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Target Existence Based MHT

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Abstract— **In a cluttered environment, measurements originate not only from the objects being tracked, but also from spurious sources. The number of existing objects (targets) to be tracked is also unknown. The Multi-Hypotheses Tracking (MHT) filter is generally considered to be the "optimal" n-scan target tracking filter in such a multi-target cluttered environment. This paper introduces a new MHT filter based on the target existence. The probability that a target exists is estimated, and the estimate of the target kinematic state is subsequently conditioned on target existence. False track discrimination uses the probability of target existence as the track quality measure. This approach simplifies the structure of the algorithm and reduces complexity. A simplified version of the algorithm, which decouples new track hypotheses from the measurement-to-existing-track allocations is also presented. A simulation study shows the effectiveness of this approach in an environment of heavy and non-uniform clutter, with multiple maneuvering targets with crossing trajectories.**

I. Introduction

Remote surveillance using sensors such as radar and sonar, generate measurements of uncertain origin. Measurements (detections) may originate from targets of interest, whose number and trajectories are unknown as well as from thermal noise and other objects. Unwanted measurements are usually termed clutter. True measurements from the targets of interest are present in each scan with only a certain probability of detection, P_D, and are perturbed by the measurement noise. Targets may change their motion model randomly by performing maneuvers.

Optimal tracking in clutter requires one hypothesis for every possible global history of measurements to target assignments [1]. The number of hypotheses in the optimal filter grows exponentially in time. Each hypothesis results in a track component. The number of components must be limited, usually by merging components, or by pruning - limiting the evolution of track components to a fixed number of scans [10]. We call the hypothesis which define a possible measurement history of a (potential) target the local hypothesis.

A global hypothesis is a measurement allocation history across all potential targets (tracks), which includes the birth process (new potential targets appearing) and the death process (potential target disappearance). Multiple Hypotheses Tracking (MHT) [2], [3] enumerates all possible global hypotheses and finds their *a posteriori* probabilities. These probabilities are used for track updates and for false track discrimination. The MHT algorithm was introduced in [2], based on measurement oriented hypotheses. A later version of MHT, whose hypotheses are based on tracks and is usually termed track oriented MHT was presented in [3].

The target existence based MHT (TEB-MHT) presented in this paper, uses the probability of target existence as the measure of track quality in the manner of the Integrated Probabilistic Data Association (IPDA) [4] and Integrated Track Splitting (ITS) [5]. It is an extension of the Joint ITS algorithm presented in [5]. We consider two models for target existence [4] propagation; Markov Chain One model assumes that targets which exist are always detectable with known probability of detection P_D. This is also called perceivability in [6]. Markov Chain Two model allows for the further possibility that a target exists and is *temporarily* not detectable (i.e. $P_D = 0$). This is useful when the target is temporarily obscured, when the probability of detection is unknown and/or varies significantly in time [7], [8]. In this text we will present formulae for TEB-MHT for the case of Markov Chain One; the extension to Markov Chain Two is straightforward.

The architecture of the TEB–MHT is similar to track oriented MHT [3]. However the use of target existence allows us to dispense with the hypotheses of track/component termination. Furthermore, global hypotheses of TEB–MHT include only one local hypothesis for each measurement-to-track allocation, compared to the global hypotheses of the track oriented MHT which have one local hypothesis for each possible measurement-to-track-component allocation. This results in a significant reduction in the number of possible global hypotheses of TEB–MHT compared to the track oriented MHT. Furthermore, a simplified version of the algorithm is also presented, which decouples updates of existing tracks from initiation of new tracks, which further significantly reduces the number of global hypotheses.

In parametric target tracking, an *a priori* clutter measurement density is assumed known while non-parametric target tracking assumes no *a priori* knowledge of the clutter measurement density and estimates it on a scan-by-scan basis. In this paper we consider only the parametric version using known clutter measurement density. If the clutter measurement density is not available (non-parametric model), it can be calculated using, for example, the method described in [5].

One method for estimating maneuvering trajectories is the Interacting Multiple Model approach (IMM) [9]. IMM runs a bank of filters, each with a different model of the target dynamics, and the filters interact with each other according to *a priori* probabilities of trajectory model switching. IMM has a favourable performance/computational resources ratio and has been combined with a number of different tracking algorithms [10]. IMM is not part of the algorithm presented in this paper, however integration of IMM is straightforward following [11]. Maneuver processing does not require separate hypotheses, rather IMM maneuver estimation can be performed once the measurement is allocated to individual tracks/components. This can be implemented in both TEB–MHT and track and measurement oriented versions of MHT [10]. In the simulations presented below, IMM is used to estimate maneuvering target trajectories.

