

An ILP approach to Multi Hypothesis Tracking

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Abstract

An Autonomous Surface Vessel (ASV) is an unmanned vessels which can for instance be used to transport cargo and people as well as for surveillance and other tasks. To ensure a safe journey, the route planer needs a real time image of its surroundings in addition to map data to avoid collision and dangerous situations with other vessels. In the maritime environment, this is primarily done by radars mounted on the ship itself.

A key challenge in radar tracking is to know which measurement (reflection) belongs together from scan to scan to get a track on each target. Multi Hypothesis Tracking (MHT) has become the preferred method for solving the data association problem in a multi-target environment. In a maritime tracking situation for anti collision, MHT demonstrates its reliability for use in safety critical systems since it compensates for missed detections by utilizing multiple scans in the association.

The problem of selecting the optimal assignment of track hypotheses in a Track Oriented Multi Hypothesis Tracker (TOMHT) is discussed and applied to off-the-shelf Integer Linear programming (ILP) solvers. This report shows that a TOMHT successfully track targets with detection probability above 70% with less than 5% average track loss in multi-target scenarios with clutter.

It also discusses the computational cost of MHT and shows the feasibility for MHT implemented on modest personal computer and potential for paralleling on high end real time systems.

Contents

| | |
|-----------------------------------------------------------|-----------|
| Abstract | ii |
| Table of Contents | iii |
| List of Figures | v |
| Glossary | vi |
| Acronyms | viii |
| Nomenclature | x |
| 1 Introduction | 1 |
| 1.1 Motivation | 1 |
| 1.2 Problem description | 1 |
| 1.3 Goals | 2 |
| 1.4 Outline of report | 2 |
| 2 Survey of multi-target tracking methods | 3 |
| 2.1 Tracking | 3 |
| 2.2 Tracking system | 3 |
| 2.3 Nearest Neighbour Filter | 4 |
| 2.4 Probabilistic Data Association Filter | 4 |
| 2.5 Joint Probabilistic Data Association Filter | 5 |
| 2.6 Multi Hypothesis Tracker | 7 |
| 2.6.1 Hypothesis Oriented MHT | 8 |
| 2.6.2 Track Oriented MHT | 10 |
| 3 Algorithm walk-through | 12 |
| 3.1 Flowchart | 12 |
| 3.2 State estimation | 12 |
| 3.3 Gating | 14 |
| 3.4 Scoring | 15 |
| 3.5 Clustering | 15 |
| 3.6 Association | 16 |
| 3.7 N-scan pruning | 16 |

| | | |
|----------|--------------------------------------|-----------|
| 4 | Linear programming | 18 |
| 4.1 | Problem formulation | 18 |
| 4.2 | Solvers | 20 |
| 5 | Implementation | 22 |
| 5.1 | Programming language | 22 |
| 5.2 | Code structure | 22 |
| 5.3 | Parallel processing | 23 |
| 5.4 | Performance considerations | 24 |
| 6 | Results | 25 |
| 6.1 | Testing scheme | 25 |
| 6.2 | Simulation data | 27 |
| 6.3 | Simulations | 27 |
| 6.4 | Runtime | 30 |
| 6.5 | Track loss performance | 33 |
| 6.6 | Time performance | 34 |
| 7 | Discussion | 35 |
| 8 | Closing remarks | 36 |
| 8.1 | Conclusion | 36 |
| 8.2 | Future work | 36 |
| | Appendices | 38 |
| A | Track performance plots | 38 |
| | References | 44 |

List of Figures

| | | |
|----|--------------------------------------------------------------------|----|
| 1 | Probabilistic Data Association Filter (PDAF) flowchart [1] | 7 |
| 2 | Algorithm flowchart | 12 |
| 3 | Validation region | 14 |
| 4 | Pruned track hypothesis tree | 17 |
| 5 | Track hypothesis tree | 20 |
| 6 | True track for scenario 1-6 | 26 |
| 7 | Track hypotheses example | 28 |
| 8 | Simulation results for all scenarios | 29 |
| 9 | Runtime for scenario 1 | 30 |
| 10 | Runtime for scenario 2 | 31 |
| 11 | Runtime for scenario 3 | 31 |
| 12 | Runtime for scenario 4 | 32 |
| 13 | Runtime for scenario 5 | 32 |
| 14 | Runtime for scenario 6 | 33 |
| 15 | Simulation results for all solvers in scenario 1 | 38 |
| 16 | Simulation results for all solvers in scenario 2 | 39 |
| 17 | Simulation results for all solvers in scenario 3 | 40 |
| 18 | Simulation results for all solvers in scenario 4 | 41 |
| 19 | Simulation results for all solvers in scenario 5 | 42 |
| 20 | Simulation results for all solvers in scenario 6 | 43 |

Glossary

AUTOSEA A collaborative research and development project between NTNU AMOS and the Norwegian maritime industry with aim to attain world leading knowledge in design and verification of control systems for ASVs.

Cluster Set of targets which share measurements.

Clutter Noise in the form of false measurements which is assumed Poison distributed.

CPLEX Optimization suite by IBM.

CUDA A compute platform by Nvidia.

Cython An optimizing static compiler for Python.

Gate An area in which a track expects and approves new measurement to associate with itself.

GLPK GNU Linear Programming Kit.

Gurobi Gurobi Optimizer by Gurobi Optimization, Inc..

Measurement A point in the measurement space where something is detected.

No-measurement hypothesis A self created measurement at the estimated position (with score 0).

Observation See Measurement.

Pruning Removal of unnecessarily branches in a tree.

Python An open-source programming language.

Radar Acronym for Radio Detection And Ranging. A device that used radio waves to measure distance and bearing to other objects.

Scan A procedure which measures the entire area of coverage of the system.

Score A measure of the goodness of a measurement-to-track association.

Solver A program that solves optimization problems.

Target an actual object which the system is trying to track.

Track a list of measurement indices, one from each scan, which is believed to originate from the same target.

Track forest A forest of track hypothesis trees.

Track hypothesis a new measurement which is inside the gate for an existing track.

Track hypothesis tree An acyclic graph spanning from the root node of each target where each node is a track hypothesis.

Tracking The process of initiating, maintaining and terminating tracks from measurements.

Acronyms

P_D Probability of detection.

AIS Automatic Identification System.

ASV Autonomous Surface Vessel.

CDF Cumulative Distribution Function.

COLAV Collision Avoidance.

CPU Central Processing Unit.

DFS Depth First Search.

FOV Field Of View.

GNNF Global Nearest Neighbour Filter.

GPU Graphics Processing Unit.

GRP Greedy Rounding Procedure.

HOMHT Hypothesis Oriented Multi Hypothesis Tracker.

ILP Integer Linear programming.

IMM Interacting Multiple Model.

JPDAF Joint Probabilistic Data Association Filter.

LP Linear programming.

MAP Maximum A Posteriori Probability.

MHT Multi Hypothesis Tracking.

MILP Mixed Integer Linear programming.

MOMHT Measurement Oriented Multi Hypothesis Tracker.

NNF Nearest Neighbour Filter.

NNSF Nearest Neighbour Standard Filter.

NTNU Norwegian University of Science and Technology.

PDAF Probabilistic Data Association Filter.

RPM Rotations Per Minute.

SSD Solid State Storage.

TOMHT Track Oriented Multi Hypothesis Tracker.

Nomenclature

| | |
|------------------------|------------------------------------------------------------------------------|
| $\bar{\mathbf{x}}$ | Predicted state |
| $\hat{\mathbf{x}}$ | Filtered state |
| cNLLR | Cumulative Negative Log Likelihood Ratio for target |
| $\text{NLLR}_{i,j}(k)$ | Negative Log Likelihood Ratio for target j at time k for measurement i |
| \bar{P} | Predicted state covariance |
| Γ | Disturbance matrix |
| \hat{P} | Filtered state covariance |
| Φ | State transition matrix |
| H | State observation matrix |
| K | Kalman gain |
| P | State covariance |
| Q | State covariance matrix |
| R | Measurement covariance matrix |
| S | Residual covariance |
| ν | Weighted measurement innovation |
| τ | Binary vector where the selected track hypotheses are 1 |
| \mathbf{v} | Observation noise |
| \mathbf{w} | Process noise |
| \mathbf{x} | State vector |

| | |
|----------------|-------------------------------------------------------------|
| \mathbf{z}_k | Measurement at time step k |
| i | Measurement index |
| j | Target index |
| k | Time index |
| l | Hypothesis index |
| M | Number of leaf nodes (track hypotheses in the track forest) |
| m_k | Number of measurements in scan k |
| N | Number of scans to keep in track tree |
| N_1 | Number of real measurements in cluster |
| N_2 | Number of targets in cluster |
| t | Time |
| t_k | Time at time index |

1 Introduction

1.1 Motivation

This report is the result of TTK4550 Engineering cybernetics specialization report at Norwegian University of Science and Technology (NTNU), where the aim is to *let the student specialize in a selected area based on scientific methods, collect supplementary information based on literature search and other sources and combine this with own knowledge into a project report*¹. The learning outcome of this project is to give the student an extensive knowledge in a current problem, good knowledge in related topics and relevant scientific literature.

1.2 Problem description

The proposed title for this project, and the following master-thesis, was "Multi-target tracking using radar and AIS". The key idea behind this formulation is that radar and the maritime Automatic Identification System (AIS) have different strengths and weaknesses, and if utilized properly, the strengths of both system can be exploited, while the weaknesses can be reduced. For this project it was decided to focus fully on the gold standard within multi-target tracking, namely Multi Hypothesis Tracking (MHT). To ensure the tracking system would be sufficiently understood, correctly implemented and thoroughly tested, the AIS integration was postponed to the master thesis.

The following task was proposed for this project:

- Write a survey on multi-target and multi-sensor tracking methods.
- Implement a multi-target tracking method.
- Describe the method and summarize the findings in a report.

¹<http://www.ntnu.edu/studies/courses/TTK4550>

1.3 Goals

The goals for this project is to implement a Track Oriented Multi Hypothesis Tracker (TOMHT) algorithm in Python, test this with simulated data and analyze the performance for different conditions and discuss methods for improvement.

1.4 Outline of report

In section 2, different methods for target tracking and data association are presented. Here the focus is to highlight the key difference between the most common tracking methods with focus on the properties these lead to. In section 3, a TOMHT is thoroughly explained, and in section 4 the integer optimization problem that arises in section 3 is elaborated. The results are presented in section 6 and discussed in section 7.

2 Survey of multi-target tracking methods

The aim of this section is to give the reader a brief overview of tracking as a problem and a feeling for the most popular methods, their assumptions and strong and weak properties as seen from an two dimensional maritime anti collision perspective.

2.1 Tracking

Tracking of an object (target) is the process of estimating its state (i.e. position and velocity) based on discrete measurements from an observation system. An observation system can be a radar, sonar or any other sensor that passively or actively detects objects within an area or volume. Any observation system will be prone to noise, both in form of internal noise and external noise from the environment. This noise will, in varying degree, cause false measurements that the tracking system must take care of. These false measurements are often refereed to as clutter.

2.2 Tracking system

A tracking system can be interpreted as either the complete system from the signal processing level to the finished tracks, or as I define it in this text: *A system that process consecutive measurements from an observation system and collects measurements from the same target into tracks or initiate new tracks.* A track is a subset of all the measurements from the observation system that is believed to originate from the same target. The challenge knowing which measurement originating from which (real) target is the core at any tracking system. This association problem is non-trivial even under ideal situations, and the addition of spurious measurements and missed targets only increases the complexity.

There has been developed a large variety of methods to solve this association problem, and most of them have several sub-variants. In the following subsections, some of the most common and popular methods will be presented.

2.3 Nearest Neighbour Filter

The Nearest Neighbour Filter (NNF) is the simplest approach in tracking, where one always selects the closest neighbour as the consecutive measurement in the track, where the distance is the Euclidean distance (1).

$$\left[(z_k - z_{k-1}) \cdot (z_k - z_{k-1}) \right]^{1/2} \quad (1)$$

This approach suffers from being very vulnerable to clutter and dense target scenarios. It can be somewhat improved by estimating an a-priori state through a Kalman Filter and selecting the nearest neighbour to the estimate. This extension is sometimes referred to as Nearest Neighbour Standard Filter (NNSF) [1] and also differs in that it used the Mahalanobis distance (2) which is a measure of the distance from a measurement to a distribution.

$$[z_k - \hat{z}_k]^T S(k+1)^{-1} [z_k - \hat{z}_k] \quad (2)$$

Under the standard assumption that each target can at maximum generate one measurement, the NNF and NNSF are both single-target methods in the way that they may assign the same measurement to more than one track. They can, however, be expanded to multi-target variants by formulating the problem as a global least squares integer optimization problem, often called Global Nearest Neighbour Filter (GNNF). With this extension, the NNSF is almost becoming a zero-scan multi hypothesis tracker, in the sense that it seeks to select the optimal combination of mutual exclusive measurement-to-track associations while only looking at the most recent scan. NNF, NNSF and GNNF can be viewed as non-probabilistic models, as they do not assume specific models for noise, clutter, false alarm rate or similar.

