Distributed Multi Static Sonar Tracking in Clutter

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***Abstract*—Multi static underwater surveillance must conserve energy by communicating between nodes as sparsely as possible. On the other hand, signal to clutter ratio is usually very low, resulting in large number of clutter measurements per ping. When the local target tracking is performed in each receiver node, the false measurements are largely eliminated and communications are used (almost) exclusively to report targets to the fusion center.**

I. Introduction

Multi Static (MS) tracking involves an emitter and a network of receivers. Each receiver measures the time difference between the direct signal (coming straight from the emitter) and the signal reflected by the target. This translates into the difference in corresponding signal path lengths, which in this paper we call the bistatic position. The Doppler frequency may also be measured, which translates into the first time derivative of the bistatic position. In some applications the azimouth information may also be available, however in this paper we assume no such information. This, or any other information, can only improve the performance.

The signal to clutter ratio is usually low, creating a number of false measurements, termed clutter. The optimal target tracking in this situation involves transmitting all measurements to a fusion center. A possible solution to centralized MS tracking has been presented in [1], [2].

However, if the receivers are battery operated, and especially if they are under water, the communication capabilities are severely restricted and the optimal measurement fusion is no longer feasible.

The distributed MS tracking approach involves some signal processing / target tracking at each receiver. Only when a receiver is (reasonably) certain of the target presence, the fusion center is contacted. One such approach involves specular MS tracking [3], [4]. Under certain target geometries relative to the receiver and emitter, the received signal increases power considerably. This enables target detection with a small probability of false alarm. This is an elegant approach, however it may result in a considerable delay before the target detection. Also, it is likely that the specular phenomenon will occur only for one of the local receivers, which implies that other receivers will still transmit a number of clutter detections.

In this paper we propose and verify a different approach. Each receiver sets the detection threshold low enough so that the target will be detected with a reasonable probability in each measurement interval (scan). This, of course, results in a large number of clutter detections in each scan. The bistatic position and velocity tracking is performed locally at each receiver.

Local tracks are initialized using measurements; that includes the target measurements (detections) as well as the clutter measurements. A large number of false tracks (which do not follow a target) are initialized, as well as the true tracks (which follow targets, provided that the targets exist in the surveillance area).

The false tracks need to be recognized and terminated, and true tracks need to be recognized and confirmed (and be subsequently transmitted to the fusion center). This procedure is termed the False Track Discrimination (FTD).

The FTD uses a track quality measure provided by the target tracking algorithm. Tracks with a low track quality measure are discarded, and tracks with a high quality measure are confirmed.

A number of target tracking algorithms are published which provide a track quality measure. The Multi Hypothesis Tracking (MHT) [5], [6] provides the track score, whilst the Integrated Probabilistic Data Association (IPDA) [7], [8] and the Integrated Track Splitting (ITS) [9], [10] provide the probability of target existence. The ITS and the MHT are multi-scan algorithms as they keep a number of trajectory estimates possibilities for each track, based on measurement histories (sequence of measurement outcomes used in a number of consecutive scans). As a consequence they often need order of magnitude higher computational resources than the single scan algorithm. Computational resources also translate into power consumption, thus in this paper we use the single scan tracking.

Single scan target trackers merge all possible measurement outcomes into one trajectory estimate; in other words the target trajectory probability density function (pdf) is approximated by a single Gaussian. A most popular approach is the Probabilistic Data Association (PDA) [11], due to its simplicity as well as its good performance in relatively high clutter. However, the PDA does not provide a track quality measure.

The IPDA is a single target tracking algorithm which

This work was supported by Defense Acquisition Program Administration and Agency for Defense Development (Republic of Korea) through Project ADD-09-70-01-03, as collaboration with the University of Melbourne, Australia under the contract UD090002DD

combines the elegance and simplicity of the PDA with the probability of target existence as the track quality measure. In this paper, the authors use Linear Multitarget IPDA (LM IPDA) [12], [13]. The Linear Multitarget is a suboptimal multi target tracking approach which combines computational efficiency with near-optimal multi target tracking.

The target and the sensor models and assumptions are presented in Section II. The distributed target tracking solution is outlined in Section III, followed the local target tracking algorithm details in Section IV. Section V presents simulations of local target tracking, validating the approach, followed by the concluding remarks in Section VI.