Section II describes the track state model. Expressions for *a posteriori* probabilities of joint events are presented in Section III, and the simplified version of TEB-MHT is presented in Section IV. A simulation study in Section V shows the effectiveness of this approach.

II. Track State

A batch of measurements is received at each sampling time k. Let z_k denote the set of m_k measurements received at scan k and let $z_{k,i}$ denote the ith measurement of z_k, with $Z^k = z_k \bigcup Z^{k-1}$ denoting the set of sets of measurements up to and including scan k. Each measurement $z_{k,i}$ consists of a kinematic measurement component $z^c_{k,i}$ and a feature component $z^f_{k,i}$. The feature component may be amplitude as in [12], [13]. Probability density functions of the feature, given that measurement $z_{k,i}$ originated from target τ or from clutter are denoted by $p^\tau(z^f_{k,i}|Z^{k-1})$ and $p^0(z^f_{k,i}|Z^{k-1})$ respectively. Let $\rho^c(z^c_k|Z^{k-1})$ denote the *a priori* density of the kinematic component of clutter measurements, and let ρ_i denote the *a priori* clutter measurement density of measurement $z_{k,i}$:

$$\rho_i = \rho^c\left(z^c_{k,i}|Z^{k-1}\right) p^0\left(z^f_{k,i}|Z^{k-1}\right). \tag{1}$$

A track may consistently use a "real" target's measurements for updates, and we call this track a true track. Otherwise, we call it a false track. The existence of a target whose measurement is used for track update is a random event. For track τ the following random events are defined at time k:

- χ^τ_k target existence,
- $\chi^\tau_{k,0}$ no selected measurement is the target detection,
- $\chi^\tau_{k,i}$ measurement $z_{k,i}$ is the target detection,

The state of track τ at time k consists of a discrete variable χ^τ_k which denotes target existence and a continuous variable x_k which denotes track trajectory estimate at time k:

$$P\left[\chi^\tau_k, x^\tau_k\right] = P\left\{\chi^\tau_k\right\} p\left(x^\tau_k|\chi^\tau_k\right). \tag{2}$$

which is usually conditioned on Z^k or on Z^{k-1}. The probability of target existence is usually used for false track discrimination. When the probability of target existence of a track falls below a pre-determined termination threshold, the track is declared to be a false track and terminated. When the probability of target existence of a track rises above a pre-determined confirmation threshold, the track is declared to be a true track and confirmed. The thresholds may be constant or variable. Let $p^\tau(z^c|Z^{k-1})$ denote the *a priori* pdf of the kinematic measurement component for track τ, given that the measurement is selected [14]. Let p^τ_i denote the *a priori* pdf of measurement $z_{k,i}$, given that it is a selected measurement of target τ:

$$p^\tau_i = p^\tau\left(z^c_{k,i}|Z^{k-1}\right) p^\tau\left(z^f_{k,i}|Z^{k-1}\right) \tag{3}$$

A track is the union of its mutually exclusive components. Each component ξ represents one possible measurement to track association history. Denote the number of components of track τ at time k by C^τ_k. The estimated state of each component is the output of a filter which is "given" a single (possibly null – no detection) measurement at each scan. A component exists if the target exists and the measurement to target association history is the correct one. Each component state consists of the probability of the component existence and the component state estimate pdf conditioned on component existence:

$$P\left[\xi^\tau_k, x^\tau_k\right] = P\left\{\xi^\tau_k\right\} p\left(x^\tau_k|\xi^\tau_k\right). \tag{4}$$

and the *a priori* pdf of measurement $z_{k,i}$, given that $z_{k,i}$ is the target τ measurement and given that the component ξ^τ_k exists is

$$p^{\tau,\xi}_i = p^{\tau,\xi}\left(z^c_{k,i}|Z^{k-1}\right) p^\tau\left(z^f_{k,i}|Z^{k-1}\right) \tag{5}$$

