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A Fuse-Before-Track Approach to Target State Estimation Using Passive Acoustic Sensors

Chris Kreucher and Ben Shapo
Integrity Applications Incorporated
900 Victors Way, Suite 220, Ann Arbor MI 48108
ckreucher, bshapo@integrity-apps.com

Abstract*[1] *- This paper describes a Bayesian fuse-before-track approach to detecting and tracking moving targets by fusing data from multiple passive acoustic arrays. We describe a surveillance application, where a collection of fixed location arrays are charged with monitoring a spatial region. Each array provides information only about target bearing relative to the array. The conventional approach is to track bearing at each array and then fuse the tracks to estimate XY position. Instead, in fuse-before-track, we fuse measurements before creating tracks. The fusion is done using a nonlinear filter, where non-thresholded measurements corrupted by non-Gaussian noise which are related non-linearly to the desired target state are combined from all arrays in one tracker. We illustrate the algorithms' efficacy on real, collected at-sea data.

Keywords: Tracking, nonlinear filtering, fuse before track, passive acoustics.

1 Introduction

This paper describes a Bayesian approach to detecting and tracking multiple moving targets by fusing acoustic data from multiple passive arrays. We focus on a surveillance application, where a collection of passive acoustic arrays are charged with monitoring a fixed spatial region to detect and track moving targets in *2D*. This regime presents two important challenges. First, bearing measurements provide incomplete target state information and couple nonlinearly to the target state. Second, because of target distance and acoustic propagation, the received signal levels are not conducive to approaches which declare target detections by thresholding signals before tracking.

Traditional tracking methods [1]–[2] are based on linear (or linearized) filters and use detections (threshold exceedances) as input. These sub-optimal methods are used for a number of good reasons in different applications. First, in some applications (e.g., RADAR) measurements occur at a very high rate, requiring the tracker to execute very quickly. Second, communication channels between the sensor and the processing unit may be limited (and this is exacerbated by the high data rate), meaning that only summary information can be sent to the processor and not the raw measurements. For these reasons, Kalman techniques which execute as a series of matrix operations are very useful.

In the passive sonar surveillance scenario, these constraints are relaxed. First, measurements are aggregated at a low rate (on the order of 1 Hertz), and the data is a vector of only a small number of bearing cells. Second, in our application, arrays are cabled to a processing center, allowing raw measurements to be transmitted faithfully. Finally, we can exploit processing capabilities that permit more computation than Kalman approaches require. Given the nonlinear measurement modality and need for an approach that uses non-thresholded data, we advocate a nonlinear track-before-detect approach to accurately model the measurement to target state coupling and operate with raw data.

In the multisensor case, conventional methods [3]-[5] develop tracks at each sensor, associate tracks between nodes and then fuse. The track-and-then-fuse approach is taken for many of the same reasons cited earlier. In contrast, our application has the bandwidth and compute power to allow data fusion from multiple nodes before tracking. Combined with low signal levels and nonlinear measurement to target coupling, this again advocates for measurement level nonlinear filtering. This fuse-before-track approach increases algorithm performance by making hard decisions about target existence and state only after all of the data has been aggregated.

Related approaches to multitarget tracking have been studied in the literature. The "PDF Tracker" work by Bethel [6], the "Unified Data Fusion" work of Stone, [7], and the "JMPD" approach of Kastella [8], and other related work [9]-[13] are all examples of Bayesian approaches which do not require thresholding, explicit measurement to track association, or linear models and Gaussian statistics. In particular, Bethel and Shapo [14] apply these ideas to single node passive acoustic tracking.

Our work differs from past efforts as it uses Bayesian filtering for detection and tracking in a *2D (X/Y)* state space using non-thresholded measurements from multiple passive acoustic arrays. The paper proceeds as follows. Section 2 describes the multisensor passive sonar setting and our application. Section 3 describes the Bayesian fuse-

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before-track approach and our implementation, which is based on a novel combination of discrete grid detection and particle filter tracking methods. Section 4 describes the multitarget generalization and our implementation. Section 5 illustrates the value of the approach on real collected passive acoustic data from a sea test. Finally, Section 6 concludes.

2 Multisensor Passive Sonar

The application we focus on is region surveillance using multiple passive acoustic arrays. This section describes the problem and develops a statistical signal model for the energy received by the arrays.

