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Erik F. Wilthil

Maritime Target Tracking with Varying Sensor Performance

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Thesis for the degree of Philosophiae Doctor

Trondheim, October 2019

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Summary

Several research and industrial projects have been started in recent years to drive the development of autonomous surface vehicles (ASVs). This thesis is one of the contributions to this emerging field, and the topic is on target tracking for maritime collision avoidance using a maritime radar. An ASV requires a full overview of the environment to plan and perform safe maneuvers. With exteroceptive sensors, such as a radar, ASVs are able to detect other vessels, also the ones that are not equipped with an automatic identification system (AIS) transponder. This is in particular relevant near harbors and urban areas, where there is a larger amount of vessels without AIS.

At the core of this thesis is a target tracking system for ASVs based on the probabilistic data association filter (PDAF). This thesis makes several contributions on compensating for varying sensor performance. This is important for enabling smaller ASVs with low-cost sensors. In addition, it also makes contributions to sensor preprocessing, tracking system architecture and integration of target tracking with collision avoidance systems.

The first contribution is on compensating for navigation system errors. An ASV is a moving platform, and uncertainty in the ownship state estimation system can be accounted for in the target tracking system. Second, the radar preprocessing and collision avoidance interfaces are described, as they are important components in practical implementations of target tracking for collision avoidance (COLAV). Third, the performance of track initiation methods are investigated. This includes a performance comparison using detection theoretic measures when the clutter and new target densities are unknown, as they often are in practical systems. Fourth, variations target detection probability is analysed, and three methods of estimating it are developed. Fifth, applications of the tracking system to maritime collision avoidance are presented.

The research goals of the thesis is primarily motivated by real data obtained in the project. The results have been verified both in simulations and in full-scale experiments.

Preface

This thesis is submitted as a partial fulfillment of the requirements for the degree of Philosophiae Doctor (PhD) at the Department of Engineering Cybernetics (ITK) at the Norwegian University of Science and Technology (NTNU).

First of all, I would like to thank my supervisor, Edmund Brekke. Thank you for your ideas, comments, feedback and guidance. I would also like to thank my co-supervisor, Morten Breivik, for your feedback and support during my PhD.

I would also like to thank Yaakov Bar-Shalom and Peter Willett at the University of Connecticut, where I had a research visit during fall 2018. I appreciate your hospitality, suggestions and feedback to my work.

To my friends at the department, thank you for four great years, both inside and outside of the office. I would especially like to thank Bjørn-Olav H. Eriksen, Andreas Flåten and Giorgio Kufoalor for their collaboration in the Autosea project. Additionally, I started my PhD together with Håkon Helgesen, Mathias Arbo and Kristoffer Gryte, and I thank you for the journey.

The partners in the Autosea project have provided great feedback and support during the last four years. In particular, I would like to thank Arild Hepsø, Kenan Trnka, Thomas Ingebretsen and Stephanie Kemna for their help during our experiments.

Last but not least, I would like to thank my family, especially my mother Britt, my father Morten and my brother Mads for their encouragements and support.

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Contents

Chapter 1

Introduction

1.1 Motivation

Autonomous ships has received significant attention in recent years. In addition to reducing the cost and increasing the safety in marine operations, new applications where manned ships have been too expensive or impractical are also emerging. A collision avoidance (COLAV) system is a key technology for using autonomous surface vehicles (ASVs) in trafficked areas, where both manned and other unmanned ships may be present. The COLAV system depends on a good object detection and tracking system in order to plan safe maneuvers. In addition to autonomous ships, manned ships also benefits from increased autonomy, by e.g. improved decision support systems.

Aids for detecting and tracking other vessels at sea have a long history, dating back to the introduction of the radar during the second World War. Since then, several improvements and aids have been introduced to improve safety and efficiency at sea, notably the automatic identification system (AIS) system. The system consists of a global navigation satellite system (GNSS) receiver, and a transmitter that sends the ASV position to other ships in the vicinity. AIS is a useful tool, but not all ships are equipped with it and should therefore not be the only source of target detection. Exteroceptive sensors can measure the state of other ships without communicating with them. However, the resulting sensor measurements are prone to missed detections and false alarms, and more advanced state estimation techniques must be applied.

As often is the case of technological development, the first ASVs were seen in military applications. However, the maritime industry is starting to develop sensors and systems that are smaller and cheaper, which is enabling ASVs in commercial and civilian applications.

1.2 The Autosea project

This PhD thesis is part of the project *Sensor fusion and collision avoidance for autonomous surface vehicles (Autosea)*. It is a competence-building project, funded by the Research Council of Norway, DNV GL, Kongsberg Maritime and Maritime Robotics. In addition to the work presented in this thesis, the project has educated another PhD [17] focusing on modelling, control and COLAV. Additionally, it has funded a postdoc and educated a large amount of master students.

