}_{km}\right]\right)$
   $\mathbf{P}^{s}_{k|k-1,m} = \mathbf{F}\mathbf{P}^{s}_{k-1|k-1,m}\mathbf{F}^T + \mathbf{Q}_s$
   $\mathbf{G}^{s}_{km} = \mathbf{P}^{s}_{k|k-1,m}\mathbf{H}^T\{\mathbf{H}\mathbf{P}^{s}_{k|k-1,m}\mathbf{H}^T + \mathbf{R}^{s}_{km}\}^{-1}$
   $\hat{\mathbf{s}}_{km} = \hat{\mathbf{s}}_{k|k-1,m} + \mathbf{G}^{s}_{km}\{\hat{\boldsymbol{\mu}}_{km} - \mathbf{H}\hat{\mathbf{s}}_{k|k-1,m}\}$
   $\mathbf{P}^{s}_{k|k,m} = \mathbf{P}^{s}_{k|k-1,m} - \mathbf{G}^{s}_{km}\mathbf{H}\mathbf{P}^{s}_{k|k-1,m}$
  end $\{m\}$
  for $l = 1, \ldots, L$
   $\mathbf{R}^{a}_{kl} = \mathbf{\Sigma}^{a}_{kl}$
   $\mathbf{P}^{a}_{k|k-1,l} = \mathbf{P}^{a}_{k-1|k-1,l} + \mathbf{Q}_a$
   $\mathbf{G}^{a}_{kl} = \mathbf{P}^{a}_{k|k-1,l}\{\mathbf{P}^{a}_{k|k-1,l} + \mathbf{R}^{a}_{kl}\}^{-1}$
   $\hat{\mathbf{a}}_{kl} = \hat{\mathbf{a}}_{k|k-1,l} + \mathbf{G}^{a}_{kl}\{\hat{\boldsymbol{\alpha}}_{kl} - \hat{\mathbf{a}}_{k|k-1,l}\}$
   $\mathbf{P}^{a}_{k|k,l} = \mathbf{P}^{a}_{k|k-1,l} - \mathbf{G}^{a}_{kl}\mathbf{P}^{a}_{k|k-1,l}$
  end $\{l\}$
end $\{k\}$

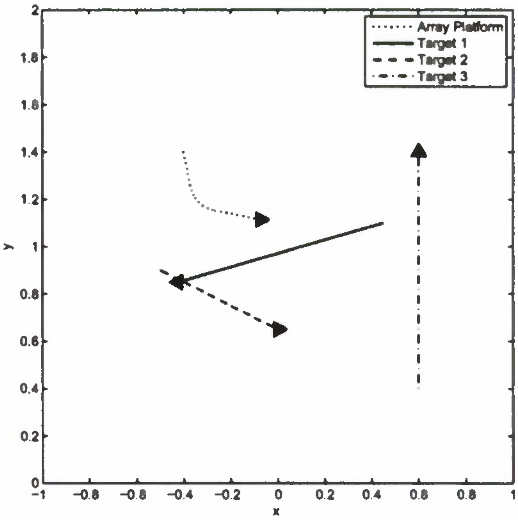

Fig. 1. Bird's eye view of array platform and target trajectories.

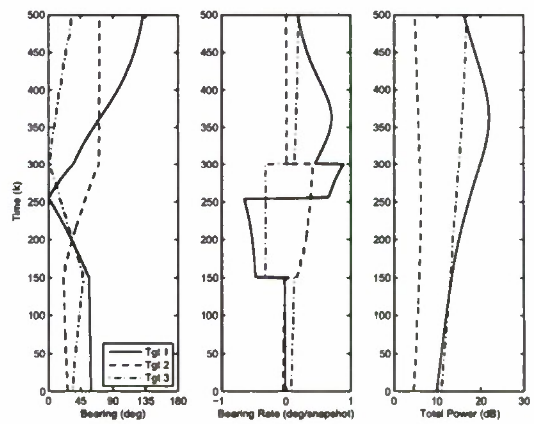

Fig. 2. Bearing, bearing rate, and total power as seen at the array.

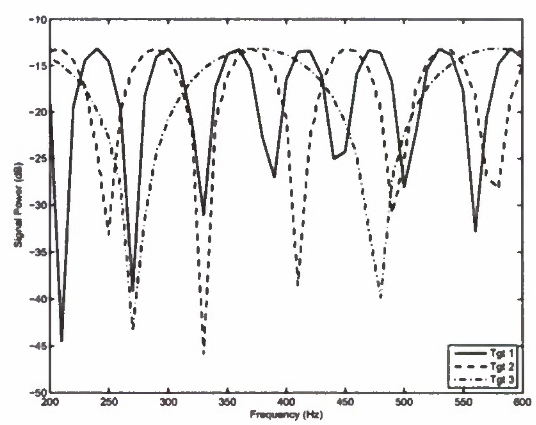

Fig. 3. Normalized target spectra.

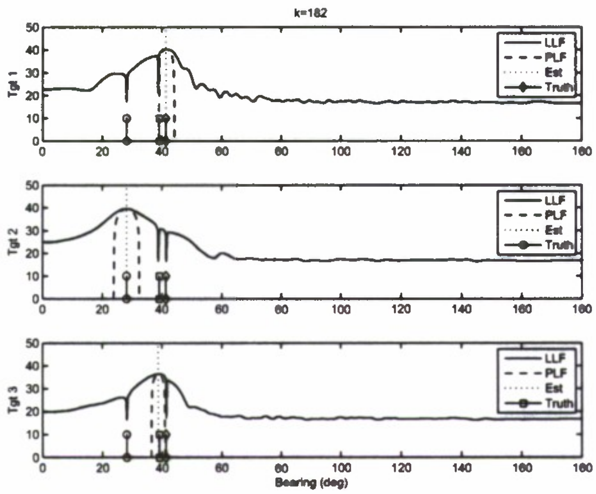

Fig. 4. Whitened likelihood functions at snapshot k=182.

