Doppler-Aided Target Tracking in Heavy Clutter *

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Abstract – *Target tracking in clutter uses measurements of uncertain origin. In addition to target detections, in every scan the sensor returns clutter measurements. Standard target tracking in clutter most often uses the position measurements only. The tracking then becomes clutter limited, and beyond a limited clutter measurement density target tracking algorithms do not perform. Using the Doppler information of each measurement can significantly increase these limits. Previous publications used Doppler measurements either to improve the data association probabilities only, or to improve trajectory state estimates only. Whilst it helps, it often is not enough. This paper extends popular Integrated Probabilistic Data Association to use Doppler information in the track update step both to enhance the Data Association probabilities, and to improve trajectory state estimation. A simulation study shows that this approach may provide reliable automatic target tracking in the case of severe clutter.*

Keywords: Target tracking, data association, Doppler, clutter, IPDA, false track discrimination

1 Introduction

Active or passive surveillance usually deals with measurements of uncertain origin. The very existence and number of targets in the surveillance space is unknown and random, and each target is detected only with the probability of detection $P_D < 1$, which is here assumed known. The usual assumption that each target can produce up to one measurement per measurement time (scan) is held here (the point target assumption). Additionally, a random number of clutter measurements are generated in each scan. Thus, the origin of each measurement is apriori unknown, and can be determined only stochastically. Here we also assume that each measurement can have only one origin, i.e. that each measurement is either a clutter measurement or a detection of one target (the usual infinite sensor resolution assumption).

Target tracking algorithms have to contend with the exponential complexity of the problem, as well as with the issue of target existence uncertainty.

The exponential complexity is dealt with by using suboptimal algorithms. Target trajectory state probability density function (pdf) in a linear system is a Gaussian Mixture with exponentially increasing number of components [1, 2]. This complexity is reduced by various methods of track component management [3]. Target trackers based on the Probabilistic Data Association (PDA) [4] approximate the posterior trajectory state pdf by a single Gaussian pdf. PDA based target tracking filters show good performance in relatively significant clutter, with high probability of detection and moderate maneuvers. When these conditions are violated, better results are obtained by target trackers which retain more track components and thus better approximate posterior trajectory state pdf [1, 2].

Tracks are initialized and updated by available measurements. Thus both true tracks (following targets) and false tracks (not following targets) exist. A false track discrimination (FTD) procedure is used to recognize and confirm true tracks, and recognize and terminate false tracks. Various tests [3] are used for FTD. In this paper we use FTD based on the probability of target existence, popularized in [1,5–7]. Integrated PDA (IPDA) [5, 6] is a PDA based target tracker, which also recursively updates the probability of target existence for each track.

Target tracking usually assumes that only position measurements (or "converted" polar measurements [8, 9]) are available. Performance of target trackers is enhanced if additional information is used. Additional measurement information (features) are usually used to improve the data association probabilities. This is the case of amplitude measurement information [10], and the Doppler measurement information [11].

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In some references, Doppler measurement information is used to improve trajectory state estimation. Extended Kalman filters are used to simultaneously use both position and Doppler measurement information, resulting in somewhat lavish use of computer resources [3, 12]. However, these approaches influence the Data Association formulae only indirectly, through somewhat smaller error covariances. [12, 13] uses Doppler information to improve track initialization. In this publication we use the Doppler measurement information to both improve the Data Association process in a manner similar to [11], and to improve trajectory state estimation of the IPDA target tracking algorithm. This is termed here simply as "Doppler IPDA" (DIPDA).

DIPDA effectively fuses two types of information; position and Doppler measurements, applying them sequentially. Resulting Kalman filters have small dimensions and are, therefore, computationally more efficient. First each position measurement is applied to create tentative track components. Then each tentative component is updated by corresponding Doppler measurement to obtain final measurement likelihoods, data association probabilities and component trajectory estimates. True to the PDA approach, all tentative components are merged into one with the Gaussian trajectory state pdf. Final measurement likelihoods are also used to update the probability of target existence for each track.

