Abstract - Automatic target tracking in clutter initiates and updates both true tracks and false tracks. True tracks follow targets, and false tracks do not. False track discrimination is the procedure which confirms (vast majority of) true tracks, and terminates (vast majority of) false tracks. False Track Discrimination requires a measure of track quality to distinguish between true tracks and false tracks in a statistical sense. This paper compares two powerful track quality measures: the track score, as used in Multi Hypothesis Tracking (MHT) and the probability of target existence, as used in Integrated Track Splitting (ITS) filter. Both theoretical and simulation comparisons are presented in a single target tracking situation.

Keywords: Tracking, Data Association, MHT, ITS, Estimation.

1 Introduction

In many radar, sonar and other target tracking applications measurements may originate from targets, whose existence and trajectories are generally not known a priori. These target detections are only present in a scan with some probability of detection, \( P_D < 1 \). In addition, detections are generated from other random sources, which are usually termed clutter.

In each scan a number of candidate measurements exist for track update. A measurement history is a sequence of measurements, one per each scan. Each such sequence will result in a target trajectory state estimate. The number of measurement histories grows exponentially in time, thus various techniques are used to control their number [1], this submission does not detail them.

Automatic track initiation and maintenance in the cluttered environment results in existence of both true and false tracks. True track follows a target, and false track does not. A false track can be created when initiating a track using one or more clutter measurements, or a true track may become false due to clutter measurements, or due to an unfavourable target detection sequence, or both. False track discrimination is a (necessary) procedure which (tries to) recognize and confirm true tracks, and recognize and terminate false tracks.

This submission compares false track discrimination properties of two powerful algorithms for automatic target tracking in clutter, Multiple Hypothesis Tracker (MHT) and Integrated Track Splitting (ITS). Both consider multiple measurement histories. For reasons of clarity and simplicity, only single target tracking in clutter is considered here. State estimate of one possible target in ITS jargon is termed a “track”, and each track is a set of “components”, each component being an estimate of target trajectory given a measurement history. In MHT jargon, track is usually termed “target”, and track component is usually referred to as a “track”. In this paper the ITS terminology is used, without any ambition to force it on the MHT community.

The Multiple Hypothesis Tracker (MHT) [2, 3] is generally regarded as optimal algorithm for target tracking in this environment. The philosophy behind this approach is to form all possible hypotheses regarding target and track-to-measurement associations and to evaluate each of these before selecting the best global hypothesis. Although a number of MHT versions have been published, they can be grouped into two main classes. The measurement-oriented MHT, often known as the Reid algorithm [2], forms new track and measurement allocation hypotheses centered around measurements. The track-oriented MHT [3] forms hypotheses based on track branching. We consider here the case of the measurement-oriented MHT.

Each MHT track is a loose collection of track components. The target trajectory state estimate of each track component is performed individually by applying a state estimator, such as the Kalman filter, to the measurement sequence. The status of each track component (tentative / confirmed / terminated) is also updated individually, based on the measurement likelihood ratio over history of this component. The logarithm of the compounded measurement likelihood ratio of the component is called the component score. In each scan MHT (usually) uses the component with highest score to determine the status of the track, disregarding other components. If the highest score component is confirmed, the track is confirmed in this scan. If not, the track is not confirmed, although there could be some other components of the track with confirmed status. In a manner of speaking, MHT is the maximum...
likelihood estimator of target existence.

The Integrated Track Splitting (ITS) tracker [4, 5, 6] also consists of components. Each component estimates the target trajectory based on its measurement history alone (in the same manner as MHT). However, false track discrimination process is completely different. ITS recursively calculates the probability of target existence on the level of track, based on the average measurement likelihood ratio of all existing components of the track. The probability of existence of every component is dependent on other components, reflecting the fact that the components are not independent, but are mutually exclusive. In a manner of speaking, ITS the the mean estimator of target existence.

