

ADVANCES IN ACTIVE SONAR TRACKING

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ABSTRACT

This paper provides an overview of an on-going research effort at the NATO Undersea Research Centre. In particular, we focus on the automatic tracking component of the active sonar signal and information processing chain that takes hydrophone data from multiple receivers and generates a unified surveillance picture. Novel features of our tracking approach include the determination and exploitation of statistically consistent contact measurement covariances, the use of a computationally efficient multi-hypothesis data association algorithm, and the instantiation of both centralized and distributed data fusion schemes to optimise tracking performance.

1. UNDERSEA SURVEILLANCE

Due to the quiet nature of current threat submarines as well as the complexity of shallow-water acoustic environments, surveillance based on active sonar technology has received considerable attention in recent years. The use of surveillance networks with a number of source-receiver detection nodes provides a powerful framework for effective surveillance, as these provide multiple detection opportunities and robustness against unfavourable source-target-receiver geometries.

A number of requirements exist in order to explore the potential of active sonar surveillance networks. The first is the availability of prototype systems to acquire test data. Multi-static sonar surveillance scenarios are generally based on one of two system concepts: mobile platforms (suitable for expeditionary tasks), and fixed/drifted deployed fields (suitable for surveillance of ports, harbors, choke points, etc.).

Both system concepts are under evaluation at the NATO Undersea Research Centre. An example of the first system concept is illustrated in figure 1, which shows the monostatic and bistatic source-receiver combinations that were available in a recent sea trial. Figure 2 illustrates the second system concept: deployable sonar equipment used in a moored configuration.

A second requirement is the availability of signal and information processing technology that produces manageable sets of contacts for each ping-source-receiver triple, contacts that can be exchanged through radio or satellite links for further

exploitation at a fusion center. Figure 3 illustrates a notional signal and information processing sequence. Further details on the processing chain used at NURC, as well as a discussion of recent advances, are provided in [1].

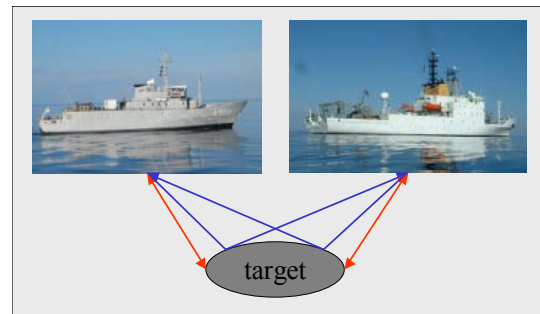


Figure 1 - An example of a mobile surveillance network

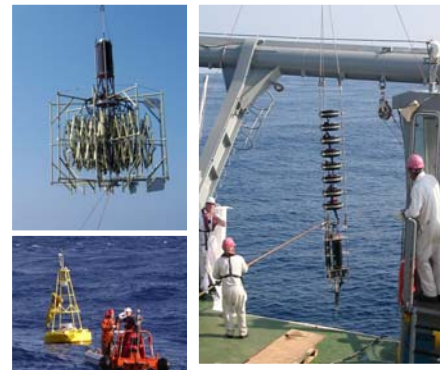


Figure 2 - An example of a fixed surveillance network

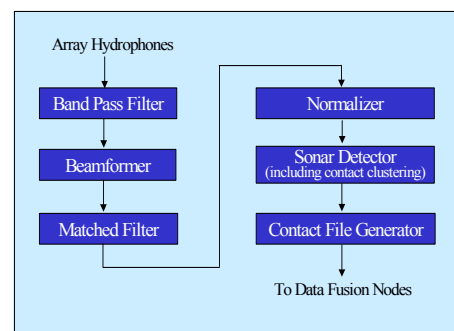


Figure 3 - An example of an active sonar processing chain

A third requirement for undersea surveillance, which is particularly critical in multi-sensor settings with a correspondingly sustained data rate, is the availability of an automated fusion and tracking capability. Typically, active sonar processing will produce hundreds of object-like contacts per ping-source-receiver triple. This may well lead to thousands of contacts per minute in a typical surveillance network. It is critical to extract from this voluminous data a small, manageable number of target-like tracks that are provided to a sonar operator for further analysis.

