Filtered Gate Structure Applied to Joint Probabilistic Data Association Algorithm for Multi-Target Tracking in Dense Clutter Environment

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Abstract

In multi-target tracking system (MTT) Improving data association process in the presence of severe clutter are discussed in this paper. New technique in dense clutter environment based on filtering gate method applied to conventional approaches as joint probabilistic data association filter (JPDAF) is introduced to overcome the issue that the data association algorithm begins to fail due to the increase in background clutter and false signals. An adaptive search based on the distance threshold measure is then used to detect valid filtered data point for multi-target tracking. Simulation results demonstrate the effectiveness and better performance when compared to conventional algorithm.

Keywords: *Data Association, Multi-Target Tracking, Joint Probabilistic Data Association Algorithm, Filtering.*

1. Introduction

Multi-target tracking is an essential requirement in surveillance systems. Measurements from diverse sources (targets of interest, clutter, noise signal) are reported by sensors; e.g., radar, sonar, and infrared (IR) sensors. In general the measurements can be received from sensors at regular time intervals (scan periods). The target tracking consists of two basic parts: data association and tracking filtering. Data association is responsible for deciding on each scan which of the received multiple measurements that lie in the specified gate of the predicted target position should update with the existing tracking target. This first part is often considered as the most important because its result is crucial for overall tracking process. A gating process is used in this part to reduce the number of candidate measurements to be considered. The gating technique in tracking a maneuvering target in clutter is essential to make the subsequent algorithm efficient but it suffers from problems since the gate size itself determines the number of valid included measurements. If we choose a too small gate size, we can miss target-originated measurements on the other hand, if we choose a gate with too large size, we will obtain many unwanted non-target measurements, giving rise to increased computational complexity and decreased performance. To find a gate volume in which we regard measurements as valid is an important consideration. There have been many types of gating techniques studied. First of all, previous approaches have used constant parameters to determine the gate size [1]-[4]. Recently, adaptive and (locally) optimal approaches to estimate gate size have also been proposed under more restricted assumptions [5]-[8]. However, this estimation is often computationally intensive. Another problem in case of tracking multiple targets, data association becomes more difficult because one measurement can be validated by multiple tracks in addition to a track validating multiple measurements as in the single target case. To solve these problems, an alternative approach known as joint probabilistic data association filter (JPDAF) has been used to track multiple targets by evaluating the measurement to track association probabilities and combining them to find the state estimate [9]-[12]. Due to increase in the false alarm rate or low probability of target detection (target in dense clutter environment), most of the data association algorithms begin to fail. We propose here an algorithm which is less sensitivity to false alarm targets in the gate region size than JPDA algorithm. This proposed algorithm reduces the number of candidate measurements in the gate by a filtering method that compares the measurement in the gate at the prediction step with the current measurement in the same gate at the update step and then avoids any measurement in the current gate less than the threshold value due to comparison. This is called filtering gate method which is similar to an idea taken from adaptive clutter suppression filtering methods used in radar signal processing [13],[14]. The filtering gate algorithm is combined with JPDA algorithm to apply the proposed algorithm in multi tracking targets in presence of various clutter densities. Simulation results showed better performance when compared to the conventional JPDA algorithm.

2. Background

2.1 State Space Model

In a dynamic state space model, the observed signals (observation/ measurements) are associated with a state and measurement noise. Consider that there are T targets being tracked at time index k. The targets are modeled as discrete-time, linear, dynamic systems described by the following equation

$$x^t(k) = A^t(k-1)x^t(k-1) + w^t(k-1) \qquad t = 1,2,...,T \qquad (1)$$

where $x^t(k-1)$ is the n x 1 target state vector, $A^t(k-1)$ is the state transition matrix describing the dynamics of the target and $w^t(k-1)$ is the target noise vector assumed to be white Gaussian noise with zero mean and covariance Q. The superscript t corresponds to the t^{th} target. The initial target state, $x^t(0)$ for t = *1,2, ..., T* , is assumed to be Gaussian With mean m_0^t and known covariance matrix p_0^t. Where the unobserved signal (hidden states) $\left\{x^t(k) : k \in N\right\}, x^t(k) \in X$ be modeled as a Markov process of transition probability $p\left(x^t(k) \mid x^t(k-1)\right)$ and initial distribution $p\left(x^t(0)\right) = N(x^t(0); m_0^t, p_0^t)$. The associated measurement equation is modeled as

$$z^t(k) = H^t(k)x^t(k) + v^t(k) \qquad t = 1,2...T \qquad (2)$$

where $z^t(k)$ is the m **x** 1 measurement vector, $H^t(k)$ is a known matrix and $v^t(k)$ is a noise vector assumed to be a zero-mean normally distributed Gaussian process with known covariance R.

The observations $\left\{z^t(k) : k \in N\right\}, z^t(k) \in Z$ are assumed to be conditionally independent given the process $\left\{x^t(k) : k \in N\right\}$ and of the marginal distribution $p\left(z^t(k) \mid x^t(k)\right)$.