II. Assumptions and Models

The usual fundamental assumptions apply here:

1) *The infinite sensor resolution.* The measurements (detections) from two or more sources remain separate. Each measurement has one source, either the clutter or a target.
   As a consequence, the clutter measurements can be modeled by (most often non-homogeneous) Poisson spatial distribution [14], [15].
2) *The point target.* Each target creates zero or one detection per measurement time (scan).

A. Target

The existence of the target being followed by a track is a random event. The target existence propagation is modeled by the Markov Chain One [7] model which assumes that the target either exists or does not exist. If the target exists, it is always detectable.

Denote by χ_k the target existence event at time k. The probability that the target exists at time (scan) k, given that it did exist at $k-1$ is

$$p_{1,1} \equiv \mathsf{P}\{\chi_k|\chi_{k-1}\}. \tag{1}$$

The probability $\mathsf{P}\{\chi_k|\overline{\chi_{k-1}}\}$ that the target exists at time k, given that it did not exist at $k-1$ is assumed to be zero [9].

The target trajectory state $\mathbf{x}_k$ at time k consists of (at least) the target position and velocity vectors $\mathbf{x}_k^{(p)}$ and $\mathbf{x}_k^{(v)}$ respectively. The state propagates by

$$\mathbf{x}_k = \mathbf{F}\mathbf{x}_{k-1} + \boldsymbol{\nu}_{k-1}, \tag{2}$$

where the plant noise sequence $\boldsymbol{\nu}_k$ is assumed to be a zero mean and white Gaussian sequence with a known covariance matrix $\mathbf{Q}$.

Denote by $\mathbf{e}$ and $\mathbf{s}$ the positions of the emitter and the local receiver respectively. Define the bistatic target trajectory by

$$\mathbf{b}_k = \begin{bmatrix} r_k & d_k \end{bmatrix}^\top \tag{3}$$

where $^\top$ denotes the matrix transpose, and

$$\begin{bmatrix} r_k \\ d_k \end{bmatrix} = \begin{bmatrix} h^{(r)}(\mathbf{x}_k) \\ h^{(d)}(\mathbf{x}_k) \end{bmatrix}. \tag{4}$$

The bistatic position r_k equals the difference between the path of the reflected signal (emitter - target - receiver) and the direct signal (emitter - receiver):

$$h^{(r)}(\mathbf{x}_k) = \|\mathbf{x}_k^{(p)} - \mathbf{e}\| + \|\mathbf{x}_k^{(p)} - \mathbf{s}\| - \|\mathbf{e} - \mathbf{s}\|, \tag{5}$$

where $\|\mathbf{x}\|$ is the norm of vector $\mathbf{x}$. The bistatic velocity is the first derivative of the bistatic position with respect to time

$$\begin{aligned} h^{(d)}(\mathbf{x}_k) &= \frac{\partial h^{(r)}(\mathbf{x}_k)}{\partial t} \\ &= (\mathbf{i}_k^{(e)} + \mathbf{i}_k^{(s)})^\top \mathbf{x}_k^{(v)}, \end{aligned} \tag{6}$$

where $\mathbf{i}_k^{(e)}$ and $\mathbf{i}_k^{(s)}$ are the unit vectors to the target from the emitter and from the receiver respectively

$$\begin{aligned} \mathbf{i}_k^{(e)} &= \frac{\mathbf{x}_k^{(p)} - \mathbf{e}}{\|\mathbf{x}_k^{(p)} - \mathbf{e}\|} \\ \mathbf{i}_k^{(s)} &= \frac{\mathbf{x}_k^{(p)} - \mathbf{s}}{\|\mathbf{x}_k^{(p)} - \mathbf{s}\|}. \end{aligned} \tag{7}$$

Unless the target is collinear with the emitter and the receiver, the propagation of the bistatic trajectory state is not linear. However, we approximate

$$\mathbf{b}_k = \mathbf{F}^{(b)}\mathbf{b}_{k-1} + \boldsymbol{\nu}_{k-1}^{(b)}, \tag{8}$$

where the plant noise sequence $\boldsymbol{\nu}_k^{(b)}$ is assumed to be a zero mean and white Gaussian sequence with a known covariance matrix $\mathbf{Q}^{(b)}$. The $\boldsymbol{\nu}_k^{(b)}$ sequence compensates for the propagation nonlinearity as well as including the projection of $\boldsymbol{\nu}_k$ into the bistatic state space. The bistatic propagation matrix $\mathbf{F}^{(b)}$ equals

$$\mathbf{F}^{(b)} = \begin{bmatrix} 1 & T \\ 0 & 1 \end{bmatrix}, \tag{9}$$

where T is the scan time interval. The plant noise covariance matrix depends on the bistatic trajectory state $\mathbf{Q}^{(b)} = \mathbf{Q}^{(b)}(\mathbf{b}_{k-1})$.