Target existence is modelled as a Markov Chain. Two models for target existence have been identified and introduced in [13]. In one, termed Markov Chain One, if the target exists, it is assumed to be always detectable, i.e. its measurements will exist in any given scan with a probability of detection \( P_D \leq 1 \). The other, termed Markov Chain Two, also allows for the possibility that the target exists, but is temporarily not detectable. Markov Chain Two model is also useful in situations of unknown and/or variable probability of detection [7, 8]. These models give additional parameters to tune the ITS performance and to tailor it to the application priorities; MHT does not have this opportunity. This submission ignores these additional capabilities of ITS, it concentrates instead on comparing the target existence paradigm of ITS and track score paradigm of MHT in single target tracking eliminating the Markov Chain parameters from the comparison. The performance criteria is the false track discrimination and track retention.

The problem statement and some common notation are presented in Section 2. In Section 3 the track score (MHT approach to false track discrimination) is described. Target existence paradigm is presented in Section 4, followed by comparison between two approaches in Section 5. A simulation study is presented in Section 6, followed by the concluding remarks in Section 7.

2 Problem Statement

Without loss of generality, we assume here a linear system, and a single model trajectory. Denoting the target trajectory state at time \( k \) by \( x_k \), the trajectory propagates as

\[
x_k = F x_{k-1} + \nu_k.
\]

where \( F \) is the state propagation matrix, process noise \( \nu_k \) is zero mean white and Gaussian noise sequence with covariance matrix \( Q_k \), uncorrelated with measurement noise.

Target measurement is present with a probability of detection \( P_D \), which may be different for different scans. The target measurement is modelled with a Gaussian pdf:

\[
z_k = H x_k + \omega_k
\]

where \( z_k \) is the measurement and \( H \) is the measurement matrix. Measurement noise \( \omega_k \) is zero mean white Gaussian noise sequence with covariance matrix \( R_k \).

Clutter measurements are also present in every scan. Their distribution is assumed Poisson, with generally non–uniform clutter measurement density denoted here by \( \rho(z) \), with \( z \) denoting a point in the measurement space.

In each scan, a number of measurements are available for track update. Assume that measurement selection [9] at scan \( k \) has been performed and also assume that, if target is detected, its measurement will be selected with a known probability \( P_D \). At scan \( k \), \( m_k \geq 0 \) measurements are selected. In the remainder of this paper \( z_k \) denotes the set of selected measurements at scan \( k \), with subscript \( i \) denoting individual measurement \( z_{k,i} \). Set of selected measurements in scans up to and including scan \( k \) is denoted by \( Z^k \):

\[
Z^k \triangleq z_k \bigcup Z^{k-1}; Z^0 = \emptyset.
\]  

(3)

Clutter measurement density at coordinate \( z_{k,i} \) will be denoted by \( \rho(z_{k,i}) \).

In this submission we use the term “track” to denote the state estimate of a possible target. Only single track update is considered here. At each time \( k \) a number \( (m_k + 1) \) of candidate measurements for track update exist, as the “null” measurement is also counted. A measurement history is defined as a sequence of one measurement per scan, for the duration of track life. The number of these measurement histories grows exponentially in time. Track state given one measurement history is termed here as a “component”.

Please note: terms “track” and “component” in this submission are usually termed in MHT community as “target” and “track” respectively. As a track may not follow a target (false track), the naming in this submission seems more logical.

A measurement history is denoted by \( \xi \), the same symbol is sometimes used here to denote the track component obtained by applying the measurement history. The exact meaning will be clear from the context. In expression

\[
\xi_a(b, c) = i
\]

(4)

\( a \) denotes current time, \( b \leq a \) denote the time of the component creation, and optional \( c \geq b \) will denote the time index in the components measurement history. The expression above means that the component \( \xi_a \) created at time \( b \) was allocated measurement with index \( i \), \( z_{k,i} \) at time \( c \).

At time \( k-1 \), i.e. when the measurement set \( z_k \) has arrived but has not been processed yet, track will have component set \( \xi_k(k-1) \). New components are created by associating measurements from the measurement set \( z_k \) with components \( \xi_k(k-1) \). At time \( k+1 \), i.e. after the measurement set \( z_k \) has been processed, the track will have component set \( \xi_{k+1}(k) \).