In linear systems, the state space model is optimally addressed by the Kalman filter [5],[15]. The functioning of the Kalman filter consists of two recursive steps: prediction and update.

2.2 Filtered Gate Method

In the prediction step, Let $Z(k-1) = \left\{z_1(k-1), z_2(k-1), \ldots, z_{wn}(k-1)\right\}$ be a set of points in the 2-D Euclidean space at time *k-1* where w_n is the number of points at time scan Δt and let $\hat{z}^t(k)$ be a predicted position of the t^{th} tracked target at time k. according to distance metric measure and gate size, let $\overline{Z}^t(k-1) = \left\{z_1(k-1), \ldots z_j(k-1), \ldots z_{m_t}(k-1)\right\}$ be a set of the candidate points detected in the t^{th} gate $G_t(k-1)$ of predicted position $\hat{z}^t(k)$ whose elements are a subset from the set $Z(k-1)$ where j =1 to mt (number of detected points in gate $G_t(k-1)$ at time *k-1*) and $\overline{Z}^t(k-1)$ be a set of all valid points $z_j(k-1)$ that satisfy the distance measure condition $\left|z_i(k-1) - \hat{z}^t(k)\right| < W$ for each target t where W is threshold value that determines the gate size and i =1 to w_n , j =1 to mt, i. e for each target t, j is initialized by 1 and is increased by $j = j + 1$ after each valid point is detected up to last mt detected points. We consider each point $z_j(k-1)$ in the gate is a center of very small square gate g_j its length is small δ where each value in the small gate g_j is approximately