B. Measurements

The measurement of an existing target is taken with a probability of detection P_D. The sensor (receiver) measures bistatic positions and velocities. The target measurement equation at scan k is

$$\begin{aligned} \mathbf{y}_k &= \begin{bmatrix} h^{(r)}(\mathbf{x}_k) \\ h^{(d)}(\mathbf{x}_k) \end{bmatrix} + \boldsymbol{\omega}_k \\ &= \mathbf{H}\mathbf{b}_k + \boldsymbol{\omega}_k, \end{aligned} \tag{10}$$

where $\mathbf{y}_k$ denotes the target measurement, $\mathbf{H} = \mathbf{I}_2$ is the identity measurement matrix and $\boldsymbol{\omega}_k$ denotes a sample of zero mean white Gaussian measurement noise with known covariance $\mathbf{R}$ and uncorrelated with the sequence $\boldsymbol{\nu}_k^{(b)}$.

The sensor also returns a random number of clutter measurements at each scan. The clutter measurements follow (in the bistatic position dimension) a non-homogeneous Poisson distribution [14], which is parameterized by its intensity, termed here the clutter measurement density.

Let $\mathbf{y}$ be a clutter measurement. The unknown clutter measurement bistatic position density $\rho^{(p)}(\mathbf{y}(1))$ is a function of the value of the bistatic position coordinate $\mathbf{y}(1)$. We assume that the bistatic velocity component of the clutter measurements follows a known pdf. For simplicity we assume a Gaussian pdf with a known standard deviation $\sigma_{(v,c)}$ and a known mean value $\mu_{(v,c)}$. The clutter measurement density $\rho(\mathbf{y})$ equals

$$\rho(\mathbf{y}) = \rho^{(p)}\left(\mathbf{y}(1)\right) \ \mathcal{N}\left(\mathbf{y}(2); \mu_{(v,c)}, \sigma^2_{(v,c)}\right), \tag{11}$$

where $\mathcal{N}(\mathbf{x}; \mathbf{m}, \mathbf{\Sigma})$ denotes the Gaussian pdf of random variable $\mathbf{x}$ with mean $\mathbf{m}$ and covariance $\mathbf{\Sigma}$.

Here we assume no bearing information. It is trivial to include the bearing information which may only improve the tracking performance.

III. Distributed Tracking

To minimize communications between receivers and the fusion node, a client-server model is assumed. Each receiver performs local tracking initializing and updating tracks using local measurements only. The major functionality is the False Track Discrimination, which recognizes and terminates (a majority of) false tracks, and recognizes and confirms (a majority of) true tracks.

Only when a track confirmation occurs, the confirmed track information is sent to the fusion center. Feedback from the fusion center can further significantly improve local tracking performance by reducing the propagation non-linearity and matrix $\mathbf{Q}^{(b)}$, however we leave this aspect for future research. In this paper we examine and evaluate local tracking at the single receiver.

Assume a stationary emitter and stationary receivers. Target trajectory propagates $\mathbf{x}_k$ linearly, however the target trajectory is not observable [16] using measurements (10) from a single receiver.

The proposed local target tracker tracks multistatic information $\mathbf{b}_k$, which is observable given measurements (10) from a single receiver. In this case, the measurement equation (10) is linear, however the bistatic trajectory $\mathbf{b}_k$ propagation is nonlinear and is linearly approximated by (8).

IV. Local Target Tracking

In this paper we consider local target tracking component of the distributed tracking solution. Only local measurements are available. Denote by $\mathbf{Z}_k$ the set of measurements returned by the sensor at time k, by M_k the cardinality of $\mathbf{Z}_k$, and by $\mathbf{Z}^k$ the sequence $\{\mathbf{Z}_1, \mathbf{Z}_2, \ldots, \mathbf{Z}_k\}$ of measurement sets. Let $\rho_{k,i} = \rho(\mathbf{Z}_{k,i})$ with $\mathbf{Z}_{k,i}$ being the ith element of $\mathbf{Z}_k$.

