Integrated Track Splitting Filter for Manoeuvring Targets*

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Abstract – *The paper presents a new algorithm for tracking a manoeuvring target in a cluttered environment. The algorithm combines the Integrated Track Splitting (ITS) filter with the Interacting Multiple Model (IMM) algorithm. The ITS filter is a multi-scan method for automatic target tracking in clutter. The multi-scan foundation provides good tracking capabilities even when the probability of detection is low or in dense or non-homogeneous clutter. The recursive updating of a track quality measure in the form of the probability of target existence allows false track discrimination. In this paper the ITS tracker is extended by the incorporation of the IMM algorithm to enable the filter to efficiently track a manoeuvring target in a cluttered environment. Simulations are used to verify the approach in an environment of heavy and non-uniform clutter.*

Keywords: target tracking, data association, manoeuvring targets, IMM, ITS

1 Introduction

The combination of the Integrated Track Splitting filter for target tracking and the use of Interacting Multiple Model filtering integrates two of the more powerful tools for target tracking. These are the use of multi-scan tracking methods along with adaptive manoeuvre tracking. This combination filter will be referred to as the ITS-IMM algorithm in the remainder of this paper.

Data association algorithms deal with situations where there are measurements of uncertain origin. In many radar and sonar applications, for example, measurements (detections) originate not only from targets being tracked, but also from thermal noise as well as from various objects such as terrain, clouds etc. Unwanted measurements are usually termed clutter. Furthermore, true measurements from the target are present during each measurement scan with only a certain probability of detection, P_D. In a multi-target situation, the measurements may have originated from one of several targets. Targets may also enter and leave the surveillance region at any time, thus at any given moment the number of targets in the surveillance area is unknown.

Automatic track initiation and termination under such conditions require some track quality measure to distinguish between a true track, which follows a target and a false track, which does not. ITS recursively updates the probability of target (track) existence as the track quality measure. A track exists if it is based on measurements from a target (which follows specified dynamic and detection models) and is not a product of random clutter only. In this paper track existence and target existence will have the same meaning.

Optimal tracking in this environment requires one hypothesis for every possible history of measurements to target assignments, including a null measurement to cater for the possibility that the target was not detected or that its measurement was not selected. The optimal filter cannot be implemented in practice as the number of hypotheses grows exponentially in time. Instead, various sub-optimal data association algorithms have been proposed. These can be broadly subdivided into two classes: *multi-scan* and *single-scan* algorithms. Single-scan algorithms form an estimate of the current target state based on the previous estimate and hypotheses about the origin of the detections in the current scan only. The most well known tracker in this class is the Probabilistic Data Association (PDA) filter [1]. In contrast, multi-scan algorithms form tracks based on measurement hypotheses going back a number of scans. The number of scans of data association history that is retained may be fixed, as in the Multiple Hypothesis Tracker (MHT) [2], or it may vary as in the Viterbi Data Association (VDA) tracker [3]. Multi-scan algorithms are generally more effective than single-scan algorithms when the probability of target detection is low or the clutter is dense or non-homogeneous. Their retention of several scans of history means they are less likely to be confused by false measurements and lose track.

The Integrated Track Splitting filter [4], in a manner similar to [5], is a multi-scan data association algorithm which recursively updates a track quality measure (the probability of target existence), as well as state estimate for each data association history hypothesis. The difference between ITS and the algorithm presented in [5], is that the ITS filter calculates the global likelihood ratio, whereas [5] calculates the likelihood ratio for each track component separately.

The standard implementations of all the trackers mentioned above use a single model for the dynamics of the target. Typically this model assumes that the target moves with constant velocity. While it is not always the case, it

[0]This research has been supported by the Centre of Expertise in Networked Decision and Sensor Systems and funded by the Defence Science and Technology Organisation Australia

is generally true that target motion is in a straight line with only occasional deviations or manoeuvres. It is well known that over-modelling, for example by using a constant acceleration model when the target is in fact moving in a straight line, leads to a decrease in tracking accuracy. The Interacting Multiple Model approach to tracking manoeuvring targets runs a bank of filters, each with a different model for the target dynamics. One model corresponds to the typical motion of the target, while the others model possible deviations from that standard model. The output of the tracker is a probability-weighted composite of each of the individual models. This approach allows the tracker to switch smoothly between different models for the motion of the target. This method was first proposed in [6] and has since been combined with a number of different tracking algorithms, see [7] for example.