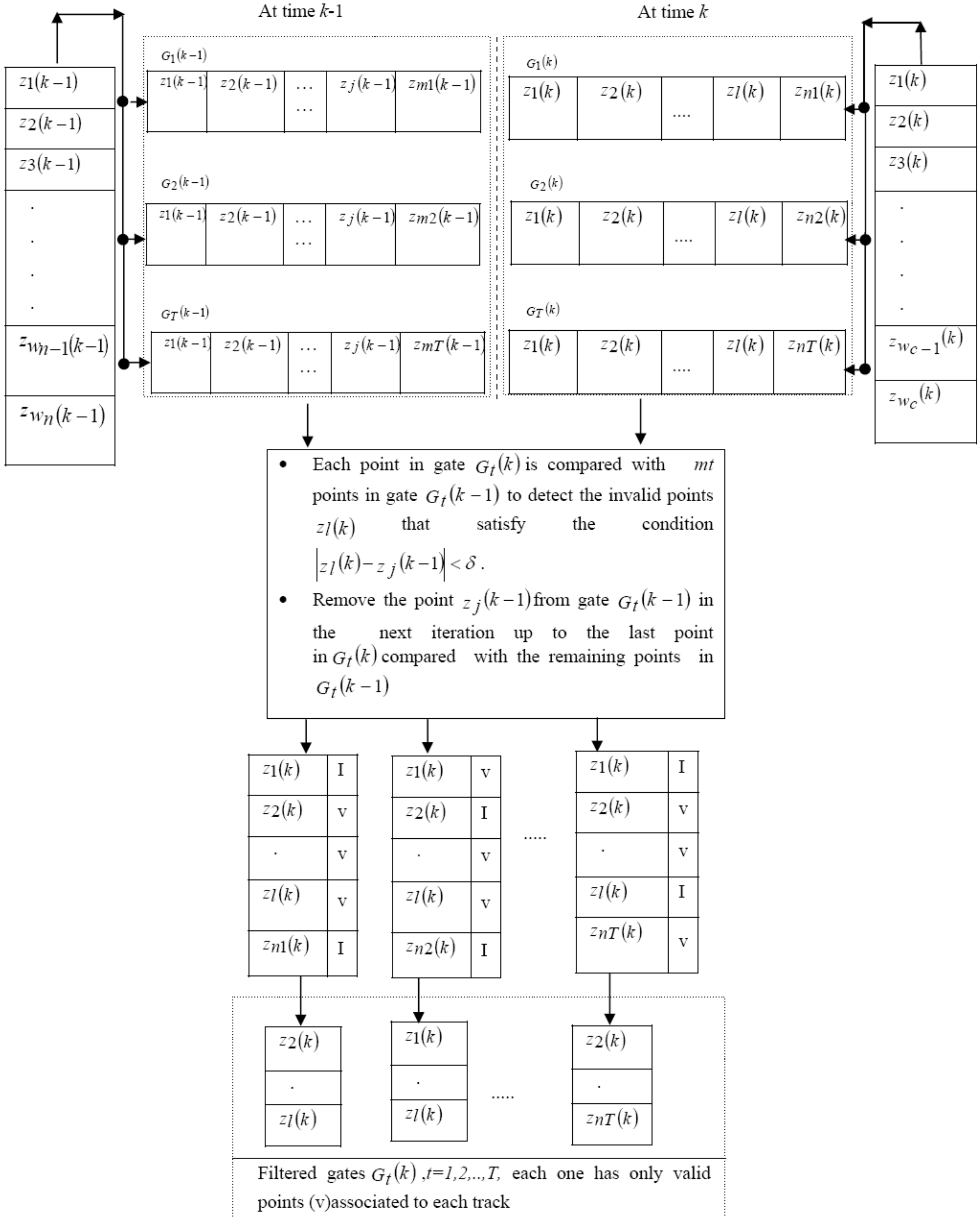

Fig.1 Filtered gate scheme for multiple target tracking

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equal to $z_j(k-1)$ i.e. $z_j(k-1) \approx z_j(k-1) - \delta/2$ to $z_j(k-1) + \delta/2$.

In the updating step, let $Z(k) = \{z_1(k), z_2(k), \ldots z_{w_c}(k)\}$ be a set of points in the 2-D Euclidean space at time k where w_c is the number of points at time scan Δt. The candidate points detected in the same gate $G_t(k)$ as $G_t(k-1)$ of the t^{th} predicted position $\hat{z}^t(k)$ be a subset $\bar{Z}^t(k) = \{z_1(k), \ldots z_l(k), \ldots z_{nt}(k)\}$ from the set $Z(k)$ where l =1 to nt (number of detected points in t^{th} gate at time k) and $\bar{Z}^t(k)$ be a set of all valid points $z_l(k)$ that satisfy the distance measure condition $|z_i(k) - \hat{z}^t(k)| < W$ for each target t where i =1 to w_c, l=1 to nt for l=l+1 after each valid point is detected. After receiving the measurement $Z(k)$ and detecting the valid measurements $\bar{Z}^t(k)$ in the gate for each target t, each point from $\bar{Z}^t(k)$ in the specified t^{th} gate at time k is compared with the previous points $\bar{Z}^t(k-1)$ in the same t^{th} gate at time k-1 to detect the invalid points when $|z_l(k) - z_j(k-1)| < \delta$ and then exclude each point $z_j(k-1)$ that satisfy the condition $|z_l(k) - z_j(k-1)| < \delta$ from the set $\bar{Z}^t(k-1)$ in the next iteration of comparison as shown in Fig. 1.

Finally, we obtain the reduced number of valid points in the gate of each target while the other invalid points is not including in the data association process.

3. Integration between Data Association and Filtered Gate

We propose an algorithm which depends on the history of observation for one scan and uses a fixed threshold but operates similar to an adaptive estimator. In conventional data association approaches with a fixed threshold, all observations lying inside the reconstructed gate are considered in association. The gate may has a large number of observations due to heavy clutter, this leading to; increasing in association process since the probability of error to associate target-originated measurements may be increased. In our proposed algorithm a filtered gate structure is used to provide the possibility to decrease the number of observations in the gate by dividing the state of observations into valid and invalid that only the valid are considered in association. The proposed algorithm can be applied to all gate based approaches, including tracking and clustering. See Fig. 2. Fig. 2(a) and 2(b) show the candidates for association in conventional Joint probabilistic data association (JPDA) at two successive scan. While using the new algorithm, the second scan is processed by our proposed filtered gate based Joint probabilistic data association (FG-JPDA) as in Fig.2(c). Red circles represent the multi gated measurements. Our approach has measurements as well as ones inside the validated regions but is divided into two states valid and invalid, yellow points represent invalid points as shown in Fig. 2(c).

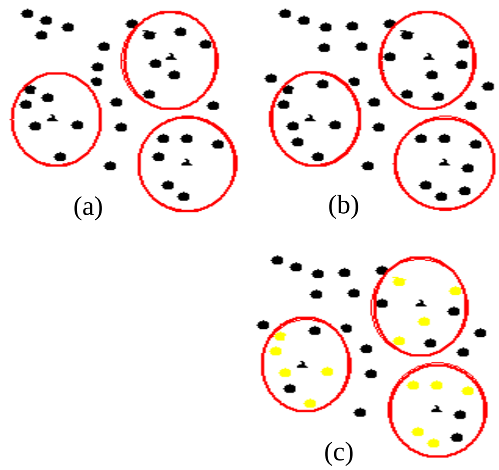

Fig. 2. Multi Gated measurements given an identical threshold for conventional JPDA and filtered gate based JPDA (FG-JPDA): (a) measurements at previous scan. (b) Measurements at current scan. (c) Filtered gate based approach at the scan of (b).

4. Implementation of Joint Probabilistic Data Association Filter Using Filtered Gate Method

The Joint Probabilistic Data Association Filter (JPDAF) is popular approach to tracking multiple moving targets in clutter. The JPDA algorithm updates the track with a weighted sum of the feasible observations. All feasible observation-to-track associations are taken into consideration when calculating the weights (probability values). The state estimate of the track therefore does not depend on a single observation but on all observations falling inside the track gate. Multiple observations in a gate occur when gates overlap or clutter is detected inside a gate.