In a typical active sonar scenario, this approach allows efficient target tracking and FTD procedure in severe clutter measurement density which effectively renders the standard [5, 6] IPDA, as well as Doppler data association [11] IPDA useless.

This paper is organized as follows. Problem statement is presented in Section 2. Track state and one cycle of track state update are detailed in Section 3. Track initialization and multi target issues are also described in Section 3. This approach is validated using simulations in Section 4 followed by the concluding remarks in Section 5.

2 Problem Statement

An unknown nonnegative number of targets exists in the surveillance space. Assume that target τ state at time k consists of (includes) target position e_k^τ and speed $v_{e,k}^\tau$

$$x_k^{\tau\top} = \begin{bmatrix} e_k^{\tau\top} & v_{e,k}^{\tau}{}^\top \end{bmatrix}. \tag{1}$$

where $^\top$ denotes matrix transpose. Target trajectory propagation is modeled by

$$x_k^\tau = F x_{k-1}^\tau + \mu_k^\tau, \tag{2}$$

where the plant noise sequence μ_k^τ is assumed to be a zero mean and white Gaussian sequence with covariance matrix Q, which is not correlated with the measurement noise sequences.

One sensor is considered here, however the results are easily extended to multi sensor fusion environment. The sensor may be stationary or mobile, and its trajectory is assumed known and at time k is denoted by:

$$x_{s,k}^\top = \begin{bmatrix} s_k^\top & v_{s,k}^\top \end{bmatrix} \tag{3}$$

where s_k and $v_{s,k}$ denote known position and speed of the sensor respectively at time k. The radius vector from the sensor to target τ at time k is given by:

$$r_k^\tau \equiv r(x_k^\tau) = e_k^\tau - s_k \tag{4}$$

with the unit vector i_k^τ equal to

$$i_k^\tau \equiv i(x_k^\tau) = \frac{r_k^\tau}{\|r_k^\tau\|} = \begin{bmatrix} \cos(\alpha(x_k^\tau)) \\ \sin(\alpha(x_k^\tau)) \end{bmatrix} \tag{5}$$

Target τ speed at time k relative to sensor is defined by

$$\Delta v_k^\tau \equiv \Delta v(x_k^\tau) = v_{e,k}^\tau - v_{s,k}. \tag{6}$$

2.1 Measurements

Target τ measurement exists at time k with a probability of detection $P_D < 1$. The sensor measures target position and Doppler speed. The measurement of target position is termed the kinematic measurement component, and the measurement of Doppler speed is termed the Doppler measurement component. The kinematic measurement equation is assumed linear

$$y_k^\tau = H\, x_k^\tau + \omega_k^\tau, \tag{7}$$

where H is the (position) measurement matrix and ω_k^τ is the white, zero mean and Gaussian kinematic measurement error sequence with covariance R. Define by $h_v(x_k^\tau)$ the function which calculates Doppler speed assuming known target trajectory state

$$h_v(x_k^\tau) = -i(x_k^\tau)^\top\, \Delta v(x_k^\tau) \tag{8}$$

The Doppler measurement equation is non-linear

$$v_k^\tau = h_v(x_k^\tau) + \epsilon_k^\tau, \tag{9}$$

where ϵ_k^τ is a sequence of zero mean, white and Gaussian Doppler measurement error sequence with covariance σ_v^2 and uncorrelated with any other noise sequence.

Clutter measurements are generated randomly at each scan. The usual model is that clutter measurements follow Poisson distribution in the surveillance (kinematic) space. The Poisson distribution is parametrized by intensity, or as termed here the clutter measurement density. We assume non-uniform clutter measurement density and denote by $\rho(e)$ value of the clutter measurement density at surveillance space coordinate e.

At time k, sensor delivers a set of z_k measurements, where $z_{k,i}$ denotes the i-th measurement of z_k. Each measurement $z_{k,i}$ has a kinematic component $e_{k,i}$ and a Doppler component $v_{k,i}$. We also use Z^k to denote the sequence of all measurement sets up to and including time k, $Z^k = \{z_k, Z^{k-1}\}$.