2.4 Probabilistic Data Association Filter

PDAF is a *single-target* Bayesian association filter which is based on single scan probabilistic analysis of measurements. The target is assumed initialized and modelled by (8). At each scan, the algorithm calculates the association probabilities for all the measurements inside a validation gate, with the assumption that at

most one of the measurements inside the validation gate is the true target. This leads to the state update equation (3) where the current state is updated with a combined innovation.

$$\boldsymbol{\nu}_k \triangleq \sum_{i=1}^{m_k} \beta_k^i \tilde{\mathbf{y}}_k^i \quad (3)$$

$$\hat{\mathbf{x}}_{k|k} = \hat{\mathbf{x}}_{k|k-1} + \mathbf{K}_k \boldsymbol{\nu}_k$$

where

β_k^i = the probability of measurement z^i being the correct one

$\tilde{\mathbf{y}}_k^i = \mathbf{z}_k^i - \hat{\mathbf{z}}_k^i$ the measurement innovation for measurement i at time step k

\mathbf{K}_k = the Kalman Gain for the k -th time step

\mathbf{x}_k = target state

PDAF is computationally modest (approximate 50% more computationally demanding than a Kalman Filter [1] p.163) and have good results in an environment with up to about 5 false measurement in a 4σ validation region [1]. PDAF does not include track initialization and assumes that at most one measurement can originate from an actual target. It also assumes that clutter is uniformly distributed in the measurement space and that the targets history is approximated by a Gaussian with a calculated mean and covariance.

PDAF can be used in multi-target scenarios, but only as multiple copies of the single-target filter [2]. PDAF can suffer from track coalescence, which is a phenomenon that merges two tracks into one. This coalescence occurs when two targets have similar paths, and the resulting tracks will be an "average" of the two (actual) tracks. There has been done some work to overcome this coalescence [3].

2.5 Joint Probabilistic Data Association Filter

The Joint Probabilistic Data Association Filter (JPDAF) is a *multi-target* extension of the Probabilistic Data Association Filter in which joint posteriori association probabilities are calculated for every target at each scan. Both PDAF and JPDAF use the same weighted sum (3), the key difference is the way the weight β_i^j is

calculated. Whereas PDAF treats all but one measurement inside its validation region as clutter, in JPDAF the targets which interacts (one cluster) are treated as connected and the connected β_i^j s are computed jointly across the cluster set with a given set of active targets inside the cluster. The probability of a measurement i belonging to a target j is [2]

$$\begin{aligned}\beta_i^j &= \sum_{\chi} P\{\chi|Y^k\} \hat{\omega}_{ij}(\chi) \\ \beta_0^j &= 1 - \sum_{i=1}^{m_k} \beta_i^j\end{aligned}\tag{4}$$

where

$$P\{\chi|Y^k\} = \frac{C^\phi}{c} \prod_{i:\tau_i=1} \frac{\exp[-\frac{1}{2}(\tilde{\mathbf{y}}_i^j)^T S_{ji}^{-1}(\tilde{\mathbf{y}}_i^j)]}{(2\pi)^{M/2} |S_{ji}|^{1/2}} \prod_{j:\delta_j=1} P_D^j \prod_{j:\delta_j=0} (1 - P_D^j) \tag{5}$$

Where

β_i^j = the probability that measurement i belongs to target j

β_0^j = the probability that no measurement belongs to target j

$\chi = \bigcap_{i=1}^{m_k} \chi_{ij_i}$ All feasible events

Y^k = all candidate measurements up to and included time k

$\hat{\omega}_{ij} = \begin{cases} 1, & \text{if } \chi_{ij} \text{ occurs} \\ 0, & \text{otherwise} \end{cases}$

m_k = number of measurements in scan k

Since the JPDAF is calculating joint probabilities for all the combinations of measurement associations in the cluster, the computation demand is growing exponentially with the numbers of tracks and measurements in the cluster. A real time implementation of the JPDAF has been developed and patented by QinetiQ [4], and described in [5].

JPDAF also suffers from the same coalescence problem as PDAF. Seen from an anti-collision perspective, track coalescence is highly undesirable. An improvement to the JPDAF has been proposed by [3].

Since JPDAF is using all the measurements inside the gate for each track, one measurement can be used to update more than one track if it is within more than one gate.

2.6 Multi Hypothesis Tracker

MHT is a decision logic which generates and maintains alternative hypotheses when new measurement are received and within the gate. By making several possible hypotheses, the decision in which measurement to choose can be propagated into the future when more information is available. Each hypothesis is given a score or probability as a measure of the goodness of the measurement, which are accumulated to evaluate the combinations of consecutive measurements.

In contrast to PDAF and JPDAF methods which in general will estimate an "average" of two closely spaced tracks as the true track (coalesce), MHT methods split when in doubt. The idea of using multiple hypotheses was first introduced by Singer. et al. [6], but the first complete algorithm was presented by Reid [7], where a Hypothesis Oriented Multi Hypothesis Tracker (HOMHT) was developed. Following this, a TOMHT was proposed in [8] and the score function for MHT was later deduced and discussed by [9] since no explicit track-score function were given in [8]. MHT is, in the same way as PDAF/JPDAF, developed under the assumption that at most one measurement can originate from each target in each scan, and that a target does not necessary show on every scan

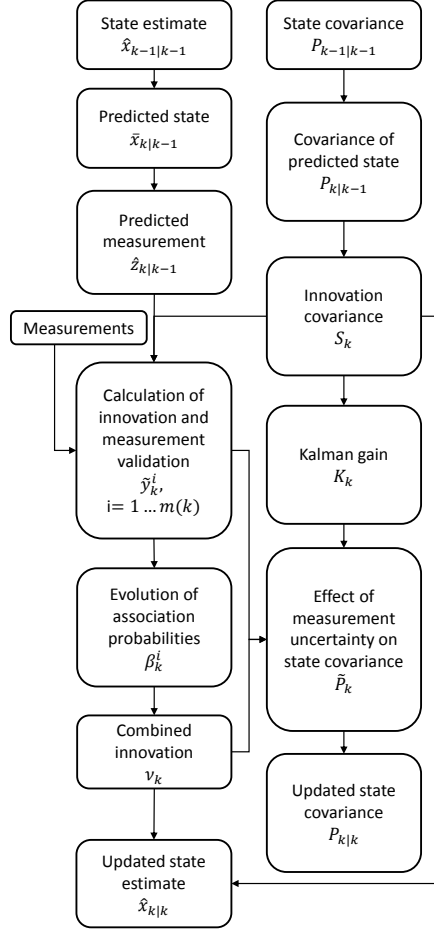


Figure 1: PDAF flowchart [1]

(Probability of detection (P_D) less than 1).

If extracting the Maximum A Posteriori Probability (MAP) hypothesis from a MHT, apparent inconsistency in the output to the user can appear whenever a new set of measurements are received since all association N time-steps back are reconsidered. If this is unwanted, an alternative representation is to output the N -best tracks and display them to the user in a way that visualises the probability. A third, and still not fully resolved option, is to output a weighted average of the tracks along with the covariance of the average.

The MHT approach to tracking and data association was by many for a long time dismissed because of its computationally large cost. The dramatic increase in computational capability from the 1980s to the late 2010s have however lead to a new spring for MHT with an increasing interest for use in tracking system. In 2004 Blackman stated “Multiple hypothesis tracking is generally accepted as the preferred method for solving the data association problem in modern multiple target tracking system” [10]. Already in 2001 did Blackman publish a demonstration that MHT is capable of real-time demands [11].

There are two main approaches to MHT, HOMHT and TOMHT.

2.6.1 Hypothesis Oriented MHT

HOMHT or Measurement Oriented Multi Hypothesis Tracker (MOMHT) is a tracking approach where direct probabilities of global joint measurement-to-target association hypothesis are calculated. The algorithm initiates tracks and handles missing measurements, it has a recursive nature and allows for clustering for quicker computation.

When a new set of measurements is received, Reids method defines a set of hypotheses, each containing a complete set of associations of the existing tracks and new measurements. By defining the hypotheses in this way, they become compatible in the sense that one and only one is the true hypothesis. When the next set of measurements arrives, each of the current hypotheses are expanded with all measurement-to-track assignments for the new measurements. This way, the hypotheses will keep their compatibility.

When evaluating the alternative hypotheses, each is assigned a probability. This probability takes into account the false-alarm statistics of the measurement system, the expected density of targets and clutter and the accuracy of the target estimates. The probability of each data association hypothesis was in [7] expressed as (6).

$$P_i^k = \frac{1}{c} P_D^{N_{DT}} (1 - P_D)^{(N_{TGT} - N_{DT})} \beta_{FT}^{N_{FT}} \beta_{NT}^{N_{NT}} \left[\prod_{m=1}^{N_{DT}} N(\mathbf{Z}_m - \mathbf{H}\bar{\mathbf{x}}, \mathbf{B}) \right] P_g^{k-1} \quad (6)$$

where

P_i^k = the probability of hypothesis Ω_i^k given measurements up through time k

P_D = the probability of detection

β_{FT} = the density of targets

β_{NT} = the density of previously unknown targets that have been detected

N_{DT} = number of designated target

N_{FT} = the number of false targets

N_{NT} = the number of new targets

N_{TGT} = is the number of targets

\mathbf{Z}_m = the m-th measurement in the current scan

\mathbf{H} = the observation matrix

\mathbf{B} = the measurement covariance

As with all MHT algorithms, it is crucial to prune the hypothesis tree to avoid an infinite memory and computational cost. In [7], several pruning techniques are utilized, where the most important one is probably the procedure to remove all hypotheses with probability below a threshold. A second technique that were proposed in [7] is to merge hypotheses with the last N data scans in common, where he also argues for the importance of preserving earlier rather than later hypotheses.

The initialization of tracks is done through the probabilities of each hypothesis, where a hypothesis would go from a tentative track to a confirmed track

when the probability of that hypothesis exceeds i.e. 99%. By treating all new measurement as tentative targets, and calculate their joint probability using information such as density of false targets, density of new targets and probability of detection and thresholding this, the algorithm has an advanced build-in initialization mechanism.

2.6.2 Track Oriented MHT

TOMHT is a "bottom-up" approach where the tracks are assumed initialized, and for each scan the track splits whenever there are more than one feasible measurement in the validation region (in addition to the no-measurement hypothesis). This give rise to a track tree, as in Figure 5, where each initialized track has a root node and multiple branches, where each level represents a scan. A hypothesis is now a set of compatible tracks, with minimum and maximum one track from each track tree, where a hypothesis' score is the sum of its tracks score. Tracks are compatible if they do not share any measurements. The optimal hypothesis is the hypothesis with the highest score.

In the special case where each track tree does not share any measurements (single target situation), the optimal track is the leaf node with the highest score, which can be found by a traversal of the tree in linear time [12]. However, when a measurement is assigned to two or more targets, the problem of selecting the optimal combination of tracks becomes a multi dimensional assignment problem, since the best hypothesis from each track tree might be mutual exclusive.

New track hypotheses are generated from the filtered estimate from a Kalman Filter, and a score is calculated for instance using (20) from [9]. Both [9] and [10] suggest that modern tracking system could improve performance in certain scenarios by using an Interacting Multiple Model (IMM) approach instead of a single Kalman Filter. However, this would inevitably increase the computational complexity. Following the addition of new track hypotheses, the tracks are divided into clusters, in which tracks with common measurements are grouped. The clusters can then be analysed as standalone global problems to find the best possible combination of (possibly mutual exclusive) measurement associations. Linear

programming (LP) and Integer Linear programming (ILP) based methods as proposed by [13] can be used to find the best combinations of newly created track hypotheses in accordance to the assumption that a measurement only can be assigned to one target and that one target can maximally create one measurement.

To limit the size of the track hypothesis tree, various pruning schemes have been developed. The maybe single most important pruning technique is the N-scan pruning, also known as N-scan sliding window. This is a simple technique for limiting the size of the track tree and the following number of leaf nodes. The pruning is done by selecting the node that is N levels higher than the current best leaf node as new root node.

