Abstract—Tracking of multiple ground targets with airborne Ground Moving Target Indicator (GMTI) sensor measurements is a challenging problem where heavy and dense false alarms with high target density are inevitably encountered in the surveillance scenes. Hence, optimal approaches require heavy computational load where the duration of overall computation rises exponentially with the number of target tracks and measurements in observation per scan. Consequently, more practical suboptimal approaches, such as Linear Multi-Target (LM) approach, is explored due to linear number of operations in the number of target tracks with a negligible performance loss compared to optimal approaches. Although LM approach performs modestly adequate with significantly less computation duration than optimal approaches, it is highly susceptible to track loss, as in the rest of suboptimal approaches, when the targets are closely spaced and the number of targets and measurements are considerably high. Simulations are carried out in realistic test scenarios to compare single target tracking algorithms including IMM-PDA and IMM-IPDA algorithms; Optimal approaches in multitarget tracking including IMM-JPDA, IMM-IJPDA and IMM-JIPDA algorithms and an example of Linear Multi-target approaches in multitarget tracking including IMM-MLIPDA algorithm. Benchmakings of these algorithms are done under RMSE performance, track loss and computation time evaluation results.

I. INTRODUCTION

Since the Gulf War in 1991, Ground Moving Target Indicator (GMTI) radar has become an extremely useful sensor for military surveillance [13], [18] as well as civilian applications [4]. Tracking of multiple ground targets with airborne GMTI sensor measurements often suffers from high clutter density and low visibility of targets under track. Tracking of multiple ground targets is a challenging problem where heavy and dense false alarms and high target density problems are inevitably encountered in the surveillance scenes. Target originated measurements may be present in each scan with a certain probability of detection. Major difficulties of tracking of ground target(s) results from the target motion origin uncertainty and the measurement origin uncertainty [1]. The target motion origin uncertainty appears in the situations where target(s) may undergo a known or unknown maneuver during an unknown time period [1]. In a fact, a nonmaneuver and different maneuvers can be described only with different dynamic motion models [3]. The use of an incorrect model at a specific time interval often causes unacceptable errors. When tracking maneuvering targets, it is very important to make a decision accurately on time the right model to use. So, instead of using a single model based filter, a bank of filters based on a set of multiple models should be considered which represent possible maneuvers under consideration [1]. Recommended approach [1] in target tracking under target motion origin uncertainty existence is to use Interacting Multiple Model (IMM) Estimator. The IMM is a recursive cost-effective and practical filter that shows elegant performance when targets being tracked undergo frequent maneuvers during unknown time periods [1]. The measurement origin uncertainty appears due to unreliable measurement(s) obtained by the sensor system. Unreliable measurements may have arisen from an irrelevant source, including clutter, false alarms, and neighboring targets, as well as the target under track. Target tracking under this kind of situation takes all measurements into account for track update in each scan. Validation of measurements is crucial in this situation in order to reduce further computation. A track quality measure should be employed to discriminate the target track(s) has been followed whether either of them true or false track(s). Under measurement origin uncertainty existence, to select the right measurement(s) to initiate true track(s), the recommended approach in the literature [1] is to use Data Association.

Single target tracking algorithms assume that validated measurements are either target originated or formed by an interfering source, often termed clutter. In multitarget tracking situation, in addition to single target tracking situation false alarm measurements may have also originated from neighboring targets. In this situation, assignment of target measurements to right target tracks has a great importance. So, formation of all feasible measurement-to-track joint events and assignment of right joint event via calculation of a posteriori probabilities of each feasible joint event in each scan are required. Hence, optimal approaches in multitarget tracking require too much computational load as the numbers of target track(s) and measurements grow linearly while the duration of overall process rises exponentially. Consequently, using optimal approaches instead, more practical suboptimal approaches, such as Linear Multi-Target approach [17] is considered due to linear number of operations in the number of target tracks and measurements.
sense with a negligible performance loss compared to optimal approaches.