Trajectory estimate of component \( \xi \) is updated by applying measurement \( \xi_{k+1}(k) \) at time \( k \) to the trajectory estimation algorithm. As we consider here a
linear system with single trajectory model (easily generalized), we can apply the Kalman filter for component trajectory estimate. Component trajectory state prediction and estimate are Gaussian pdfs:

\[
p(x_k | \xi_k(k-1), Z^{k-1}) = N(\tilde{x}_{k|k-1}(\xi_k(k-1)), P_{k|k-1}(\xi_k(k-1)))
\]

\[
p(x_k | \xi_k(k), Z^k) = N(\tilde{x}_{k|k}(\xi_k(k)), P_{k|k}(\xi_k(k))),
\]

with

\[
\tilde{x}_{k|k-1}(\xi_k(k-1)) = F\tilde{x}_{k-1|k-1}(\xi_k(k-1))
\]

\[
P_{k|k-1}(\xi_k(k-1)) = FP_{k-1|k-1}(\xi_k(k-1))F^t + Q
\]

and

\[
\tilde{x}_{k|k}(\xi_k(k)) = \tilde{x}_{k|k-1}(\xi_k(k-1)) + K_k(\xi_k(k))(z_{k,i} - \tilde{x}_{k|k-1}(\xi_k(k-1)))
\]

\[
P_{k|k}(\xi_k(k)) = (I - K_k(\xi_k(k))H)P_{k|k-1}(\xi_k(k-1))
\]

where \(X^t\) denotes matrix \(X\) transpose, \(I\) denotes the identity matrix and

\[
\tilde{z}_k(\xi_k(k-1)) = H \cdot \tilde{x}_{k|k-1}(\xi_k(k-1))
\]

\[
S_k(\xi_k(k-1)) = H \cdot P_{k|k-1}(\xi_k(k-1)) \cdot H^t + R
\]

\[
K_k(\xi_k(k)) = P_{k|k-1}(\xi_k(k-1)) \cdot H^tS_k^{-1}(\xi_k(k-1)).
\]

The measurement prediction pdf at time \(k\) is

\[
p(z_{k,i}|\xi) \triangleq p(z_{k,i}|\xi_k(k-1)) = N(\tilde{z}_k(\xi_k(k-1)), S_k(\xi_k(k-1)))
\]

with \(p(z_{k,i}|\xi)\) being a shorthand notation for \(p(z_{k,i}|\xi_k(k-1))\).

3 MHT - Track Score

Each MHT [2] track is a loose set of components, where each component is updated independently. At time \(k\), measurement likelihood ratio is calculated for each component \(\xi\) by

\[
\lambda(\xi_k(k), k) = \left\{ \begin{array}{ll}
1 - P_{DP}P_G; & \xi_k(k, k) = 0 \\
P_{DP}P_G \frac{p(z_{k,i}|\xi_k(k, k))}{p(z_{k,i}|\xi_k(k, k))}; & \xi_k(k, k) > 0
\end{array} \right.
\]

where the total measurement likelihood ratio for component \(\xi_k(k)\) is the product of measurement likelihood ratios for each time of component life, assumed below to start at scan 1.

\[
\Lambda(\xi_k(k)) = \prod_{\ell=1}^{k} \lambda(\xi_k(\ell, \ell)).
\]

It is often convenient for computational reasons to maintain the logarithm of the total measurement likelihood ratio

\[
L(\xi_k(k)) \triangleq \ln(\Lambda(\xi_k(k))) = \sum_{\ell=1}^{k} \ln(\lambda(\xi_k(\ell, \ell)))
\]

which is termed component (or track in the MHT jargon) score.

MHT track is confirmed or terminated on a component by component basis. If a component has score which has fallen below a threshold, this component is terminated; however the other components of the same track remain unaffected. If a component has score which has risen above a threshold at time \(k\), that component is confirmed. The other components at time \(k\) are unaffected. Any descendant component of a confirmed component will also have confirmed status. If no antecedent of a component was confirmed, this component will also be unconfirmed.

At each scan MHT creates a complete set of global hypothesis. Each global hypothesis includes a component from each track, with the constraint that no two components in one global hypothesis may share a measurement. The most likely global hypothesis is chosen to represent the tracks. If an unconfirmed component of a track is part of the most likely global hypothesis at time \(k\), the track will be effectively unconfirmed, even though it may contain some confirmed components.