One of the largest drawback with the TOMHT approach is the difficulty of track initialization. This is because TOMHT normally only considers measurements that are within any (already initialized) targets gate, and automatically discards the unused measurements in order to limit the computation time. An alternative could be to treat all unused measurements as new targets. This would however increase the computational demand and runtime considerably. The most common approach to add track initialization to TOMHT is to run a separate initialization algorithm in parallel with the tracking loop. This initialization method can be chosen freely, and some popular alternatives are; a dedicated HOMHT running on all or the unused measurements from the main loop, a N-of-M method that can be based on either nearest neighbour or PDAF/JPDF or simply a manual initialization by the user. The options for this aiding module are endless, and the specific situation will influence the choice of method.

3 Algorithm walk-through

3.1 Flowchart

Figure 2 shows a flowchart of the TOMHT algorithm presented in this section. An important difference between this approach compared to Reid's original HOMHT [7], is the need for external initialization of targets as mentioned in section 2.6.2.

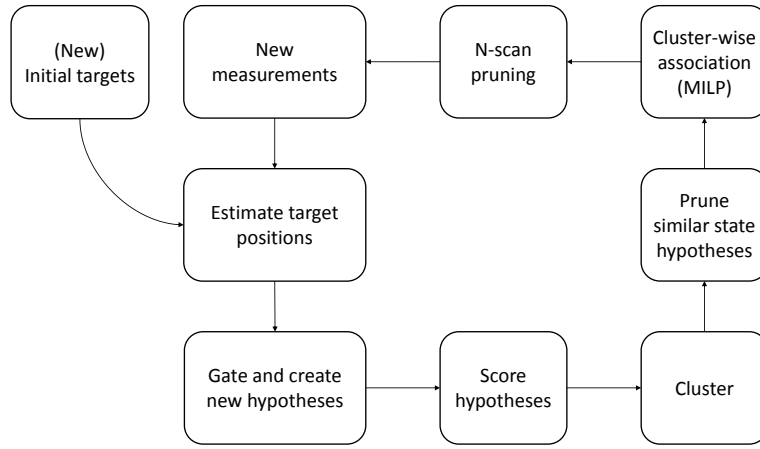


Figure 2: Algorithm flowchart

3.2 State estimation

When a new set of measurement arrives, it is desirable to "guess" where the target might be before looking for matching measurements. This can be done through a model of the targets dynamics and a state estimator. For the purpose of tracking ships in a local frame (Cartesian plane), we compose a state vector with four states

$$\mathbf{x} = \begin{bmatrix} x & y & \dot{x} & \dot{y} \end{bmatrix}^T \quad (7)$$

where the change of velocity (acceleration) is assumed zero. The latest assumption is compensated with an increased system noise covariance in the model. For a linear system with white and uncorrelated system and measurement noise, the

Kalman Filter is an optimal estimator with (8) as time evolution model,

$$\begin{aligned}\mathbf{x}(k+1) &= \mathbf{\Phi}\mathbf{x}(k) + \mathbf{\Gamma}\mathbf{w} \\ \mathbf{z}(k) &= \mathbf{H}\mathbf{x}(k) + \mathbf{v}\end{aligned}\tag{8}$$

where

$$\begin{aligned}\mathbf{\Phi} &= \text{the state transition matrix} \\ \mathbf{\Gamma} &= \text{the disturbance matrix} \\ \mathbf{w} &= \text{the process noise} \\ \mathbf{H} &= \text{the measurement matrix} \\ \mathbf{v} &= \text{the observation noise}\end{aligned}\tag{9}$$

. The procedure of predicting the target state at the next time step is according to the "time update" equations of the Kalman Filter (10),

$$\begin{aligned}\bar{\mathbf{x}}(k+1) &= \mathbf{\Phi}\hat{\mathbf{x}}(k) \\ \bar{\mathbf{P}}(k+1) &= \mathbf{\Phi}\hat{\mathbf{P}}(k)\mathbf{\Phi}^T + \mathbf{Q}\end{aligned}\tag{10}$$

where \mathbf{Q} is the process noise covariance matrix. The model have the following parameters,

$$\begin{aligned}\mathbf{\Phi} &= \begin{bmatrix} 1 & 0 & T & 0 \\ 0 & 1 & 0 & T \\ 0 & 0 & 1 & 0 \\ 0 & 0 & 0 & 1 \end{bmatrix} & \mathbf{\Gamma} &= \begin{bmatrix} 0 & 0 \\ 0 & 0 \\ 1 & 0 \\ 0 & 1 \end{bmatrix} & \mathbf{H} &= \begin{bmatrix} 1 & 0 & 0 & 0 \\ 0 & 1 & 0 & 0 \end{bmatrix} \\ \mathbf{Q} &= \sigma_v^2 \begin{bmatrix} \frac{T^3}{3} & 0 & \frac{T^2}{2} & 0 \\ 0 & \frac{T^3}{3} & 0 & \frac{T^2}{2} \\ \frac{T^2}{2} & 0 & T & 0 \\ 0 & \frac{T^2}{2} & 0 & T \end{bmatrix} & \mathbf{R} &= \sigma_r^2 \begin{bmatrix} 1 & 0 \\ 0 & 1 \end{bmatrix}\end{aligned}$$

where T is the time between the current and the previous measurement, σ_v^2 is the system velocity variance and σ_r^2 is the measurement variance. This model, known as the constant velocity model, is very common due to its simplicity, and is used in among others [7], [14] and [15].

3.3 Gating

To avoid calculating the likelihood for all possible combinations of targets and measurements, some sort of selection criteria is needed when creating new hypotheses. One way of doing this selections is to select all measurements that are within a certain confidence region or gate (11), illustrated in Figure 3.

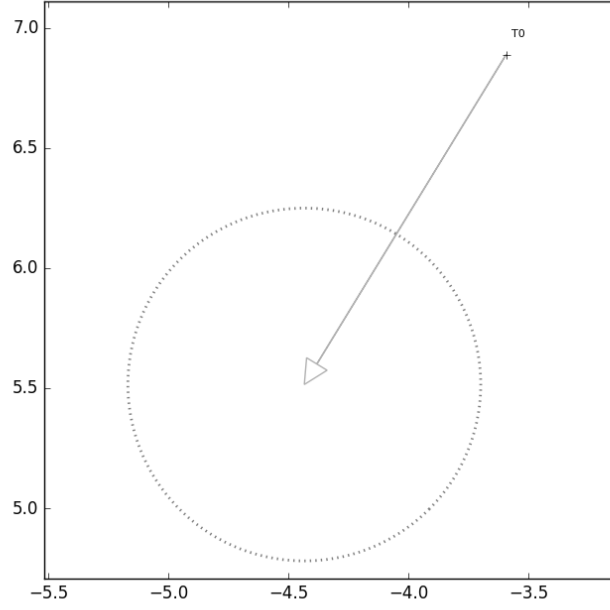


Figure 3: Validation region

$$\begin{aligned} \mathbf{B} &= \mathbf{H}\bar{\mathbf{P}}\mathbf{H}^T + \mathbf{R} \\ (\mathbf{Z}_m - \mathbf{H}\bar{\mathbf{x}})^T \mathbf{B}^{-1} (\mathbf{Z}_m - \mathbf{H}\bar{\mathbf{x}}) &\leq \eta^2 \end{aligned} \tag{11}$$

This is a very common approach, and is used by most tracking systems at some stage in the processing of new measurements. In (11), η is the inverse Cumulative Distribution Function (CDF) of the chi-square distribution for a given confidence with degrees of freedom equal to the sensor system. For each measurement inside the region, a filtered state and covariance is calculated using the "measurement update" equations in the Kalman Filter (12), followed by the

creation of a new track hypothesis.

$$\begin{aligned}
\tilde{\mathbf{y}} &= \mathbf{z} - \mathbf{H}\bar{\mathbf{x}} \\
\mathbf{S} &= \mathbf{H}\bar{\mathbf{P}}\mathbf{H}^T + \mathbf{R} \\
\mathbf{K} &= \bar{\mathbf{P}}\mathbf{H}^T\mathbf{S}^{-1} \\
\hat{\mathbf{x}}(k) &= \bar{\mathbf{x}} + \mathbf{K}\tilde{\mathbf{y}} \\
\hat{\mathbf{P}}(k) &= (\mathbf{I} - \mathbf{K}\mathbf{H})\bar{\mathbf{P}}
\end{aligned} \tag{12}$$

The χ^2 value for selected confidence values are listed in Table 1, where 95% – 99% is a common interval for gate size.

| Confidence | 70% | 80% | 90% | 95% | 97.5% | 99% | 99.5% |
|------------|------|------|------|------|-------|------|-------|
| η^2 | 2.41 | 3.22 | 4.61 | 5.99 | 7.38 | 9.21 | 10.60 |

Table 1: Inverse χ^2 CDF for two degrees of freedom

3.4 Scoring

Each track hypothesis are scored according to [9]:

$$\begin{aligned}
\text{NLLR}_{i,j}(k) &= \frac{1}{2} \left[\tilde{\mathbf{y}}_k^j(i)^T \mathbf{S}_k^{j-1} \tilde{\mathbf{y}}_k^j(i) \right] + \ln \frac{\lambda_{ex} |2\pi \mathbf{S}_k^j|^{1/2}}{P_D} \\
\tilde{\mathbf{y}}_k^j(i) &= \mathbf{z}_k^i - \hat{\mathbf{z}}_{k|k-1}^j
\end{aligned} \tag{13}$$

The cumulative NLLR is then

$$\text{cNLLR}_k^j \triangleq \sum_{l=0}^k \text{NLLR}_{i,j}(l) \tag{14}$$

3.5 Clustering

Since the global problem of finding the optimal selection of hypotheses is growing exponentially with the number of hypotheses, it is computationally beneficial to split the problem into smaller problem. This can only be done to targets that does not share any measurements. The clustering can be done efficiently

through breath-first-search or depth-first-search on a graph made from the hypothesis tree.

By constructing a 0-1 adjacency matrix describing the connection between all the nodes in the track forest, the clustering problem is equivalent to the *connected components* problem in graph theory [16].

3.6 Association

When the targets are divided into independent clusters, each of them can be treated as a global problem where we want to minimize the cost or maximize the score of the selected track hypotheses (leaf nodes), while fulfilling the constraints that each measurement can only be a part of one track and that minimum and maximum one hypothesis can be selected from each target. Since only binary values, selected or not selected, is desired for selection of hypotheses, the problem becomes an ILP. A solution to this problem is explained in section 4.

3.7 N-scan pruning

To keep the computational cost within reasonable limits, it is necessary to limit the amount of time steps backwards in time that the algorithm computes. This is done by removing all branches but the active track hypothesis at the current root node, and assign the (one) remaining node as new root node. This procedure is graphically explained in Figure 4, where a solid square frame indicates the current root node, and a dotted square frame indicates the new root node. The bold arrows in the figure represents the active track.

A similar, and in scenarios with low P_D perhaps better strategy, is N-observation pruning proposed by [10]. The idea is to prune N *measurements* back in time instead of N *scans*. This approach will lead to larger and more costly track trees for tracks that have low probability of detection. Therefore, in any practical implementation a N-observation pruning scheme will be followed by a traditional M-scan pruning, where M is larger than N . The combination of these two methods can be seen on as a form of adaptive pruning where tracks with high prob-

ability of detection can manage with fewer history steps than tracks with low probability of detection.

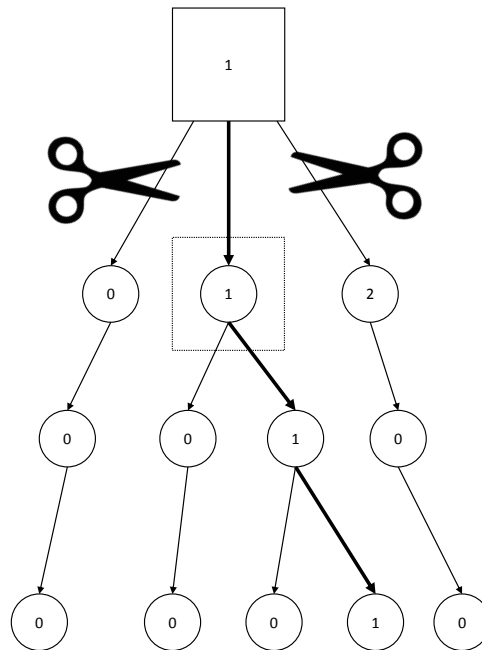


Figure 4: Pruned track hypothesis tree

4 Linear programming

The aim of this section is to elaborate the use of LP to solve the data association problem in MHT that arises when there are multiple (possible mutual exclusive) possibilities of measurement arrangements within the existing set of tracks. As with any optimization problem, we need an objective function which tells us how good or bad a given assignment is, and a set of constraints that limits the solution to physical limits and our assumptions.