This paper describes the ITS-IMM algorithm for tracking a single, manoeuvring target in clutter. This approach can also be applied to the Joint ITS (JITS), Linear Joint ITS (LJITS) filters [4] and Linear Multitarget ITS (LMITS) filter [8], to construct trackers for multiple, manoeuvring targets in clutter. However, only the single target implementation is presented here for clarity. An overview of the ITS filter, assuming a single model for the target motion, is given Section 2. T Section 3 describes how the Interacting Multiple Model method is incorporated into the basic ITS filter. Section 4 illustrates the performance of the ITS-IMM filter using an example of a target that both undergoes a number of abrupt manoeuvres and also traverses regions of heavy clutter.

2 The Integrated Track Splitting Filter

The ITS filter is a single target, multi-scan tracking algorithm. A track quality measure, used for false track discrimination, is the probability of target existence, as in [9]. The track state estimate probability density function (pdf) is updated using selected measurements, under the assumption that the track is a true track; i.e that there exists a target whose trajectory is being followed. The track state, therefore, consists of the probability of target existence and the track state estimate pdf conditioned on the target existence.

Each track is the union of a number components. The estimation state of each component is the output of a filter which is given a single (possibly null – no detection) measurement at each scan. Thus each component represents a possible measurement-to-target association history, and components are mutually exclusive. Each component state consists of the probability of the component existence and the component state estimate pdf conditioned on the component existence.

Two versions of the ITS-IMM filter are possible: parametric and non-parametric. In the parametric version, an *a priori* clutter measurement density is assumed known; the non-parametric version assumes no *a priori* knowledge of the clutter measurement density. In this paper, the non-parametric version is presented; a parametric version is presented in [10]. ITS filter presented in [10] incorporates measurement feature information, such as amplitude; for reasons of simplicity this is omitted in this presentation.

2.1 Target and Component Existence Propagation

There are two common models for target existence propagation: Markov Chain One and Markov Chain Two, [9]. For reasons of brevity only ITS-IMM with Markov Chain One will be presented in this paper. The Markov Chain Two extension is straightforward.

A track is false if it does not follow a target's trajectory. Except when a false track crosses a target's trajectory, it is being updated by clutter measurements only. Alternatively, a track is true track if it is being updated by a target's measurements (and perhaps a few clutter measurements as well) over a period of time. The target existence event is, therefore, synonymous with the event that the track is a true track. The event of component existence is a complex event. It implies both target existence and the event that the measurement-to-track history of the component is the correct one. The component of a true track with correct measurement-to-track history we call the true component.

A track is the union of its mutually exclusive components. Denote the number of components of a track at time k with C_k. Let the event that the target exists at time k, and therefore the track is a true track, be denoted by χ_k. A selected set of measurements, z_k, is used to update the track state at scan k, with $Z^k = \{z_k, Z^{k-1}\}$ denoting the set of all selected measurements up to and including scan k. Thus the *a posteriori* probability of target existence is given by

$$P\left\{\chi_k|Z^k\right\} = \sum_{c=1}^{C_k} P\left\{\chi_k^c|Z^k\right\} \tag{1}$$

where $P\{\chi_k^c|Z^k\}$ is the probability of existence of the c-th component. The *a priori* probability of target existence is defined similarly, with the conditioning being on the measurement set Z^{k-1}.