Notation for JPDAF Approach

The JPDAF calculates for each target separately [5],[16],[17] the associated probability of each element of the set of validated measurements at time *k*, denoted as $\bar{Z}^t(k) = \{z_i(k)\}_{i=1:c^t(k)}$ where $z_i(k)$ is the i^{th} validated measurement lie inside the t^{th} target gate and $c^t(k)$ is the number of measurements in the validation region of the tracked target *t* at time *k*. under the Gaussian assumption for the prediction kernel $p(x^t(k)|z_{1:k-1})$, the validation region is commonly taken to be the elliptical region

$$V^t(k) = \{ z : (z_i(k) - H^t(k)\bar{m}^t(k))' S^t(k)^{-1} (z_i(k) - H^t(k)\bar{m}^t(k)) \le \gamma \} \quad (3)$$

Where γ is a given threshold, $(.)'$ denote transpose and the covariance is defined by $s^t(k) = H^t(k)\bar{P}^t(k)H^t(k)' + R$. We define the accumulation of validated measurements is $Z_{1:k} = \{Z_j, \ for \ j \in \{1,....,k\}\}$.

4.1 Prediction Step in JPDAF Approach

We define the posterior distribution of $x^t(k)$ given the past sequence of observations $Z_{1:k-1}$ in the prediction step, i.e., $p(x^t(k)|z_{1:k-1})$ this process is equivalent to the Prediction step of standard Kalman filter. The prediction distribution is defined by

$$p(x^t(k)|z_{1:k-1}) = N(x^t(k); \bar{m}^t(k), \bar{p}^t(k))$$

,where

$$\bar{m}^t(k) = A^t(k)m^t(k-1)$$

and

$$\bar{p}^t(k) = A^t(k)p^t(k-1)A^t(k)' + Q$$

4.2 Update Step in JPDAF Approach

As mentioned in section 2.1, the hidden variables of the state space model are recursively estimated by the prediction and updating steps. The JPDAF can be modeled as a state space model which can also be estimated using these recursive operations. First of all, the update step in JPDAF approach is as

$$P(x^t(k)|Z_{1:k}) = \sum_{i=0}^{c^t(k)} N(x^t(k); m_i^t(k), p_i^t(k)) \beta_i^t(k) \quad (4)$$

where the $p(i^t|z_{1:k}) = \beta_i^t(k)$ is association probability and

$$p_i^t(k) = \left[\bar{p}^t(k)^{-1} + H^t(k)' R^{-1} H^t(k) \right]^{-1}$$

and

$$m_i^t(k) = p_i^t(k)\left[H^t(k) R^{-1} z_i(k) + \bar{p}^t(k)^{-1} \bar{m}^t(k) \right] \quad (5)$$

For $i \in \{0,......,c^t(k)\}$, *t=1,2,..T*. Since, we have $m_0^t(k) = \bar{m}^t(k)$ and $p_0^t(k) = \bar{p}^t(k)$ for *i* = 0 where there is no target-originated measurement (i.e., $z_0(k) = nil$).

4.3 Estimating Conditional Probability in JPDAF Approach

In order to obtain the filtering density, we require an estimate for the parameter $\beta_i^t(k)$ for each track for $i \in \{0,......,c^t(k)\}$, *t=1,2,….T*. Under the assumption of a poisson clutter model, the association probability $\beta_i^t(k)$ can be estimated as in [16]-[19] by three basic steps namely

1. Generation of a validation matrix. Binary matrix representing all feasible observation-track pairing (result of Gating). Assume there are *m* measurements and *T* targets being tracked. The validation matrix is an *m* x *(T+1)* rectangular matrix,

$$\Omega = [\omega_{it}] = \overbrace{\begin{pmatrix} 1 & \omega_{11} & \omega_{12} & \cdots & \omega_{1T} \\ 1 & \omega_{21} & \omega_{22} & \cdots & \omega_{2T} \\ \vdots & \vdots & \vdots & \vdots & \vdots \\ 1 & \omega_{m1} & \omega_{m2} & \cdots & \omega_{mT} \end{pmatrix}}^{t:\ 0\ 1\ 2\ \cdots\ T} \left.\begin{matrix}1\\2\\\vdots\\m\end{matrix}\right\} i \quad (6)$$

In the above matrix the value ω_{i0} = 1 implies the measurement originated from clutter where

$$\omega_{it} = \begin{cases} 1 & \text{If measurement } i \text{ is in the gate of target } t \\ 0 & \text{If measurement } i \text{ is not in gate of target } t \end{cases} \quad (7)$$

For *i=1,2,…m*, *and t=1,2,…..T*.