The local tracker implements the Linear Multitarget Integrated Probabilistic Data Association algorithm (LMIPDA) [7], [12], [17]. The LMIPDA is a single scan suboptimal multitarget tracking algorithms with excellent false track discrimination capabilities and frugal computational requirements. The LMIPDA also automatically eliminates duplicate true tracks [12], removing the need for track merging procedures. Superscripts τ and ψ are used to indicate the track under consideration.

The LMIPDA for each track τ calculate the probability of target existence χ_k^τ and the pdf of the target trajectory $\mathbf{b}_k^\tau$ and the track pdf is

$$p\left[\chi_k^\tau, \mathbf{b}_k^\tau\right] = \mathsf{P}\left\{\chi_k^\tau\right\} \ p\left(\mathbf{b}_k^\tau | \chi_k^\tau\right), \tag{12}$$

conditioned on the appropriate measurement set sequence $\mathbf{Z}^{k-1}$ (propagation) or $\mathbf{Z}^k$ (update). The target trajectory $\mathbf{b}_k^\tau$ pdf is only defined conditioned on target existence χ_k^τ; however in the interest of clarity this conditioning will only be implied in the rest of the paper. The updated $\mathbf{b}_k^\tau$ pdf is approximated by a Gaussian pdf (the standard PDA [11] approximation)

$$p\left(\mathbf{b}_k^\tau | \mathbf{Z}^k\right) \approx \mathcal{N}\left(\mathbf{b}_k^\tau; \hat{\mathbf{b}}_{k|k}^\tau, \mathbf{P}_{k|k}^\tau\right). \tag{13}$$

The track recursion [7], [12], [17] consists of

- propagation,
- measurement selection and likelihoods,
- clutter density estimation and LM approximation,
- data association and
- track update

which are detailed in this section below.

A. Propagation

Track recursion at time k starts from the track update at time $k-1$, where the track is parametrized with $\mathsf{P}\{\chi_{k-1}^\tau | \mathbf{Z}^{k-1}\}$, $\hat{\mathbf{b}}_{k-1|k-1}^\tau$ and $\mathbf{P}_{k-1|k-1}^\tau$. The probability of target existence propagates as per (1)

$$\mathsf{P}\left\{\chi_k^\tau | \mathbf{Z}^{k-1}\right\} = p_{1,1} \mathsf{P}\left\{\chi_{k-1}^\tau | \mathbf{Z}^{k-1}\right\}, \tag{14}$$

whereas the bistatic trajectory estimate propagates by

$$\begin{bmatrix} \hat{\mathbf{b}}_{k|k-1}^\tau & \mathbf{P}_{k|k-1}^\tau \end{bmatrix} = \mathsf{KF}_\mathsf{P}\left(\hat{\mathbf{b}}_{k-1|k-1}^\tau, \mathbf{P}_{k-1|k-1}^\tau, \mathbf{F}^{(b)}, \mathbf{Q}^{(b)}(\hat{\mathbf{b}}_{k-1|k-1}^\tau)\right), \tag{15}$$

where KF_P denotes the standard Kalman filter prediction and the plant noise covariance matrix is a function of $\hat{\mathbf{b}}_{k-1|k-1}^\tau$.

B. Measurement selection and likelihoods

At time k each track τ selects a subset $\mathbf{z}_k^\tau$ of received measurement set $\mathbf{Z}^k$ for track update. Denote by m_k^τ the cardinality of $\mathbf{z}_k^\tau$ and denote by $\mathbf{z}_{k,i}^\tau$ the ith element of $\mathbf{z}_k^\tau$. Selection test is

$$(\mathbf{z}_{k,i}^\tau - \hat{\mathbf{b}}_{k|k-1}^\tau)^\top \mathbf{S}_k^{-\tau} (\mathbf{z}_{k,i}^\tau - \hat{\mathbf{b}}_{k|k-1}^\tau) \leq \gamma^2, \tag{16}$$

with

$$\mathbf{S}_k^\tau = \mathbf{H}\mathbf{P}_{k|k-1}^\tau \mathbf{H}^\top + \mathbf{R} \tag{17}$$

and γ is a constant which determines the selection probability P_G, i.e. the probability that the target measurement $\mathbf{y}_k^\tau \in \mathbf{z}_k^\tau$, given that the target exists and is detected.