Denote by $\rho_{k,i} \equiv \rho(e_{k,i})$. Composite clutter measurement density $\rho^*_{k,i}$ of measurement $z_{k,i}$ is the product of kinematic clutter measurement density and clutter likelihood p^0 of the Doppler measurement component $v_{k,i}$

$$\rho^*_{k,i} = \rho_{k,i} \cdot p^0(v_{k,i}). \tag{10}$$

2.2 False Track Discrimination

Tracks are initialized using measurements. Due to the uncertain origin of each measurement, both true tracks (which follow targets) and false tracks (which do not follow targets) are initialized. Additionally, tracks will change their description. Each true track will sooner or later become a false track, either because its target has left the surveillance space, or has disappeared (destroyed?). Also, a true track may become a false track by losing its target due to unfavourable detection/measurement noise sequence, multi target effects, or any combination thereof.

Every surveillance system is useless unless true and false tracks can be reliably classified as such. False track discrimination (FTD) procedure recognizes and confirms (majority of) true tracks, and recognizes and terminates (majority of) false tracks. In this paper we concentrate on the FTD performance of proposed algorithm.

IPDA [5] recursively updates the probability of target existence as a track quality measure used for FTD. We follow a simple logic. Each new track is assigned a "tentative" status. When the probability of target existence of a tentative track rises above the confirmation threshold, the tentative track becomes confirmed (and remains confirmed until termination). When the probability of target existence of a track, either confirmed or tentative, falls below the termination threshold, the track is deemed false and terminated.

3 Track Update Cycle

3.1 Track State

In common with IPDA, the DIPDA track τ state is hybrid; i.e. it has a binary part χ^τ_k which is the target existence, and a continuous part which is the trajectory state x^τ_k. Track state pdf is expressed as

$$p\left[\chi^\tau_k, x^\tau_k\right] = P\{\chi^\tau_k\} p(x^\tau_k|\chi^\tau_k). \tag{11}$$

where target trajectory pdf is calculated only conditioned on target existence. Track state pdf, equation (11), is conditioned on measurement set Z^{k-1} to obtain predicted or propagated track state pdf, or on measurement set Z^k to obtain updated track state pdf. We use the following shortcuts

$$\psi^\tau_{k|k} \equiv P\{\chi^\tau_k|Z^k\}; \quad \psi^\tau_{k|k-1} \equiv P\{\chi^\tau_k|Z^{k-1}\} \tag{12}$$

in the text below.

3.2 Doppler Measurement Fusion

Measurement likelihood is value of measurement pdf at $z_{k,i} = \{e_{k,i}, v_{k,i}\}$:

$$\begin{aligned} p^\tau_{k,i} \equiv & p^\tau(z_{k,i}|\chi^\tau_k, Z^{k-1}) \\ = & p^\tau(e_{k,i}, v_{k,i}|\chi^\tau_k, Z^{k-1}), \end{aligned} \tag{13}$$

which may be expressed as

$$p^\tau_{k,i} = p^\tau(e_{k,i}|\chi^\tau_k, Z^{k-1})\, p^\tau(v_{k,i}|\chi^\tau_k, e_{k,i}, Z^{k-1}), \tag{14}$$

where conditioning $e_{k,i}, Z^{k-1}$ implies that the kinematic measurement component is applied to update the target trajectory state prediction.

The update of the trajectory state estimate follows in the similar manner:

$$\begin{aligned} & p(x^\tau_k|\chi^\tau_k, z_{k,i}, Z^{k-1}) = \\ & = \frac{p(v_{k,i}|x^\tau_k, \chi^\tau_k)}{p(v_{k,i}|\chi^\tau_k, e_{k,i} Z^{k-1})} p(x^\tau_k|\chi^\tau_k, e_{k,i}, Z^{k-1}) \end{aligned} \tag{15}$$

First the kinematic component $e_{k,i}$ of measurement $z_{k,i}$ is applied to obtain $p(x^\tau_k|\chi^\tau_k, e_{k,i}, Z^{k-1})$. As the measurement equation of the kinematic component is assumed linear, we can use standard Kalman filter. Then the Doppler measurement component $v_{k,i}$ is applied. As the Doppler measurement equation is non-linear, we have to use a non-linear estimation method. In this case we find that extended Kalman filter (EKF) works satisfactorily.