2.1 The Surveillance Problem

A region of large spatial extent is to be monitored by a collection of fixed passive acoustic arrays. There are I hydrophone arrays and the position of the center element is denoted $\{x_{(i)}, y_{(i)}\}$, for array $i=\{1, \ldots, I\}$. The surveillance region is defined by its extent $\{x^{min}; x^{max}; y^{min}; y^{max}\}$. Ideally, the arrays are located and orientated conveniently with respect to the surveillance region, e.g., along the boundaries and at right angles to each other.

Undersea and surface targets emit acoustic energy which is received at the passive arrays. We are interested in detecting and tracking *2D* position and *2D* velocity of the targets from this received energy. Received energy can be used to estimate target bearing relative to each array. For well separated arrays (with respect to target range) this allows triangulation to compute target range and *2D* position. Tracking over time results in variance reduction. Our application involves low energy targets not amenable to detect before track (i.e., thresholding) approaches.

2.2 The sensor model

Each of the I physically separated arrays consists of M hydrophones. Energy impinges each element m in array i from acoustic sources. The time series of received energy is recorded as $s_{(i),m}(t)$, which is used to generate estimates of target energy as a function of bearing from the array.

Processing is typically done according to delay-and-sum beamforming method [15]. The spatial separation of individual elements causes propagation times from a target source to each element to differ. Denote the propagation time delay from a source at bearing θ to hydrophone m by $\Psi_m(\theta)$. For a linear array with elements separated by Δ, $\Psi_m(\theta)=m\Delta\cos(\theta)/c$. For candidate arrival angle θ, the beamformer imparts appropriate delays at each element to force signals arriving from that direction to add coherently, i.e., the coherent sum at array i for arrival direction θ as a function of time is

$$S_{(i),\theta}(t) = \sum_{m=1}^{M} s_{(i),m}\left(t - \Psi_m(\theta)\right) \quad (1)$$

Computation is typically done in the frequency domain with short (on the order of 1-second) time blocks of data as

$$\tilde{S}_{(i),\theta}(f) = \sum_{m=1}^{M} \tilde{s}_{(i),m}(f) e^{-j2\pi f \Psi_m(\theta)} \quad (2)$$

In practice, the beamformer proposes a set of candidate arrival directions (beams) numbered $j=\{1,\ldots,J\}$. For each beam, energy is non-coherently aggregated across frequency yielding what we refer to as the measurement from array i at beam j, $z_{(i),j}$.

Under certain conditions on element bandwidth and snapshot time, the beamformer value at individual frequencies are independent random Gaussian variables [16]. Therefore, we model the statistics of $z_{(i),j}$ as such. The parameters of the Gaussian random variable depend on whether or not there is a target at direction θ_j.

3 Single Target Tracking

This section describes Bayesian single target detection and tracking using multiple passive arrays. For the purposes of this section, we assume there is at most one target present. This assumption is removed in Section 4.

3.1 Notation

Denote the state of a target at time k as x^k, which for this work refers to the targets' $2D$ position and velocity, i.e., $x^k = [x\ x'\ y\ y']$. Additionally, let H^k_0 denote the hypothesis that no target is present at time k, and let H^k_1 denote the hypothesis that a target is present.

The following notation describes the measurements: $z^k_{(i),j}$ continues to denote the measurement received by array i in bearing beam j at time k; $z^k_{(i)}$ denotes the vector of all measurements received by i at k, i.e., $z^k_{(i)} = \{z^k_{(i),1}, \ldots, z^k_{(i),J}\}$; z^k denotes measurements received by all arrays at time k, i.e., $z^k = \{z^k_{(1)},\ldots, z^k_{(I)}\}$; finally, Z^k denotes the collection of all measurements received by all arrays up to and including time k, i.e., $Z^k = \{z^1,\ldots, z^k\}$.

3.2 Approach

The Bayesian method is to estimate the joint probability a target is present (H^k_1 is true) at each state x^k given the measurements. Mathematically, this means we wish to estimate the hybrid continuous-discrete probability density function (PDF)

$$p(x^k, H_1^k \mid Z^k) \quad (3)$$

for all x^k, as well as the discrete probability

$$p(H_0^k \mid Z^k) = 1 - \int p(x^k, H_1^k \mid Z^k) dx^k \quad (4)$$

Notice we can write

$$p(x^k, H_1^k \mid Z^k) = p(H_1^k \mid Z^k) p(x^k \mid H_1^k, Z^k) \quad (5)$$

i.e., the density is the product of the *target present probability* $p(H_1^k|Z^k)$ and the *target state probability* $p(x^k|H_1^k,Z^k)$. The problem is thus treated as the separate (but coupled) tasks of estimating the target present probability and the estimating target state probability.