2. Generation of feasibility matrices from the validation matrix. This represents all the non-competing events in which an observation *i* is associated with only one track *t* except for *t = 0*. The *t = 0* track is the clutter track (measurement originated from clutter). The number of feasibility matrices rapidly explodes as the number of

tracks and observation increase. These feasibility matrices are subject to the following two restrictions:

- Each measurement can have only one origin, whether it is a real target or clutter.
- No more than one measurement can originate from any given target.

Thus only one element per raw may be chosen from the validation matrix so that there is at most one value per column.

These feasibility matrices provide a format in which to examine every possible observation-track combinations. This is also known as the individual events of the joint association event θ ; $\theta = \bigcap_{i=1}^{m} \theta_{it_i}$ where θ_{it} means measurement i is originated from target t and $i=1,\ldots m$; $t=0,1,\ldots T$ and ti is the index of the target to which measurement i is associated in the event under consideration. All of these events may be represented by a feasible matrix,

$$\hat{\Omega}(\theta) = [\hat{\omega}_{it}(\theta)] \tag{8}$$

This consist of the unit values in the validation matrix, Ω, corresponding with the associations assumed in the event θ. $\hat{\Omega}$ is the same size as the validation matrix Ω with $\hat{\omega}_{it} = 1$ only if measurement i is hypothesized to be either from clutter ($t=0$) or from a target t $(t \neq 0)$.

3. Calculation of the probabilities $\beta_i^t(k)$ for each track-observation pair at time step k from the feasibility matrices by summing over all joint events in which the marginal event of interest occurs as

$$\beta_i^t(k) = p(\theta_{it} \mid Z(k)) = \sum_{\theta} p(\theta \mid Z(k)) \hat{\omega}_{it}(\theta) \tag{9}$$

The joint association probabilities $p(\theta \mid Z(k))$ can be calculated by two versions; parametric and nonparametric as:

With parametric JPDA

$$p(\theta \mid Z(k)) = \frac{1}{C1} \prod_i \left\{ \lambda^{-1} f_{t_i}[z_i(k)] \right\}^{\tau_i} \prod_t (p_D)^{\delta_t} (1 - p_D)^{1-\delta_t} \tag{10}$$

$$f_{t_i}[z_i(k)] = N\left(z_i(k) \mid \hat{z}^t(k), s^t(k)\right) = \left|2\pi s^t(k)\right|^{-\frac{1}{2}} \exp\left[-\frac{1}{2}\left(z_i(k) - \hat{z}^t(k)\right)' s^t(k)^{-1}\left(z_i(k) - \hat{z}^t(k)\right)\right]$$

where

$\hat{z}^t(k) = H^t(k) \overline{m}^t(k)$

c_1 is the normalized constant, P_D is the detection probability of target t and τ_i is the measurement association indicator ; $\tau_i = \sum_{t=1}^{T} \hat{\omega}_{it}(\theta)$ and δ_t is target detection indicator; $\delta_t = \sum_{i=1}^{m} \hat{\omega}_{it}(\theta)$ and λ is the spatial density of the false measurements required to parametric JPDA.

With nonparametric JPDA

$$p(\theta \mid Z(k)) = \frac{1}{c_2} \phi! \prod_i \left\{ V f_{t_i}[z_i(k)] \right\}^{\tau_i} \prod_t (p_D)^{\delta_t} (1 - p_D)^{1-\delta_t} \tag{11}$$

where c_2 is the normalized constant, ϕ is the number of false measurement $\phi = \sum_{i=1}^{m} (1 - \tau_i)$,V is the volume of the surveillance region.

The proposed filtering gate based JPDAF is represented in algorithm 1. The algorithm is divided into four major parts: prediction, finding validated regions, estimating conditional probability and finally an update step. Since only finding validated regions component is fundamentally different from the conventional JPDAF, we look at this in more detail.

Algorithm 1 JPDAF using filtered gate

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1. for $t = 1$ *to* T do
2. Do prediction step,

$x^t(k \mid k-1) \sim p(x^t(k) \mid Z_{1:k-1}) = N\left(x^t(k); \overline{m}^t(k), \overline{p}^t(k)\right)$

where

$\overline{m}^t(k) = A^t(k) m^t(k-1)$

$\overline{p}^t(k) = A^t(k)\, p^t(k-1)\, A^t(k)' + Q$

3. Finding validated region according to Algorithm 2.

4. Estimating conditional probability, $\beta_i^t(k)$

For $i \in \{\ 0,\ldots\ldots, c^t(k)\}$.

