Integrated Particle Filter for Multi Target Tracking

Zvonko Radosavljević, Dejan Ivković and Branko Kovacević

***Abstract*— Target tracking in heavy cluttered environment requires methodology for false track discrimination and data association. Recently, we present a new particle filter (PF) approach which recursively calculates the probability of target existence for the false track discrimination. Our approach treats possible detections of targets followed by other tracks as additional clutter measurements. It starts by approximating the a priori probabilities of measurement origin. The posterior data association probabilities are calculated to discriminate clutter measurements when updating trajectory probability density function. A new complete recursive track initiation, confirmation and deleting algorithm based on PF and Integrated Track Splitting (ITS) and named Integrated Particle Filter (IPF) is presented. Through the extended simulations showed the effectiveness of this approach in a five targets scenario.**

***Index Terms*—Target tracking, data association, particle filter, Integrated Track Splitting.**

I. Introduction

Each sensor measurements may either be a spurious (clutter) or a target measurement. The target existence and trajectory are not a priori known [1]. The tracks are initialized using measurements, thus both true tracks and false tracks simultaneously exist. The false track discrimination (FTD) is a procedure to terminate a majority of false tracks and confirm majority of true tracks [2],[3]. A track quality measure needs to be calculated for successful FTD. The multiple hypothesis tracker (MHT) [4][5] is one of the first widely used algorithm for target tracking in clutter. The measurement-oriented MHT, often known as the Reid algorithm [1], forms new tracks and measurement allocation hypotheses centered around global origin of measurements. The MHT uses statistical methods (track score) to discriminate between false and true tracks. The probability of target existence obtained by utilizing Markov chain propagation models and Bayes update is used as the track quality measure in Integrated Probabilistic Data Association (IPDA) of [6] and Integrated Track Splitting (ITS) [7],[8].

The application of the Sequential Monte Carlo estimation framework to real multi-target tracking problems is plagued by many difficulties. Among other things, realistic models for the target dynamics and measurement processes are often nonlinear and non-Gaussian, so that no closed-form analytic expression can be obtained for the tracking recurs.

When tracking a single object closed-form expressions are generally not available for nonlinear or non-Gaussian models, and approximate methods are required. The extended KF liberalizes models with weak nonlinearities around the current state estimate, so that the KF recursions can still be applied. However, the performance of the EKF degrades rapidly as the nonlinearities become more severe. To alleviate this problem the unscented KF (UKF) [9], [10] maintains the second-order statistics of the target distribution by recursively propagating a set of carefully selected sigma points [11]. This method requires no linearization, and generally yields more robust estimates.

When tracking with Particle Filter [12],[13] an analog to the predicted measurements covariance is not directly available and could only be constructed as an approximation to the current particle cloud. A common alternative is to use a form of soft gating based upon a Student'st likelihood, combine the same function and probabilistic data association approaches to develop a new method for tracking in clutter using a particle filter. This is done by deriving an expected likelihood from known measurements and clutter statistics.

In this paper, we propose the integrated particle filter (IPF) solution for the target tracking in clutter. Each track trajectory pdf is represented by a disjoint set of particles, and the probability of target existence is integrated into the track state, similar to [14], [15], [16]. The FTD may use the probability of target existence as the track quality measure. The standard IPF is a single-target tracker, and we also include multi target approach [17] for target tracking. They all share common recursion elements, being distinguished by the data association calculus. In addition to the recursive calculation of the probability of target existence and non-uniform clutter, we also include the state dependent probability of target detection, and maneuvering (multi-model) target trajectories [18].

Rest of the paper is organized as follows. The models and the particle filter background are presented in Section 2. The common IPF framework is detailed in Section 3, and the implementations of IPF is presented in Section 4. This approach is indicated by simulations in Section 5, followed by the concluding remarks in Section 6.

II. Problem Statements

The dynamic target trajectory state models at the time k are given by the:

$$x_k = Fx_{k-1} + \nu_k \tag{1}$$

where F is the propagation matrix, ν_k is a zero mean and

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white Gaussian sequence with covariance *R*. At each scan the sensor returns a random number of random target and clutter measurements. The measurement of existing and detectable target is taken with a probability of detection P_D. At time *k*, one sensor delivers a set of measurements $z_k = \{z_{k,j}\}_{j=1}^{M_k}$ track out of which a set of measurements are selected for track update. Converted target measurement *y* is given by [19] :

$$y_k = Hx_k + w_k \tag{2}$$

where *H* is measurements matrix and the measurements noise w_k is zero mean and white Gaussian sequence. A measurements of target is present in each scan with a probability of detection P_D . Clutter measurements follow the Poisson distribution characterized at location by clutter measurements density $\rho_k(y)$ [19].