This third requirement has been the focus of an ongoing research effort at NURC that was initiated in early 2002. This effort has leveraged the availability of mobile-platform and deployable-fields datasets and the corresponding contact-level data files. A comprehensive discussion of system-level issues associated with multistatic operations and data processing is provided in [2].

This paper is organized as follows. In section 2, we briefly identify the fundamental approaches to tracking and fusion that exists in the literature. In section 3, we summarize our algorithmic approach and identify key research milestones. Section 4 describes a new target kinematic model that we will leverage in future tracker evaluations. Section 5 identifies our current research directions.

2. TARGET TRACKING

Numerous approaches to multi-sensor fusion and tracking are documented in the literature. Most of these follow one of two basic paradigms: contact-based, Kalman filter based approaches [3-5], and unified detection and tracking approaches [6]. Each of the well-known references that we indicate exhibits the particular bias of the authors for a distinct approach to the tracking problem:

- *Probabilistic data association* (PDA): scan-based, with soft data association [3];
- *Probabilistic multi-hypothesis tracking* (PMHT): batch-processing based with soft data association [4];
- *Multi-hypothesis tracking* (MHT): multi-scan based, with hard data association [5];
- *Bayesian tracking*: likelihood-surface based tracking, with matched-filtered or contact-level inputs [6].

Each approach has spawned its own literature, with various enhancements including the Interacting Multiple Model (IMM) filter, particle filters, the use of amplitude and classification information, etc. A recent multi-laboratory benchmarking effort for active sonar trackers is described in [7]. Generally, MHT approaches will outperform other scan-based approaches, albeit with a larger computational burden.

3. RECENT ADVANCES

Over the past several years, the NATO Undersea Research Centre has investigated multi-sensor tracking as part of its research into multistatic active sonar. Our approach to target

tracking is contact-based, as in [3-5]. This choice is motivated by the relative maturity of these approaches relative to unified detection and tracking approaches. In addition, in network-centric operations, the limited bandwidth requirements associated with the exchange of contact data are highly attractive. Lastly, in the face of possible data registration or alignment errors, contact-based fusion is more robust than lower-level fusion approaches.

Our target-tracking research has achieved the following milestones. We will briefly discuss each of these in turn.

- Development of statistically consistent measurement models for target contact data, to account for a variety of system and measurement errors [8]; application of these models to an analysis of intra-ping simplifying approximations [9] and to sensor placement [10];
- Development of multistatic capabilities of increasing complexity and performance, with nearest-neighbor [11], multi-hypothesis [12], and distributed multi-hypothesis [13] data association;
- Development of centralized and distributed tracker performance models that account for target fading effects [13].

3.1 Contact Localization

It is critical for effective fusion and tracking to have a statistically consistent characterization of the accuracy of contact data. Our analytical expressions for measurement covariance matrices are a function of assumed standard deviations for errors in source and receiver locations, speed of sound, array heading, and contact-specific timing and bearing information. These expressions are valid for bistatic and monostatic geometries or with multiple source-receiver detections, they are well matched to true error statistics for modest-sized errors, and they generalize the localization analysis that have appeared in the literature [14-17].

Figure 4 illustrates the localization accuracy (square root of trace of measurement covariance) achieved for all possible target locations in a region of interest, given two source-receiver bistatic detectors and the following error statistics (standard deviations): 0.01sec contact timing error, 1deg contact bearing error, 1deg array heading error, no errors in sound speed, and no errors in source and receiver locations.

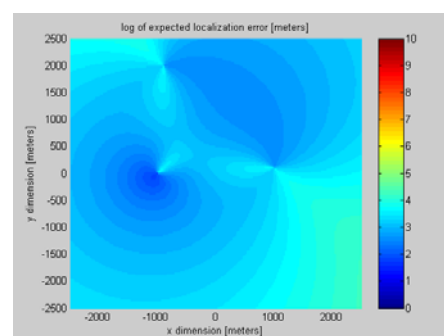


Figure 4 - Multistatic localization error

The contact localization expressions support sensitivity studies on the impact of simplifying approximations whereby ping time is used as target ensonification time, and receiver location at ping time is used in contact localization [9]. Furthermore, the localization expression combined with sonar performance modelling supports sensor placement optimisation, whereby one seeks to maximize the information provided to the tracker [10].