$$\beta_i^t(k) = p(\theta_{it} \mid Z(k)) = \sum_{\theta} p(\theta \mid Z(k))\, \hat{\omega}_{it}(\theta)$$

where

$$p(\theta \mid Z(k)) = \frac{1}{C1} \prod_i \left\{\lambda^{-1} f_{t_i}[z_i(k)]\right\}^{\tau_i} \prod_t (p_D)^{\delta_t}(1-p_D)^{1-\delta_t}$$

$$f_{t_i}[z_i(k)] = N\left(z_i(k); \hat{z}^t(k), s^t(k)\right) = \left|2\pi s^t(k)\right|^{-\frac{1}{2}} \exp\left[-\frac{1}{2}\left(z_i(k) - \hat{z}^t(k)\right)' s^t(k)^{-1}\left(z_i(k) - \hat{z}^t(k)\right)\right]$$

$$\hat{z}^t(k) = H^t(k)\,\overline{m}^t(k)$$

5. Do update step,

6. Calculate the distribution of the missing observation $p(x^t(k) \mid z_{1:k-1})$ which is for $i = 0$, $m_0^t(k) = \overline{m}^t(k)$, $p_0^t(k) = \overline{p}^t(k)$

7. Calculate the distribution of the associated observation,

$$P(\ x^t(k) \mid z_i(k), Z_{1:k-1}) = N\ (\ x^t(k); m_i^t(k), p_i^t(k))$$

for $i = \{\ 1,\ldots., c^t(k)\}$

$$p_i^t(k) = \left[\overline{p}^t(k)^{-1} + H^t(k)'\, R^{-1} H^t(k)\right]^{-1}$$

$$m_i^t(k) = p_i^t(k)\left[H^t(k) R^{-1} z_i(k) + \overline{p}^t(k)^{-1}\, \overline{m}^t(k)\right]$$

8. Calculate marginalized probability using Gaussian approximation,

$p(x^t(k) \mid z_{1:k}) = N\left(x^t(k); m^t(k), p^t(k)\right)$ *where*

$$m^t(k) = \sum_{i=0}^{c^t(k)} \beta_i^t(k)\, m_i^t(k)$$

$$p^t(k) = \sum_{i=0}^{c^t(k)} \beta_i^t(k)\left[p_i^t(k) + \left(m_i^t(k) - m^t(k)\right)\left(m_i^t(k) - m^t(k)\right)'\right] \tag{12}$$

9. end for

For finding the validated region, the filtered gate FG_JPDAF after the prediction step checks the number of measurements $z_i(k-1)$ at time *k-1* that lying inside the gate of the predicted position of the track *t* that determined by the same way of JPDAF, then in the update step at time *k* also checks the number of measurements $z_i(k)$ that lying in the same gate *t*. If any measurement in the current gate has approximately the same weight (position) to any measurement detected in the previous frame for the same gate within tolerance value with very small threshold δ as mentioned before, we consider this measurement be invalid in the gate and not taken in consideration to data association process.

4.4 Filtering the validation region to valid/invalid observations

Intuitively, we find measurements in the gate with fixed size which are associated to the predicted position of the existing target before receiving new measurements. To update the predicted position, the new measurements in the gate is compared with the detected previous measurements in the same gate and avoid these new measurements which have approximately the same weight from data association process as described in algorithm 2.

Algorithm 2 Finding Validated Region of Filtered Gate based JPDAF

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1. Find validated region for measurements at time ***k*-1**:

$\overline{Z}^t(k-1) = \{z_i(k-1)\}, \quad i = 1,\ldots mt$

By accepting only those measurements that lie inside the gate *t*:

$$\overline{Z}^t(k-1) = \left\{\ Z\ : \left(z_i(k-1) - H^t(k)\overline{m}^t(k)\right)' S^t(k)^{-1} \left(z_i(k-1) - H^t(k)\overline{m}^t(k)\right) \le \gamma\ \right\}$$

2. Find validated region for measurements at time **k**:

$\overline{Z}^t(k) = \{z_i(k)\}, \quad i = 1,\ldots nt$

By accepting only those measurements that lie inside the gate *t*

$$\overline{Z}^t(k) = \left\{\ Z\ : \left(z_i(k) - H^t(k)\overline{m}^t(k)\right)' S^t(k)^{-1} \left(z_i(k) - H^t(k)\overline{m}^t(k)\right) \le \gamma\ \right\}$$

where $s^t(k) = H^t(k)\,\overline{P}^t(k)\,H^t(k)' + R$

3. for i = 1 to nt do

4. If $\left|z_i(k) - z_j(k-1)\right| < \delta \quad j = 1,\ldots.mt$

Set $z_i(k)$ to I,

Remove $z_j(k-1)$ from the set $\bar{Z}^t(k-1)$,

and set $mt = mt - 1$

5. Else

Set $z_i(k)$ to V

6. End if

7. End for

8. Obtain valid (V) measurements $c^t(k)$ are included for data association process where the invalid (I) measurements $\bar{c}^t(k)$ are excluded, i.e.:

$\bar{Z}^t(k)$ *be a set of all measurements* $\{z_i(k)\} = V$,

$i = 1$ *to* $c^t(k)$ *where* $\bar{c}^t(k) = nt - c^t(k)$.