The most practical method for multitarget tracking is basically to run a bank of single target tracking algorithms, based on different dynamic motion models per track. This method has rarely been proven satisfactory in practice [17] because almost all suboptimal algorithms in the literature [1], [17], [23] suffer from deficiencies in performance. Particularly, these algorithms have been shown in [34] to be more susceptible to “track loss” where heavy and dense false alarms are often encountered and targets are closely spaced [17] and the numbers of targets and measurements are considerably high [34].

In this study, simulations are carried out in realistic test scenarios, where actual ground target(s)’s movement taken into consideration, dealing with single target tracking, tracking of multiple targets moving in convoy fashion, two targets merging-departing in junctions and multitarget tracking under isolated tracks situations in order to compare single target tracking algorithms including IMM-PDA and IMM-IPDA algorithms; Optimal approaches in multitarget tracking including IMM-JPDA, IMM-IJPDA and IMM-JIPDA algorithms and the IMM-LMIPDA algorithm.

II. BACKGROUND

A. Target Motion Origin Uncertainty and Kinematic State Estimation

Target tracking is defined in [2], [4] as a hybrid estimation problem which involves both continuous and discrete uncertainties. Challenging problem in tracking of maneuvering target(s) results from the target motion origin uncertainty [4]. The target motion origin uncertainty [1] appears in the situations where target(s) may undergo a known or unknown maneuver during an unknown time period. In fact, a nonmaneuver motion and different maneuvers can only be described with different dynamic motion models [3]. In target tracking, for Kinematic State (e.g. position, velocity, acceleration) Estimation of target(s) under track, the mathematical modeling of all possible target motion dynamics / kinematics is essential [1], [3]. The use of incorrect models or insufficient number of models often causes undesired consequences [1]. Generally, a continuous-valued process noise is considered to cover the unknown modeling errors or deviations of the mathematical model from the exact behavior of the system. However, while tracking a maneuvering target, deciding accurately on time the right model to use constitutes vital importance. In order to handle this situation, all the models according to possible target motion dynamics should be formed and considered, the right model which fits to true target kinematics at that time should be selected. Hence, the major approach naturally is to consider a method where more than one model - multiple models are taken into account.

The major approach in target tracking under target motion origin uncertainty existence is to use a Multiple Model (MM) method which is one of the most consented approaches to solve hybrid estimation [2], [4] problem. MM method recommends using a bank of filters based on a set of multiple models that represent/cover possible system behavior patterns (e.g. maneuvers) for the problem under consideration [1]. These system behavior patterns are discrete in nature and referred to as system modes. The system mode at specific instant has stair-case type trajectory which may stay unchanged or jump. For such a system the transition between system modes, shortly modal state is generally modelled with Markov Chain due to its nature and consistency in theory [4].

The early results of Static (“Non-interacting”) Multiple Model (SMM) estimation were valid for targets with a time-invariant unknown or uncertain system mode while they are ineffective in frequent system mode transitions [5]. By the development of the highly cost-effective Interacting Multiple Model (IMM) estimator [8], the MM approach has become not only capable of handling frequent mode transitions (e.g. maneuvers) but also practical for maneuvering target tracking applications where in [1], [4], [5], [7], [9], [10] has been proven.

For target(s) under track, many different maneuver models are possible where all of them may not be represented sufficiently by a small set of models. To accomplish better performance, use of large filter banks based on different motion models may be necessary. Use of more model based filters in IMM estimator has been shown in [3], [11] that does not guarantee enhancement in performance. Because, use of more models increases the computational complexity very considerably. In fact, increment in the number of model based filters in the IMM Estimator deteriorates estimator’s performance significantly due to the fact that model likelihood difference between the models decreases [3]. Thus, using less and sufficient number of models in the IMM Estimator has been shown theoretically in [11], [12] yields better performance with less computation complexity which has also been discussed in [1], [3].

Hence, instead of using more models in the IMM Estimator, for sake of better performance with less computation complexity, we consider to use 2 models which is sufficient and also recommended to use at [3]: CV with Low Process Noise for nonmaneuvering motion and CV with High Process Noise for any maneuvers including coordinated turns and acceleration modes.

B. Measurement Origin Uncertainty and Data Association

The measurement origin uncertainty arises from unreliable measurement(s) obtained by the sensor system. Unreliable measurement(s) may have arisen from an interfering source, including clutter, false alarms, and neighboring targets, as well as the target under track. This situation constitutes the “greatest” challenge for ground target tracking applications. Tracking targets in a measurement origin uncertainty with frequently high density makes the problem much more difficult to solve.