In the Bayesian approach, we assume a prior probability (perhaps completely uninformative), and generate a recursion that relates probabilities at time *k-1* to those at time *k*. This is done in two steps, as in the Kalman Filter: the temporal update, which predicts the distribution forward in time, and the measurement update which corrects the prediction given new received measurements.

3.3 Time Update

The first step in recursive Bayesian filtering is to predict the relevant probability distributions forward in time using statistical models on target kinematics. The temporal update of the target present density is

$$p(H_1^k \mid Z^{k-1}) = \sum_{i=0}^{1} p(H_1^k \mid Z^{k-1}, H_i^{k-1}) p(H_i^{k-1} \mid Z^{k-1}) \quad (6)$$

where the quantity $p(H_1^k|Z^{k-1},H_i^{k-1})$ is a statistical model to be specified by studying the target arrival properties.

Similarly, the time-predicted target state density is based on a model of how targets move

$$\begin{aligned} p(x^k \mid H_1^k, Z^{k-1}) &= \left(\frac{p(H_1^{k-1} \mid Z^{k-1})}{p(H_1^k \mid Z^{k-1})} \right) \times \\ &\int p(x^k, H_1^k \mid x^{k-1}, H_1^{k-1}) p(x^{k-1} \mid H_1^{k-1}, Z^{k-1}) dx^{k-1} \end{aligned} \quad (7)$$

where the density $p(x^k,H_1^k| x^{k-1},H_1^{k-1})$ is a model on target kinematics specified in the particular implementation. The normalizing term does not need to be evaluated as the density can be forced to integrate to 1. In this work, we assume the nearly constant velocity (NCV) model for the target. Other models, or even multiple models are admissible under the Bayesian framework [17].

3.4 Measurement Update

The second step in Bayesian filtering is to accommodate measured data into the probability estimate. The measured data comes into the picture through the likelihood ratio

$$\lambda(z^k \mid H_1^k, x^k) \equiv \frac{p(z^k \mid H_1^k, x^k)}{p(z^k \mid H_0^k)} \quad (8)$$

where the functional form of $\lambda(z^k|H_1^k,x^k)$ is a model specified by sensor physics. Recall measurements are not just threshold exceedances, but rather a vector of beamformer outputs from all sensors at all beams.

With this definition, the target present and target absent probabilities are measurement updated using the law of total probability and Bayes rule, yielding

$$\begin{aligned} p(H_1^k \mid Z^k) &= p(H_1^k \mid Z^{k-1}) \left(\frac{p(z^k \mid H_0^k)}{p(z^k \mid Z^{k-1})} \right) \times \\ &\int \lambda(z^k \mid H_1^k, x^k) p(x^k \mid H_1^k, Z_1^k) dx^k \end{aligned} \quad (9)$$

These express the current target present and absent hypothesis probabilities in terms of the target present, target absent, and target state probabilities predicted from the previous time step and the conditional likelihood of incoming measurements. The normalization constant does not need to be computed since $p(H_1^k|Z^k)+p(H_0^k|Z^k)=1$.

The target state probability is updated similarly,

$$\begin{aligned} &p(x^k \mid H_1^k, Z^k) = \\ &p(x^k \mid H_1^k, Z^{k-1}) \lambda(z^k \mid x^k, H_1^k) \left(\frac{p(z^k \mid H_0^k)}{p(z^k \mid H_1^k, Z^{k-1})} \right) \end{aligned} \quad (10)$$

Again, constants independent of x^k do not need to be computed. In the multisensor passive array application, the likelihood ratio $\lambda(z^k|H_1^k,x^k)$ is computed as follows. We assume measurements from different arrays are independent conditioned on the target state, i.e.

$$p(z^k \mid x^k, H_1^k) = \prod_{i=1}^{I} p(z_{(i)}^k \mid x^k, H_1^k) \quad (11)$$

and the measurements a particular array takes in each beam are independent conditioned on the target state, i.e.,

$$p(z_{(i)}^k \mid x^k, H_1^k) = \prod_{j=1}^{J} p(z_{(i),j}^k \mid x^k, H_1^k) \quad (12)$$

For each array i, the state x^k corresponds to a bearing, which maps to beam $\hat{j}_{(i)}$ (here we ignore extended target effects such as sidelobes). With this notation, we write

$$\begin{aligned} p(z_{(i)}^k \mid x^k, H_1^k) &= p_1\left(z_{(i),\hat{j}(i)}^k\right) \prod_{\substack{j=1 \\ j \neq \hat{j}(i)}}^{J} p_0(z_{(i),j}^k) \\ &= \frac{p_1\left(z_{(i),\hat{j}(i)}^k\right)}{p_0\left(z_{(i),\hat{j}(i)}^k\right)} \prod_{j=1}^{J} p_0(z_{(i),j}^k) \end{aligned} \quad (13)$$

where $p_1(z)$ is the probability density on received energy in beams where the target exists (the target present density) and $p_0(z)$ is the probability density on the received energy in beams where no targets exist (the target absent density).