3.3 One Track Update Cycle

3.3.1 Prediction

The prediction step propagates track state from time $k-1$ to current time k. The probability of target existence propagates by

$$\psi^\tau_{k|k-1} = p_{1,1} \psi^\tau_{k-1|k-1}, \tag{16}$$

where $p_{1,1}$ is the probability that the target will not disappear between scans. Due to assumed linear trajectory propagation model, the trajectory state propagation is handled using standard Kalman filter prediction

$$\hat{x}^\tau_{k|k-1} = F \hat{x}^\tau_{k-1|k-1}, \tag{17}$$

$$P^\tau_{k|k-1} = F P^\tau_{k-1|k-1} F^\top + Q. \tag{18}$$

3.3.2 Measurement Likelihood and Selection

The kinematic likelihood of measurement $z_{k,i}$ is given by

$$p^\tau(e_{k,i}|\chi^\tau_k, Z^{k-1}) = \frac{1}{P_G} \mathcal{N}\left(e_{k,i}; H\hat{x}^\tau_{k|k-1}, S^\tau_k\right) \tag{19}$$

where P_G denotes the selection probability and predicted covariance S^τ_k of kinematic measurement is defined by

$$S^\tau_k = H P^\tau_{k|k-1} H^\top + R \tag{20}$$

To determine the Doppler likelihood of measurement $z_{k,i}$, we first update trajectory state by kinematic measurement $e_{k,i}$ using standard Kalman filter estimate

$$\begin{aligned}\left[\hat{x}^{\tau}_{k|k,i-}, P^{\tau}_{k|k,i-}\right] &= \\ &= \mathrm{KF_E}\left(e_{k,i}, R, \hat{x}^{\tau}_{k|k-1}, P^{\tau}_{k|k-1}, H\right)\end{aligned} \tag{21}$$

Doppler component measurement likelihood is approximated by

$$\begin{aligned}&p^{\tau}(v_{k,i}|\chi^{\tau}_k, e_{k,i}, Z^{k-1}) \approx \\ &\approx \frac{1}{P_G}\mathcal{N}\left(v_{k,i}; h_v(\hat{x}^{\tau}_{k|k,i-}), S_v(\hat{x}^{\tau}_{k|k,i-}, P^{\tau}_{k|k,i-})\right)\end{aligned} \tag{22}$$

with the predicted Doppler measurement covariance $S_v(x, P)$ equal to

$$S_v(x, P) = H_v(x) P H_v(x)^{\top} + \sigma_v^2 \tag{23}$$

where the measurement Jacobian $H_v(x)$ is defined by

$$H_v(x) \equiv \frac{\partial h_v(x)}{\partial x} \tag{24}$$

and is equal to

$$H_v(x) = -\begin{bmatrix}(\Delta v(x) + h_v(x)\ i(x)) / \|r(x)\| \\ i(x)\end{bmatrix}^{\top} \tag{25}$$

Applying equations (14), (19) and (22), we calculate likelihood $p^{\tau}_{k,i}$ of measurement $z_{k,i}$.

Measurements are selected based on the kinematic and the Doppler measurement components. Performing the selection tests separately on the kinematic and the Doppler measurement components brings significant computational benefits. The kinematic selection uses the kinematic innovation calculated by

$$\nu^{\tau}_{k,i,e} = e_{k,i} - H\hat{x}^{\tau}_{k|k-1} \tag{26}$$

and measurement $z_{k,i}$ passes the kinematic selection test if

$$\left(\nu^{\tau}_{k,i,e}\right)^{\top} (S^{\tau}_k)^{-1} \nu^{\tau}_{k,i,e} < \tau_e \tag{27}$$

The Doppler selection uses the Doppler innovation calculated by

$$\nu^{\tau}_{k,i,D} = v_{k,i} - h_v(\hat{x}^{\tau}_{k|k,i-}) \tag{28}$$

and measurement $z_{k,i}$ passes the Doppler selection test if

$$\left(\nu^{\tau}_{k,i,D}\right)^{\top}\left(S_v(\hat{x}^{\tau}_{k|k,i-}, P^{\tau}_{k|k,i-})\right)^{-1}\nu^{\tau}_{k,i,D} < \tau_v. \tag{29}$$

Measurement $z_{k,i}$ is selected for track update if it passes both kinematic and Doppler selection tests. If a measurement is not selected by track τ, it is either ignored during the track τ update, or its likelihood with respect to track τ is set equal to zero.