Data Association algorithms [1], [7], [9], [14]–[17] are required in situations where target tracking is being attempted with unreliable measurements where measurements of uncertain origin situation (as illustrated in Figure 1) appears. Moreover, the target measurements are unreliable and are only present at each scan time with a certain “Probability of Detection (P_D)”. Reliable initiation, confirmation and deletion of tracks under such conditions is greatly assisted if data association probabilities are computed.

Use of a gating technique is required for eliminating unlikely measurement-to-track pairings. An elliptical gate [9] is formed about the predicted measurement and all observations that fall within the gate are considered for track update. Gate is often called with a name validation region in literature and
The number of joint events can grow exponentially in a dense possible combination of measurement to track assignments [1] mentioned in [23] because it creates a joint event for each target existence information. JPDA is also rather complex as and track maintenance is difficult without the probability of differentiated according to the probability of target existence, that the target(s) exist(s) in each scan. Tracks are not differentiated according to the probability of target existence, while these old data association techniques work reasonably well with benign targets in sparse scenarios [1], they begin to fail as the false alarm rate increases or with low probability of detection, or with low or partial observability. Instead of using only one measurement among the received ones and discarding the others, an alternative approach is proposed in [7], [19], using all the latest validated measurements with different weights, which is known as Probabilistic Data Association (PDA).

PDA is a recommended [7] method for data association when tracking a single target in clutter, however, it is derived under the assumption that a track exist in the validated region(gate) at each scan with a certain gating probability $P$; which is very close to 1 and consequently is unable to provide the probability of track existence information for unreliable target measurements. In [24], [25], PDA algorithm is rederived without an initial assumption of track existence and the resulting algorithm is named Integrated Probabilistic Data Association (IPDA) which simultaneously and recursively provides expressions for both probability of track existence and data association.

Data association becomes more difficult with multiple targets where the targets compete for measurements. It has been shown in [20], [21] that PDAF can get "confused" under these circumstances and start following a different target, or it can diverge altogether and stop following any target. To compensate for this situation, the Joint Probabilistic Data Association (JPDA) algorithm has been developed [20], [21]. As in the PDA, JPDA algorithm is based on pre-assumption that the target(s) exist(s) in each scan. Tracks are not differentiated according to the probability of target existence, and track maintenance is difficult without the probability of target existence information. JPDA is also rather complex as mentioned in [23] because it creates a joint event for each possible combination of measurement to track assignments [1]. The number of joint events can grow exponentially in a dense clutter situation. To improve upon JPDA, the Integrated JPDA (IJIPDA) algorithm has been proposed [32]. It builds upon IPDA algorithm proposed in [33] and also uses the probability of target perceivability to develop recursive expressions for the a-posteriori probability of target perceivability and data association for each track. In IJPDA, the number of joint events is much higher than in case of JPDA [32] because perceivability or unperceivability information for each target track is taken into consideration via adding an extra event vector to all feasible event matrices describing perceivability state of each target track.

The Joint IPDA (JIPDA) algorithm [26], [30] is developed in a similar fashion to the IPDA algorithm given in [24], [25]. It uses the probability of target existence and results in recursive expressions for the probability of target existence and data association probabilities. The number of joint events is the same as in the case of JPDA [26], [30]. However, JIPDA still has the same complexity as JPDA, which may preclude it from being used on all tracks in a dense clutter situation. Optimal approaches has been mentioned so far [20], [21], [26], [30], [32], generate and evaluate all possible hypotheses of measurement origin in the current scan whereas the number of these hypotheses grows exponentially with the number of tracks and the number of measurements involved. As the number of such hypotheses grows exponentially with the number of scans, these approaches are not used in practice [23], especially in cases where a large number of targets are close to each other, or in a dense clutter situation with a large number of false tracks. Instead, various suboptimal data association algorithms such as in [6], [22] have been proposed with an inevitable performance errors and loss of tracks. A notable exception to these algorithms, which has been proposed in [27], is the Linear Joint Integrated Probabilistic Data Association (LJIPDA) algorithm, which is basically a multitarget version of IPDA [24], [25] with only a “linear” number of operations within the number of tracks and the number of measurements in present. LJIPDA uses a-priori probabilities of measurement origin to calculate (for each track and for each measurement) the probability that the measurement belongs to some other track. The a-priori probabilities of measurement origin are the major conduit for inter-track information transfer. These probabilities are then used to calculate the probability of track existence and data association probabilities. In this manner, multitarget tracking is achieved without exhaustive measurement-to-track hypothesis processing. Rather than forming joint events by creating all possible combinations of measurement-to-track assignments, only a single track is processed at a time. Therefore, the number of operations is linear in the number of tracks and the number of measurements. This important property permits target tracking in much denser clutter or closely-spaced target situations by using less computational resources than optimal approaches such as JPDA, IJPDA, or JIPDA.