3.2 Distributed MHT

Key elements of our tracker include the following:

- Scan-based (rather than batch) processing, as required for real-time surveillance tasks;
- Tangent-plane based coordinate system, with all target motion constrained to the plane;
- Logic-based track management, with M-of-N track initiation logic, and termination after K missed detections (or after T minutes without a measurement update);
- Nearly constant velocity target motion model, a 4-dimensional target state with position and velocity components in x and y, and extended Kalman filtering of contact measurements expressed either in Cartesian or polar coordinates;
- Track-oriented multi-hypothesis formulation of the contacts association problem [5], with an efficient linear programming based solution scheme [12];
- Scan-based track fusion, with a number of instantiations of MHT modules, known as the distributed MHT (D-MHT) [13].

A tracking example is illustrated in figure 5. Multistatic contacts based on three platforms (9 source-receiver pairs) are shown in magenta; platform ground truth trajectories are in red, and tracks on two mobile and one fixed target are in blue. Note the dramatic false-object reduction and small localization error of tracks as compared with target contacts.

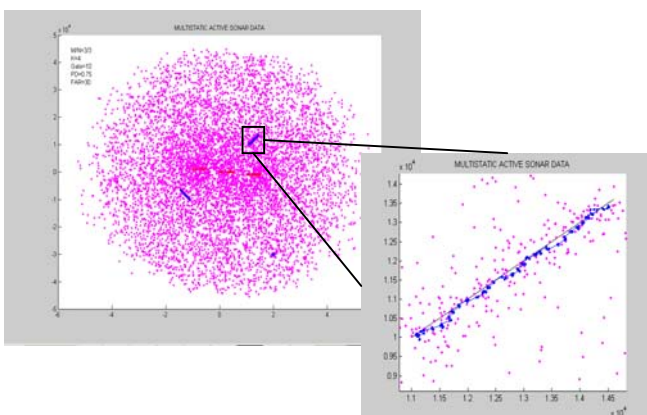


Figure 5 - Multistatic tracking with simulated active sonar data

A difficulty in tracking with active sonar data is not seen here: the presence of extended features on the seabed gives rise to contact sequences that “move” as the mobile platform.

This gives rise to tracks induced by the so-called “pipeline effect”.

The motivation for logic-based track management rather than more mathematically sophisticated techniques rests on the difficulty to have accurate performance predictions of target SNR, from which the target detection probability can be inferred. (Often, the more elaborate schemes are tuned so as to result in reasonable behavior consistent with logic-based schemes).

The primary novelty in our tracking approach is the D-MHT algorithm. This allows for flexibility in the fusion process, as it allows for partitioning and multi-stage processing of contact data, with detection-level and track-level inputs at each stage. The power of the multi-stage approach is that it allows for the exploitation of detection streaks observed at each source-receiver pair; indeed, detection performance depends highly on slowly varying geometric and environmental conditions. Thus, often we achieve improved performance by tracking separately on data from each source-receiver pair, followed by scan-based track fusion.

3.3 Tracker Modelling

We have developed a tracker performance model that extends past research in tracker performance modeling [3, 5, 18] by including targets with fading detection performance and allowing for a multi-stage fusion architecture. Details on the model are described in [13]. The model provides a simple tool that predicts performance as a function of parameters including target maneuverability, sensor performance, and tracker settings. We use simplifying assumptions that allow for tractable analysis. Metrics include detection performance, fragmentation, and localization accuracy. In [13], we provide preliminary model validation that indicates that, while optimistic, performance trends are accurate for low FAR settings.

An example of model-based ROC curve performance prediction is in figure 6. We see that, with low FAR data and with significant detection streaks, distributed tracking outperforms centralized tracking. In addition, 4-sensor results outperform single-sensor results, and 20-sensor results are best.

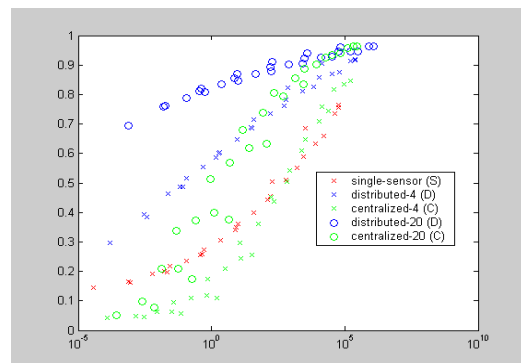


Figure 6 – Model-based ROC curves as a function of tracker architecture and sensor network size

4. TARGET KINEMATIC MODELING

Tracker testing is vital in detecting implementation errors as well as in quantifying the value of algorithmic upgrades. Thus, in addition to sea trial based evaluation, we perform tracker benchmarking with simulated datasets. Simulated datasets of current interest are identified in [7] and constitute the basis for a multi-laboratory benchmarking effort.