3.3.3 Data Association

Measurement set z_k likelihood ratio is given by [5]:

$$\Lambda^{\tau}_k = 1 - P_D P_G + P_D P_G \sum_{j=1}^{m_k} \frac{p^{\tau}_{k,i}}{\rho^{*}_{k,i}} \tag{30}$$

Data association probabilities $\beta^{\tau}_{k,i}$ are probabilities that measurement $z_{k,i}$ is the target τ detection, given that target τ exists at time k, and they are equal to

$$\beta^{\tau}_{k,0} = \frac{1 - P_D P_G}{\Lambda^{\tau}_k} \tag{31}$$

for null (none of the selected) measurement and

$$\beta^{\tau}_{k,i} = \frac{P_D P_G}{\Lambda^{\tau}_k} \cdot \frac{p^{\tau}_{k,i}}{\rho^{*}_{k,i}} \tag{32}$$

for $i > 0$.

3.3.4 Update and Output

The probability of target existence is updated by [5]

$$\psi^{\tau}_{k|k} = \frac{\Lambda^{\tau}_k \psi^{\tau}_{k|k-1}}{1 - (1 - \Lambda^{\tau}_k)\psi^{\tau}_{k|k-1}}, \tag{33}$$

where Λ_k is defined by equation (30). The probability of target existence is then used to update track status (false track discrimination).

Given that none of the selected measurements is the target detection, the trajectory state update pdf equals trajectory state prediction pdf:

$$\left[\hat{x}^{\tau}_{k|k,0}, P^{\tau}_{k|k,0}\right] = \left[\hat{x}^{\tau}_{k|k-1}, P^{\tau}_{k|k-1}\right]. \tag{34}$$

Given that measurement $z_{k,i},\ i > 0$ is the target detection, trajectory state update mean and covariance are obtained by first using the Kalman filter update (21) to apply kinematic measurement $e_{k,i}$, followed by the extended Kalman filter update to apply the Doppler measurement $v_{k,i}$

$$K_v = P^{\tau}_{k|k,i-} H_v^{\top}(\hat{x}^{\tau}_{k|k,i-}) S_v(\hat{x}^{\tau}_{k|k,i-}, P^{\tau}_{k|k,i-})^{-1} \tag{35}$$

$$\hat{x}^{\tau}_{k|k,i} = \hat{x}^{\tau}_{k|k,i-} + K_v\left(v_{k,i} - h_v(\hat{x}^{\tau}_{k|k,i-})\right) \tag{36}$$

$$P^{\tau}_{k|k,i} = (I - K_v H_v(\hat{x}^{\tau}_{k|k,i-})) P^{\tau}_{k|k,i-} \tag{37}$$

where $S_v(\hat{x}^{\tau}_{k|k,i-}, P^{\tau}_{k|k,i-})$ and $H_v(\hat{x}^{\tau}_{k|k,i-})$ are defined by (23) and (25) respectively.

Trajectory estimate is approximated by a single Gaussian pdf, defined by its mean and covariance [4]:

$$\begin{aligned}\hat{x}^{\tau}_{k|k} &= \sum_{i=0}^{m_k} \beta^{\tau}_{k,i}\hat{x}^{\tau}_{k|k,i} \\ P^{\tau}_{k|k} &= \sum_{i=0}^{m_k} \beta^{\tau}_{k,i}(P^{\tau}_{k|k,i} + \hat{x}^{\tau}_{k|k,i}(\hat{x}^{\tau}_{k|k,i})^{\top}) - \\ &\quad - \hat{x}^{\tau}_{k|k}(\hat{x}^{\tau}_{k|k})^{\top},\end{aligned} \tag{38}$$

where data association probabilities $\beta_{k,i}$ are defined by (31) and (32).