By the following of this pioneering approach, a generic procedure has been proposed in [29], namely Multi-target Linear Converter (MLC), which converts any single target data association algorithm belonging to a certain class, into an equivalent multitarget data association algorithm using a number of operations which is linear in the number of tracks and the number of measurements as in LJIPDA. MLC uses a similar approach to LJIPDA by using the probabilities of measurement origin as a conduit for information exchange between
tracks. The difference is that MLC uses “a-posteriori” probabilities of measurement origin calculated by the single target data association algorithm considered as a core. It corrects these probabilities to allow for multitarget existence and uses them directly to calculate the probability of track existence and data association probabilities for each track. Thus, MLC simply converts single target data association algorithms into multitarget data association algorithms. The only requirement for MLC on the single target data association algorithm is that it must provide the a-posteriori probabilities of measurement origin information. Single target data association algorithms such as IPDA [24], [25], IMMPDAF [7], [19], IPDA [33] can be considered.

Both MLC and LJIPDA algorithms achieve multitarget data association capability by splitting the measurements according to the a-posteriori or a-priori probabilities of measurement origin. In situations when a measurement is allocated to multiple tracks, it is “split”, and each track uses a “fragment” of the measurement [31]. The algorithm presented in [16], [17], [28], [31] is also a multitarget data association algorithm with a linear number of operations in the number of tracks and the number of measurements, with apparently negligible performance penalty compared to optimal approaches such as JIPDA [28]. However, the difference between both MLC and LJIPDA, it is derived by modifying the clutter density with the foreign target measurement density. The resulting new approach is called Linear Multi-Target (LM) procedure [16], [17], [28], [31]. It is a general procedure for converting certain class of single target data association algorithms into multitarget data association algorithms. In effect, the LM approach is to run a bank of “coupled” single target data association filters, where the coupling is achieved through modifying the clutter density for each tracking filter. The clutter density at each measurement point is modified by the pdf of measurements originating from neighboring tracks. Briefly, other tracks are treated as additional clutter sources [31]. This coupling eliminates most of the problems experienced when running single target data association filters in a multitarget tracking situation with very little additional computational cost. Use of the LM method means “each measurement” in the current scan may potentially be used to update more than one track which has been shown [17], [28] to be better performance than previously proposed algorithms, LJIPDA and MLC, using a “fragment” of the measurements in track coalescence situations. The differences in implementation complexity between a single target tracking data association algorithm and its LM equivalent are also very small. The difference in implementation complexity between a single target tracking data association algorithm and its LM equivalent is recognized by the prefix “LM”, which stands for Linear Multi-Target such as LMIPDA [16], [31].

C. Tracking of Target(s) in Clutter

So far, we investigate the problems have been encountered in both kinematic state estimation and data association separately for tracking of ground target(s) in a cluttered environment. Although, the problems and proposed solutions to problems are seemed to be discrete naturally, the solutions should be logically fused to make them incorporate to achieve a complete solution. The most common known method has been proposed by Bar-Shalom et.al to achieve a complete solution to tracking a single maneuvering target in clutter problem is proposed as a combination of IMM algorithm with PDA algorithm is called IMMPDAF [7]. For convenience with other section IMMPDAF will be denoted as IMM-PDA where IMM is the approach considered for kinematic state estimation as the solution for target motion origin uncertainity and PDA is the approach considered to achieve the right measurement-to-track assignment as the solution for measurement origin uncertainity problem.