The equation that updates $P\{\chi_k^c|Z^k\}$ will be given in Section 2.3. The *a priori* probability of component existence is updated using the Markov Chain One model propagation formulae [9] for component c and track respectively:

$$\begin{aligned} P&\left\{\chi_k^c|Z^{k-1}\right\} \\ &= \pi_{11}^c P\left\{\chi_{k-1}^c|Z^{k-1}\right\} + \pi_{21}^c\left(1 - P\left\{\chi_{k-1}^c|Z^{k-1}\right\}\right) \end{aligned} \tag{2}$$

$$\begin{aligned} P&\left\{\chi_k|Z^{k-1}\right\} \\ &= \pi_{11} P\left\{\chi_{k-1}|Z^{k-1}\right\} + \pi_{21}\left(1 - P\left\{\chi_{k-1}|Z^{k-1}\right\}\right) \end{aligned} \tag{3}$$

where $\pi_{11} = \pi_{11}^c$ denotes the probability that the true track remains a true track, e.g. the target will not disappear; π_{21} denotes the probability that formerly false track will accidentally become a true track; and π_{21}^c denotes the probability that formerly false component will accidentally become a true one. There are three problems with the event of a false track becoming a true one. These are:

- While an existing target may disappear, a non-existent target usually does not appear.

- In the event that a false track/component becomes a true one, its state pdf, which is based on past measurements and thus implicitly conditioned on the target existence in the past, becomes meaningless.

- To preserve the relationship (1), and given a constant π_{21}, π_{21}^c must depend on the number of components.

Therefore, we recommend $\pi_{21} = \pi_{21}^c = 0$ in equations (2)–(3), and let the initiation process handle the case of new targets appearing.

2.2 Track State Estimate

Similarly, the probability density function of the target state estimate is the mixture of mutually exclusive component state estimate pdfs. The component state estimate pdf is conditioned on the target existence and component data association history being the correct one and the track state estimate pdf is conditioned on the target existence. Thus the *a posteriori* track state pdf is given by

$$p(x_k|Z^k) = \frac{\sum_{c=1}^{C_k} P\left\{\chi_k^c|Z^k\right\} p^c(x_k|Z^k)}{P\left\{\chi_k|Z^k\right\}} \tag{4}$$

where $p^c(x_k|Z^k)$ is the *a posteriori* component state estimate pdf.

If the target motion model is linear and Gaussian, the estimated mean and variance of the state estimates are sufficient statistics for these pdfs. Letting $\hat{x}_{k|k}$ and $\Sigma_{k|k}$ be the *a posteriori* mean track state estimate and error covariance respectively we have

$$\hat{x}_{k|k} = \frac{1}{P\left\{\chi_k|Z^k\right\}} \sum_{c=1}^{C_k} P\left\{\chi_k^c|Z^k\right\} \hat{x}_{k|k}^c \tag{5}$$

$$\begin{aligned} \Sigma_{k|k} = & \frac{1}{P\left\{\chi_k|Z^k\right\}} \sum_{c=1}^{C_k} P\left\{\chi_k^c|Z^k\right\} \left(\Sigma_{k|k}^c + \hat{x}_{k|k}^c \hat{x}_{k|k}^{c\,\prime}\right) \\ & - \hat{x}_{k|k}\hat{x}_{k|k}^{\prime} \end{aligned} \tag{6}$$

where $\hat{x}_{k|k}^c$ and $\Sigma_{k|k}^c$ are the component c's mean track state estimate and error covariance respectively.

2.3 Component Propagation

At the start of scan k, the ITS filter has C_k components. Associated with each component c is an *a priori* existence probability, $P\{\chi_k^c|Z^{k-1}\}$ and an *a priori* component measurement pdf, $p^c(z|Z^{k-1})$, which is derived from the filtered component state estimate pdf and sensor measurement model. Then, in the same fashion as in (4), the track measurement pdf is given by

$$p(z|Z^{k-1}) = \frac{\sum_{c=1}^{C_k} P\left\{\chi_k^c|Z^{k-1}\right\} p^c(z|Z^{k-1})}{P\left\{\chi_k|Z^{k-1}\right\}} \tag{7}$$

Each component has a validation window with volume V_k^c, which selects a subset z_k^c of m_k^c measurements of the available measurement set at scan k. The validation window is set in such a manner that the probability the target measurement is in the window, assuming the target exists and is detected, will be P_W. We will assume this gating probability is the same for each component. The set of track selected measurements, z_k, of m_k measurements is the union of component selected measurement sets: $z_k = \bigcup_{c=1}^{C_k} z_k^c$.