3.3.5 Track Initialization

Tracks are initialized at each scan using available measurements. There are many ways that measurements can be used for track initialization. Two point differencing has been presented in a number of papers, see for example [6, 14].

As in [12, 13], we use here one point track initialization, where each measurement in each scan initializes a track. Let the new track be initialized at time k by measurement $z_{k,i}$. The new track is given initial probability of target existence

$$\psi_{k|k} = \Psi_0 P_{k,i}^0, \tag{39}$$

where Ψ_0 is the prior probability of new target per measurement, and $P_{k,i}^0$ is the probability that measurement $z_{k,i}$ is not a detection of any of the existing tracks. For single target tracking, such as DIPDA, value of $P_{k,i}^0 = 1$ is appropriate.

Measurement $z_{k,i}$ has two components, the kinematic component $e_{k,i}$ and the dynamic component $v_{k,i}$. Prior target position may be assumed to have zero information, as the new target may appear anywhere in the surveillance region. Prior speed information is assumed to have mean velocity equal to zero, and velocity covariance determined by the maximum expected velocity, $V_{\max}$.

Thus, after applying $e_{k,i}$, trajectory estimate of new track is

$$\hat{x}_{k|k,i-} = \begin{bmatrix} e_{k,i} & 0 \end{bmatrix}^\top \tag{40}$$

$$P_{k|k,i-} = \begin{bmatrix} R & 0 \\ 0 & V_{\max}^2 I_M/3 \end{bmatrix}^\top, \tag{41}$$

where M denotes the number of position measurement $e_{k,i}$ dimensions, and I_M denotes identity matrix of the Mth order. Finally, Doppler measurement EKF, equations (35)-(37) are applied to use the Doppler measurement and obtain $\hat{x}_{k|k}$ and $P_{k|k}$.

3.3.6 Multi Target Tracking Issues

This paper describes target existence based, singe–scan, single–target DIPDA tracking which fully uses Doppler measurements. In many instances more than one targets may exist in the surveillance space, selecting common measurements. Also, as often happens in many active sonar applications, one target may be physically big enough to produce more than one measurement per scan. These extended targets can also be modeled by a collection of close point targets.

Multi target tracking may use so called optimal or “joint” multi target approach [15, 16], which enumerates and evaluates all global measurement to track assignments. Using Doppler measurements in the manner described in this paper is feasible in, for example Joint IPDA [16]. The problem with that approach is complexity (number of global assignments) which grows combinatorially in the number of measurements and the number of tracks. In heavy clutter environments and when more than a very small number of targets exists, this approach is simply not practical. In most situations sub–optimal multi target tracking is the preferred solution. A possible suboptimal approach is the Linear Multitarget [17, 18] approach to convert single target trackers (such as DIPDA) into multi target trackers (in this case LM DIPDA). Linear Multitarget delivers “almost optimal” multi target performance and has complexity which grows only linearly in the number of tracks and the number of measurements involved.

Linear Multitarget modulates the clutter measurement density observed by each track by the possible clutter contributions of “other” tracks. This paper does not detail the process due to lack of space, but the Linear Multitarget formulae are extended to include Doppler information in a straightforward manner.

4 Simulations

The purpose of simulations is to demonstrate the benefits of proposed approach. Three algorithms are being compared:

- Standard IPDA, which ignores Doppler information, and is described in [5, 6],
- Doppler data association IPDA, which uses Doppler information only to enhance data association, and is described in [11], and
- Doppler IPDA, as described in this paper.

For reasons of simplicity, all algorithms assume known clutter measurement density and probability of detection.

Each simulation experiment consists of 500 simulation runs. Each simulation run has 25 scans, with the scan time equal to 4 seconds. In each simulation run, a single target repeats the uniform motion trajectory, defined by an initial position vector of $(100, 400)$m, and an initial speed vector of $(10, 0)$m/s. The probability of target detection is $P_D = 0.9$. The target position measurement noise is a zero mean, white two dimensional Gaussian process with covariance $R = 40^2 I_2 \mathrm{m}^2$, where I_2 denotes the identity matrix of 2nd order. The target Doppler measurements are also taken, with the Doppler measurement errors being a zero mean, white Gaussian sequence with standard deviation of 0.05m/s. The maximum target speed is assumed to be $V_{\max} = 35$m/s.