1) Combining IMM with a Probabilistic Data Association Algorithm: One important feature of the PDA [19] algorithm or any Probabilistic Data Association based algorithms such as IPDA [24], JPDA [20], LMIPDA [17],...etc. is the relatively straightforward manner in which either of them can be combined with IMM filtering. These methods are discussed in more detail in [7], [16], [31], however, this Section only summarizes the pioneer method IMMPDAF [7], denoted as IMM-PDA. If we assume that a track has been formed at (k−1)th scan and there are M IMM Filter models [1]. Given the data received through scan k − 1, each IMM filter will have its model probability, state prediction and Kalman Filter Covariance matrix for use with the next data set (scan k). Then, the next step is to define a validation region (gate) in order to determine which observations are to be considered for track update. Given the new data (at scan k), the IMM-PDA process is illustrated on flowchart on Figure 2.

2) Track Initiation and Deletion: The original PDA [19] method did not include explicit provisions for track initiation and deletion. It was implicitly assumed that tracks had been established and the main issue was track maintenance. Since then, IMM-PDA [7] method is modified to handle this issue via using “target” and “no target” [7] models and Integrated PDA (IPDA) is derived in [24], [25] under “track exists” and “track

Fig. 2. IMM-PDA Flowchart
does not exist” possibilities taken into account via probability of track existence parameter computed recursively as an extra state.

[16], [24], [25] have shown that in IPDA-based algorithms [16], probability of track existence parameter is also considered in track initiation and deletion operation. However, in our simulations, we consider this parameter for track maintenance purpose in order to update data association probabilities recursively. Instead of using probability of track existance parameter as in the references [16], [24], [25], for track initiation, confirmation and deletion operations, Log Likelihood Ratio (LLR) testing under Sequential Probability Ratio Test (SPRT) procedure [9] is preferred in our simulation studies.

III. Simulations

The estimation accuracy of each target tracking algorithm under test has been compared via RMSE performance evaluations. In our simulations, RMSE performance of each algorithm is computed by considering simulation runs are taken into account, where the same number of confirmed true tracks has been established at each run for all target tracking algorithms.

Let us consider that $K$ is achieved as the number of successful runs out of total $L$ runs, so, $K$ runs are taken into account for RMSE performance computation. Among $L$ runs, if $N$ total successful confirmed true tracks out of $M$ overall total tracks in $M$ scans over all runs have been established by the target tracking algorithm under concern, has $M-N$ track losses. These $L-K$ run periods are not taken into account for RMSE performance computation. However, these run periods are taken into account for the computation of the percentage of track loss which has been defined in [39]. To compare the reliability [39] of the target tracking algorithm under concern, the percentage of track loss is computed by averaging $M-N$ over total $M$ scans in $L$ runs. Then, overall formula for the percentage of track loss of the target tracking algorithm becomes

\[
\text{the percentage of track loss} = \frac{M-N}{M} \times 100\%
\] (1)

In our simulations, for fair comparison of RMSE performances, the number of successful runs, $K$, is fixed as 100 which means the number of total runs, $L$, ($L \geq 100$) may vary for each target tracking algorithm to achieve $K$ succesful runs, ($K = 100$).

We have carried out simulations in four consecutive test scenarios to compare the RMSE performance of single target tracking algorithms including IMM-PDA [7], IMM-IPDA [16] and optimal approaches in multitarget tracking including IMM-JPDA [1], IMM-JPDA [32], IMM-JIPDA [16] algorithms, and the IMM-LMPDA [16] algorithm. At the end of each section, we present the computation time of each algorithm has been used in these test scenarios to achieve the computational load evaluations.

We conduct the simulations in MATLAB 2008 platform with: Intel®CoreM3 - 2100 CPU with 3.10 GHz with 4 GB RAM in order to get the following RMSE Performance plots and the tables showing the percentage of track loss and execution time of the target tracking algorithms.