Therefore, the likelihood ratio with multiple arrays is

$$\lambda(z^k \mid x^k, H_1^k) = \prod_{i=1}^{I} \frac{p_1\left(z_{(i),\hat{j}(i)}^k\right)}{p_0\left(z_{(i),\hat{j}(i)}^k\right)} \quad (14)$$

3.5 Implementation

If the probability density of interest is well approximated by a Gaussian or sum-of-Gaussians, techniques such as the Extended Kalman Filter or Gaussian Sum Filter are preferred. In the multisensor passive acoustic case, however, the density is poorly approximated by such parameterizations. We instead rely on two nonlinear filtering approaches, the discrete grid and particle filter.

Discrete grid details [17][18] are briefly reviewed here:

1) Density Representation: The PDF of x is discretized onto a 4*D* grid (corresponding to the four dimensional state vector x^k) of *Nx***Nx'***Ny***Ny'* cells. This method is appropriate here, given we wish to perform surveillance over a region of fixed spatial extent.

2) Kinematic and Measurement Update: The NCV model we adopt leads to the Fokker-Plank Equation [18][20]

$$\frac{\partial p}{\partial t} = -\dot{x}\frac{\partial p}{\partial x} - \dot{y}\frac{\partial p}{\partial y} + \frac{\sigma_{\dot{x}}^2}{2}\frac{\partial^2 p}{\partial \dot{x}^2} + \frac{\sigma_{\dot{y}}^2}{2}\frac{\partial^2 p}{\partial \dot{y}^2} \quad (15)$$

Computationally, we discretize the probability onto a grid and the update is computed with a backward Euler method. This approach has nice stability properties in both δt and δx. We use Thomas' algorithm as a fast tridiagonal solver giving computation linear in the number of cells [19][21]. The temporal evolution of the target present probability assumes constant target arrival/removal. The discrete grid probability is updated with measurements by pointwise multiplication of each cell in the discrete representation by the corresponding data likelihood ratio.

An alternative method of representing $p(x^k|H_1^{k-1},Z^k)$ is via a particle filter. Particle filtering is an adaptive grid method of representing and numerically updating a PDF temporally and with measurements [22]. The details are briefly reviewed here.

1) Density Representation: In a single target particle filter, the density of interest is approximated by a set of *Npart* weighted samples (particles):

$$p(x \mid z) \approx \sum_{p=1}^{N_{part}} w_p \delta_D (x - x_p) \tag{16}$$

where δ_D represents the usual Dirac delta function.

2) Kinematic and Measurement Updates: The model update and the measurement update are simulated by the following three step recursion. First, the particle locations at time k are generated using the particle locations x_p at time k-1 and the current measurements z^k by sampling from an importance density, denoted $q(x^k|x^{k-1},z^k)$. The design of the importance density is a well studied area, as the choice of the importance density can have a dramatic effect of the efficiency of the particle filter algorithm.

Particle weights are updated according to the weight equation, which involves the likelihood, the kinematic model, and the importance density [22].

$$w_p^k = w_p^{k-1} \frac{p(z^k \mid x_p^k) p(x_p^k \mid x_p^{k-1})}{q(x_p^k \mid x_p^{k-1}, z^k)} \tag{17}$$

When using the kinematic prior as the importance density, the weight reduces to $w_p^k = w_p^{k-1} * p(z^k|x_p^k)$. Finally, a resampling step is used to prevent particle degeneracy.

We represented the region by a discrete grid at onset. As this has been cast as a hypothesis test between the target present and absent hypotheses, we declare a target present when $p(H_1^k|Z^k)$ exceeds a threshold in accordance with the standard Neyman-Pearson approach. Once the target present probability exceeds a threshold, indicating the density is well localized, the approximation is transitioned to a particle representation by sampling particles from the $Nx*Nx'*Ny*Ny'$ discrete grid. This hybrid approach allows good performance when the PDF is broad (at onset) as well as good tracking performance once a target is found.