4.1 Problem formulation

Multiple optimization formulations of the association problem for multi-target tracking have been proposed through the history. The first was [17] where a 0-1 ILP was proposed, later an ILP scheme with LP relaxation and Greedy Rounding Procedure (GRP) as solver was proposed by [13], and a framework for both association and removal of competing tracks were proposed by [18].

All three mentioned publications have essentially the same objective functions, though some use minimize and other use maximize in their formulation. The essence of them all is (15), where \mathbf{c} is a vector of costs (minimize) or scores (maximize) and $\boldsymbol{\tau}$ is a selection vector, where each row in \mathbf{c} and $\boldsymbol{\tau}$ represents one branch in the track hypothesis tree.

$$\min_{\boldsymbol{\tau}} \quad \mathbf{c}^T \boldsymbol{\tau} \quad (15)$$

Further, the constraints that shall ensure that each measurement is not assigned to more than one track are generally formulated as (16) or (17), where \mathbf{A} is a binary matrix whose rows are branches in a track hypothesis tree and \mathbf{b} is a vector with ones.

$$\begin{aligned} \mathbf{A}\boldsymbol{\tau} &= \mathbf{b} \\ \boldsymbol{\tau} &\in \{0, 1\}^M \end{aligned} \quad (16)$$

$$\begin{aligned} \mathbf{A}\boldsymbol{\tau} &\leq \mathbf{b} \\ \boldsymbol{\tau} &\in \{0, 1\}^M \end{aligned} \quad (17)$$

The difference between (16) and (17) originates in some fundamental assumptions in different MHT versions. When used on a HOMHT tree, (16) includes track initialization since it demands that all measurements must be assigned. On the other hand, both (17) and (18) requires a-priori knowledge about the number of tracks.

In this work, the problem is formulated slightly different, in that there are two sets of constraints (18), one equality and one inequality. The inequality constraints $\mathbf{A}_1 \boldsymbol{\tau} \leq \mathbf{b}_1$ ensures that each measurement are maximum (but not minimum) used one time. The equality constraints $\mathbf{A}_2 \boldsymbol{\tau} = \mathbf{b}_2$ ensures that minimum and maximum one track from each track tree is selected. The complete ILP formulation becomes (18), where $\boldsymbol{\tau}$ is a binary vector with dimension equal the number of leaf nodes in the track forest.

$$\begin{aligned}
& \max_{\boldsymbol{\tau}} \quad \mathbf{c}^T \boldsymbol{\tau} \\
& \text{s.t.} \quad \mathbf{A}_1 \boldsymbol{\tau} \leq \mathbf{b}_1 \\
& \quad \mathbf{A}_2 \boldsymbol{\tau} = \mathbf{b}_2 \\
& \quad \boldsymbol{\tau} \in \{0, 1\}^M
\end{aligned} \tag{18}$$

\mathbf{A}_1 is a $N_1 \times M$ binary matrix with N_1 real measurements and M track hypotheses (all leaf nodes), where $\mathbf{A}_1(l, i) = 1$ if hypothesis l are utilizing measurement i , 0 otherwise. The measurements and hypothesis are indexed by the order they are visited by Depth First Search (DFS). \mathbf{A}_2 is an $N_2 \times M$ binary matrix where N_2 is the number of targets in the cluster and $\mathbf{A}_2(l, j) = 1$ if hypothesis l belongs to target j . \mathbf{b}_1 is a N_1 long vector with ones and \mathbf{b}_2 is a N_2 long vector with ones. \mathbf{c} is a M long vector with a measure of the goodness of the track hypotheses. For example, in Figure 5 at time step 2, the \mathbf{A} matrices and \mathbf{C} vector would be (19).

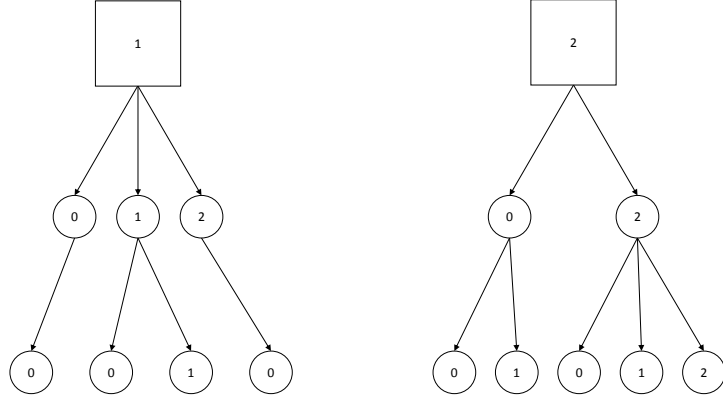


Figure 5: Track hypothesis tree

$$\begin{aligned}
 \mathbf{A}_1 &= \begin{bmatrix} 0 & 1 & 1 & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 1 & 0 & 0 & 1 & 0 & 1 & 0 \\ 0 & 0 & 0 & 1 & 0 & 0 & 1 & 1 & 1 \\ 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 1 \end{bmatrix} \quad \mathbf{b}_1 = \begin{bmatrix} 1 \\ 1 \\ 1 \\ 1 \end{bmatrix} \\
 \mathbf{A}_2 &= \begin{bmatrix} 1 & 1 & 1 & 1 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 1 & 1 & 1 & 1 & 1 \end{bmatrix} \quad \mathbf{b}_2 = \begin{bmatrix} 1 \\ 1 \end{bmatrix} \\
 \mathbf{c} &= [\lambda_1 \quad \lambda_2 \quad \lambda_3 \quad \lambda_4 \quad \lambda_5 \quad \lambda_6 \quad \lambda_7 \quad \lambda_8 \quad \lambda_9]^T
 \end{aligned} \tag{19}$$

The explicit enumeration that becomes necessary when creating these \mathbf{A} matrices is exhaustive since dimension of $\boldsymbol{\tau}$, which is equal to the number of leaf nodes in the track forest, can be very large. Both \mathbf{A}_1 and \mathbf{A}_2 grows quadratically with the number of track hypotheses and real measurements or number of targets respectively.

4.2 Solvers

There are a lot of of-the-shelf ILP and Mixed Integer Linear programming (MILP) solvers on the market, both free open source and commercial. Since our problem is formulated on standard form, it can easily be executed on several solvers, and

we can compare runtime and performance. In this report, the following solvers are tested:

- CBC (Free, COIN-OR)
- CPLEX (Commercial (Free academic), IBM)
- GLPK (Free, GNU)
- Gurobi (Commercial (Free academic), Gurobi)

5 Implementation

The aim of this section is to elaborate the decisions that were made during the implementation of the algorithm outlined in section 3 and 4.

5.1 Programming language

This work is done as a part of a larger project (AUTOSEA) where all code is developed in Python. Python is known for its large pool of modules, easy portability and quick programming, which makes it a great choice for research and development of algorithms. It is far from the fastest out-of-the-box programming language available, there are however side versions of python like Cython that allows for optimisation and compilation of Python to C code. If Graphics Processing Unit (GPU) acceleration should be possible and desirable, Python also have modules that allows for very easy and powerful usage of CUDA cores from Nvidia products.

To maximize the capability with other code in this project, all implementation was done in Python 3. Further was data storage and calculations done as much as possible in modules like NumPy and SciPy, which both have excellent runtime for many common operations.

5.2 Code structure

The code is structured in an object oriented style with two primary classes, a *Tracker* and a *Target* class. The Tracker is the class the user initializes and configures with parameters that are not target specific, like P_D , λ_ν , λ_ϕ , η^2 , N and state space model. The Tracker is also the root for the track forest, that meaning that all tracks are trees of Target objects originating from a single Tracker object.

When a new track is initialised, an *initiateTarget* procedure is called on the tracker, and a new root for a track hypothesis tree is created in the form of a Target object. As new scans are received, the trackers *addMeasurementList* method is called with the measurements, where upon all targets are predicted, gated,

scored, pruned, selected and pruned, before the result is return to the user, see Figure 2.

5.3 Parallel processing

Of the aforementioned steps, the prediction, gating and creation of new track hypotheses is the most time consuming. These steps will be referred to as the *tree growing* task. For example, a scan which takes 1758 ms in total to process, where 1496 ms are used to grow the track hypothesis tree when running on a single Central Processing Unit (CPU) core. When utilizing multiple cores to run computation in parallel, Table 2 compares the run time averaged over 10 runs, for the same scan with different amount of parallel processes on a 4 core computer.

Since the growing task is the only part of the algorithm that is cunning on multiple cores, it is the only task that changes significantly. The multi processing of the growing task is implemented in a master-worker configuration, where the task is divided into $n - 1$ equal chunks running on $n - 1$ cores with the main process handling all the "worker" processes. As expected increases the runtime from one to two processes, since the entire job is copied over to another process, processed, and copied back. With any further increase in processor count, the execution time is expected to decline, which is the case. At a certain core count, the time used splitting up the task, distribute to all the cores and collecting their results will become larger than the benefit of faster computation in each core. At this point, the overhead of parallizing the work leads to starvation of the workers and increased total run-time. From Table 3, we can see that the tree growing task is responsible for about one quarter of the run-time for this particular scan.

| Processes | Total | Grow | Cluster | Optimize | Prune |
|-----------|-------|------|---------|----------|-------|
| 1 | 1718 | 1453 | 1 | 262 | 2 |
| 2 | 1880 | 1602 | 1 | 276 | 2 |
| 3 | 1222 | 958 | 1 | 262 | 2 |
| 4 | 1034 | 768 | 1 | 263 | 2 |

Table 2: Runtime of a scan with different amount of processes (time in ms)

| Processes | Grow | Cluster | Optimize | Prune |
|-----------|------|---------|----------|-------|
| 1 | 85% | 0% | 15% | 0% |
| 2 | 85% | 0% | 15% | 0% |
| 3 | 78% | 0% | 21% | 0% |
| 4 | 74% | 0% | 25% | 0% |

Table 3: Runtime distribution percentage

| Processes | Search | Predict | Create | Add |
|-----------|--------|---------|--------|-----|
| 2 | 0% | 2% | 98% | 0% |
| 3 | 0% | 3% | 97% | 0% |
| 4 | 0% | 3% | 97% | 0% |

Table 4: Worker runtime distribution percentage

5.4 Performance considerations

6 Results

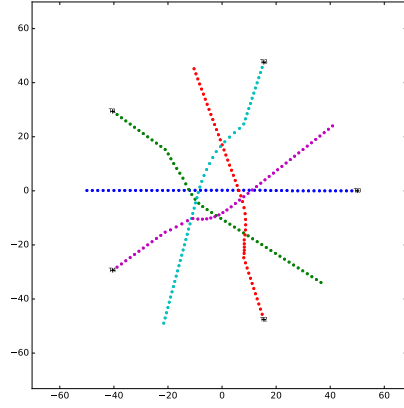
6.1 Testing scheme

The evaluation of the MHT algorithm is two-sided, firstly the algorithm must be able to track under challenging conditions, secondly it must be able to do this without having an ever growing computationally cost and run time. The first performance metric is how well the algorithm is estimating the true position to the object it is tracking. We measure this by means of the Euclidean distance between the estimated and true track (20).