Markov Chain One probability of component existence propagation is given by

$$P\left\{\xi^\tau_k\right\} = p_{11} P\left\{\xi^\tau_{k-1}\right\} + p_{21}\left(1 - P\left\{\xi^\tau_{k-1}\right\}\right) \tag{6}$$

and is used to calculate *a priori* probability of component existence $P\left\{\xi^\tau_k|Z^{k-1}\right\}$ for time k from the *a posteriori* probability of target existence at time $k-1$; $P\left\{\xi^\tau_{k-1}|Z^{k-1}\right\}$. Transition probability p_{21} should be 0 [11] as the event of a non-existent target becoming existent will invalidate the definition of the component. Components are mutually exclusive random events, thus

$$P\left\{\chi^\tau_k|Z^s\right\} = \sum_{\xi^\tau_k} P\left\{\xi^\tau_k|Z^s\right\} \tag{7}$$

$$p(x^\tau_k|\chi^\tau_k, Z^s) = \frac{\sum_{\xi^\tau_k} P\left\{\xi^\tau_k|Z^s\right\} p(x^\tau_k|\xi^\tau_k, Z^s)}{P\left\{\chi^\tau_k|Z^s\right\}} \tag{8}$$

where $s = k-1$ indicates *a priori* and $s = k$ indicates *a posteriori* values. The *a priori* pdf of measurement $z_{k,i}$, given that it is a selected measurement of the target followed by track τ is

$$p^\tau_i = \frac{\sum_{\xi^\tau_k} P\left\{\xi^\tau_k|Z^s\right\} p^{\tau,\xi}_i}{P\left\{\chi^\tau_k|Z^s\right\}} \tag{9}$$

Each component ξ^τ_k selects a subset $z^{\tau,\xi}_k$ of $m^{\tau,\xi}_k$ measurements at scan k, with gating probability P_W. Without loss of generality we assume the same gating probability for each component. The set of track selected measurements, z_k^τ, of m_k^τ measurements is the union of component selected measurement sets: $z_k^\tau = \bigcup_{\xi_k^\tau} z_k^{\tau,\xi}$ [5], [14].

At scan k, each pair (component ξ_k^τ, selected measurement $i \geq 0$) creates a new component of track τ. The original parent component ξ_k^τ is split into $m_k^\xi + 1$ new components. The state estimate of new components is obtained by applying measurement $z_{k,i}$ to the state prediction pdf of the parent component ξ_k^τ. This update may be performed with a choice of estimation algorithms. We have used a single Kalman filter [15] and IMM [11]; extended or unscented Kalman as well as particle filters are some of other possible options. The *a posteriori* probability of new component existence is equal to the *a posteriori* probability of component ξ_k^τ existence and the event that measurement $i \geq 0$ is the measurement of target τ, which is denoted with $P\left\{\xi_k^\tau, \chi_{k,i}^\tau | Z^k\right\}$.

The number of components grows exponentially in time, which is not sustainable with practical computational platforms. The number of components is reduced most often by component pruning [10] or merging [16]. When pruning of depth N is used at scan k, only a single most probable candidate measurement is chosen at scan $k-N$, and the components which do not contain the chosen measurement in their histories are terminated. Remaining components become conditional on "surviving" the pruning operation, and their probabilities of existence must be corrected by

$$\frac{1}{1 - \sum_{\xi_k^\tau removed} P\left\{\xi_k^\tau | Z^k\right\}} \tag{10}$$

Recursion of each track consists of prediction and measurement update. Prediction handles track evolution between two measurement updates, and is usually handled on a track-by-track basis. The probability of target existence evolution is handled with equation (6), and track state prediction is standard random process evolution [17].

In [3] a track component is simply called "track", and the set of components which follow one target (in this paper called track) is referred to as a "target".

III. Joint Data Association

Joint Data Association delivers the probabilities of measurement origin for each track in a multi target situation. Multiple tracks interfere with each other when two or more tracks have at least one common measurement in their validation windows in a particular scan.

In each scan, tracks select measurements and are then grouped (partitioned) into clusters. A cluster is a set of tracks, which selected no measurements in common with any track not belonging to the cluster. Thus, a single isolated track is a cluster. A trivial cluster is the set of all tracks. However, as the number of operations grows exponentially with the number of tracks in a given cluster, each cluster should contain the minimal set of tracks conforming to the definition.

A single cluster of tracks in one scan is examined in this Section. Any track and any measurement mentioned below belong to the same cluster and cluster area respectively. In this Section, z_k will denote the measurements belonging to the cluster, and Z^{k-1} will denote all measurements selected by all tracks in the cluster in previous scans. Let T denote the number of the tracks in the cluster.

A number of possible assignments of measurements to tracks exists, and we consider each feasible assignment to be a separate joint event. The following constraints must be observed for each joint event:

- each track can be assigned zero measurements or one of the measurements which falls in the individual window of the track,
- each measurement can be allocated to zero or one of the existing tracks,
- each measurement not allocated to one of the existing tracks can either be a clutter or a new track measurement.