We are in the process of expanding our contact data simulator to include Doppler-sensitive (CW) detections in addition to Doppler-insensitive (FM) detections. In addition, we have extended the simulator to include data based on higher-fidelity target motion models. The latter effort is addressed below.

In past simulated datasets, target ground truth trajectories were either defined deterministically, or they were based on the *nearly constant velocity* (NCV) motion model. The latter is the model of choice in most recursive filters utilized in the tracking process. Extensions include the interacting multiple model (IMM) filter that uses a bank of Kalman filters, efficiently allowing for model-to-model transitions.

While deterministic ground truth simulation is often adequate, it does not reflect the presence of non-zero inertial navigational system (INS) errors (whereby perceived location and orientation are inaccurate), nor does it reflect velocity actuator errors (whereby desired target velocity will not correspond to actual target velocity).

Stochastic ground truth simulation based on the NCV model poses difficulties as well. Target motion follows a generalized “random walk” behavior that is not well related to any operational objective. Further, target velocities are not bounded and often are not target-like, particularly in lengthy scenarios.

4.1 Position Control Model

In [6], the *Ornstein-Uhlenbeck* (OU) and *Integrated Ornstein-Uhlenbeck* (IOU) processes are defined. These models introduce biasing terms whereby target location (or velocity) tend to zero. These models in part address the non target-like properties of lengthy NCV-based trajectories. We augment the OU model to account for non-zero desired trajectories, and introduce a second noise process to model INS errors. The result is the *position control* (PC) model.

The continuous-time PC model expressed in one dimension is as follows:

$$\begin{bmatrix} \dot{x}(t) \\ \dot{z}(t) \end{bmatrix} = \begin{bmatrix} -\beta & \beta \\ 0 & 0 \end{bmatrix} \begin{bmatrix} x(t) \\ z(t) \end{bmatrix} + \begin{bmatrix} w_x(t) \\ v(t) + w_z(t) \end{bmatrix}, \quad (1)$$

where $x(\cdot)$ is the target trajectory, $z(\cdot)$ is the INS-adjusted desired target trajectory, $v(\cdot)$ is the piecewise-constant desired velocity trajectory, $\beta \geq 0$ is the feedback gain, and

$w_x(\cdot)$, $w_z(\cdot)$ are white noise sequences that reflect velocity actuator and INS disturbances, respectively. We have

- $E[w_x(t)] = E[w_z(t)] = 0$;
- $E[w_x(t)w_x(\tau)] = q_x\delta(t-\tau)$;
- $E[w_z(t)w_z(\tau)] = q_z\delta(t-\tau)$;
- $E[w_x(t)w_z(\tau)] = 0$.

4.2 Discrete-Time Position Control Model

It is useful to define motion models in continuous time, since their discretization to the sensor observation times will preserve the proper dependence on time. Nonetheless, from a recursive-filtering perspective, what is required is a discrete-time kinematic model.

We assume the discrete-time sequence (t_0, t_1, \dots) includes the times of discontinuity in $v(\cdot)$. The eigenvalues of the state dynamics matrix are given by $\lambda = 0, -\beta$, with corresponding eigenvectors $l = [1 \ 1]^T, [1 \ 0]^T$. Thus we have:

- $P = \begin{bmatrix} 1 & 1 \\ 1 & 0 \end{bmatrix}, P^{-1} = \begin{bmatrix} 0 & 1 \\ 1 & -1 \end{bmatrix}, \tilde{A} = P^{-1}AP = \begin{bmatrix} 0 & 0 \\ 0 & -\beta \end{bmatrix}$;
- $\Phi(t) = \exp(At) = P \exp(\tilde{A})P^{-1} = \begin{bmatrix} \exp(-\beta t) & 1 - \exp(-\beta t) \\ 0 & 1 \end{bmatrix}$.