4 Multitarget Tracking

4.1 Approach

In multitarget detection and tracking, we wish to estimate the hybrid continuous-discrete density

$$p(x_1^k, ..., x_T^k, T^k \mid Z^k) \tag{18}$$

for all T and $x_1, \ldots, x_T$, where T is the number of targets (T = 0, 1, …) and $x_1, \ldots, x_T$ are the states of the individual targets. For notational convenience, we define

$$X = [x_1^k, ..., x_T^k] \tag{19}$$

i.e., X denotes the multitarget state vector, where the cardinality will be clear by context.

As in the single target case, the joint multitarget density can be expressed as the product of the target number density and the target state density as

$$p(X^k, T^k \mid Z^k) = p(T^k \mid Z^k) p(X^k \mid T^k, Z^k) \tag{20}$$

The target number temporal update is given by

$$p(T^k \mid Z^{k-1}) = \sum_{T^{k-1}=0}^{\infty} p(T^k \mid T^{k-1}, Z^{k-1}) p(T^{k-1} \mid Z^{k-1}) \tag{21}$$

And the target state temporal update can be expressed

$$\begin{aligned} p(X^k \mid T^k, Z^{k-1}) = \left(\frac{p(T^{k-1} \mid Z^{k-1})}{p(T^k \mid Z^{k-1})} \right) \times \\ \sum_{T^{k-1}} \int p(X^k, T^k \mid X^{k-1}, T^{k-1}) p(X^{k-1} \mid T^{k-1}, Z^{k-1}) dX^{k-1} \end{aligned} \tag{22}$$

where $p(X^k,T^k| X^{k-1},T^{k-1})$ is a statistical model on target kinematics and the integral over X^{k-1} is to be interpreted as performing T integrations over the domain of x.

The recursive update of the target number probability is given in a form analogous to the single target case as

$$\begin{aligned} p(T^k \mid Z^k) = p(T^k \mid Z^{k-1}) \left(\frac{p(z^k \mid T^k = 0)}{p(z^k \mid Z^{k-1})} \right) \times \\ \int \lambda(z^k \mid X^k, T^k) p(X^k \mid T^k, Z^{k-1}) dX^k \end{aligned} \tag{23}$$

where the constant term does not need to be computed since the probability mass function sums to 1. Furthermore, in extension of the definition given earlier, we define the multitarget likelihood ratio as

$$\lambda(z^k \mid X^k, T^k) \equiv \left(\frac{p(z^k \mid X^k, T^k)}{p(z^k \mid T^k = 0)} \right) \tag{24}$$

In multiple target situations, it is possible more than one target project into the same bearing cell. T targets with states $x_1, \ldots, x_T$ will project into bearing cells $\hat{j}_{1,(i)}, \ldots, \hat{j}_{T,(i)}$. Let S denote the set of all beams the hypothesized targets occupy, i.e., $S = \hat{j}_{1,(i)} U\, \hat{j}_{2,(i)}\, U \ldots U\, \hat{j}_{T,(i)}$. Let $O(\hat{j})$ denote the occupation number (i.e., the number of targets that are hypothesized to exist in cell $\hat{j}$). Then we have

$$p(z_{(i)}^k \mid x_1^k, ..., x_T^k, H_1^k, ..., H_T^k) \propto \prod_{\hat{j} \in S} \frac{p_{O\hat{j}(i)}(z_{(i),\hat{j}(i)}^k)}{p_0(z_{(i),\hat{j}(i)}^k)} \tag{25}$$

The target state update is then written as

$$\begin{aligned} p(X^k \mid T^k, Z^k) = \left(\frac{p(z^k \mid T^k = 0)}{p(z^k \mid T^k, Z^{k-1})} \right) \times \\ p(X^k \mid T^k, Z^{k-1}) \lambda(z^k \mid X^k, T^k) \end{aligned} \tag{26}$$

where the constant term does not need to be computed since the PDF integrates to 1.

4.2 Implementation

The dimension of the state space required to directly estimate the joint multitarget probability grows exponentially with the number of targets. This "curse of dimensionality" makes it impractical to directly estimate the full multitarget density when there are more than 1 or 2 targets in the surveillance region of interest [23][24].

This is addressed in the literature in two ways. In typical Kalman multitarget methods [1], [2] the approach is to run a bank of single target trackers (one for each target) and use data association to determine which measurements go into each filter. This assumes input data is thresholded and can be treated by linear or linearized methods. Other approaches [24]–[26] fully model the joint multitarget density, but use procedures which amount to factoring the joint density into a product of smaller dimensionality densities. Sophisticated approaches do this adaptively at each time step, selecting which targets are "close" and performing more intense processing to account for the coupling of measurements on these targets.