5. Simulation Results

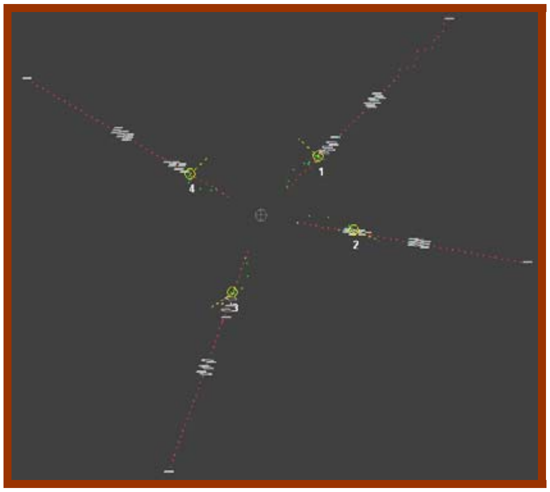
We used a synthetic dataset to highlight the performance of the proposed algorithm. The performance of the FG-PDAF is compared with a conventional JPDAF. The synthetic data has four tracks which continues from the first frame to the last frame. The mean and covariance for the initial distribution $p(x^t(0))$ is set to m_0^1 = [14, 12, 0, 0], m_0^2 = [14.5, 13.2, 0, 0], m_0^3 = [12.4, 14.5, 0, 0], m_0^4 = [11.45, 12.2, 0, 0], and p_0^t = diag ([1600, 1600, 100, 100]), t = *1,2,3,4*. The row and column sizes of the volume (V= $S_W \times S_H$). We initiate the other parameters as: ,V=25x25 , λ = 0.01 , Δt = 4.25 sec , T =153 sec,

p_D =0.99, in addition, we also set the matrices of (1),(2) as

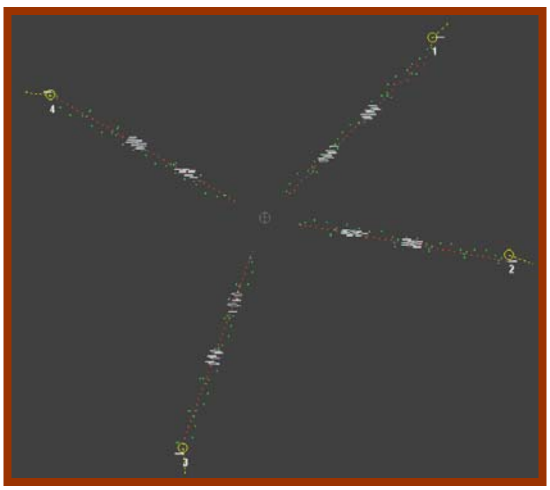
$$A = \begin{bmatrix} 1 & 0 & \Delta t & 0 \\ 0 & 1 & 0 & \Delta t \\ 0 & 0 & 1 & 0 \\ 0 & 0 & 0 & 1 \end{bmatrix}, H = \begin{bmatrix} 1 & 0 & 0 & 0 \\ 0 & 1 & 0 & 0 \end{bmatrix}, Q = G \quad G^T,$$

$$R = \begin{bmatrix} 20 & 0 \\ 0 & 20 \end{bmatrix}, \quad G = \begin{bmatrix} \frac{\Delta t^2}{2} & 0 \\ 0 & \frac{\Delta t^2}{2} \\ \Delta t & 0 \\ 0 & \Delta t \end{bmatrix}$$

Given a fixed threshold ($\gamma = 10^{-5}$), we showed that the proposed FG-JPDAF succeeded to track a target in dense clutter environment while the other conventional JPDAF failed to track a target as shown in Fig. 3. We obtained trajectories for X- and Y- components as shown in Fig. 4(a),(b) for the conventional JPDA and the proposed FG-JPDA respectively. In this figure, the colored solid line represents the underlying truth targets of the trajectory (each target with different color) while the colored + symbol represents trajectory of the tracked targets. Our proposed algorithm (+ symbol with different color) detects and associates the proper sequence of observations very well compared to JPDAF (fail to continue). We also compared error root mean square value (RMSE) for the different two approaches each with four targets as shown in Fig. 5. Our proposed algorithm has far lower error, RMSE values than JPDAF over frame numbers.