Two-dimensional surveillance scenarios are formed where one/two point target(s) is/are present which can move either on-road or off-road. Multiple targets move at the same time, may accelerate or decelerate independently at some time instants, generally on-road in the course of straight movement. So, their trajectories may intersect at some points. They may turn either some direction at junction points. They may break to off-road or enter the road at some points. The simulation scenarios are formed where real ground targets’ movement taken into consideration. Measurement noise is added inherently to actual states (positions) of the target(s) under track with a variance $30 m$ to simulate the target observations obtained from the system. Clutter measurements are generated per scan for each target (per target track) where the number of clutter measurements is Poison distributed with a rate $\lambda = 10$ at each scan where they are distributed uniformly on the surveillance region. This corresponds to a heavy clutter scenario. In the first scenario, a single target is present. In the second scenario, two targets move in a convoy fashion. In the third scenario, differently from previous scenario, two targets start movement at distant points after 40 seconds they join in a junction point and continue moving in a convoy fashion. After approximately 90 seconds later they start movement to distant directions in a junction point and depart completely. They move independently, may accelerate or decelerate at some time instants independently which conveys the possibility that their trajectories may intersect or at some points or depart completely from eachoether after the time instant they merge together. In the last scenario, two targets start movement at the same point but one of the targets stops and does not move.

In all simulations, each track is initiated from a single measurement in a scan. New measurements will become the predicted positions of the new tracks in the next scan. In the next scan, around the predicted positions elliptical validation regions (gates) are formed individually and independently for each track and new tracks are formed from each measurement that fall into each validation gate individually. Each track is formed, maintained or deleted independently as in the single target tracking case. To control the number of tracks formed in each scan, measurements are divided into sets. All sets consists of the measurements used to update an individual existing track. Each track has an independent validation gate which means that some measurements from the other validation gate may be used to update more than one track.

For all probability of track existence based target tracking algorithms (IMM-JPDA, IMM-JIPDA, IMM-JIPDA and IMM-LMPDA), the initial probabilities of track existence are considered as 0.2 individually in our simulations, as recommended in [24], [25]. Markov Chain One model uses transition matrix $\Pi$ with entries:

\[
\Pi_{11} = 0.98; \quad \Pi_{21} = 0;
\]

\[
\Pi_{11} = 0.02; \quad \Pi_{21} = 1;
\]

as in references [24], [25].

Pruning is considered only in the second scenario before the application of optimal approaches in multitarget data association algorithms including JPDA, JPDA and JIPDA in IMM-JPDA, IMM-JPDA and IMM-JIPDA, respectively, where the
measurements at the intersection region of the gates are taken into consideration to reduce the computation requirements to a feasible level. In [26], [30], JIPDA and IJPDA are applied only on confirmed tracks, for unconfirmed tracks IPDA [24], [25] and IPDA [33] is applied respectively. In our simulations, JPDA, IJPDA and JIPDA are applied on all tracks and the measurements at the intersection region of the gates.

During tracking, tracks are confirmed or deleted as in the single target tracking case, but herein, in multitarget tracking case, all the operations are done individually and independently for each track. In the application of multitarget data association algorithms only data association operation is carried out jointly but at the end marginal data association probabilities are extracted from joint data association probabilities to update individual tracks under concern.

For the kinematic state estimator, an IMM estimator with two model-based Kalman Filters is considered consisting of CV(Constant Velocity) with Low Process Noise for nonmaneuvering motion and CV with High Process Noise for any maneuvers including coordinated turns and acceleration modes, with process noise values are considered with standard deviations 2.5 m, 30 m respectively, as in the single target tracking case. As discussed in [3], it is sufficient to use two model-based filters because our targets move in a constraint fashion, not any evasive, high or different maneuvers are expected. The target and observation models used in Kalman Filters are taken from the references [3] and [1], respectively.

Each simulation experiment consists of $K = 100$ runs. In each simulation run, target(s) retrace(s) the trajectory, however, for the measurements obtained from the target(s) as well as clutter measurements, the numbers and positions of all measurements are generated independently from a pre-specified distributions per each run and scan.