The likelihood of measurement $\mathbf{Z}_{k,i} \in \mathbf{Z}_k$ with respect to track τ equals

$$p^{\tau}_{k,i} \equiv p^{\tau}\left(\mathbf{Z}_{k,i}|\mathbf{Z}^{k-1}\right) \quad (18)$$
$$= \begin{cases} \frac{1}{\mathsf{P}_{\mathrm{G}}}\mathcal{N}\left(\mathbf{Z}_{k,i};\mathbf{H}\hat{\mathbf{b}}^{\tau}_{k|k-1},\mathbf{S}^{\tau}_{k}\right); & \mathbf{Z}_{k,i} \in \mathbf{z}^{\tau}_{k} \\ 0; & \mathbf{Z}_{k,i} \notin \mathbf{z}^{\tau}_{k} \end{cases}.$$

C. Clutter Density Estimation and LM Approximation

Data association formulae require values of the clutter measurement densities at the measurement coordinates $\mathbf{Z}_{k,i}$, given (11) we obtain

$$\rho(\mathbf{Z}_{k,i}) = \rho^{(p)}\left(\mathbf{Z}_{k,i}(1)\right)\ \mathcal{N}\left(\mathbf{Z}_{k,i}(2);\mu_{(v,c)},\sigma^2_{(v,c)}\right), \quad (19)$$

where $\rho^{(p)}(\mathbf{Z}_{k,i}(1))$ is unknown and needs to be estimated using measurements. In this paper we use the adaptive clutter measurement density estimator [14].

Let Δ_i denote the distance between $\mathbf{Z}_{k,i}(1)$ and the second nearest bistatic position measurement. Then

$$\rho^{(p)}\left(\mathbf{Z}_{k,i}(1)\right) = 1/\Delta_i. \quad (20)$$

The Linear Multitarget (LM) approach to multi target tracking is detailed and derived in [12]. The essence of the LM approach is to, when updating track τ, modulate the clutter measurement density with possible contributions of other tracks $\psi \neq \tau$. This suboptimal approach is achieved in two steps. The first step calculates the single target probabilities $\mathsf{P}^{\tau}_{k,i}$ that measurement $\mathbf{Z}_{k,i}$ is the detection of the target being followed by track τ, for all tracks τ and all measurements $\mathbf{Z}_{k,i}$:

$$\mathsf{P}^{\tau}_{k,i} = \mathsf{P}_{\mathrm{D}}\mathsf{P}_{\mathrm{G}}\mathsf{P}\left\{\chi^{\tau}_{k}|\mathbf{Z}^{k-1}\right\}\frac{p^{\tau}_{k,i}/\rho_{k,i}}{\sum\limits_{j=1}^{M_k} p^{\tau}_{k,j}/\rho_{k,j}}. \quad (21)$$

The modulated clutter measurement density equals

$$\mho^{\tau}_{k,i} = \rho_{k,i} + \sum_{\psi\neq\tau} p^{\psi}_{k,i}\frac{\mathsf{P}^{\psi}_{k,i}}{1-\mathsf{P}^{\psi}_{k,i}} \quad (22)$$

D. Data Association

Measurement likelihood ratio λ^{τ}_{k} of track τ at time k equals [7], [12]

$$\lambda^{\tau}_{k} = 1 - \mathsf{P}_{\mathrm{D}}\mathsf{P}_{\mathrm{G}} + \mathsf{P}_{\mathrm{D}}\mathsf{P}_{\mathrm{G}}\sum_{i:\mathbf{Z}_{k,i}\in\mathbf{z}^{\tau}_{k}}\frac{p^{\tau}_{k,i}}{\mho^{\tau}_{k,i}}. \quad (23)$$

The updated probability of track τ target existence equals

$$\mathsf{P}\left\{\chi^{\tau}_{k}|\mathbf{Z}^{k}\right\} = \frac{\lambda^{\tau}_{k}\mathsf{P}\left\{\chi^{\tau}_{k}|\mathbf{Z}^{k-1}\right\}}{1-(1-\lambda^{\tau}_{k})\,\mathsf{P}\left\{\chi^{\tau}_{k}|\mathbf{Z}^{k-1}\right\}}. \quad (24)$$