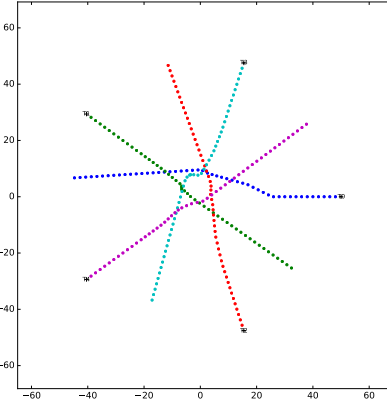
$$\Delta P = \|\mathbf{p}_{track} - \mathbf{p}_{target}\|_2 \quad (20)$$

The track is considered correct if $\Delta P \leq \varepsilon_p$ for all t after initial convergence. If a track is deviating more than the threshold and is never within the threshold again, it is considered lost at the time-step when it exceeded the threshold. If the track should converge after exceeding the threshold, it is considered restored at the time-step it is returning within the limit. The algorithm is tested on six scenarios:

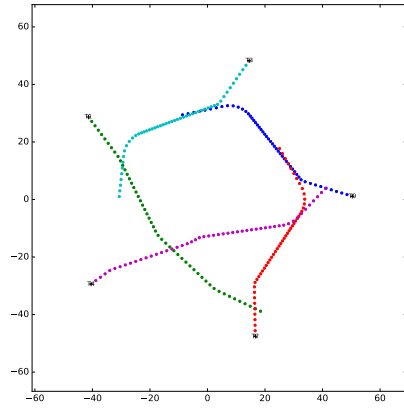
- Five fully cooperating ships
- Five partially cooperative ships
- Five ships avoiding obstacles with large space
- Five ships avoiding obstacles with little space
- Five almost parallel ships (normal speed radar)
- Five almost parallel ships (high speed radar)



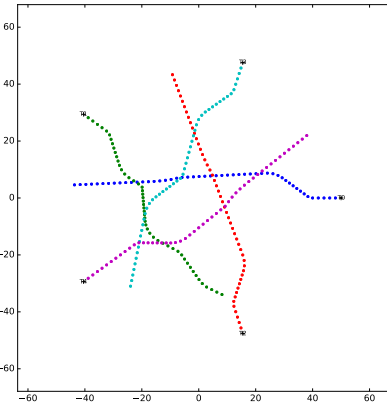
(a) First scenario



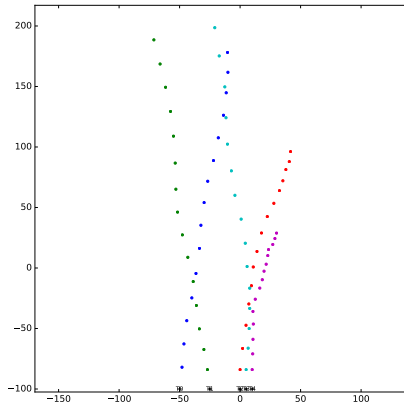
(b) Second scenario



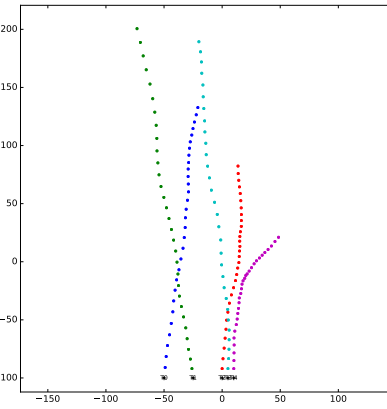
(c) Third scenario



(d) Fourth scenario



(e) Fifth scenario



(f) Sixth scenario

Figure 6: True track for scenario 1-6

6.2 Simulation data

Scenario one through four was generated as a recording of time and position from an Autonomous Surface Vessel (ASV) simulator with Collision Avoidance (COLAV), developed by Dr. D. Kwame Minde **Kufolaor** at NTNU. The ships are configured such that they need to maneuver to avoid collision with each other, which allows for tracking of maneuvering targets in close proximity to each other. These scenarios were sampled at 1 Hz which is a little faster than a normal high speed vessel radar at 0.8 Hz (48 Rotations Per Minute (RPM)). The fifth scenario was generated as a part of this project, and is composed by linear parallel paths with white Gaussian system noise as maneuvering. This data set was sampled at 0.5 Hz which is a little higher than a normal maritime coastal radar at 0.4 Hz (24 RPM) and at 1 Hz to compare the two most common radar update frequencies. Scenario 1 to 4 have a sensor Field Of View (FOV) of a Table 5 shows the expected number of clutter measurements in each of the two different fields of view.

6.3 Simulations

Scenario one through six was simulated with the following variations with all four solvers.

$$\begin{aligned}\mathbf{P}_D &= \begin{bmatrix} 0.5 & 0.6 & 0.7 & 0.8 & 0.9 \end{bmatrix} \\ \mathbf{N} &= \begin{bmatrix} 0 & 1 & 3 & 6 & 9 \end{bmatrix} \\ \lambda_\phi &= \begin{bmatrix} 0 & 1 \cdot 10^{-4} & 2 \cdot 10^{-4} & 4 \cdot 10^{-4} & 6 \cdot 10^{-4} & 8 \cdot 10^{-4} \end{bmatrix}\end{aligned}$$

| Scenario | Radar range | FOV | $\lambda_\phi \cdot FOV$ | | | | |
|----------|-------------|----------------------|--------------------------|------|------|------|------|
| | | | 1 | 2 | 4 | 6 | 8 |
| 1-4 | 65m | $1.3 \cdot 10^4 m^2$ | 1.3 | 2.6 | 5.2 | 7.38 | 9.21 |
| 5-6 | 155m | $7.5 \cdot 10^4 m^2$ | 3.22 | 4.61 | 5.99 | 7.38 | 9.21 |

Table 5: Expected number of clutter measurements in scenarios

Each variant was simulated 160 times with different seeded random clutter measurements and misdetections. For each simulation, the estimated tracks were compared with the true tracks and categorised in successful and lost tracks, the track loss threshold ϵ_p was 4 meters. Figure 7 display a mid-simulation plot with current best tracks in solid lines, and hypotheses in dotted lines.

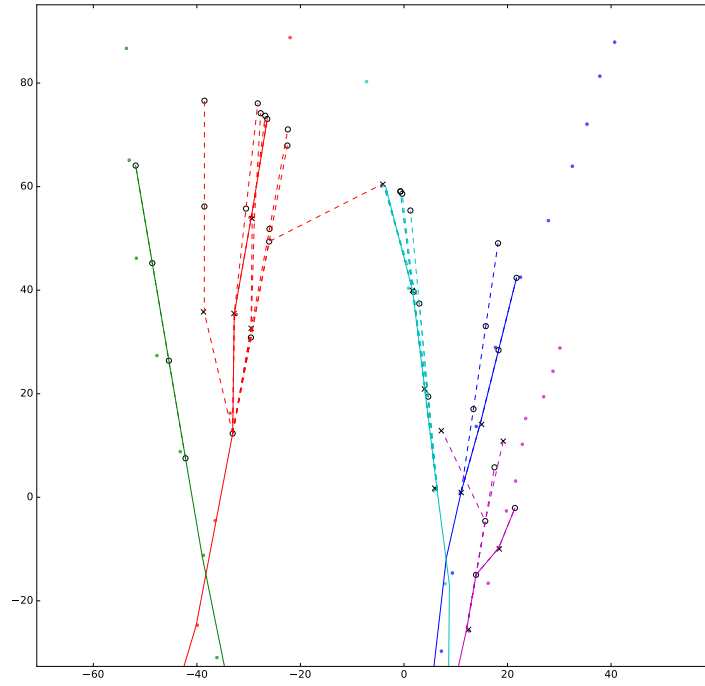
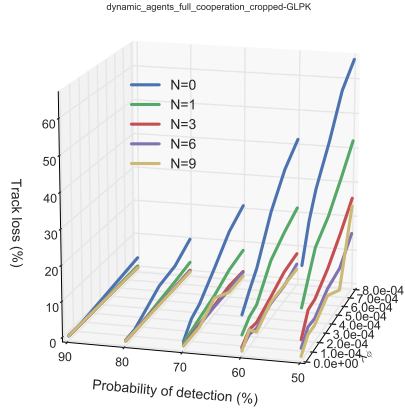
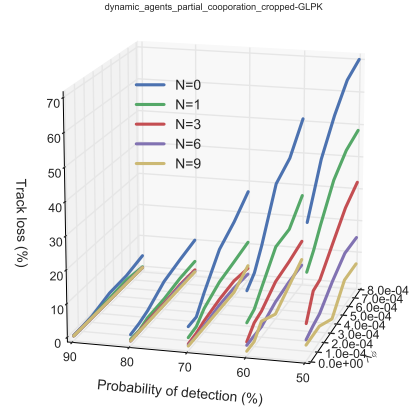


Figure 7: Track hypotheses example

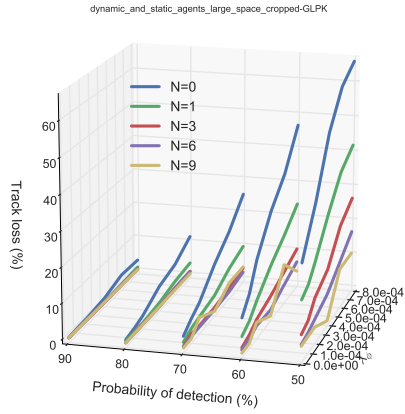
Figure 15 - 18 show the averaged track loss percentage for all simulations variants. Figure 8 shows the track performance from the "GLPK" solver.



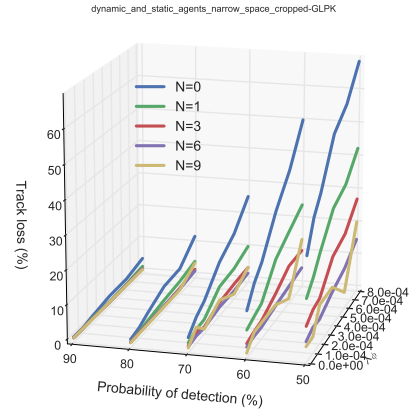
(a) Scenario 1



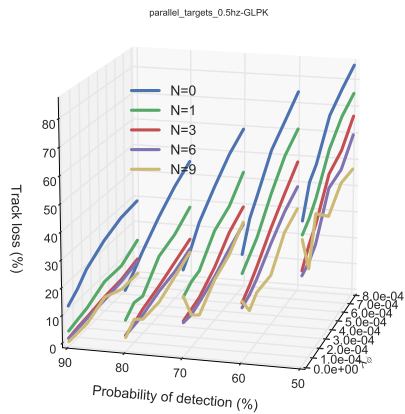
(b) Scenario 2



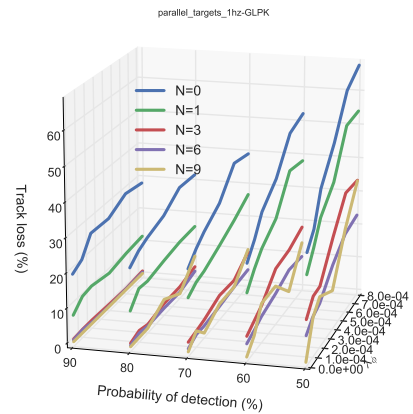
(c) Scenario 3



(d) Scenario 4



(e) Scenario 5



(f) Scenario 6

Figure 8: Simulation results for all scenarios

6.4 Runtime

Figure 9 to 13 displays average the runtime for the entire scenario for the different solvers. The runtime along the z-axis displays the time used for simulating the entire scenario.