We take a similar approach which adaptively determines which targets are close in sensor space and treat these pairs (or triplets, etc.) jointly. In this case, the individual particle filter approximation to the multiple targets is combined into a single multiple target density and this density is time and measurement updated jointly. The main effect is that multitarget sensor modeling now becomes relevant. In particular, the measurement likelihood for a pair of targets where both targets project into the same beam takes a different functional form from when they project into different beams. In practice, this high fidelity modeling prevents track coalescence onto the stronger track and/or dropping of the weaker track.

5 Experimental Results

This section illustrates the proposed technique on a set of real collected passive acoustic data. The Shallow Water Array Performance (SWAP) array is located off the eastern cost of Florida near Ft. Lauderdale. The SWAP array has 4 linear segments, each of which are approximately 200m long and contain 125 hydrophones. The hydrophone locations are known with high accuracy. A small number of the hydrophones did not operate during the collection, but these elements are known and have been excluded from the beamforming process. The 4 segments are labeled 1, 2, 3, and 4 with segment 1 closest to shore (westernmost) and segment 4 farthest from shore (easternmost). The elements in each segment run approximately west-to-east. Segment 1 is oriented approximately 0:6 degrees (relative to east), and Segment 4 is oriented approximately -0.4 degrees. All hydrophones are approximately 265m deep.

The environment has heavy commercial and recreational traffic. The experiments shown here use data collected by segments 1 and 4 on 9 August 2007 starting at 1115 local time. The data was recorded as part of a four day sea test. We selected a time segment with two targets of opportunity. This data includes a challenging situation where the two targets cross in sensor space and therefore the adaptive algorithm must temporarily treat the joint target state to prevent target coalescence or removal.

The raw sensor data was prepared according to the process in Section 2. This is briefly summarized as follows. Each hydrophone sampled and recorded raw acoustic data. This raw data was decoded and interpolated to obtain 1000 samples per second at equal intervals, time synchronized at all hydrophones. A conventional beamformer, followed by integration over frequency, was used to produce bearing time records at 1Hz. BTRs describe the received energy versus bearing and time, and constitute the input to the tracker. This is consistent with Navy standard processing and is representative of the input surface a fielded tracker will see. Figure 1 shows the input data surfaces.

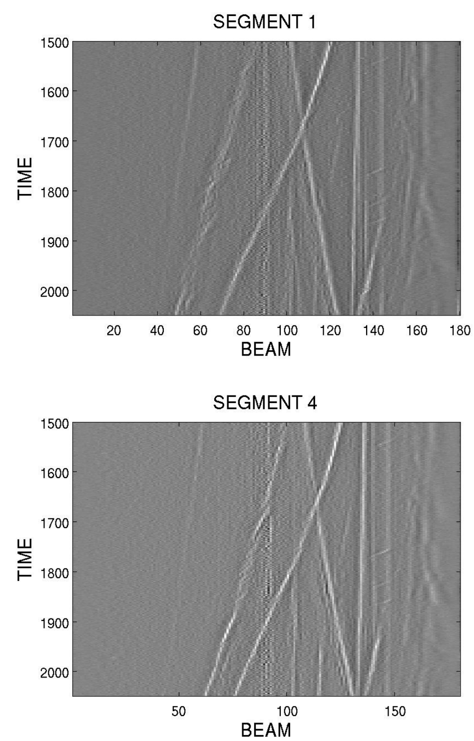

Figure 1. The input surfaces to the tracker.

The surveillance region is defined as the 5km x 5km region shown in Figure 2. It was implemented using a $2x2$ set of overlapping discrete grids. Each discrete grid is fixed spatially and is made up of $51x13x51x13$ cells with spatial and velocity resolution of 50m and 2m/s, respectively. Each single target detector is measurement and time updated according to the method of Section 3. When a detectors' estimate of the target present probability $p(H_1|Z)$ exceeds a threshold, the target is transitioned to a particle filter representation according to the description in Section 3. Note that the figure also indicates the locations of the two sensor arrays near the bottom center, with the labels "SEGMENT 1" and "SEGMENT 4," respectively.