Denote by $\kappa^{\tau}_{k,i\geq 0}$ the event that measurement $\mathbf{Z}_{k,i}$ (or no measurement for $i=0$) is the measurement of the target being followed by track τ. The data association probabilities are defined as probabilities of events $\kappa^{\tau}_{k,i}$ conditioned on target τ existence and are calculated for $i=0$ and for $i:\mathbf{Z}_{k,i}\in\mathbf{z}^{\tau}_{k}$

$$\beta^{\tau}_{k,i} \equiv \mathsf{P}\left\{\kappa^{\tau}_{k,i}|\chi^{\tau}_{k},\mathbf{Z}^{k}\right\}$$
$$= \frac{1}{\lambda^{\tau}_{k}}\begin{cases} 1-\mathsf{P}_{\mathrm{D}}\ \mathsf{P}_{\mathrm{G}}, & i=0 \\ \mathsf{P}_{\mathrm{D}}\ \mathsf{P}_{\mathrm{G}}\ p^{\tau}_{k,i}/\mho^{\tau}_{k,i}, & i:\mathbf{Z}_{k,i}\in\mathbf{z}^{\tau}_{k} \end{cases}. \quad (25)$$

E. Track Update

The LM IPDA track update is identical to the PDA [11] update. Denote by $\hat{\mathbf{b}}^{\tau}_{k,i|k}$ and $\mathbf{P}^{\tau}_{k,i|k}$ the mean and covariance trajectory given measurement outcome $\kappa^{\tau}_{k,i}$:

$$\left[\hat{\mathbf{b}}^{\tau}_{k,i|k} \quad \mathbf{P}^{\tau}_{k,i|k}\right] = \quad (26)$$
$$\begin{cases} \left[\hat{\mathbf{b}}^{\tau}_{k|k-1} \quad \mathbf{P}^{\tau}_{k|k-1}\right], & i=0 \\ \mathsf{KF}_{\mathsf{U}}(\mathbf{Z}_{k,i},\mathbf{R},\hat{\mathbf{b}}^{\tau}_{k|k-1},\mathbf{P}^{\tau}_{k|k-1},\mathbf{H}), & i>0, \end{cases}$$

where KF_{U} is the standard Kalman filter update operation. The posterior pdf $p(\mathbf{b}^{\tau}_{k}|\mathbf{Z}^{k})$ is a Gaussian Mixture, which is approximated by a first two moments preserving Gaussian pdf with mean $\hat{\mathbf{b}}^{\tau}_{k|k}$ and covariance $\mathbf{P}^{\tau}_{k|k}$ [11].

$$\hat{\mathbf{b}}^{\tau}_{k|k} = \sum_{i=0,i:\mathbf{Z}_{k,i}\in\mathbf{z}^{\tau}_{k}}\beta^{\tau}_{k,i}\hat{\mathbf{b}}^{\tau}_{k,i|k} \quad (27)$$

$$\mathbf{P}^{\tau}_{k|k} = \sum_{i=0,i:\mathbf{Z}_{k,i}\in\mathbf{z}^{\tau}_{k}}\beta^{\tau}_{k,i}\mathbf{P}^{\tau}_{k,i|k} \quad (28)$$
$$+ \sum_{i=0,i:\mathbf{Z}_{k,i}\in\mathbf{z}^{\tau}_{k}}\beta^{\tau}_{k,i}\hat{\mathbf{b}}^{\tau}_{k,i|k}\left(\hat{\mathbf{b}}^{\tau}_{k,i|k}\right)^{\top} - \hat{\mathbf{b}}^{\tau}_{k|k}\left(\hat{\mathbf{b}}^{\tau}_{k|k}\right)^{\top}.$$

F. False Track Discrimination

Every measurement is used to initialize a new track. Both true tracks (which follow targets) and false tracks (which do not follow targets) exist. The False Track Discrimination (FTD) uses the probability of target existence to recognize and terminate false tracks, and to recognize and confirm true tracks.

In the simulation experiments described in Section V the following FTD procedure is implemented:

- Each new track has a tentative status,
- If and when the updated probability of target existence is above a predetermined confirmation threshold for 4 consecutive scans, the track gets confirmed and stays confirmed until termination,
- When the updated probability of target existence falls below a predetermined termination threshold the track is terminated.