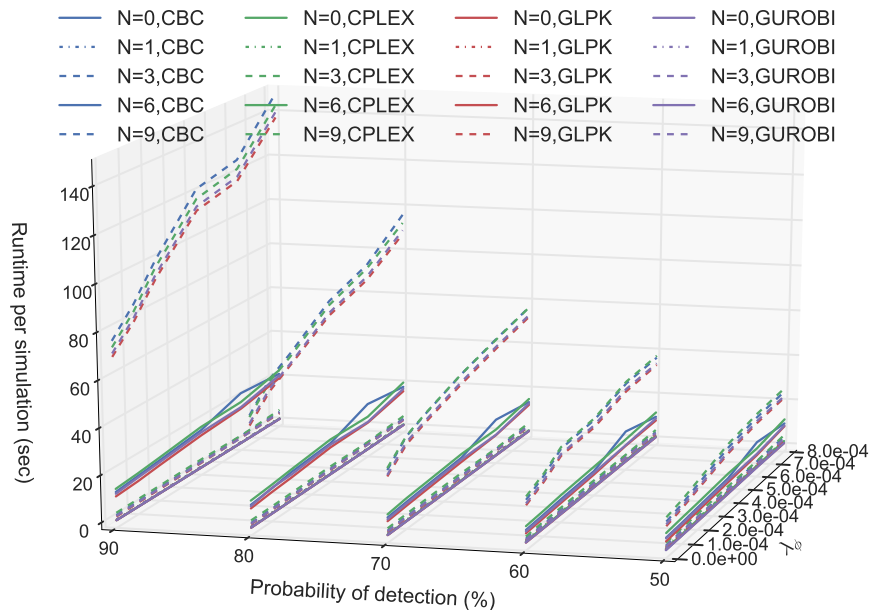


Figure 9: Runtime for scenario 1

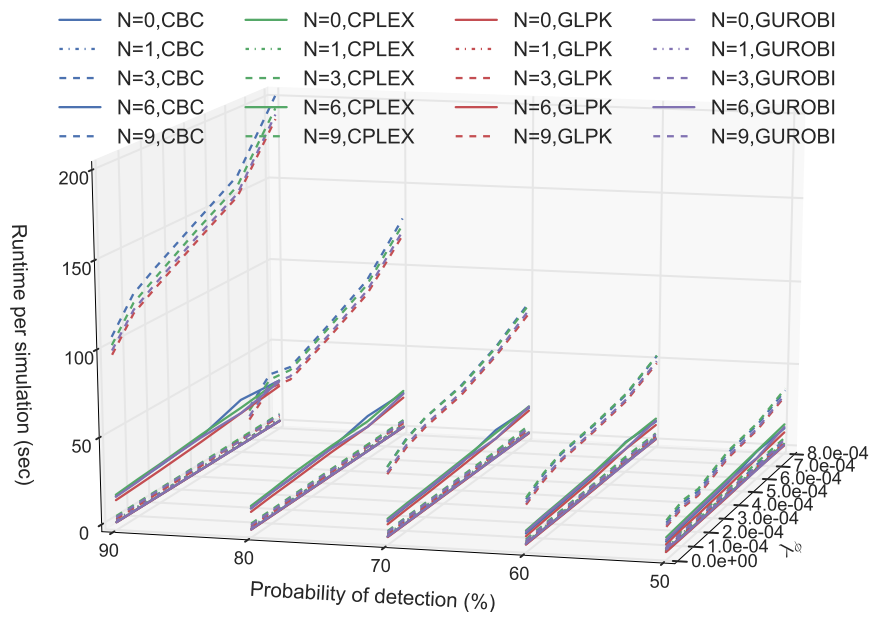


Figure 10: Runtime for scenario 2

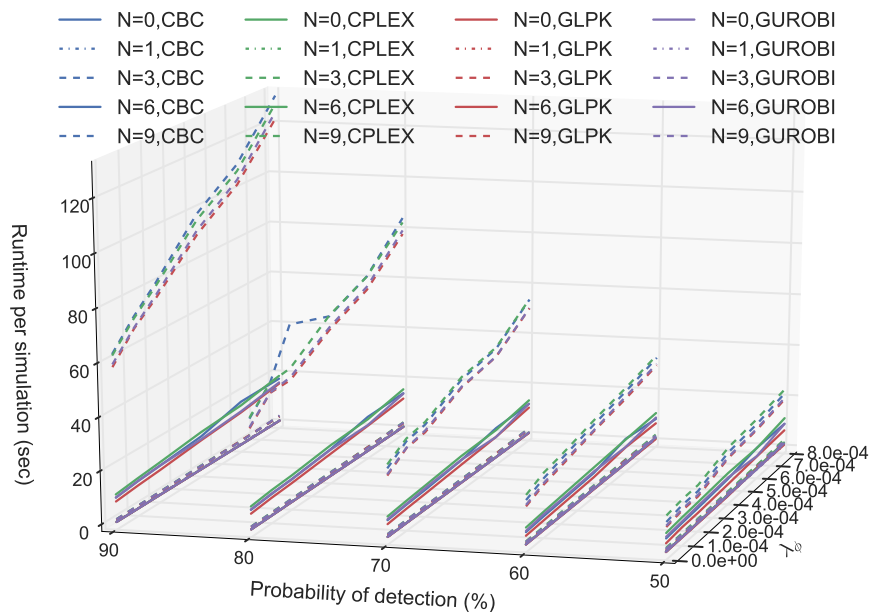


Figure 11: Runtime for scenario 3

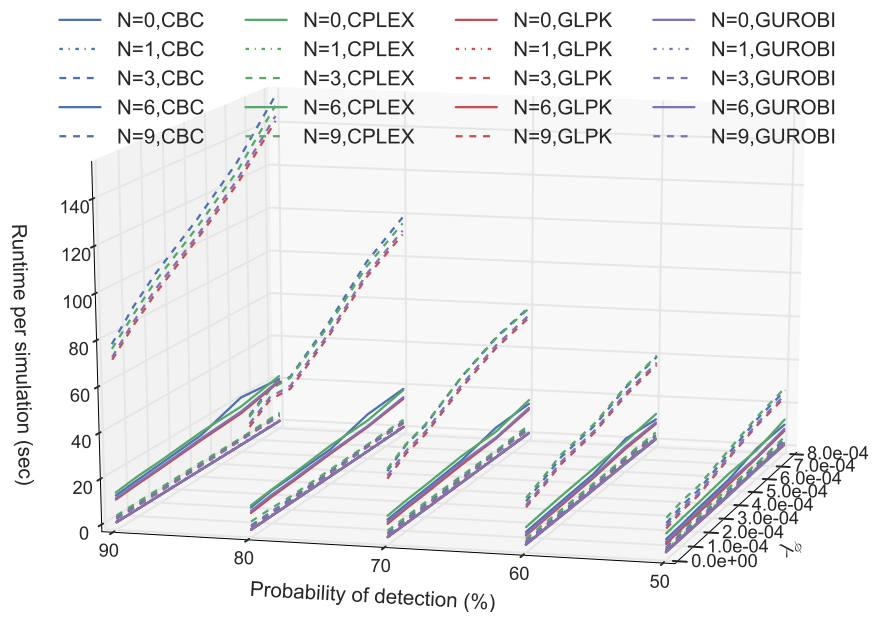


Figure 12: Runtime for scenario 4

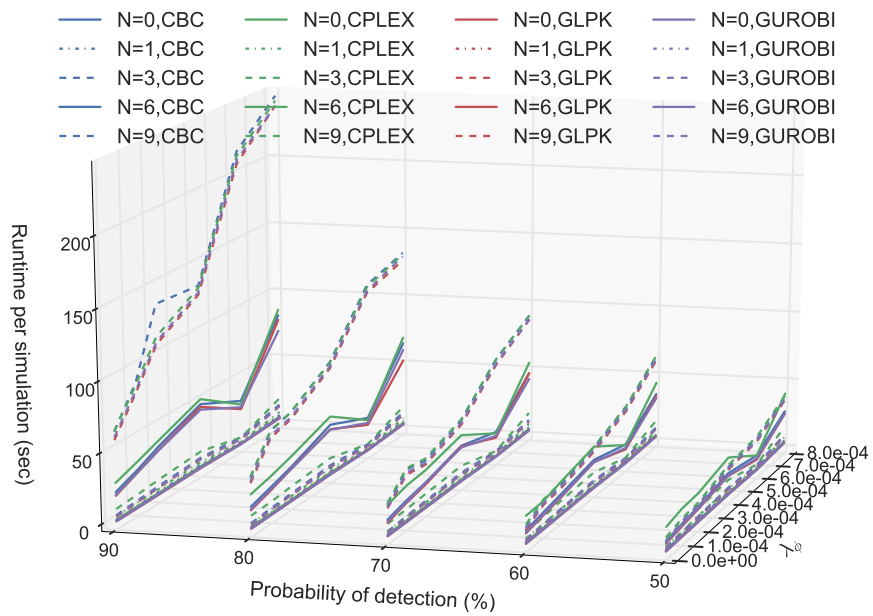


Figure 13: Runtime for scenario 5

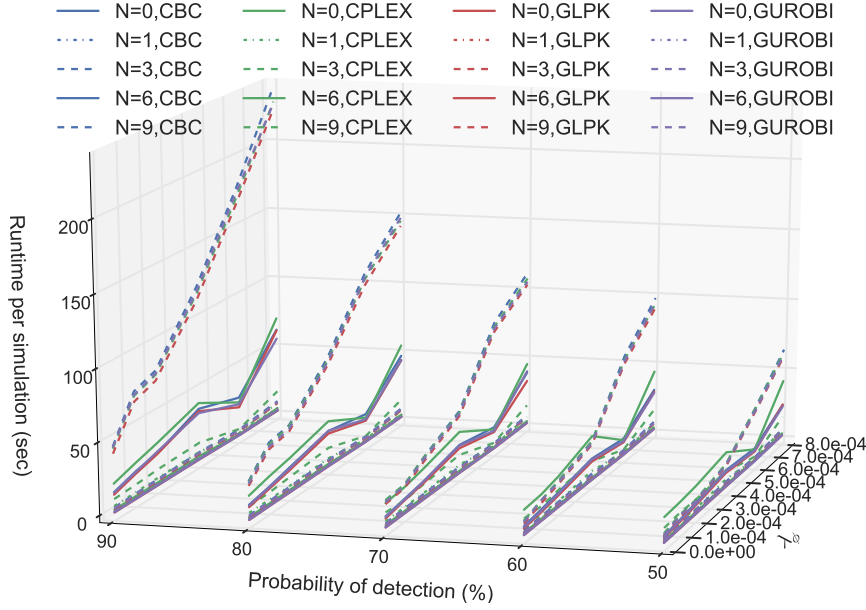


Figure 14: Runtime for scenario 6

6.5 Track loss performance

From the simulation results in Figure 15 to 19 it can be observed that the different solvers perform practically identically when it comes to track performance. From Figure 8, it can be seen that the number of lost tracks is proportional to the clutter level at an inverse proportional rate to the probability of detection P_D . An interesting observation is the return on investment regarding the number of scans to evaluate (N -scan). For instance, with $P_D = 0.7$ the difference between $N = 3$ and $N = 6$ is marginal, at least when the clutter level is within reasonable levels ($\lambda_\phi < 4 \cdot 10^{-4}$). With $P_D = 0.5$ we see that the pay-off is much higher for the extra computational cost with 15% improvement between $N = 3$ and $N = 6$.

Scenario 1-4 was simulated within a very small area where the targets had good separation both at the start and end of the simulation. This gives the algorithm more scans to figure out the correct association after any multi-target conflicts that could arise when close to other target, and hence better track loss figures. In scenario 5-6 the targets start off spatially much closer and are moving

faster. This leads to a situation more vulnerable to misdetections where a high N -scan is beneficial.

6.6 Time performance

From Figure 9 to 14 it can be seen that the solvers are all in the same area, though with a very consistent difference in scenario 1 to 4. In these scenarios the GLPK solver is the fastest with between 5-10 seconds compared with CPLEX which is the slowest in these scenarios. This trend is most likely caused by the different amount of overhead in the solvers, where IBM's CPLEX which is marked leading in many ways might have way more initialization and setup procedures compared GNU's GLPK. In scenario 5 and 6, a different and more varying trend is visible. Here we see that both Gurobi and GLPK are fastest in different situations, and generally all other solvers than CPLEX perform quite similar.

The run time increases linearly with the amount of clutter, which is expected as most of the operations run in the algorithm are based on tree operations with $O(E + V)$ run time. The structure in a track-tree implies that each vertex has one edge, hence any DFS based operations will have run time $O(2V) = O(V)$. The run time increases near exponentially with the size of N , which is natural since the number of hypotheses that must be considered is exponentially larger.

7 Discussion

The field of tracking and data association has been dominated by first military applications and secondly civil aviation control, both of which are areas with high performance demands and large development contracts. Although much work is published on this topic, few comparisons have been made between actual implementations of different trackers and filters. This may to some extent be due to the nature of business secrets and military classifications to hide the intricate details that goes into an actual implementation and optimization of any tracking system. It is also, on a slightly more speculative note, due to disagreements about what kind of performance measures that one should use.

One of the main objective for this work was to examine the feasibility of using off-the-shelf solvers to solve the assignment problem in a MHT system. And does it? The short answer is yes, but with a quite large set of drawbacks. When using off-the-shelf solvers, the assignment problem must be written to a file that the solver can interpret. This is a major drawback with this approach, but can be partially compensated for with fast Solid State Storage (SSD) instead of traditional rotating hard drives. Another major drawback is the need of explicit enumeration of all hypotheses in the ILP formulation, which is costly and in many situations unnecessary. This could possibly be addressed by column generating optimization [19] methods, which starts with a feasible set of columns and adds more and more columns (constraints) until it reaches the optimal assignment. Intuitively this makes sense, since most of the constraints will never be active, and therefore not needed for finding the optimal solution. This would however make the optimization a lot more tailor-made to this application, and the render the usage of off-the-shelf solvers impossible.

8 Closing remarks

8.1 Conclusion

This report has shown that off-the-shelf ILP solvers, both free and commercial, are capable solving the data association problem in a TOMHT. It has also provided evidence that the tracking performance does benefit very little from more than $N = 3$ scan history in moderate manoeuvring scenarios when $P_D > 70\%$, even with severe amounts of clutter.