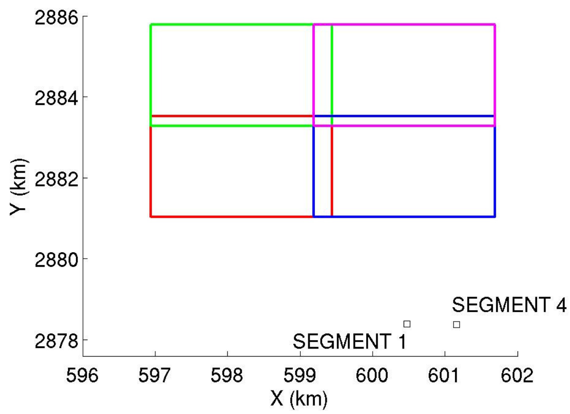

Figure 2. The surveillance region.

Here we illustrate the benefit offered by our target space tracking method (XY) over traditional track-fusion methods, which create tracks on individual data surfaces and then fuse the results. The track-fusion approach proceeds as follows. First, a tracker is executed on each BTR separately, which produces a bearing track for each sensor. The tracker enforces kinematics on the individual data surfaces, rather than the XY space in which the target actually operates. Next, the tracks from each BTR are associated between sensors and the targets' XY position are computed using trigonometry. We have simulated the track-fusion method here by hand-truthing the traces in the BTR as shown in Figure 3. We have also hand-associated the tracks. This non-casual hand-truthing and hand-association is an upper bound of the potential performance of an automated track-fusion method.

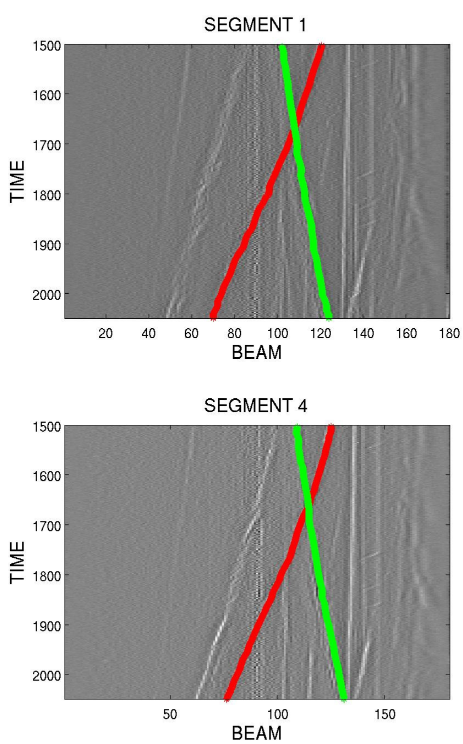

Figure 3. Hand-truthed tracks on the input BTRs.

Whether done by hand or with an automated tracker that operates independently at each node, this approach does not take into account kinematic models operating in XY space, but instead only enforces kinematics on the bearings. As a consequence, the XY tracks associated with this hand truthing are non-physical in the XY domain. Figure 4 shows the noisy tracks that result from tracking in bearing and then associating the tracks, characterized by non-physical jumps in X and Y.

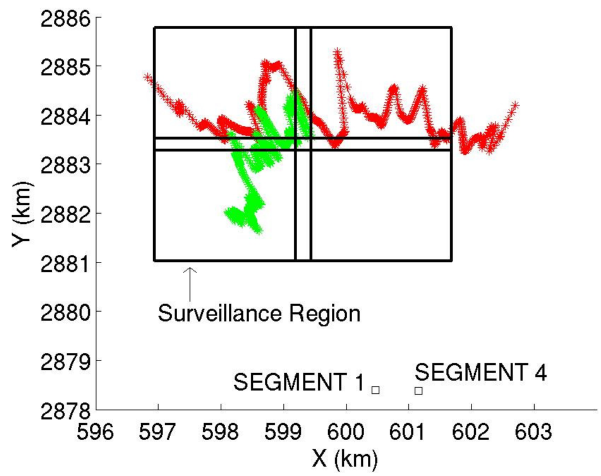

Figure 4. Track-fusion estimated XY positions.

In contrast, the proposed tracker constructs a PDF by combining XY kinematic models and measurements. The complete nonparametric target PDF it estimates was used to produce XY point estimates and covariance ellipses for display purposes in Figure 5. Targets were automatically detected and initiated according to the methodology of Section 3. Since this was a controlled experiment, we also have latitude and longitude truth sources from the Automatic Identification System (AIS) for some of the contacts in the collection. One of the targets in our surveillance region during the period of interest was an AIS equipped vessel, and its truth track (dashed gray line) is shown in the plot for comparison to the tracker output. The tracks are color coded to distinguish the traces.