Denote by $\hat{m}_k$ and $\hat{m}_k^c$ the expected number of clutter measurements in the window of the track and a track component respectively. Then

$$\hat{m}_k = \begin{cases} 0 & m_k = 0 \\ m_k - P_D P_W P(\chi_k|Z^{k-1}) & m_k > 0 \end{cases} \tag{8}$$

$$\hat{m}_k^c = \begin{cases} 0 & m_k = 0 \\ m_k^c - P_D P_W P(\chi_k|Z^{k-1})\lambda_k^c & m_k > 0 \end{cases} \tag{9}$$

where m_k is the total number of validated measurements at scan k, $z_{k,i}$ is the i-th measurement and

$$\lambda_k^c = \frac{\sum_{i=1}^{m_k^c} p(z_{k,i}^c|Z^{k-1})}{\sum_{i=1}^{m_k} p(z_{k,i}|Z^{k-1})} \tag{10}$$

The volume of the validation window for the track, V_k, is the volume of the union of each of the component windows. In general, the calculation of this volume is highly complex. An effective approximation to V_k is given in [4].

Consider a single component c and its set of validated measurements at scan k. There are $i = 0, \dots, m_k^c$ possible measurement association hypotheses, where $i = 0$ indicates that none of the measurements belong to the target and $i > 0$ indicates that the i-th measurement is from the target. Association of the ith measurement with component c creates a new component. Thus the original, single parent component track c is split into $m_k^c + 1$ new component tracks.

The state estimate of new components is obtained by updating the state prediction pdf of the parent component c with the measurement $z_{k,i}^c$. To complete the derivation of the ITS filter, we need to calculate the *a posteriori* existence probabilities, $P\{\chi_k^{c,i}|Z^k\}$, for each of the new child components. Denote with $\chi_{k,i}^c$ the event that the i-th measurement selected by component c is the target measurement. The desired *a posteriori* component existence probabilities for each new component are

$$P\left\{\chi_k^{c,i}|Z^k\right\} = P\left\{\chi_k^c, \chi_{k,i}^c|Z^k\right\} \tag{11}$$

These values are given by

$$P\left\{\chi_k^c, \chi_{k,0}^c|Z^k\right\} = \frac{(1 - P_D P_W) P\left\{\chi_k^c|Z^{k-1}\right\}}{1 - \delta_k P\left\{\chi_k|Z^{k-1}\right\}} \tag{12}$$

$$\begin{aligned} & P\left\{\chi_k^c, \chi_{k,i}^c|Z^k\right\} \\ & = \frac{P_D P_W V_k p^c(z_{k,i}^c|Z^{k-1}) P\left\{\chi_k^c|Z^{k-1}\right\}}{\hat{m}_k (1 - \delta_k P\left\{\chi_k|Z^{k-1}\right\})} \end{aligned} \tag{13}$$

where

$$\delta_k = P_D P_W \left(1 - \frac{V_k}{\hat{m}_k} \sum_{i=1}^{m_k} p(z_{k,i}|Z^{k-1})\right) \tag{14}$$

for $m_k > 0$ and

$$\delta_k = P_D P_W \tag{15}$$

for $m_k = 0$.

Note that the denominator of the new component probabilities is a function of the track and is therefore the same for all the components. This is in contrast to the mixing probabilities in [5].

2.4 Component Management

As the number of components grows exponentially in time, any practical implementation of the ITS filter must include procedures to control this growth. Such procedures are pruning, merging and component termination. A discussion of the applications of these techniques to the ITS tracker can be found in [4]. A more general overview of such methods can be found in [11].

3 The ITS-IMM Filter

The Interacting Multiple Model approach to tracking manoeuvring targets assumes that the target obeys not just a single dynamical model, but one of a finite set of models. It further assumes that the target motion switches between these models according to a Markov chain with known transition probabilities. Thus the ITS-IMM filter operates as described in Section 2 but with a bank of filters for each component, rather than a single filter.