We consider single target tracking here. Thus the most likely global hypothesis will always contain the most likely component of the track being considered.

Quite often in heavy clutter, pruning the components with low score is not enough to counter the exponential growth of number of components. In that case more sophisticated methods can be employed [1]. A whole component subtree can be pruned [10], or components may be merged [11].

4 ITS - Target Existence Paradigm

The state of each track at time \(k\) is defined by (at least) a discrete variable \(\chi_k\) which denotes the target [12] existence and a continuous variable \(x_k\) which denotes the track trajectory estimate at time \(k\). The track state pdf is given by:

\[
P[\chi_k, x_k] = P(\chi_k)p(x_k|\chi_k),
\]

where \(\chi_k\) denotes the event of target existence, Note that the track trajectory state estimate pdf is conditional on target existence and that the track state estimate pdf given target non-existence is undefined.

The track state evolves between scans as a Markov process and is updated at each scan with measurements. Only the update of the probability of target existence is described below. The process for predicting the track trajectory state estimate to the next time
using the model is well known and descriptions can be found in references such as [10].

The Markov Chain One model for the propagation of the probability of target existence assumes that the target is always detectable with probability $P_D$, if it exists. It is defined by Markov propagation

$$P \{ \chi_k | Z^{k-1} \} = \Delta_{11} P \{ \chi_{k-1} | Z^{k-1} \} + \Delta_{21} P \{ \chi_{k-1} | Z^{k-1} \}$$

and is used to calculate the a priori probability of target existence $P \{ \chi_k | Z^{k-1} \}$ at time $k$ from the a posteriori probability of target existence at time $k-1$, $P \{ \chi_{k-1} | Z^{k-1} \}$. The transition probabilities are defined as

$$\Delta_{11} \triangleq P \{ \chi_k | \chi_{k-1} \}$$

$$\Delta_{21} \triangleq P \{ \chi_k | \bar{\chi}_{k-1} \}$$

where superscript 1 denotes Markov Chain One model for target existence. Markov Chain Two model for target existence [13] separates detectability and existence; i.e. target is allowed to exist but be temporarily obscured. As MHT does not incorporate Markov Chain Two, this submission will not dwell further on this model.

Each ITS track is a set of components, where the probability of each component depends on other components [5]. Each component $\xi$ at time $k$ is described by its state which is given by

$$P \{ \xi_k(\ell), x_k \} = P \{ \xi_k(\ell) \} P \{ x_k | \xi_k(\ell) \}. \quad (16)$$

with $\ell$ having values of $k-1$ and $k$ for the components created at time $k-1$ and $k$ respectively. ITS track state prediction is given by

$$P \{ \chi_k | Z^{k-1} \} = \sum_{\xi_k(k-1)} P \{ \xi_k(k-1) | Z^{k-1} \}$$

$$p(x_k | \chi_k, Z^{k-1}) = \sum_{\xi_k(k-1)} \beta^\xi_k(k-1) p(x_k | \xi_k(k-1), Z^{k-1})$$

$$\beta^\xi_k(k-1) \triangleq P \{ \xi_k(k-1) | \chi_k, Z^{k-1} \} = \frac{P \{ \xi_k(k-1) | Z^{k-1} \}}{P \{ \chi_k | Z^{k-1} \}}$$

with estimate given by

$$P \{ \chi_k | Z^k \} = \sum_{\xi_k(k)} P \{ \xi_k(k) | Z^k \}$$

$$p(x_k | \chi_k, Z^k) = \sum_{\xi_k(k)} \beta^\xi_k(k) p(x_k | \xi_k(k), Z^k)$$

$$\beta^\xi_k(k) \triangleq P \{ \xi_k(k) | \chi_k, Z^k \} = \frac{P \{ \xi_k(k) | Z^k \}}{P \{ \chi_k | Z^k \}}$$

The $\beta$s in equations (17) and (18) will be referred to as the relative probabilities of components.