Two joint events are different if the assignment of at least one measurement is different. The joint events generated in this manner are mutually exclusive, and they should form a complete set.

Let ψ_i denote the joint event i, and let Ψ denote the number of joint events in the cluster. Let $T_0(i)$ and $T_1(i)$ denote the set of tracks allocated no measurements, and the set of tracks allocated one measurement respectively in the joint event. The set of measurements which are declared to be clutter is denoted by $M_0(i)$, and let $M_1(i)$ denote the set of measurements which are new track measurements. The *a posteriori* probability of ψ_i is

$$\begin{aligned} P\left\{\psi_i | Z^k\right\} &= C^{-1} \prod_{\tau \in T_0(i)} \left(1 - P_D^\tau P_W^\tau P\left\{\chi_k^\tau | Z^{k-1}\right\}\right) \\ &\times \prod_{\tau \in T_1(i)} \left(P_D^\tau P_W^\tau P\left\{\chi_k^\tau | Z^{k-1}\right\} \frac{p_{l(\tau,i)}^\tau}{\rho_{l(\tau,i)}}\right) \\ &\times \prod_{\omega \in M_0(i)} \frac{\rho_\omega}{\rho_\omega + \rho_\omega^t} \times \prod_{\omega \in M_1(i)} \frac{\rho_\omega^t}{\rho_\omega + \rho_\omega^t} \end{aligned} \tag{11}$$

where $l(\tau,i)$ denotes the index of the measurement which is allocated to track τ in the joint event ψ_i, and ρ_ω^t denotes new target density (which includes the feature component) at measurement $z_{k,\omega}$. The joint events form a complete set and the constant C is calculated using

$$\sum_{j=1}^{\Psi} P\left\{\psi_j | Z^k\right\} = 1 \tag{12}$$

The *a posteriori* probabilities of the individual track events are obtained by summing the *a posteriori* probabilities of all joint events containing the event. Denote with $\Xi(\tau,i)$ the set of joint events in which track τ has been allocated measurement i, with measurement $i = 0$ denoting no measurement. The set $\Xi(\tau,i)$ may be empty. The *a posteriori* probability that no measurement originates from the track τ is

$$P\left\{\chi_{k,0}^\tau | Z^k\right\} = \sum_{\psi \in \Xi(\tau,0)} P\left\{\psi | Z^k\right\} \tag{13}$$

and the *a posteriori* probability that track τ exists and that measurement $i > 0$ originated from track τ is

$$P\left\{\chi_k^\tau, \chi_{k,i}^\tau | Z^k\right\} = \sum_{\psi \in \Xi(\tau,i)} P\left\{\psi | Z^k\right\} \tag{14}$$

The probability of existence of the component spawned from component ξ_k^τ using the null measurement is

$$P\left\{\xi_k^\tau, \chi_{k,0}^\tau | Z^k\right\} = P\left\{\chi_{k,0}^\tau | Z^k\right\} \times \times \frac{\left(1 - P_D^\tau P_W^\tau\right) P\left\{\xi_k^\tau | Z^{k-1}\right\}}{1 - P_D^\tau P_W^\tau P\left\{\chi_k^\tau | Z^{k-1}\right\}} \tag{15}$$

and the probability of existence of the component spawned from component ξ_k^τ using measurement i is

$$P\left\{\xi_k^\tau, \chi_{k,i}^\tau | Z^k\right\} = P\left\{\chi_k^\tau, \chi_{k,i}^\tau | Z^k\right\} \times \times \frac{p_i^{\tau,\xi} P\left\{\xi_k^\tau | Z^{k-1}\right\}}{p_i^\tau P\left\{\chi_k^\tau | Z^{k-1}\right\}} \tag{16}$$

The probability that measurement ω is the start of a new track ν is

$$P\left\{\chi_k^\nu | Z^k\right\} = \sum_{\psi \in \Omega(\omega)} P\left\{\psi | Z^k\right\} \tag{17}$$

where $\Omega(\omega)$ denotes the set of joint events which declare measurement ω to be the start of a new track. Probability $P\left\{\chi_k^\nu | Z^k\right\}$ is the initial probability of target existence for the new track ν.

IV. Simplified Joint Events

The number and density of targets is usually unknown, and furthermore the number of clutter measurements is usually much bigger than the number of undetected targets in the cluster. Under these assumptions, the number of joint events can be significantly reduced by decoupling the measurement to existing tracks association, and new target hypotheses.