Denote with N the number of possible target dynamic models, and denote with $M_k^{c,j}$ the event that the target dynamic model at time k was $j, j = 1,\ldots,N$ and that component c is the true component, given that the target exists. Define the component model probability as

$$\mu_{k|s}^{c,j} = P\left\{M_k^{c,j}|Z^s\right\} \tag{16}$$

At time k and conditioned on measurements Z^s, each component state estimate pdf $p^c(x_k|Z^s)$ is now described with component model state estimate pdfs and component model probabilities, $p^{cj}(x_k|Z^s)$ and $\mu_{k|s}^{c,j}$, $j = 1,\ldots,N$:

$$p^c(x_k|Z^s) = \sum_{j=1}^{N} \mu_{k|s}^{c,j} p^{c,j}(x_k|Z^s) \tag{17}$$

In the same manner, the component measurement pdf (4) is given with

$$p^c(z|Z^{k-1}) = \sum_{j=1}^{N} \mu_{k|k-1}^{c,j} p^{c,j}(z|Z^{k-1}) \tag{18}$$

For reasons of clarity, in the text below we assume that each component model state estimate pdf $p^{c,j}(x_k|Z^s)$ is Gaussian and described with its mean $\hat{x}_{k|s}^{c,j}$ and error covariance $\Sigma_{k|s}^{c,j}$. Then

$$p^{c,j}(z|Z^{k-1}) = \frac{1}{P_W}\mathcal{N}\left(z, \hat{z}_{k|k-1}^{c,j}, S_{k|k-1}^{c,j}\right) \tag{19}$$

where $\hat{z}_{k|k-1}^{c,j}$ is the predicted measurement using model j for component c and $S_{k|k-1}^{c,j}$ is the associated measurement error covariance matrix from the Kalman filter.

3.1 IMM Update

At time k, the target track recursion starts with the newly selected measurements z_k. A new component is created by associating measurement $z_{k,i}$ with component c. The new component is denoted by n. The component n model j state estimate pdf $p^{n,j}(x_k|Z^k)$ is obtained by applying measurement $z_{k,i}$ to $p^{c,j}(x_k|Z^{k-1})$. In the case of Gaussian component model pdfs, $p^{n,j}(x_k|Z^k)$ is described with $\hat{x}_{k|k}^{n,j}$ and $\Sigma_{k|k}^{n,j}$. The posterior probability that model j is correct, given that component n is the true component, is

$$\mu_{k|k}^{n,j} = \frac{\mu_{k|k-1}^{c,j} p^{c,j}(z_{k,i}|Z^{k-1})}{\sum_r \mu_{k|k-1}^{c,r} p^{c,r}(z_{k,i}|Z^{k-1})} \tag{20}$$

3.2 IMM Output

The filtered track state estimate and error covariance values for the ITS-IMM are then calculated using (5) – (6) where the the component n state estimate mean and error covariance are given by

$$\hat{x}_{k|k}^{n} = \sum_{r=1}^{N} \mu_{k|k}^{n,r} \hat{x}_{k|k}^{n,r} \tag{21}$$

$$\Sigma_{k|k}^{n} = \sum_{r=1}^{N} \mu_{k|k}^{n,r} \left(\Sigma_{k|k}^{n,r} + \hat{x}_{k|k}^{n,r} \hat{x}_{k|k}^{n,r\prime}\right) - \hat{x}_{k|k}^{n} \hat{x}_{k|k}^{n\,\prime} \tag{22}$$

3.3 IMM Mixing

IMM mixing produces an initial model state estimate for the time interval k – $k+1$. Let the known Markov model transition probabilities be given by

$$\alpha_{qr} = Pr(M_k^{n,r}|M_{k-1}^{n,q}) \tag{23}$$

then the model prediction probabilities are calculated as

$$\mu_{k+1|k}^{n,j} = \sum_{r=1}^{N} \alpha_{rj} \mu_{k|k}^{n,r} \tag{24}$$

The model prediction probabilities are used in the IMM Update at time $k+1$. It is straightforward to show that

$$\sum_r \mu_{k|k-1}^{c,r} P_D P_W \left(1 - \sum_i \frac{V_k}{\hat{m}_k} p^{c,r}(z_{k,i}|Z^{k-1})\right) = P_D P_W \left(1 - \sum_i \frac{V_k}{\hat{m}_k} p^{c}(z_{k,i}|Z^{k-1})\right) \tag{25}$$

therefore the association probabilities in (12)–(13) do not change and ITS filter equations are applicable to ITS-IMM filter.