A priori pdf of measurement $z_{k,i}$ is a linear combination of a priori pdfs of measurement $z_{k,i}$ given measurement history:

$$p(z_{k,i}) \triangleq p(z_{k,i} | \chi_k, Z^{k-1}) = \sum_{\xi_{k}(k-1)} \beta^\xi_k(k-1) p(z_{k,i} | \xi_{k}(k-1)). \quad (19)$$

Measurement likelihood ratio at time $k$ is given by

$$\lambda_k \triangleq \frac{p(z_k | \chi_k, Z^{k-1})}{p(z_k | \bar{\chi}_k, Z^{k-1})} = 1 - P_D P_G + P_D P_G \sum_{i=1}^{m_k} \frac{p(z_{k,i})}{p(z_{k,i})}. \quad (20)$$

At each time $k$ new components are formed by pairing old components and selected measurements. The a posteriori relative probability of new component is given by

$$\beta^\xi_k(k) = \frac{P(\xi_k(k-1), \xi_k(k) = i | \chi_k, Z^k)}{\lambda_k} = \frac{\beta^\xi_k(k-1)}{\lambda_k} \left\{ \begin{array}{ll} 1 - P_D P_G; & i = 0 \\ P_D P_G \frac{p(z_{k,i})}{p(z_{k,i})}; & i > 0 \end{array} \right. \quad (21)$$

Equation (14) can be written as

$$\left[ \begin{array}{c} P(\chi_k | Z^{k-1}) \\ P(\bar{\chi}_k | Z^{k-1}) \end{array} \right] = \Pi^k \left[ \begin{array}{c} P(\chi_{k-1} | Z^{k-1}) \\ P(\bar{\chi}_{k-1} | Z^{k-1}) \end{array} \right]. \quad (22)$$

The probability of target existence update is [13]

$$P(\chi_k | Z^k) = \frac{\lambda_k \cdot P(\chi_k | Z^{k-1})}{1 - (1 - \lambda_k) \cdot P(\chi_k | Z^{k-1})} \quad (23)$$

Equation (23) can be written as

$$\frac{P(\chi_k | Z^k)}{P(\bar{\chi}_k | Z^k)} = \lambda_k \frac{P(\chi_{k-1} | Z^{k-1})}{P(\bar{\chi}_{k-1} | Z^{k-1})} \quad (24)$$

which also follows from the Bayes formula in a straightforward manner.

ITS track status update is based on the probability of target existence. At time $k$ the whole track may be confirmed or terminated based on $P(\chi_k | Z^k)$. Component management is similar to MHT component management. Based on relative component probability, components may be pruned [10] or merged [11] in a similar manner to MHT. Also, component may be pruned so that only most likely component subtree of a certain depth remains, as in MHT.

5 Target Existence and Track Score

If Markov Chain One transition matrix $I^2$ in equation (22) equals identity matrix $I^2$ then equation (24) becomes

$$\frac{P(\chi_k | Z^k)}{P(\bar{\chi}_k | Z^k)} = \lambda_k \frac{P(\chi_{k-1} | Z^{k-1})}{P(\bar{\chi}_{k-1} | Z^{k-1})} \quad (25)$$

and using induction

$$\frac{P(\chi_k | Z^k)}{P(\bar{\chi}_k | Z^k)} = \left( \prod_{t=1}^{k} \lambda_t \right) \frac{P(\chi_0)}{P(\bar{\chi}_0)} \quad (26)$$
where $\Lambda_k$ denotes measurement likelihood ratio over the life of the track

$$\Lambda_k \triangleq \prod_{\ell=1}^{k} \lambda_\ell$$  \hspace{2cm} (27)

For the reasons of simplicity, in this Section we assume identity Markov Chain One transition matrix II.