If $\rho_\omega \gg \rho_\omega^t$, then all joint events with non-zero cardinality of set M_1 in equation (11) can be assumed to have negligible *a posteriori* probabilities, and equation (11) reduces to

$$P\left\{\psi_i | Z^k\right\} = C^{-1} \prod_{\tau \in T_0(i)} \left(1 - P_D^\tau P_W^\tau P\left\{\chi_k^\tau | Z^{k-1}\right\}\right) \times \prod_{\tau \in T_1(i)} \left(P_D^\tau P_W^\tau P\left\{\chi_k^\tau | Z^{k-1}\right\} \frac{p_{l(\tau,i)}^\tau}{\rho_{l(\tau,i)}}\right) \tag{18}$$

The probability that measurement ω is the beginning of new track is approximated with

$$P\left\{\chi_k^\nu | Z^k\right\} = \frac{\rho_\omega^t}{\rho_\omega + \rho_\omega^t} \sum_{\psi \in \Xi(0,\omega)} P\left\{\psi | Z^k\right\} \tag{19}$$

When the assumption $\rho_\omega \gg \rho_\omega^t$ is not correct, and we do not expect many new targets in the cluster area, the approximation described in this Section will still yield acceptable results while considerably reducing the number of joint events.

V. Simulations

The simulation study presented below shows the effectiveness of TEB-MHT in an environment of non-uniform clutter and multiple, highly maneuvering targets with crossing trajectories.

A two dimensional surveillance system is modelled. The linear sensor introduces independent measurement noise with standard deviation of 5 m in both coordinates. The probability of detection for each target is assumed known and is $P_D = 0.9$. The background clutter is non-uniform with base density of $2\mathrm{e}^{-5}\,\mathrm{m}^{-2}$ per scan, and heavy clutter region density of $1\mathrm{e}^{-4}\,\mathrm{m}^{-2}$ per scan. The environment and trajectories of two simulated targets are shown in Fig. 1.

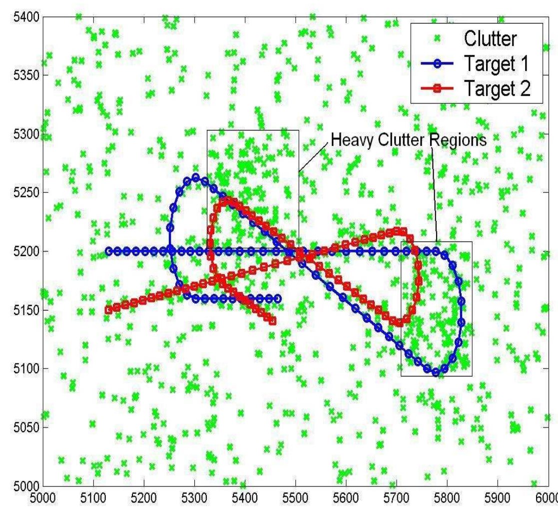

Fig. 1. Test Tracks and Clutter Distribution

Both trajectories consist of 8 segments each 10 seconds in duration as follows:

1) uniform motion with constant velocity of 18 m/s for target one and 17.12 m/s for target two,
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 $\alpha = 0.05\ \mathrm{s}^{-1}$ for target one and $\alpha = 0.04\ \mathrm{s}^{-1}$ for target two,
3) exponential deceleration, with $\alpha = -0.05\ \mathrm{s}^{-1}$ for target one and $\alpha = -0.04\ \mathrm{s}^{-1}$ for target two,
4) right turn with angular velocity of $\pi/9\,\mathrm{rad/s}$ for target one and $\pi/8.8\,\mathrm{rad/s}$ for target two,
5) exponential acceleration with $\alpha = 0.05\ \mathrm{s}^{-1}$ for target one and $\alpha = 0.06\ \mathrm{s}^{-1}$ for target two,
6) exponential deceleration with $\alpha = -0.05\mathrm{s}^{-1}$ for target one and $\alpha = -0.06\ \mathrm{s}^{-1}$ for target two,
7) left turn with angular velocity $\pi/9\,\mathrm{rad/s}$ for target one and $\pi/10\,\mathrm{rad/s}$ for target two, and
8) uniform motion for both targets.

Both targets start moving from location $(5130, 5200)$ and $(5130, 5150)$ at time $k = 1$ and approach each other with an angle of approximately 21° as shown in Fig. 1. The IMM filter used by TEB-MHT consists of four models of target motion:

1) Uniform motion: target moves on a straight line with constant velocity.
2) Acceleration: target moves with constant acceleration
3) Target is executing a left coordinated turn with constant angular velocity $\omega = \pi/9\,\mathrm{rad/s}$.
4) Target is executing a right coordinated turn with constant angular velocity $\omega = \pi/9\,\mathrm{rad/s}$.