The resulting RMSE Performance plots for Target 1 and Target 2 are obtained individually and presented in Figures 3, 4, 6, 8 and 5, 7 respectively. The percentage of track loss and the computation time of algorithms in comparison are presented on Tables I, III, V and II, IV respectively, in where IMM-PDA and IMM-IPDA considered in multitarget tracking scenarios, shown with “MTT” in parenthesis, in single target tracking scenario, shown with “STT” in parenthesis.

Before starting comparison of performances of target tracking algorithms, an important result is presented via comparison of the Figure 3 with Figures 4 and 5 where the performance of single target tracking algorithms deteriorates significantly in multitarget tracking situations as also shown in [20], [21]. The result shown in Figure 3 demonstrates that, IMM-IPDA shows modestly better performance than IMM-PDA due to the probability of track existence parameter updated as an additional state. Performance improvements are observed over observation time period when the target undergoes maneuver where it may fall out of the validation region easily.

The result shown in Figure 3 is an important outcome which will supply us a “ground truth” to compare the performance of multitarget tracking algorithms. The results in Figures 4 and 5 demonstrate that, IMM-IPDA shows slightly better performance, also in multitarget tracking situations, than IMM-PDA due to the probability of track existence parameter updated as an additional state and used for track update. However, in multitarget tracking situations, IMM-

### TABLE I. TRACK LOSS STATISTICS IN CONVOY SCENARIO

<table>
<thead>
<tr>
<th>Target Tracking Algorithm</th>
<th>The percentage of Track Loss (%)</th>
</tr>
</thead>
<tbody>
<tr>
<td>IMM-PDA (STT)</td>
<td>0.245</td>
</tr>
<tr>
<td>IMM-IPDA (STT)</td>
<td>0.374</td>
</tr>
<tr>
<td>IMM-PDA (MTT)</td>
<td>0.545</td>
</tr>
<tr>
<td>IMM-IPDA (MTT)</td>
<td>0.374</td>
</tr>
<tr>
<td>IMM-LMIPDA</td>
<td>35.2517</td>
</tr>
<tr>
<td>IMM-JPDA</td>
<td>0.3985</td>
</tr>
<tr>
<td>IMM-IJPDA</td>
<td>0.57796</td>
</tr>
<tr>
<td>IMM-JIPDA</td>
<td>0.12931</td>
</tr>
</tbody>
</table>

Fig. 3. RMSE Performance Comparison of IMM-PDA with IMM-IPDA in Single Target Tracking Scenario
IPDA still consists a single target data association algorithm, which is basically IPDA for each target track. Hence, much performance improvement than achieved is not expected than any multitarget tracking algorithms.

A notable performance improvement has been accomplished with IMM-LMIPDA than both IMM-PDA and IMM-IPDA as shown in Figures 4 and 5 due to multitarget tracking capability by modifying clutter density with a priori probability of measurement origin parameter [16], [17], [28], [31] interchanged between tracks.

In the comparison of optimal approaches in multitarget tracking, the results shown in Figures 4 and 5 proves the theoretical enhancement of IPDA algorithm [32] that IMM-JPDA shows dramatically better performance than IMM-JPD due to the probability of track perceivability parameter computed recursively to calculate track state estimates. IMM-JPDA shows the “best” performance among all multitarget tracking algorithms due to the probability of track existence parameter updated as an additional state used for both track update and track state estimate calculations which is also convenient with the results presented in [26], [30].

An important result can also be inferred from Figures 4 and 5 that IMM-LMIPDA follows the RMSE performance of optimal approaches closely with apparently negligible performance deterioration.

As inferred from Figures 6 and 7 that IMM-LMIPDA shows close performance with IMM-IPDA in isolated tracks situation where tracks are sufficiently far apart where their validation regions (gates) do not intersect. As mentioned in [16], [17], [28], [31], IMM-LMIPDA algorithm turns into two independent IMM-IPDA estimators where the target tracks are sufficiently far apart, because clutter measurement density update from individual tracks is unavailable. The enhancement in the RMSE performance of IMM-LMIPDA which is clearly observed after the first 40 and last 30 seconds in Figures 6 and 7 where the gates of tracks do not overlap.