The FTD details are not specified by the LM IPDA algorithm [12], the LM IPDA merely provides the probability of target existence and the practitioner may find other possibilities.

G. Track Initialization

Each measurement in every scan initializes a new track. We now consider the new track τ being initialized by measurement

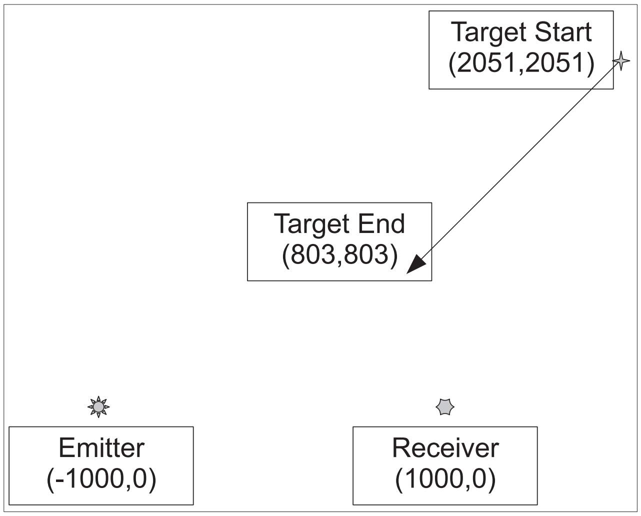

Fig. 1. Simulation Scenario

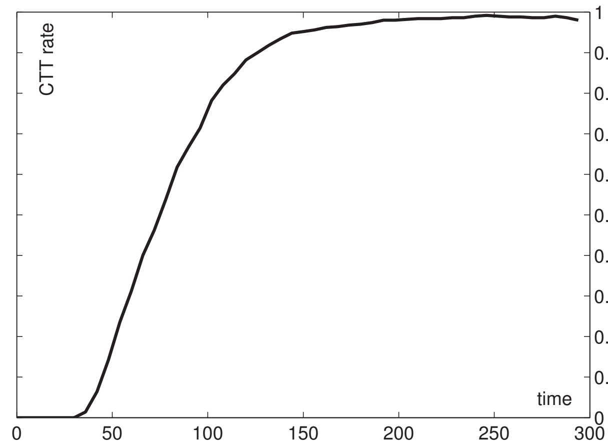

Fig. 2. Confirmed True Track Rate

$\mathbf{Z}_{k,i}$. As the measurement matrix $\mathbf{H}$ is an identity matrix, the initial track bistatic state equals the measurement:

$$\left[\hat{\mathbf{b}}^{\tau}_{k|k} \quad \mathbf{P}^{\tau}_{k|k}\right] = \left[\mathbf{Z}_{k,i} \quad \mathbf{R}\right]. \tag{29}$$

The initial probability of target existence is proportional to the probability $\mathsf{P}^0_{k,i}$ that measurement $\mathbf{Z}_{k,i}$ is not a detection of any existing target

$$\mathsf{P}\left\{\chi^{\tau}_{k}|\mathbf{Z}^k\right\} = c_0 \; \mathsf{P}^0_{k,i} \tag{30}$$

where $c_0 \in (0, 1]$ is theoretically the prior probability that an isolated measurement is a new target detection. However, due to our lack of prior information, c_0 becomes a tuning parameter.

V. Simulations

The surveillance situation is depicted on Figure 1.

The scan time interval equals 6 s, which is compatible with the maximum bistatic range of 4000 m. Each simulation run has 50 scans, and the performance statistics are accumulated over 500 simulation runs. Total simulated time is 150,000s, or 1 day, 17 hours and 40 minutes. The emitter and the receiver are both stationary, whilst the target moves with a uniform motion.

The target is detected with the detection probability $\mathsf{P}_{\mathrm{D}} = 0.6$, which is assumed constant and known. The receiver is assumed to have 1000 detection cells of 4m each, with signal to clutter ratio of 3 dB. Assuming the exponential power pdf of both target and clutter signal, this translates to the average number of clutter measurements per scan equal to 216. The true (and assumed unknown) bistatic position clutter measurement density is uniform $\rho^{(p)} = 0.054\mathrm{m}^{-1}$. The clutter measurement density is estimated as described in Section IV-C.