Please note that the IMM models are not accurate models of target trajectory segments, which is a common situation in practice. The transition probability matrix of the IMM models is:

$$\Pi = \begin{bmatrix} 0.91 & 0.03 & 0.03 & 0.03 \\ 0.03 & 0.91 & 0.03 & 0.03 \\ 0.05 & 0.05 & 0.9 & 0 \\ 0.05 & 0.05 & 0 & 0.9 \end{bmatrix} \tag{20}$$

The state vector is modelled as

$$x = \begin{bmatrix} \xi & \dot{\xi} & \zeta & \dot{\zeta} & \ddot{\xi} & \ddot{\zeta} \end{bmatrix}^T \tag{21}$$

where (ξ, ζ) denote Cartesian coordinates. All models have white plant noise with covariance matrix:

$$Q = Q_0 \begin{bmatrix} \frac{1}{4}T^4 & \frac{1}{2}T^3 & 0 & 0 & \frac{1}{2}T^2 & 0 \\ \frac{1}{2}T^3 & T^2 & 0 & 0 & T & 0 \\ 0 & 0 & \frac{1}{4}T^4 & \frac{1}{2}T^3 & 0 & \frac{1}{2}T^2 \\ 0 & 0 & \frac{1}{2}T^3 & T^2 & 0 & T \\ \frac{1}{2}T^2 & T & 0 & 0 & 1 & 0 \\ 0 & 0 & \frac{1}{2}T^2 & T & 0 & 1 \end{bmatrix} \tag{22}$$

where $Q_0 = 0.004$ for the uniform motion model and $Q_0 = 0.4$ for other models, and the sampling interval is $T = 1$ s. The transition probabilities of track existence are $p_{11} = 0.98$ and $p_{21} = 0$.

The simplified non-parametric version of TEB-MHT was applied. Clutter density was estimated using the procedure described in [5]. The measurement feature was not simulated and only kinematic components are used. The number of track components was controlled by merging components with similar state [16]. The number of components per track was limited to 20.

Tracks are initiated using the two-point differencing [18], [19]. The initial probability of target existence for each track is calculated as in Section IV. Fixed termination and confirmation thresholds were used.

Each simulation consists of 500 runs. The number of confirmed true tracks is shown in Fig. 2. The number of confirmed false track scans is less then 1 in 200 scans.

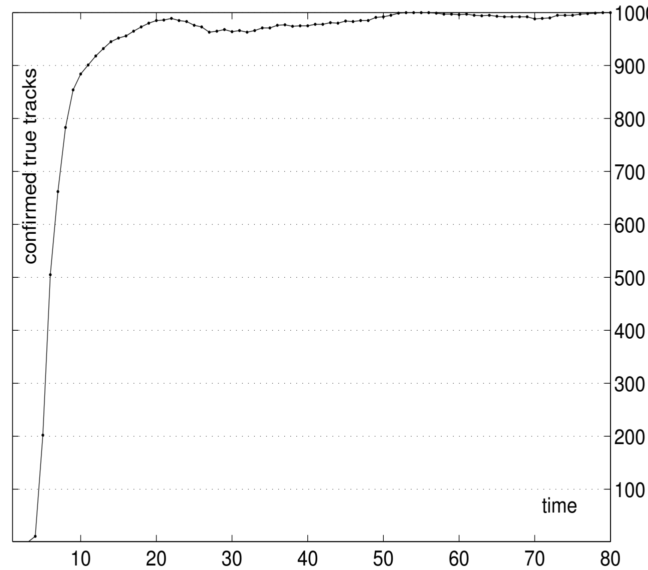

Fig. 2. Number of Confirmed True Tracks

VI. Conclusions

This paper presents a new target existence based Multi Hypothesis Tracking filter for multi target tracking in clutter. By calculating the probability of target existence and by calculating measurement oriented joint data association probabilities, the number of global hypothesis for TEB–MHT is significantly smaller than the number of global hypotheses for track oriented MHT. This allows us to retain longer measurement histories for the same computational requirements, with potential performance benefits.

Due to computational requirements which increase exponentially in time, TEB-MHT (and its simplified version) need to implement component control which reduces their optimality to N-scan measurement allocation.

A simulation study has shown the effectiveness of this approach.

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