Particle filtering samples at the continuous posterior density function of interest into a set of weighted particles. If the weights are chosen appropriately, then these weighted set of particles represent the posterior density in a way that the posterior density function can be made arbitrarily close to the equivalent set of weighted particles. The target trajectory state *pdf* at scan *k* is defined by set of particles $\{x_k, w_k\}$, parameterized by set of *N* particles $\{w_l^i, x_k^i\}_{i=1}^N$ where should be satisfied $\sum_{i=1}^{N} w_l^i = 1$. Using sequential importance sampling [xx], particle filters can approximate the posterior density function, regardless of the time interval k of the trajectory model [20].

III. INTEGRATED PARTICLE FILTER

The track state consists of the target existence event, and the trajectory state, and for each track we recursively calculate the probability of target existence, and the trajectory state probability density function (pdf). The trajectory state pdf are only defined conditioned on target existence. Depending on the calculated probability of target existence we may conclude that the target exists and confirm the track. Each confirmed track stays confirmed until termination. Alternatively, if the calculated probability of target existence dips below certain level we conclude that the target does not exist and terminate the track [21].

Key topics of new IPF algorithms are:

- new particles arise by re-sampling;
- heavy particles are multiply,
- weak particles are extinguished
- measurements are used to correct the weight of the particles and the probabilities of target existence.

At begin, lets define key parameters. The number of particles from $(k-1)^{th}$ scan, $N_{k-1} = N$ does not change from scan to scan. Lets represent particle $\{x_{k-1}^i, w_{k-1}^i\}$, $i = 1,..., N_{k-1}$ from $(k-1)^{th}$ scan , mean and weight. Number of measurements arriving from k^{th} scan are M_k, and $N_p = N$ is number of particles after re-sampling step. Probability of target detection, as the function of target trajectory state is $p_D(x_k) = P_D$. Also we have equation [22]:

$$\widetilde{P}_D = \sum_i w_{k-1}^i p_D(x_k^i) = P_D \sum_i w_{k-1}^i = P_D \tag{3}$$

Proposed IPF algorithm is perform by the following steps:

- prediction step,
- measurements likelihood calculating
- update step and
- re-sampling step.

A. *Prediction step:*

At begin, we calculate probability of target existence, by the:

$$\psi_{k|k-1} = \Delta_{11} \cdot \psi_{k-1|k-1} \tag{4}$$

The mean of particle is given by the:

$$x_k^i = f(x_{k-1}^i, v_k^i) = Fx_{k-1}^i + v_k^i \tag{5}$$

where particle propagation noise is $v_k^i \approx N(0,Q)$ and measurements sets is given by $Z_k = \{z_k^1, ..., z_k^{M_k}\}$

B. *Measurements likelihoods*

After KF prediction, we estimate measurements by the:

$$\hat{y}_k^i = Hx_k^i \tag{6}$$

In order to compute statistical distance:

$$d^2{}_{ij} = (z_{k,j} - \hat{y}_k^i)^T (R_k)^{-1} (z_{k,j} - \hat{y}_k^i), \; j = 1,..., M_k \tag{7}$$

Probability density function is given by the:

$$p_{k,j}^i = \frac{1}{\sqrt{\det(2\pi R_k)}} \exp[-0.5 \cdot d^2{}_{ij}] \tag{8}$$

where likelihoods of measurements is:

$$p_{k,j} = \sum_i w_{k-1}^i \cdot p_{k,j}^i \tag{9}$$

Now, we can calculate measurements likelihood ratio, by the equation:

$$\Lambda_k = 1 - P_D + P_D \sum_j \frac{p_{k,j}}{\rho_{k,j}} \tag{10}$$

Beta's coefficients we can update by the:

$$\beta_{k,j} = \frac{1}{\Lambda_k} \begin{cases} 1 - P_D, & j = 0 \\ P_D \dfrac{p_{k,j}}{\rho_{k,j}}, & j > 0 \end{cases} \tag{11}$$

C. *Update step:*

In update step, we first calculate weight of particles, in purpose of trajectory state update, by the [23]:

$$w_k^i = w_{k-1}^i \cdot (\beta_{k,0} + \sum_{j=1}^{M_k} \beta_{k,j} \frac{p_{k,j}^i}{p_{k,j}}) \tag{12}$$

At the end of update step, we calculate target existence probability of track, by the equation:

$$\psi_{k|k} = \frac{\Lambda_k \psi_{k|k-1}}{1-(1-\Lambda_k)\psi_{k|k-1}} \tag{13}$$