The mixing probabilities $\mu_{k|k+1}^{n}(r,j)$ are calculated as

$$\mu_{k|k+1}^{n}(r,j) = \frac{\alpha_{r,j} \mu_{k|k}^{n,r}}{\mu_{k+1|k}^{n,j}} \tag{26}$$

and the mixed component model state estimate mean and covariance are

$$\hat{x}_{k|k}^{n,j,m} = \sum_{r=1}^{N} \mu_{k|k+1}^{n}(r,j) \hat{x}_{k|k}^{n,r} \tag{27}$$

$$\Sigma^{n,j,m}_{k|k} = \sum_{r=1}^{N} \mu^{n}_{k|k+1}(r,j)\left(\Sigma^{n,r}_{k|k} + \hat{x}^{n,r}_{k|k}\hat{x}^{n,r\prime}_{k|k}\right) - \hat{x}^{n,j,m}_{k|k}\hat{x}^{n,j,m\prime}_{k|k} \tag{28}$$

3.4 IMM Prediction

IMM prediction involves the component model mixed state estimate propagation from time k to time $k+1$. In the case of Gaussian component model state estimate pdf, this step is simply a Kalman filter prediction.

4 Simulations

The performance of the ITS-IMM algorithm on a single manoeuvring target in dense, non-homogeneous clutter was evaluated using simulations. The simulated target trajectory is shown in Figure 1. The target trajectory consists of 8 segments of 10 seconds duration. The target motion during each segment was:

1. uniform motion with constant velocity of $18\,\mathrm{m/s}$,
2. exponential acceleration motion, with acceleration $a = v_0\alpha\exp(\alpha t)$, where v_0 is velocity at the start of the segment, t denotes time since segment start, and $\alpha = 0.05/\mathrm{s}$,
3. exponential deceleration, with acceleration $a = v_0\alpha\exp(\alpha t)$, where v_0 is velocity at the start of the segment, t denotes time since segment start and $\alpha = -0.05/\mathrm{s}$,
4. right turn with the radial velocity of $\pi/9\,\mathrm{rad/s}$,
5. exponential acceleration with $\alpha = 0.05/\mathrm{s}$,
6. exponential deceleration with $\alpha = -0.05/\mathrm{s}$,
7. left turn with radial velocity $\pi/9\,\mathrm{rad/s}$, and
8. uniform motion.

Clutter measurements were generated in clusters, with two areas of heavy clutter. These are marked on Figure 1. The number of clutter measurements follows a Poisson distribution with background clutter density of $1\cdot10^{-4}\,/\mathrm{m}^2$, and heavy clutter area density of $7\cdot10^{-4}\,/\mathrm{m}^2$.

The set of models for the IMM portion of the tracker consisted of the following four models:

1. constant velocity motion;
2. constant acceleration motion;
3. coordinated turn to the left with constant radial velocity $\omega = \pi/9\,\mathrm{rad/s}$; and a
4. coordinated turn to the right with constant radial velocity $\omega = \pi/9\,\mathrm{rad/s}$.

Note that the actual target motion includes behaviour that is not modelled by these four target motion models. Therefore, the performance of the filter will suffer during these periods.

The state vector was modelled as

$$x = \left(\xi, \dot{\xi}, \zeta, \dot{\zeta}, \ddot{\xi}, \ddot{\zeta}\right)^T \tag{29}$$

where (ξ, ζ) are Cartesian coordinates. All models have white plant noise whose covariance matrix is given by

$$Q = \frac{3}{4}\begin{bmatrix} \frac{1}{4}T^4 & \frac{1}{2}T^3 & 0 & 0 & \frac{1}{2}T^2 & 0 \\ \frac{1}{2}T^3 & T^2 & 0 & 0 & T & 0 \\ 0 & 0 & \frac{1}{4}T^4 & \frac{1}{2}T^3 & 0 & \frac{1}{2}T^2 \\ 0 & 0 & \frac{1}{2}T^3 & T^2 & 0 & T \\ \frac{1}{2}T^2 & T & 0 & 0 & 1 & 0 \\ 0 & 0 & \frac{1}{2}T^2 & T & 0 & 1 \end{bmatrix} \tag{30}$$

where the sampling time $T = 1s$. A two dimensional radar system was modelled, which provides measurements of track position every T seconds. The measurement noise had a standard deviation of 5 m in range and 1 mrad in bearing at a range of 5 km. The probability of target detection was set to $P_D = 0.9$.