The measurement noise is assumed to be zero mean Gaussian with correlation matrix

$$\mathbf{R} = \begin{bmatrix} 1.33\mathrm{m}^2 & 0 \\ 0 & 1(\mathrm{m/s})^2 \end{bmatrix}. \tag{31}$$

Although the measurement noise correlation matrix $\mathbf{R}$ indicates no correlation between bistatic position and bistatic velocity measurements, the proposed tracking solution automatically incorporates correlated bistatic position - bistatic velocity measurements.

The clutter bistatic velocity measurements follow the zero mean Gaussian pdf with standard deviation of $\sigma_{(v,c)} = 6\mathrm{m/s}$.

Two experiments are simulated. In both experiments approximately 5,400,000 clutter measurements are generated over 25,000 simulated scans. Each measurement in each scan initializes a track, which is then updated in subsequent scans and subjected to the False Track Discrimination as described in Section IV-F.

In the first experiment the target is absent and each (confirmed) track is a (confirmed) false track. In this environment, the total number of confirmed false tracks over the simulated time (1 day, 17 hours and 40 minutes) was two. This corresponds to 5,400,000 clutter measurements processed (and 5,400,000 initialized false tracks) which confirms that this approach offers considerable communication savings and vindicates the approach.

In the second experiment, the target is present from the first scan onwards. Clutter measurements are generated as well, and both true tracks and false tracks are initialized as described in Section IV-G. The true target confirmation rate is measured and presented on Figure 2. The track is followed by a confirmed track in more than 99% simulation runs.

Only confirmed tracks are transmitted to the fusion center, thus we are only interested in the estimation outcomes of the confirmed true tracks. RMS estimation errors for bistatic position and bistatic velocity are presented in Figure 3 and Figure 4 respectively. We notice that the RMS errors increase

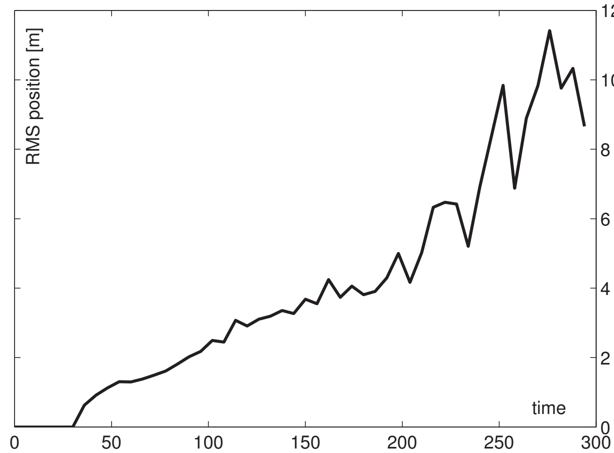

Fig. 3. RMS bistatic position

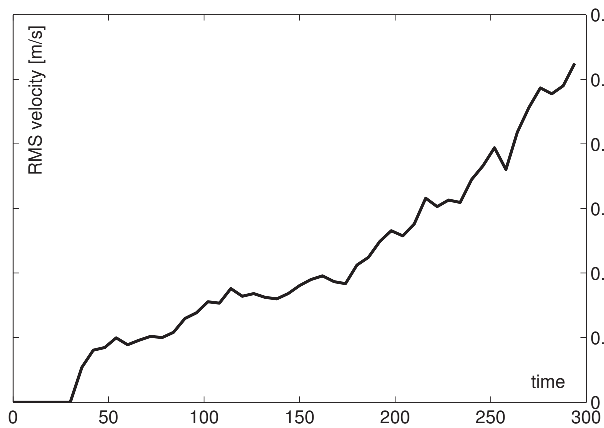

Fig. 4. RMS bistatic velocity

in time, as the propagation nonlinearity increases when the target approaches the origin.

The simulations were executed on a Windows 7 platform using the Matlab package, using the 2.66 GHz CPU. Total simulation time per experiment was approximately 7,000s, which is approximately 21 times faster than the simulated time. Taking into account computational inefficiencies of the platform used, real time tracking in this environment can be achieved with an inexpensive platform requiring low electrical power.

VI. Conclusion

This paper proposes a solution to distributed sonar Multi Static target tracking. Local target tracking tracks bi-static trajectory state and performs efficient false track discrimination. Confirmed false track rate is very low which prevents wasting energy transmitting clutter measurements. The reliable true track confirmation ensures efficient track fusion and final target trajectory estimation in the fusion center.

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