D. *Resampling step:*

Resampling step calculates mean and weight of particles, by the foloowing [24]:

$$\{x_k^i, w_k^i\} \Rightarrow \left\{ x_k^I, w_k^I = \frac{S_w}{N_p} = \frac{1}{N} \right\}, I = 1,2,...,N \tag{14}$$

where

$$S_w = \sum_{i=1}^{N_{k-1}} w_k^i = 1 \tag{15}$$

$$u_1 = U\left[0, \frac{1}{N}\right] \tag{16}$$

$$u_l = u_1^l + (l-1)\frac{1}{N}, i_c = i_{c-1} + w_k^i, i = 1,...,N \tag{17}$$

where S_w is sum of weights, U[.] means uniform distribution, u_l is interval of weights.

E. *Output Calculation*

Finally, we can calculate the output state estimate and covariance (for output purpose only):

$$\hat{x}_{k|k} = \sum_{l=1}^{Np} w_k^l x_k^l \tag{18}$$

$$P_k = \left(\sum_{l=1}^{Np} w_k^l \cdot x_k^l \cdot x_k^{l\,T} \right) - \hat{x}_k \cdot \hat{x}_k^{\ T} \tag{19}$$

IV. IMPLEMENTATION OF IPF

In this section, a brief instruction of IPF sofware implemenattion, we describe. Track initiation and termination is an part for establishing the records of the new targets and terminating the unwanted records of the inexistent targets when they leave the surveillance region. But in the heavy cluttered environment, there exists due to the unknown state of the target and the sequence of measurements which originate from the target. Here, we present a track management procedure.

Track initiation is composed of two parts:

- produce temporal tracks and
- confirm the temporal tracks.

Track termination is of two meanings:

- reject the temporal tracks;
- terminate the confirmed tracks when the detected targets leave the surveillance region.

A. *Software implementation of IPF*

One cycle of the recursive IPF algorithms software implementation consists of the following procedure:

for scan = 1 : number of scans
--Read Measurements
-Target Tracking with IPF
-Initializing of Measurements Selection
-Measurements selection (measurement likelihood for all particles)
-Taking into account clutter density
-Update Tracks of IPF
-Single Target Track Data Association
-Update Weights
-Resampling
-Estimate IPF
-Tracks Initializing
-Update Old Samples
-Update Status
-Update Age
-Eliminate Wide
-Merge Close Tracks
-Eliminate Tracks -Out of Bound
-Update Tracks (Confirmation and Deleting)
-Prediction of IPF
-Determine Target Track
-Target Statistics of Scans (True, False, Confirmed,…)
-Reduce Tracks
End

V. SIMULATIONS

For the purpose of research, a simulation scenario with five targets motion scenario (Fig.1). Targets are initially positioned at the edges of a circle with the center at (500,500) and a radius of 450. Each target moves with a uniform speed towards the center of the circle, which they should reach in 20 scans, after which they carry on with uniform motion for further 20 scans. A random (noise) component is added to the speed vector of each target, with covariance (2*R/400).

A random component is added to the speed vector of each target, thus at scan 20 the variance of the distance between each target and the centre of the circle will be double the sensor measurement error noise covariance matrix. In the two targets scenario, the targets initial separation is 20^o, instead of fifteen targets scenario with the targets initial separation 10^o. The following definitions of true and false tracks are used. Each initiated track is false with respect to all existing targets. A false track becomes a true track with respect to a target when the state estimate is sufficiently close to the true target state.

Each simulation experiment consists of a number of simulation runs. In each simulation run, targets will repeat their trajectories. The measurements are generated independently. Each algorithm uses the same set of measurements. False tracks may be initiated using target measurements, either in a conjunction with a clutter measurement, or by using measurements from different targets in different scans.

Thus, the average number of initialized false tracks per scan will depend on the number of targets present. The average number of initialized false tracks per scan was 8, and 120 for the two and fifteen targets experiments, respectively. A confirmed false track in one scan is 300 and 200 for the two and fifteen targets cases, respectively. The performance measures used to compare the algorithms confirmed true tracks, root mean square error positions and target retention statistics. Results are presented by a number of confirmed true tracks and Root Mean Square Error Position.

The target retention statistics was obtained by noting the identity of the confirmed true track following each of the targets at scan 14. These identities are checked again at scan 38, and the following statistics is accumulated for each experiment:

nCases: total number of cases of a target being followed by a confirmed track at scan 14;

nOK: percentage of tracks still following the original target at scan 38;

nSwitched: percentage of tracks that end up following a different target at scan 38;

nLost: percentage of tracks not following any target at scan 38,

nMerged: percentage of tracks lost due to merging between tracks counted in nCases between scans 14 and 38

For the target retention statistics, each algorithm identifies the confirmed true track for a specific interval that includes intersection of trajectories. The targets intersect at scan 24 and many joint events occur around that time. In the experiment, the identities of the confirmed true tracks are obtained at scan 17 for performance comparison.