An important result is inferred via comparison of Figure 8 with Figure 3 that all multitarget tracking algorithms can also achieve single target tracking via suitable measurement-to-track assignments in isolated tracks situation. In the literature [1], [17], [26], [28], [30], [32] all multitarget tracking algorithms are mentioned to be derived as “the generalization of single target tracking algorithms to track multiple targets”. IMM-JPDA which is the multitarget generalization of IMM-PDA obviously achieves the close performance with IMM-PDA shown in Figure 3. IMM-JPDA which is the multitarget generalization of IMM-IPDA, achieves also good performance with negligible performance degradation compared with IMM-IPDA shown in Figure 3. Obviously IMM-LMIPDA shows also a close performance, like IMM-JPDA, with IMM-IPDA in Figure 3 in isolated tracks situation where tracks are sufficiently far apart where their validation regions (gates) do not intersect.

Tables II, IV and VI prove that, IMM-LMIPDA takes negligibly small increment in execution time more than both IMM-PDA (MTT) and IMM-IPDA (MTT); where the increment is linear when compared with the execution time of both IMM-PDA (STT) and IMM-IPDA (STT) in the number of target tracks sense. All optimal multitarget tracking algorithms (IMM-JPDA, IMM-JPDA and IMM-JPDA) require bursts of computation time compared to IMM-LMIPDA and single target tracking algorithms IMM-PDA (MTT) and IMM-IPDA (MTT) due to finding all feasible joint events for measurement-to-track assignments and computation of probabilities and likelihoods of all joint events. As Table I indicates, even if pruning of distant gate measurements are applied before data association, the computation time requirement of optimal multitarget tracking algorithms (IMM-JPDA, IMM-JPDA and IMM-JPDA) remain more than 30 times of computation time requirement of IMM-LMIPDA and single target tracking algorithms IMM-PDA (MTT) and IMM-IPDA (MTT). Table V shows again and proves that, IMM-LMIPDA takes small increment in execution time whereas for optimal multitarget tracking algorithms execution time become more than 60 times of nominal values as inferred from Table II.

Although IMM-LMIPDA shows close RMSE performance with less computation time when compared with optimal approaches (IMM-JPDA, IMM-JPDA and IMM-JPDA), Tables I, III and V indicate that IMM-LMIPDA suffers from track loss inevitably which is one of common problems of general suboptimal approaches where detailed analysis is given in references [17], [34]–[36]. The results are convenient with the results presented in [37]–[39], where in [37]–[39] percentage of track loss parameter is computed for each target individually, whereas on Tables I, III and V, the averaged values are presented.

![Fig. 6. RMSE Performance Comparison of IMM-LMIPDA with Single Target Tracking Algorithms in Merging-Departing in junctions Scenario for Target 1](image_url)
The use of multitarget data association algorithms has been shown to improve the performance significantly in multitarget tracking situations. It has been shown that single target tracking can also be achieved by the use of any multitarget data association algorithms due to the fact that multitarget data association algorithms are nothing more than generalizations of single target data association algorithms under concern.

The use of optimal approaches in multitarget tracking proved the fact that they still offer a good solution in multitarget tracking situations, only in small numbers of measurements and target tracks cases. However, in a ground target tracking application, where heavy and dense measurements and target tracks are present optimal approaches require huge computation load.

Instead of optimal approaches, the use of Linear Multi-Target (LM) approaches has been shown to be very efficient method to achieve multitarget tracking, with apparently negligible RMSE performance error compared to optimal approaches, in a dense clutter environment with linear number of operations in the number of tracks and the number of measurements which is comparable with single target tracking algorithms and much less than optimal approaches.

Although LM approaches has been shown modestly better in RMSE performance with significantly less computation time than optimal approaches, these methods have rarely proved satisfactory in practice. It has been shown that, they are highly susceptible to track loss when the targets are closely spaced and the number of targets and measurements are considerably high.

Hence, use of LM approaches, i.e. IMM-LMIPDA, in ground target tracking applications, can be a very efficient method to achieve multitarget tracking in a heavy and dense clutter environment on condition that high track loss problem is taken into consideration.

**REFERENCES**


[33] J. Dezert, N. Li and X. R. Li, *A New Formulation of JPDAF for Tracking in Clutter*, European Control Conference (ECC09), Karlsruhe, Germany, September 1999.