The sensor is stationary and positioned at coordinates $(600, 0)m$. The surveillance area is rectangular, with opposite points at $(0, 0)$m and $(1200, 1000)$m. Clutter measurements are generated in each scan, with Poisson distribution and position clutter measurement density of $5 \cdot 10^{-5}\mathrm{m}^{-2}$. Each clutter measurement also has a Doppler component, which is uniform in the range of $-V_{\max}, V_{\max}$.

Each received measurement in each scan is used to initialize one new track, as proposed in this paper. The probability of target existence for each new track is initialized to to the value of $\Psi_0 = 0.02$. Both true tracks and false tracks are initialized and maintained. At the end of each simulation run all true tracks are removed from memory, however the false tracks are left to propagate in the subsequent simulation runs. This builds up a steady state field of false tracks, simulating a long and continuous surveillance operation. False track discrimination (FTD) procedure uses the probability of target existence to confirm and terminate tracks. If the probability of target existence of a track crosses over confirmation threshold equal to 0.975, that track is confirmed and remains confirmed until termination. When the probability of target existence of a track falls below termination threshold equal to 0.02, the track gets terminated and removed from memory.

This is quite a severe environment. In each simulation experiment approximately $750,000$ false tracks get initialized. The average number of selected measurements per track in the first scan after initialization is 13.4, followed by 11.7 and 8.9 in subsequent scans for the Doppler IPDA.

Standard IPDA, as well as IPDA with Doppler Data Association are not able to cope with this amount of clutter, and do not confirm any tracks, either true or false, and even with reduced track confirmation thresholds.

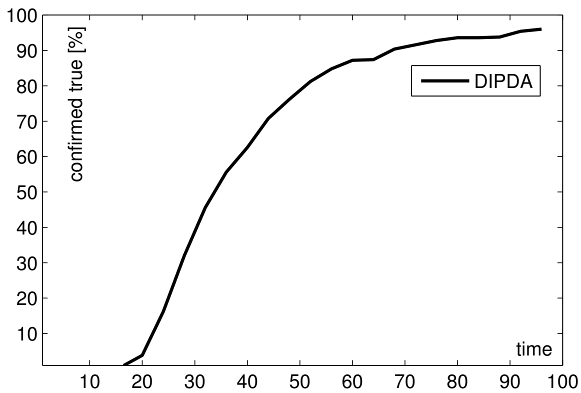

Figure 1: True track confirmation success rate

Results for the Doppler IPDA are quite decent. Eight false tracks are confirmed in the simulation experiment (out of the total of $750,000$ initialized false tracks). A confirmed false track was visible in only 46 scans (out of the total of $500 * 25 = 12,500$). After 25 scan times (100 seconds), the success rate of establishing and confirming true track was 96%. Computational requirements were quite modest for this environment. The average CPU time per scan was 0.83s, which included simulation overheads such as measurement generation and statistics update. Furthermore, the platform was also quite modest: a 1.73 GHz Pentium M processor running Matlab and Windows XP.

5 Conclusions

In this paper a Doppler IPDA algorithm for recursive target tracking in clutter is presented. DIPDA improves upon standard IPDA by using the Doppler measurement components to both enhance the data association probabilities, and to improve the trajectory state estimates.

DIPDA updates the probability of target existence, which can be used as the track quality measure for false track discrimination. Thus, the algorithm presented here can be a complete automatic target tracking solution when Doppler measurements are available.

Simulation results validate this approach. In an environment which was so heavily cluttered that neither standard IPDA [5, 6], nor Doppler data association IPDA [11] could not reliably confirm true tracks, the Doppler IPDA algorithm managed to have high true track confirmation success rate, with a very small number of confirmed false tracks.

Current research aims to further improve achieved results.

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