Parameters were used: probability of target detection is pD=0.8, number of Monte Carlo runs is 100, duration of one recursion 40, measurements noise matrix -R=[25 0; 0 25], maximum of target speed -25 [m/s], variance of acceleration q =0.75, number of particles -1000, maximum number of components -40, starting cross statistics in 14 scan, ending cross ststistics scan 38.

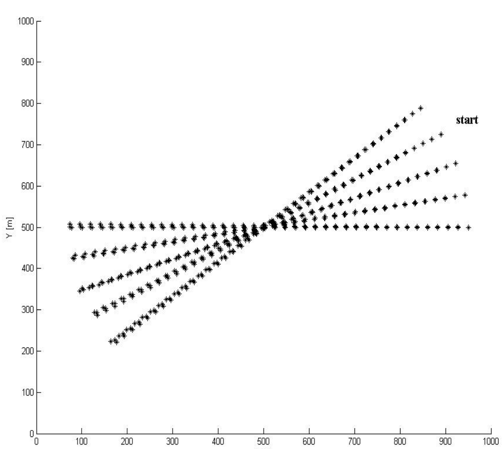

Fig. 2. Simulation scenario (Five targets)

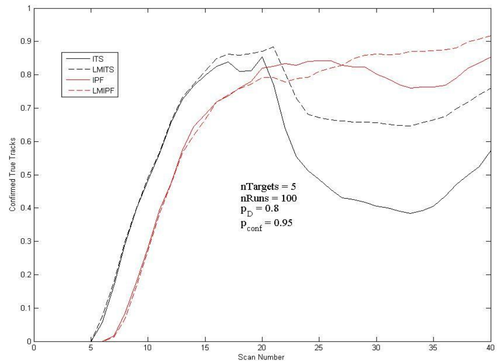

Fig. 2. confirmed true tracks diagram over time (five target)

The sampling period of radar sensor is T=1s. Duration of the scenario is 40 scans. The system input is modeled as follows: vector state $\mathbf{x}(k) = [x\ \dot{x}\ y\ \dot{y}]^T$ where the Cartesian coordinates of the target position are, and are the appropriate velocities. Transition matrix and process noise matrix are given by:

$$F = \begin{bmatrix} 1 & T & 0 & 0 \\ 0 & 1 & 0 & 0 \\ 0 & 0 & 1 & T \\ 0 & 0 & 0 & 1 \end{bmatrix} \quad (20)$$

$$Q_k = q\begin{bmatrix} T^3/3 & T^2/2 & 0 & 0 \\ T^2/2 & T & 0 & 0 \\ 0 & 0 & T^3/3 & T^2/2 \\ 0 & 0 & T^2/2 & T \end{bmatrix} \quad (21)$$

respectively. Measurements matrix and measurements noise matrix is given by:

$$H = \begin{bmatrix} 1 & 0 & 0 & 0 \\ 0 & 0 & 1 & 0 \end{bmatrix},\ R_k = \begin{bmatrix} \sigma_x^2 & 0 \\ 0 & \sigma_y^2 \end{bmatrix} \quad (22)$$

respectively.

All simulations were done in a software package MATLAB, with CPU Intel Core i7, 2.93 GHz. Results of simulation are governed by the number of confirmed true tracks (Fig, 2) and target retention table. We compare standard ITS and proposed IPF algorithms.

Target retention table

	ITS	**IPF**
nCases[n]	**91**	**80**
nOK[%]	31.86	42.5
nSwit[%]	15.38	18.75
nLost[%]	52.76	38.75
merged	26	14
CPU [s]	1.65	1.81

The results confirm the justification of the proposed IPF approach compared to standard ITS algorithm. IPF has a smaller percentage of losses and switched targets and higher percentage of full tracking targets with approximately the same CPU consumption.

VI. CONCLUSION

The multiple target tracking algorithm, known IPF, is proposed and was tested in a special scenarios with five crossing targets. It uses the well-known features of ITS algorithms that account the probability of target existence of objective forms, trace and ease of use offered by the Particle Filter. A Simulation results with two-dimensional scenario showed that the proposed algorithm ends up with good performance and small computational load. Proposed algorithm, which has been presented for tracking multi, have the ability to estimate the number of targets. Tracking the trajectories of the target over time, operate with missed detections and give the trajectories of the targets.

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