Through simulations on a single-core implementation of a TOMHT in Python, it have also shown the feasibility for real-time applications with five closely spaced targets with $N = 5$ in a heavy clutter scenario ($\lambda_\phi = 1 \cdot 10^{-3}$), and $N = 6$ for a moderate clutter scenario ($\lambda_\phi = 5 \cdot 10^{-4}$). Further, this report has outlined the possibilities for significant run-time improvements through the use of multi-core CPUs and GPUs.

8.2 Future work

One area where there might be substantial benefits is in more complex pruning and merging of hypotheses. By nature, many hypotheses will have very similar paths and could therefore be candidates for being merged to one. The danger with this is that the assignment problem could be rendered infeasible and crash the algorithm. A novel approach could be to formulate the pruning as an optimization problem. With this approach it is possible to also remove hypotheses with a low score, subject to the problem still being feasible.

In the maritime context, it could also be very beneficial to use the maritime AIS to aid the tracking. There are different approaches to include this extra set of data, all with their pros and cons. One option could be to use the AIS track to weight the measurements from the radar; this way the measurement that are more likely to originate from a target is given a higher score. Another possibility is to do track-to-track fusion / filtering, where the best or N-best tracks from the radar are filtered with the tracks from the AIS system. Track-to-track fusion can

also be handled within the ILP framework, see [14].

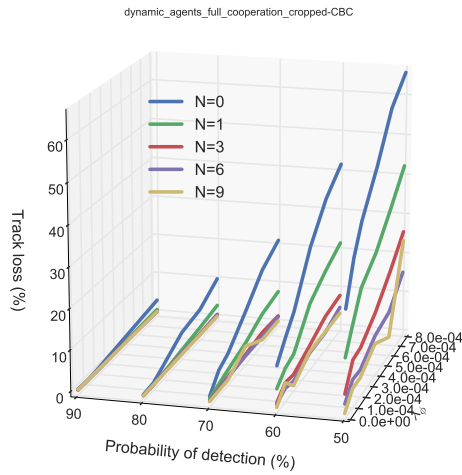
Another improvement that would benefit the run time requirement is to parallelize the algorithm. Since many of the operations in the algorithm are independent, they are excellent candidates for running in parallel. Today CPU's can be delivered with as many as 24 cores per die, and with hyper threading they can process up to 48 threads. With server grade motherboards capable of one to four CPU's, there is potential to run almost 200 threads if necessary. This would however be a pure brute force approach, which would push the boundary of how many targets the system would be able to track simultaneously, but not the run time as a function of the problem size.

A final but very important piece, that is required for the system to be complete, is track initialization. As with AIS assisted tracking, there are plenty of ways to tackle this challenge. One alternative, and probably the most common for TOMHT is to run a separate system besides the tracking loop to initiate targets. This system can be based on recursive RANSAC, PDAF-based techniques, etc., with a selection criterion for declaring a target born. The most common is a N out of M threshold, where N and M may be 4 and 6 respectively. These separate initialization trackers can run on all measurements, or maybe preferably on the non-associated measurements from the primary system.