The transition probabilities for the Markov Chain One model of track existence were $\pi_{11} = \pi^c_{11} = 0.98$ and $\pi_{21} = \pi^c_{21} = 0.0$. The switching between the target motion models had the transition probability matrix

$$A = \begin{bmatrix} 0.91 & 0.03 & 0.03 & 0.03 \\ 0.03 & 0.91 & 0.03 & 0.03 \\ 0.05 & 0.05 & 0.90 & 0.00 \\ 0.05 & 0.05 & 0.00 & 0.90 \end{bmatrix} \tag{31}$$

therefore

$$\mu_{k|k-1} = A^T\mu_{k-1|k-1} \tag{32}$$

where $\mu(k|k-1) = \left(\mu^1_{k|k-1}, \mu^2_{k|k-1}, \mu^3_{k|k-1}, \mu^4_{k|k-1}\right)^T$.

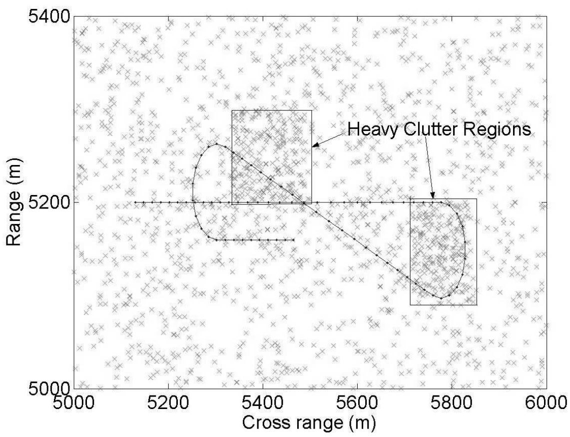

Fig. 1: Target Scenario

The performance of the tracker was evaluated using Monte Carlo simulations of 250 runs. The IPDA-IMM [12] was run on the same data for comparison. Both trackers were optimized for this environment. The parametric

(MAP) versions of the algorithms were compared, using the clutter map as described in [13]. ITS-IMM used component merging to limit the growth of the number of components to 35.

Figures 2 and 3 show the total number of confirmed true and false tracks over time. These figures show that the ITS-IMM algorithm has superior false track discrimination properties compared to IPDA-IMM algorithm at the price of increased computational complexity.

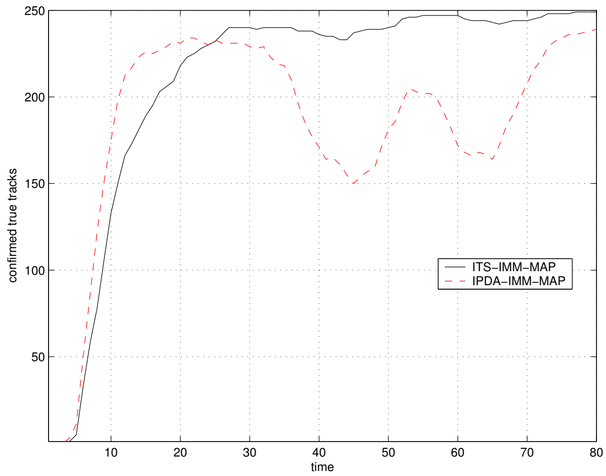

Fig. 2: Number of confirmed true tracks over time. The solid line gives the results for the ITS-IMM tracker. The dotted line gives the results for the IPDA-IMM tracker.