From equations (10) and (21), the a posteriori component probability is given by

$$\beta^c_k(k) = \beta^c_{k-1}(k-1) \frac{\lambda(\xi_k(k,k))}{\lambda_k},$$  \hspace{2cm} (28)

where we have used the fact that $\beta^c_{k-1}(k-1) = \beta^c_k(k-1)$. Applying induction from time 1 to $k$, we obtain

$$\beta^c_k(k) = \prod_{\ell=1}^{k} \frac{\lambda(\xi_\ell(k,\ell))}{\lambda_\ell} = \frac{\Lambda(\xi_k(k))}{\Lambda_k}$$  \hspace{2cm} (29)

Thus, the component score is proportional to the a posteriori component probability and is given by

$$\Lambda(\xi_k(k)) = \beta^c_k(k) \cdot \Lambda_k$$

$$= \beta^c_k(k) \frac{P[\chi|Z^k]}{P[\chi]} \frac{P[Z^0]}{P[\chi]}$$  \hspace{2cm} (30)

The component with the highest score is also the component with the highest probability. When using MHT, the highest probability component is likely to be incorporated into the highest probability global hypothesis; in the single target tracking example that we are investigating here, it is certain. If the highest probability component is confirmed, the track will be confirmed. Thus we can say that MHT is, with a slight abuse of terminology, a maximum likelihood estimator of target existence.

Target existence approach, exemplified here by ITS, at time $k$ uses the average measurement likelihood ratio. Denote by $\lambda(\xi_k(k-1))$ measurement likelihood ratio at time $k$, given component $\xi_k(k-1)$:

$$\lambda(\xi_k(k-1)) \triangleq \frac{p(z_k|\xi_k(k-1),Z^{k-1})}{p(z_k|Z^{k-1})} = 1 - P_D P_G + P_D P_G \sum_{i=1}^{m_k} \frac{p(z_{k,i}|\xi)}{p(z_{k,i})}$$  \hspace{2cm} (31)

Measurement likelihood ratio at time $k$ is the mean of measurement likelihood ratios of individual components:

$$\lambda_k = \sum_{\xi_k(k-1)} \beta^c_k(k-1) \lambda(\xi_k(k-1))$$  \hspace{2cm} (32)

Thus, again with a slight abuse of terminology, we can say that ITS is a mean estimator of target existence, across all components.

Additional difference between MHT and ITS application lies in the track status update. MHT, in addition to pruning / merging control of the number of components, confirms or terminates each component separately based on its likelihood, as given by equations (11) and (10). An MHT track is terminated only when all track components are terminated. ITS may terminate individual components based on their probabilities, given by equation (21). This procedure will never terminate all components, as their relative probabilities $\beta^c_k(k)$ must sum to one. All ITS track components are terminated only when the track itself is terminated, based on its probability of target existence, given by equation (23).

Target existence paradigm (ITS) offers additional parameters which can be tuned for better results, depending on the tracking environment. One is the initial probability of target existence, and the other is the target existence propagation matrix II. Markov Chain Two model for target existence propagation may also be employed; its usefulness has been demonstrated when the target is temporarily obscured, or when the probability of target detection is unknown and/or variable [8].

6 Simulation Study

The purpose of the simulation study is to compare false track discrimination performance of track score based tracking (single target MHT) and target existence based tracking (ITS) in an environment of single target tracking, with uncertain detections and significant clutter. Track retention performance is also compared.

For the purpose of this experiment, which is to compare track score and target existence, both MHT and ITS algorithms are simplified. MHT algorithm uses the single target tracking variant, where it is assumed that at most one target exists. Global hypotheses are not formed, and the most likely global hypothesis is formed by taking most likely component from each track. ITS is a single target tracking filter, although multi target tracking versions exist. It is simplified by not using Markov Chain One propagation matrix to further optimize the performance. Instead, Markov Chain One propagation matrix equals the unity matrix, multiplied by 0.9999 to eliminate numerical instabilities in equation (30).

Automatic track formation is performed by initializing new tracks at each time step using two-point differencing, without prior knowledge of measurement origin. Thus both true tracks and false tracks are created in every scan of every simulation run. These new tracks are given a prior target state density, based on the two measurements used for initialisation, assigned an initial existence probability (in the case of ITS) and added to the set of tentative tracks.