Then, time integration of (1) leads to the following:

$$\begin{bmatrix} x_{k+1} \\ z_{k+1} \end{bmatrix} = \Phi_k \begin{bmatrix} x_k \\ z_k \end{bmatrix} + v_k + w_k, \quad (2)$$

where:

- $x_0 = z_0$ (known - deterministic);
- $v_k = v(t_k) \left[\frac{(t_{k+1} - t_k) + \frac{\exp(-\beta(t_{k+1} - t_k)) - 1}{\beta}}{(t_{k+1} - t_k)} \right]$;
- $E[w_k] = 0$;
- $E[w_k w_k'] = \begin{bmatrix} Q_{11} & Q_{12} \\ Q_{21} & Q_{22} \end{bmatrix}$;
- $Q_{11} = \frac{q_x}{2\beta} (1 - \exp(-2\beta(t_{k+1} - t_k)))$
 $+ q_z(t_{k+1} - t_k) - \frac{2q_z}{\beta} (1 - \exp(-\beta(t_{k+1} - t_k)))$;
 $+ \frac{q_z}{2\beta} (1 - \exp(-\beta(t_{k+1} - t_k)))$;
- $Q_{12} = Q_{21} = q_z(t_{k+1} - t_k) - \frac{q_z}{\beta} (1 - \exp(-\beta(t_{k+1} - t_k)))$;
- $Q_{21} = q_z(t_{k+1} - t_k) - \frac{q_z}{\beta} (1 - \exp(-\beta(t_{k+1} - t_k)))$;
- $Q_{22} = q_z(t_{k+1} - t_k)$.

The velocity “state” is determined by first-differences of the positional state:

$$\dot{x}_k = \frac{x_{k+1} - x_k}{t_{k+1} - t_k}. \quad (3)$$

The model can be immediately generalized to two dimensions.

One can check that the model is well posed (i.e. $Q > 0$). Furthermore, the small feedback gain limit leads to the classical nearly constant position model for $x(\cdot)$, decoupled from $z(\cdot)$. The large feedback gain limit leads to identical $x(\cdot)$ and $z(\cdot)$ trajectories. Naturally, the nature of typical realizations will depend on the magnitudes of β , q_x , and q_z .

In figure 7, we illustrate one ten-hour realization for two target based on the PC model. Both targets travel at a speed of a few knots, with some speed and heading adjustments. The realization is performed in both x and y, leading to positional trajectories for both targets that increasingly deviate from the planned trajectory, and that tend to the INS-adjusted trajectories. In this example, we have $\beta = 0.001$, $q_x = 1 \text{ m}^2/\text{s}$, and $q_x = 100 \text{ m}^2$.

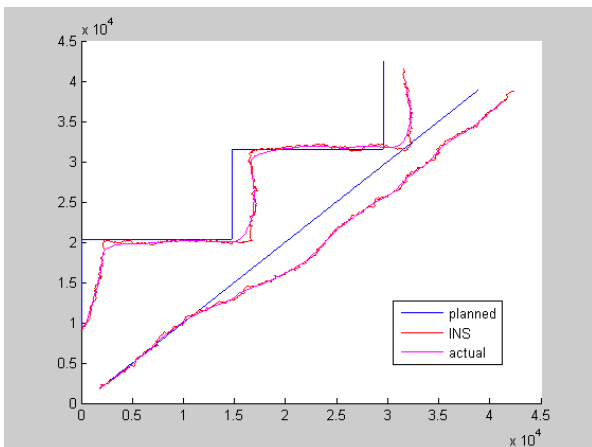


Figure 7 – Stochastic realization of motion of two submarine targets based on position control model.

The PC model allows considerable flexibility in ground truth realizations to reflect target operational objectives, sea conditions, and INS accuracies.

5. CURRENT RESEARCH

There are a number of directions for future research in support of network-centric tracking for undersea surveillance. Our priorities include (1) an evaluation of the relative merits of single-ping-scoring and state-augmentation approaches to feature-aided tracking; (2) Doppler-aided tracking, (3) coupled detection and tracking through adaptive detection thresholds, (4) intelligent waveform selection and ping scheduling for optimal tracking performance, and (5) D-MHT based data registration.

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