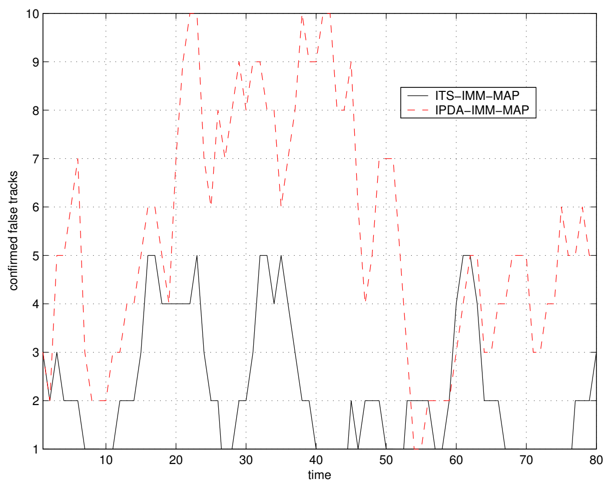

Fig. 3: Number of confirmed false tracks over time. The solid line gives the results for the ITS-IMM tracker. The dotted line gives the results for the IPDA-IMM tracker.

Figures 4 and 5 show the root mean square errors in the estimate of the ξ and ζ co-ordinates over time. From scan 30 to 40 and from scan 60 to 70 the target is turning in the heavy clutter regions. As would be expected, during these periods the errors in the estimates are relatively high, with the ITS-IMM performing significantly better. Further filter tuning may improve upon these results.

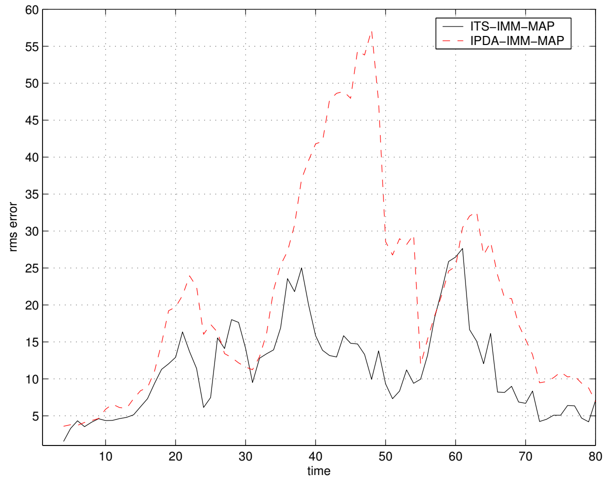

Fig. 4: Root mean square error in the ξ co-ordinate over time. The solid line gives the results for the ITS-IMM tracker. The dotted line gives the results for the IPDA-IMM tracker.

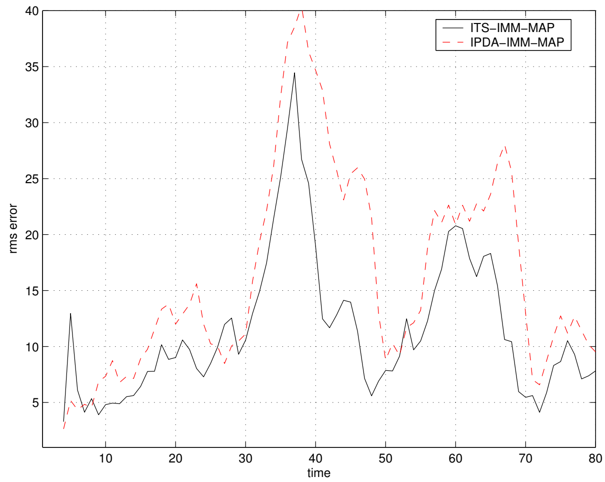

Fig. 5: Root mean square error in the ζ co-ordinate over time. The solid line gives the results for the ITS-IMM tracker. The dotted line gives the results for the IPDA-IMM tracker.

5 Conclusions

In this paper a new algorithm for tracking a single, manoeuvring target in clutter has been presented. This tracker combines the Integrated Track Splitting filter flexibility and performance in heavy clutter or low target detection probability environment, with the manoeuvre handling capabilities of the Interacting Multiple Model to produce a highly effective tracking algorithm. A simulation study shows the effectiveness of this approach.

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