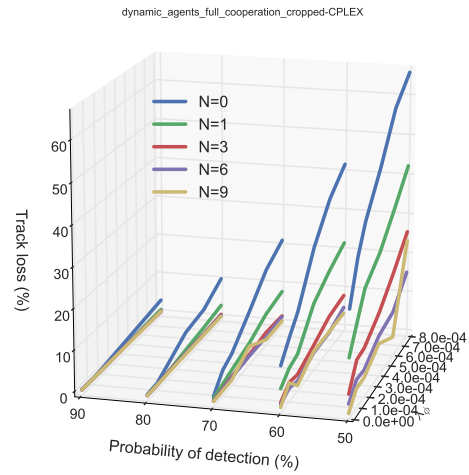
Appendices

A Track performance plots

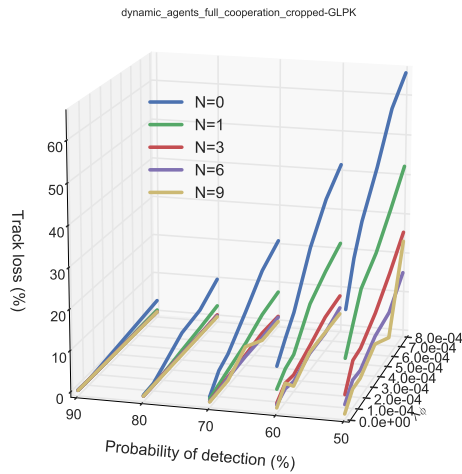
Scenario 1 - Track performance



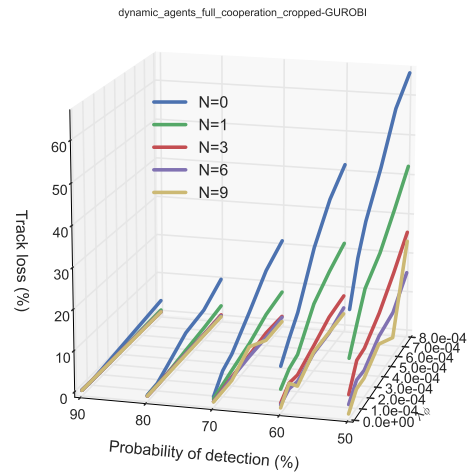
(a) CBC solver



(b) CPLEX solver



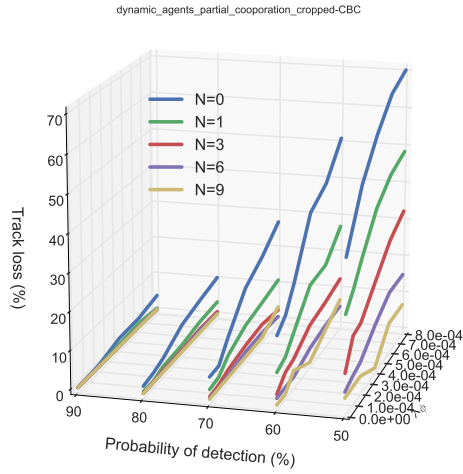
(c) GLPK solver



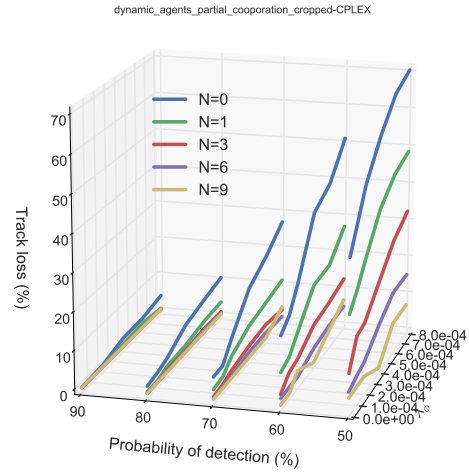
(d) GUROBI solver

Figure 15: Simulation results for all solvers in scenario 1

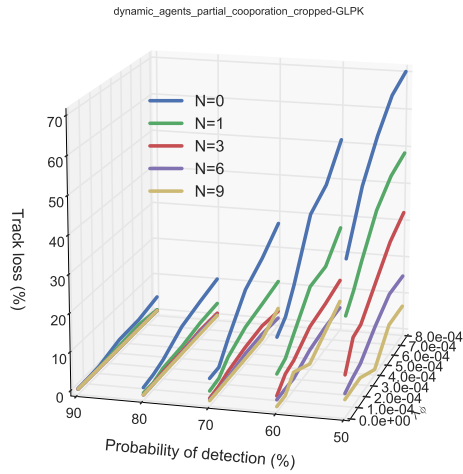
Scenario 2 - Track performance



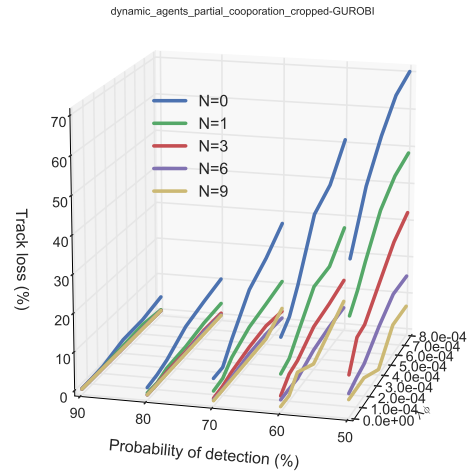
(a) CBC solver



(b) CPLEX solver



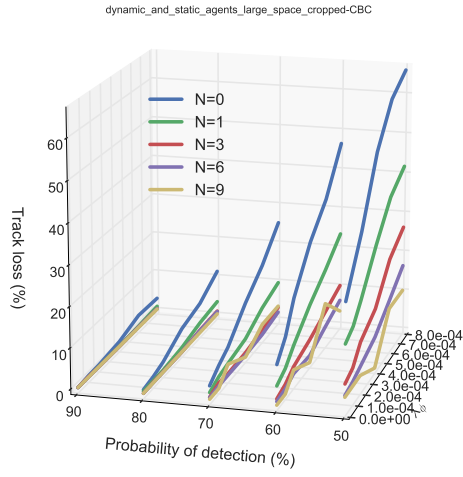
(c) GLPK solver



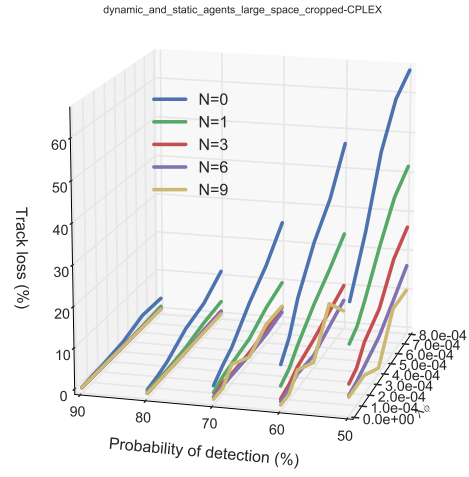
(d) GUROBI solver

Figure 16: Simulation results for all solvers in scenario 2

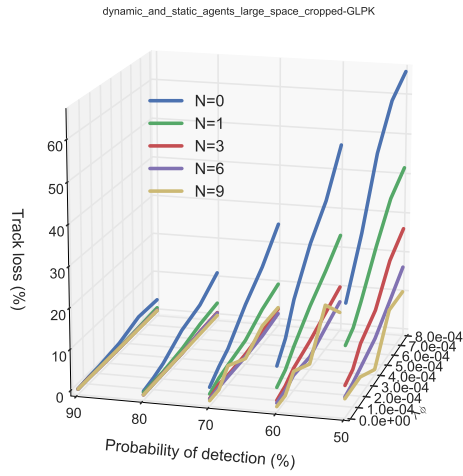
Scenario3 - Track performance



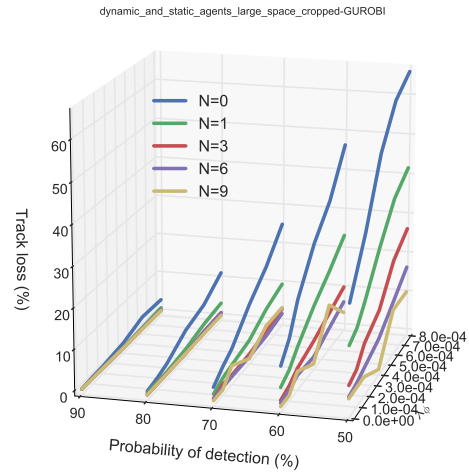
(a) CBC solver



(b) CPLEX solver



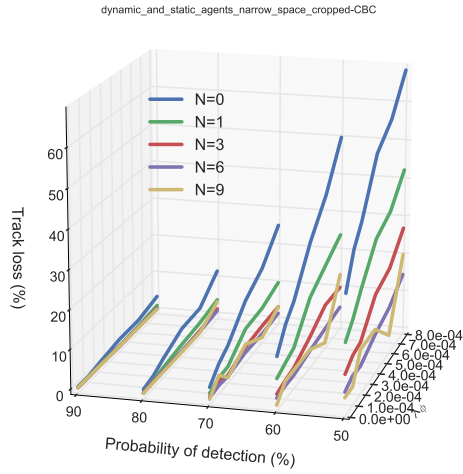
(c) GLPK solver



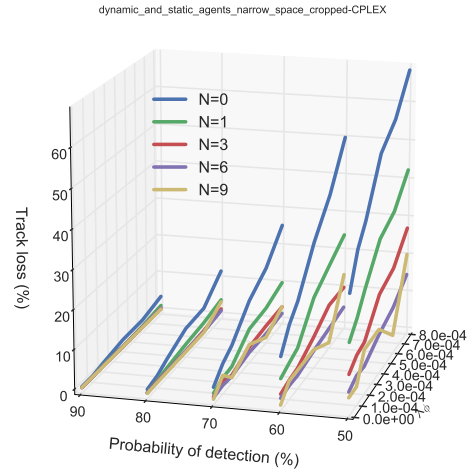
(d) GUROBI solver

Figure 17: Simulation results for all solvers in scenario 3

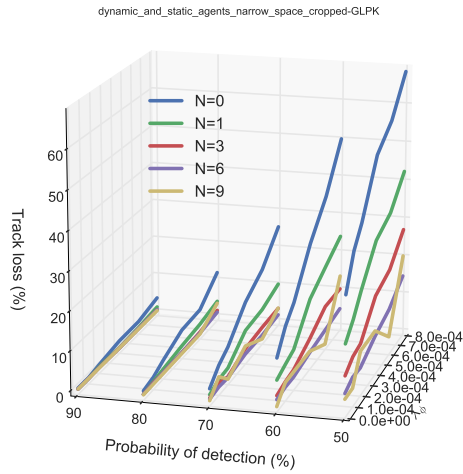
Scenario 4 - Track performance



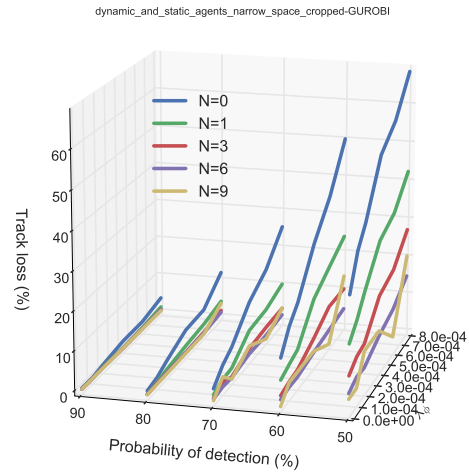
(a) CBC solver



(b) CPLEX solver



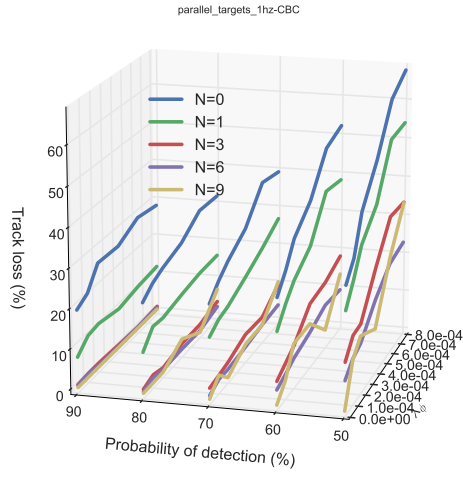
(c) GLPK solver



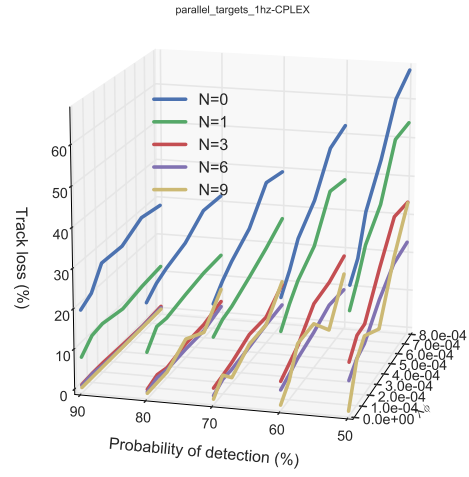
(d) GUROBI solver

Figure 18: Simulation results for all solvers in scenario 4

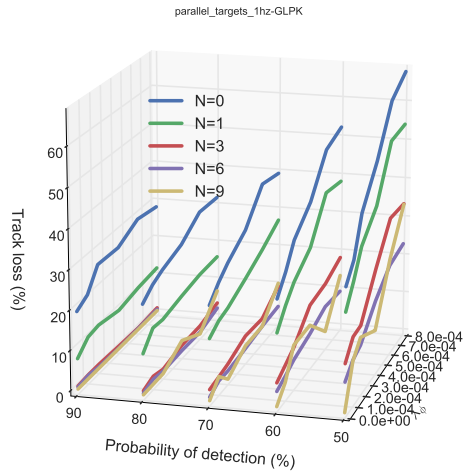
Scenario 5 - Track performance



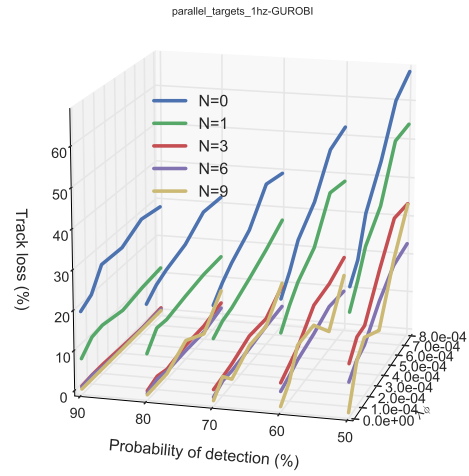
(a) CBC solver



(b) CPLEX solver



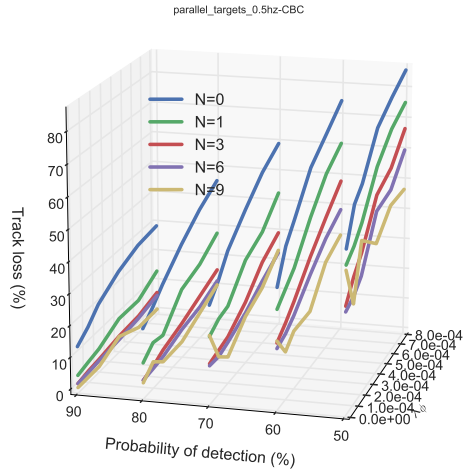
(c) GLPK solver



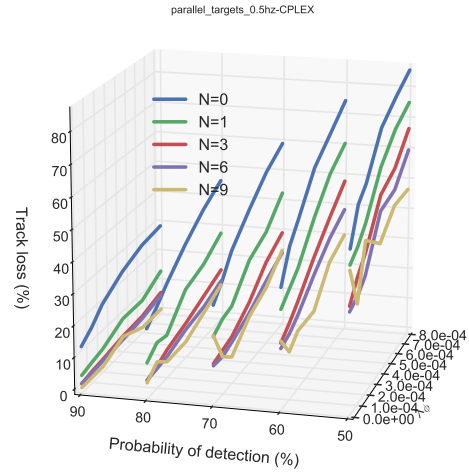
(d) GUROBI solver

Figure 19: Simulation results for all solvers in scenario 5

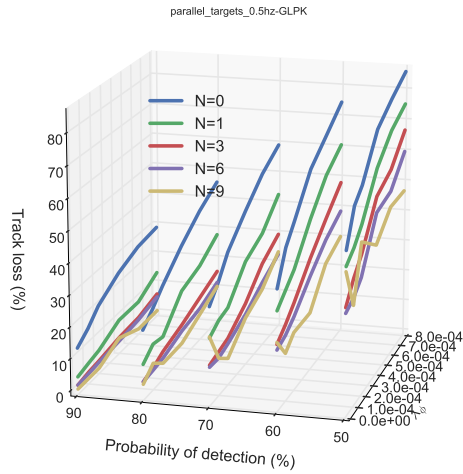
Scenario 6 - Track performance



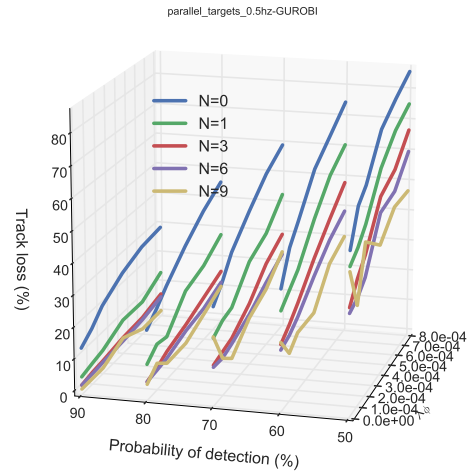
(a) CBC solver



(b) CPLEX solver



(c) GLPK solver



(d) GUROBI solver

Figure 20: Simulation results for all solvers in scenario 6

References

- [1] Y. Bar-Shalom and T. E. Fortmann, “Algorithms for Tracking A Single Target In Clutter,” in *Tracking and Data Association*, pp. 119–185, New York: Academic, 1998.
- [2] T. Fortmann, Y. Bar-Shalom, and M. Scheffe, “Sonar tracking of multiple targets using joint probabilistic data association,” *IEEE Journal of Oceanic Engineering*, vol. 8, no. 3, pp. 173–184, 1983.
- [3] H. A. P. Blom and E. Bloem, “Probabilistic Data Association Avoiding Track Coalescence,” in *IEEE Transactions on Automatic Control*, vol. 45, pp. 247–259, 2000.
- [4] QinetiQ, “Efficient hypothesis management,” 2003.
- [5] P. Horridge and S. Maskell, “Real-time tracking of hundreds of targets with efficient exact JPDAF implementation,” in *2006 9th International Conference on Information Fusion, FUSION*, 2006.
- [6] R. Singer, R. Sea, and K. Housewright, “Derivation and evaluation of improved tracking filter for use in dense multitarget environments,” *IEEE Transactions on Information Theory*, vol. 20, no. 4, pp. 423–432, 1974.
- [7] D. Reid, “An algorithm for tracking multiple targets,” *IEEE Transactions on Automatic Control*, vol. 24, no. 6, pp. 843–854, 1979.
- [8] T. Kurien, “Issues in the design of practical multitarget tracking algorithms,” in *Multitarget-Multisensor Tracking: Application and Advances*, ch. 3, pp. 219–245, Artech House, first ed., 1990.
- [9] Y. Bar-Shalom, S. S. Blackman, and R. J. Fitzgerald, “Dimensionless score function for multiple hypothesis tracking,” *IEEE Transactions on Aerospace and Electronic Systems*, vol. 43, no. 1, pp. 392–400, 2007.

- [10] S. Blackman, "Multiple hypothesis tracking for multiple target tracking," *IEEE Aerospace and Electronic Systems Magazine*, vol. 19, no. 1, pp. 5–18, 2004.
- [11] S. S. Blackman, R. J. Dempster, and R. W. Reed, "Demonstration of Multiple Hypothesis Tracking (MHT) Practical Real-Time Implementation Feasibility," *Proceedings of SPIE Vol. 4473*, vol. 4473, pp. 470–475, 2001.
- [12] R. Tarjan, "Depth-first search and linear graph algorithms," *12th Annual Symposium on Switching and Automata Theory (swat 1971)*, vol. 1, no. 2, pp. 146–160, 1971.
- [13] P. Storms and F. Spieksma, "An LP-based algorithm for the data association problem in multitarget tracking," *Computers and Operations Research*, vol. 30, no. 7, pp. 1067–1085, 2003.
- [14] S. Coraluppi, C. Carthel, M. Luetzgen, and S. Lynch, "All-Source Track and Identity Fusion," in *DTIC Technical Reports (U.S. Defence Technical Information Center)*, 2000.
- [15] E. Brekke, O. Hallingstad, and J. Glattetre, "Improved target tracking in the presence of wakes," *IEEE Transactions on Aerospace and Electronic Systems*, vol. 48, no. 2, pp. 1005–1017, 2012.
- [16] S. Chen, L. Liang, and Y. Tian, "The number of connected components in a graph associated with a rectangular (0,1)-matrix," *Linear Algebra and its Applications*, vol. 487, pp. 74–85, 2015.
- [17] C. L. Morefield, "Application of 0–1 Integer Programming to Multitarget Tracking Problems," *IEEE Transactions on Automatic Control*, vol. AC-22:302, pp. 303–312, 1977.
- [18] S. Coraluppi and C. Carthel, "Multi-hypothesis sonar tracking," *7th International Conference on Information Fusion.*, pp. 33–40, 2004.

- [19] C. Barnhart, E. L. Johnson, G. L. Nemhauser, M. W. P. Savelsbergh, and P. H. Vance, “Branch-and-price: Column generation for solving huge integer programs,” *Operations Research*, vol. 46, no. 3, pp. 316–329, 1998.