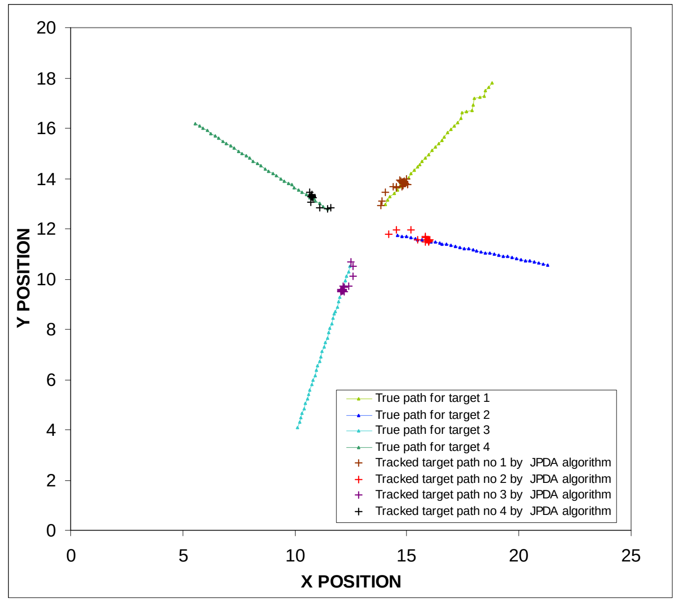


(a)

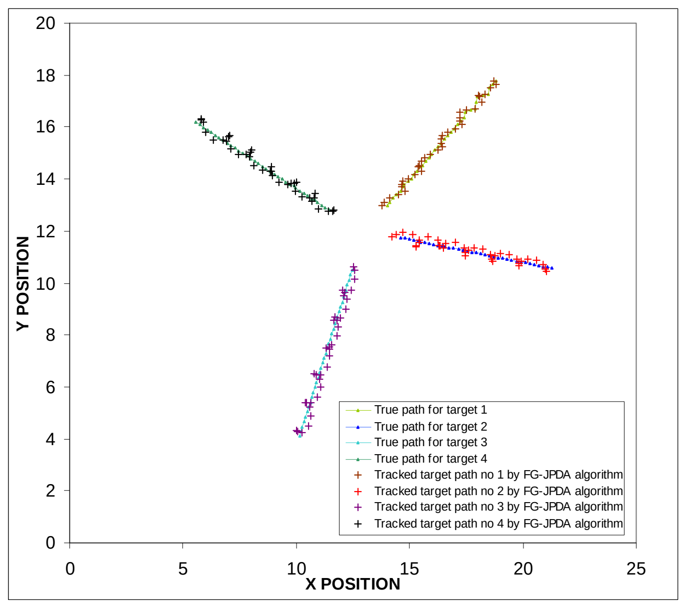


(b)

Fig. 3. The state of tracking multi-targets (4 targets) moving in heavy clutter using 2 approaches algorithm (a) JPDAF failed to track (b) FG-JPDAF succeeded to track.



(a)



(b)

Fig. 4. Trajectory for X-,Y- components for the 2 approaches algorithm used in tracking 4 targets (+ symbol) in dense clutter and the true target path (solid line). (a) Trajectory for X-,Y- by JPDA (b) Trajectory for X-,Y- by FG-JPDA.

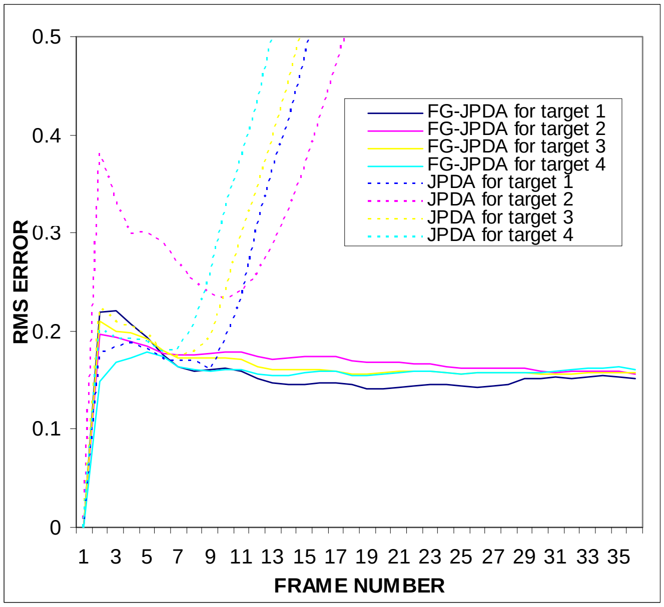


Fig. 5. The root mean square error[RMSE] for each target (4 targets) separately over frame number (each frame take 4.25 sec / one scan) for the 2 approaches algorithm and the RMSE is maintained minimum for the proposed FG-JPDA and less sensitivity to dense clutter.

6. Conclusions

From the results obtained in the simulations, we have showed that in dense clutter environment the joint probabilistic data association filter (JPDAF) fails to track the targets while the filtered gate (FG-JPDAF) algorithm can overcome the failing during the tracking process. The FG-JPDAF avoids the false targets from the valid based measurement regions using a filtering method and thus decreases the generation number of the feasibility matrices that are considered as the biggest computational burden of the JPDA algorithm. This approach can be used to overcome the clutter of gate based approaches in tracking. With even high threshold values for gate size, we can obtain smaller validated measurement regions with improving data association Process which have been shown to give targets the ability to continue tracking in dense clutter.

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