Tentative tracks are classified as confirmed, i.e., they are deemed to belong to a target, or are terminated on the basis of the probability of target existence in the case of ITS. Additionally, all components with relative probability smaller than 0.02 are terminated. MHT confirmation is based on component score, once a component is confirmed so are all its descendents. MHT termination is also based on component score, each component is terminated separately. A track is terminated once all its components have been termi-
nated. Both algorithms employ component subtree pruning \cite{10} of depth 4 to control the number of existing components.

A two dimensional surveillance situation is considered. The area under surveillance is 1000m long and 400m wide. Clutter measurements satisfy a Poisson distribution, with uniform clutter measurements density of $10^{-4}$ measurements/scan/m$^2$. The single target MHT and ITS use non-parametric versions; i.e. they estimate the clutter density at each scan in the manner of \cite{13}.

Sensor is linear in Cartesian coordinates, and at each scan detects targets with the probability of detection for each target equal to 0.9. The sensor introduces measurement errors with the error covariance matrix of $25I_2$, where $I_2$ is the two dimensional identity matrix.

A single target follows a constant speed trajectory with the initial state of

$$[x \ ˙x \ y \ ˙y] = [50 \ 15 \ 200 \ 0] \quad (33)$$

Each simulation experiment consists of 1000 runs, and each run consists of 50 scans. At the end of each simulation run all true tracks are terminated, and the false tracks were retained, to attain a stable field of false tracks. The number of confirmed false tracks were approximately 220 (or approximately one in 230 scans). To put this number in perspective, 24 false tracks are initiated on the average in each scan.

The performance measures are:

- target retention statistics of confirmed true tracks and,
- false track discrimination.

The target retention statistics were obtained by noting the identity of confirmed true track (if any) following each the target at scan 20. These identities are checked again at scan 48, and the following statistics are accumulated:

- total number of cases (nCases) of target being followed by a confirmed track at scan 20,
- total number of tracks still following the original target (nOK) at scan 48, and
- total number of tracks which did not make it to the scan 48 (nLost).

The target retention statistics are summarized in Table 1.

<table>
<thead>
<tr>
<th>Table 1: Target retention</th>
<th>MHT</th>
<th>ST</th>
<th>ITS</th>
</tr>
</thead>
<tbody>
<tr>
<td>nCases</td>
<td>791</td>
<td>872</td>
<td></td>
</tr>
<tr>
<td>nOK</td>
<td>664</td>
<td>789</td>
<td></td>
</tr>
<tr>
<td>nLost</td>
<td>127</td>
<td>83</td>
<td></td>
</tr>
</tbody>
</table>

Mean track life $\tilde{\psi}$ of confirmed true tracks was not measured directly, but can be approximated by values from Table 1:

$$e^{-\frac{48 - 20}{\psi}} = \frac{nOk}{nCases}$$

$$\tilde{\psi} = 28/\ln\left(\frac{nCases}{nOk}\right) \quad (34)$$

which delivers value of mean confirmed track life of 160 and 280 for single target MHT and for ITS respectively. These results indicate that average confirmed track life of ITS may be much longer than the average confirmed true track life of MHT.

False track discrimination statistics are presented in Figure 1, which shows the success rate of target being followed by a confirmed track over simulation run time.

![Figure 1: True Track Success Rate](image)

These results indicate that in this environment target existence based multiscan target tracking (ITS) performs slightly better than track score based multiscan target tracking (single target MHT). Both the false track discrimination and track retention results are just the initial results; further investigation needs to be carried out over different environments and different range of parameters before final conclusions may be drawn.

7 Conclusions

In this paper both the theoretical and simulated comparison between two approaches to false track discrimination in multiscan target tracking in clutter are presented. Track score approach is used by MHT target tracking, and target existence is used by ITS target tracking. Track score is a “maximum likelihood” approach, where the criterion is the maximum component measurement likelihood. Target existence is a “mean estimate” approach, where the criterion is the measurement likelihood averaged over track components.

In this sense target existence approach uses more information, and one would expect this approach to be more successful in false track discrimination. Additionally, target existence approach has more parameters to tune, and also offers the Markov Chain Two case for tracking temporarily obscured targets.
Simulation experiments have verified this expectation in one environment, however these results must be regarded as only preliminary. More theoretical research as well as more simulation studies are needed before final conclusions may be drawn.

References