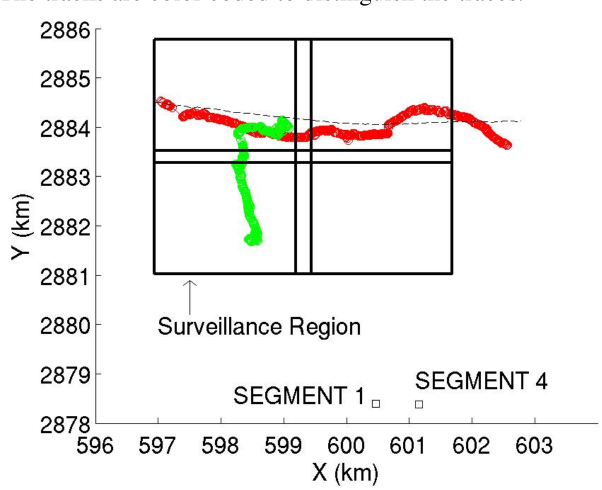

Figure 5. Fuse-before-track estimated XY positions.

A comparison of the track fusion results (Figure 4) with the fuse-before-track result (Figure 5), shows that using physical kinematic models in the target's natural coordinate system provides significant value.

Figure 6 shows a track and the tracker estimated covariance ellipses at equally spaced time steps. The main axis of uncertainty is in range direction with respect to the (bearings-only) sensors. For example, when the target is northwest of the sensors, uncertainty is mainly in the north-west direction. Likewise, when the target is northeast of the sensors, uncertainty is oriented in the north-east direction. Furthermore, as time progresses (the target moves left-to-right), the tracker covariance ellipse tightens.

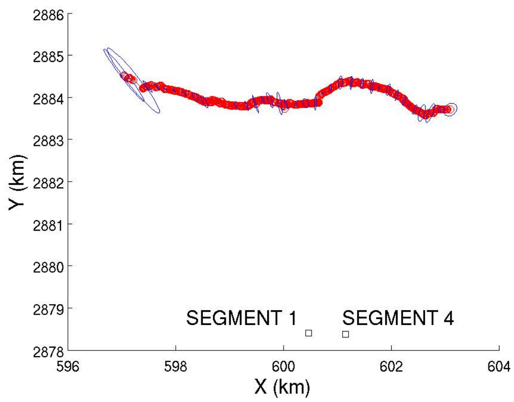

Figure 6. Fuse-before-track estimated XY positions of a track, with associated covariance ellipses.

Figure 7 shows the tracker estimates projected back onto the two original input surfaces.

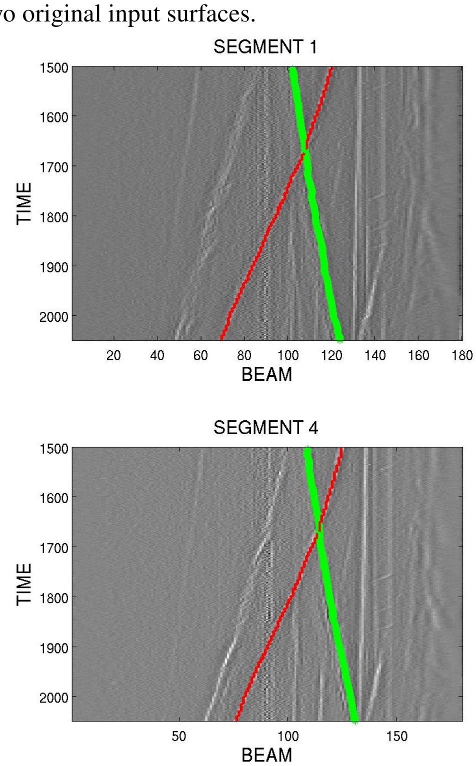

Figure 7. The fuse-before-track estimates projected back onto the input surfaces.

Note the tracker operates in XY but these XY tracks can be reprojected onto the input surfaces to show algorithm efficacy, as is done here. Some contacts visible in the BTRs do not have associated tracks. This is because the XY locations of those contacts are outside the surveillance region.

6 Conclusion

This paper has presented a Bayesian fuse-before-track approach for detecting and tracking multiple moving targets by fusing data from multiple passive acoustic arrays. The method uses a nonlinear filter, where non-thresholded measurements corrupted by non-Gaussian noise which are related non-linearly to the desired target state are synthesized optimally. We have illustrated the of algorithm on real, collected at-sea data and compared its performance to a track-fusion approach.

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