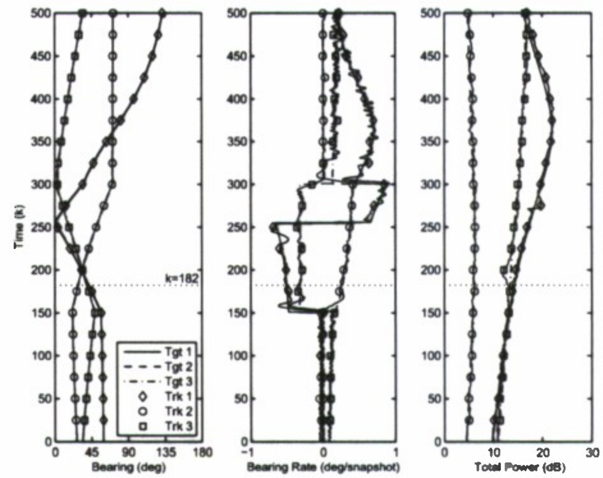

Fig. 5. Bearing, bearing rate and total power tracks overlaid on true values.

During the bearing estimation step, the bearing of each target is found separately by maximizing a penalized, whitened likelihood function, where the other targets are considered to be interference and whitening is performed with respect to the combined noise and interference. The whitened likelihood function for each target used in the MAP-PF tracker at time $k = 182$ is shown in Figure 4. The dashed line is the penalized likelihood function, where values away from the current target state are suppressed. In each whitened likelihood function, other targets and the colored noise are effectively suppressed, and good bearing estimates are obtained.

The bearing, bearing rate, and total power tracks are shown in Figure 5, with excellent results. All three target tracks are well maintained through target crossings and when the targets move through array endfire during the maneuver. Key features of the algorithm that contribute to the performance are using the CRB as the penalty function parameter, and including the target spectra and noise parameters along with the DOA parameters in the state vector that is tracked.

5. SUMMARY

We have developed a technique for tracking the bearing and bearing rate of multiple broadband targets in unknown colored noise based on the MAP-PF tracking approach. A sequential update procedure was developed in which penalized ML estimates of target bearings and spectra, and noise parameters are found and then used as synthetic measurements in a set of Kalman filter trackers in which the target spectra and noise parameters are tracked as well as the bearing and bearing rate. The parameter estimation and tracking steps are coupled via the penalty function, which is critical to the success of the technique. During parameter estimation, it prevents erroneous outlier estimates which can cause the tracker to lose track. During the tracking step, it determines the influence of the parameter estimates on the final track estimates by adaptively adjusting the measurement error variance.

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REPORT DOCUMENTATION PAGE

Form Approved
OMB No. 0704-0188

1. REPORT DATE *(DD-MM-YYYY)*	**2. REPORT TYPE**	**3. DATES COVERED** *(From - To)*
30-09-2009	Final Technical Report	01-01-2008 through 30-09-2009

4. TITLE AND SUBTITLE
MAP-PF Detection and Tracking of Underwater Acoustic Targets

5a. CONTRACT NUMBER

5b. GRANT NUMBER
N00014-08-1-0225

5c. PROGRAM ELEMENT NUMBER

6. AUTHOR(S)
Bell, Kristine L.

5d. PROJECT NUMBER

5e. TASK NUMBER

5f. WORK UNIT NUMBER

7. PERFORMING ORGANIZATION NAME(S) AND ADDRESS(ES)
George Mason University
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Fairfax, VA 22030-4444

8. PERFORMING ORGANIZATION REPORT NUMBER

9. SPONSORING/MONITORING AGENCY NAME(S) AND ADDRESS(ES)
Office of Naval Research
875 North Randolph Street
Arlington, VA 22203-1995

10. SPONSOR/MONITOR'S ACRONYM(S)
ONR

11. SPONSORING/MONITORING AGENCY REPORT NUMBER

12. DISTRIBUTION AVAILABILITY STATEMENT
Approved for Public Release; distribution is Unlimited.

13. SUPPLEMENTARY NOTES

14. ABSTRACT
The goal of this project was to develop an automated detection and tracking algorithm for broadband targets using complex hydrophone data from a passive acoustic array. The algorithm is an integral part of a larger Coherent Automated Multi-Target Tracker (CAMTT) system under development by Metron, Inc. for Detection, Classification, and Localization (DCL) for passive Anti-Submarine Warfare (ASW). The algorithm integrates the Maximum a Posteriori Penalty Function (MAP-PF) tracking algorithm with the Likelihood Ratio Detection and Tracking (LRDT) methodology. The detection and tracking problem is treated as a joint detection and estimation problem and the combined system automatically (1) detects and drops targets, (2) jointly estimates bearing vs. time tracks for all targets, and (3) jointly estimates the received spectrum of these targets. The spectral estimates improve the detection and tracking capability and are used to aid the classification component of the CAMTT system.

15. SUBJECT TERMS
Multitarget tracking, sensor array, detection, localization

16. SECURITY CLASSIFICATION OF:			**17. LIMITATION OF ABSTRACT**	**18. NUMBER OF PAGES**	**19a. NAME OF RESPONSIBLE PERSON**
a. REPORT	**b. ABSTRACT**	**c. THIS PAGE**	UU	12	Kristine L. Bell
U	U	U			**19b. TELEPONE NUMBER** ***(Include area code)*** 703-993-1707