The project has focused on closing the loop between target tracking and COLAV as shown in Fig. 1.1, by using exteroceptive sensors instead of AIS. The sensor fusion module is responsible for estimating the target state, and needs a set of navigation sensors in order to integrate AIS data and nautical

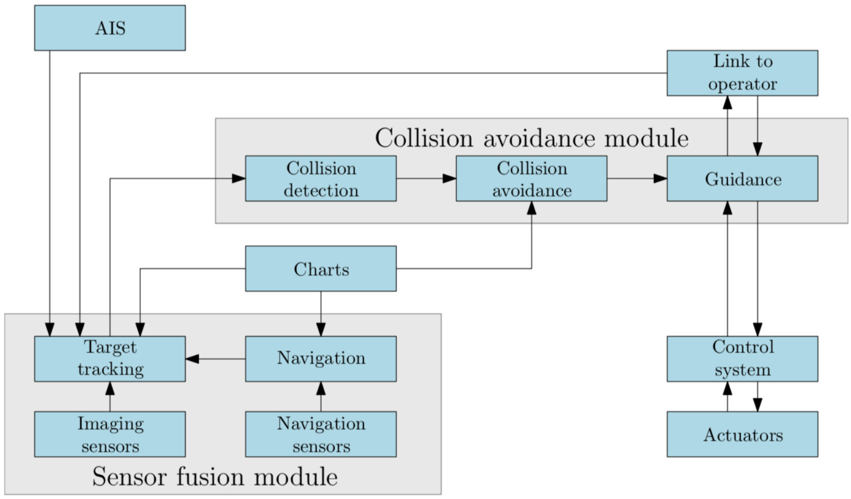

Figure 1.1: The main focus of Autosea was on using exteroceptive sensors for COLAV. The block diagram shows the main architecture and information flow in such a system.

charts with the imaging sensors onboard the ASV. The tracks are then sent to the COLAV, which plans a safe route for the ASV.

One of the main focuses in Autosea has been experimental validation of closed-loop COLAV. Before the interaction between the methods were tested, they have been verified independently. The first experiments were concerned with gathering raw sensor data, in order to design the sensor preprocessing and tracking system. Simultaneously, control input response data were collected to obtain a model for the experimental vessel. After the tracking system and control system had been verified, the first closed-loop tests were conducted in May 2017. Since then, both the target tracking and the COLAV system have been continuously improved and tested in full-scale experiments. Table 1.1 shows an overview of the experiments in the Autosea project and their purpose.

Table 1.1: Autosea experiment overview.

Time	Purpose
Winter 2015	Sensor data acquisition
	Model identification experiments
Fall 2016	Controller verification
Spring 2017	Tracking system verification
	Closed-loop experiments
Fall 2017	Closed-loop experiments
Fall 2018	Closed-loop experiments
Summer 2019	Final demonstration

1.3 Contributions at a glance

This thesis makes several contributions to target tracking for maritime collision avoidance. As ASVs can be small and are often equipped with low-cost sensors, the sensor performance can vary significantly, which has been a running theme for this work.

In order to track targets in a world-fixed reference frame, or to reference world-fixed features such as landmarks from nautical charts in a body-fixed reference frame, the ASV requires an accurate navigation system. However, low-cost navigation systems may have lower performance than systems for larger vessels such as supply ships. Additionally, the performance may be temporarily degraded due to the reduced availability of GNSS systems. If the estimation error covariance is provided by the navigation system, the tracking system can compensate for this error. This thesis describes two methods for this.

Although the entire tracking system is important for maritime COLAV, reliable and quick track initiation is a key component. As most collision avoidance methods does not consider the existence probability of targets, it must be decided what tracks are to be passed on to the COLAV system, i.e. what tracks should be confirmed tracks, and what tracks the decision should be deferred for. With respect to this, the contributions of this thesis is a detection-theoretic comparison of track initiation methods. In addition to the established track initiation method, a sequential probability ratio test (SPRT) with a new target density is also derived and compared with the other methods. The tests were performed in an area with spatially varying clutter, and tests were performed with and without knowledge of the clutter density.

When performing COLAV experiments with multiple targets, it was discovered that the detection probability varied significantly both over time and from target to target. It was investigated if target aspect angle could account for these variations, in which case the trackers could possibly adjust the detection probability based on the estimated aspect angle. Although aspect angle seems to contribute, the variations in detection probability likely originate from several sources. This necessitated methods for tracking with a random model for the detection probability, and this thesis contains three methods for tracking targets with varying detection probability. Two extensions of the integrated probabilistic data association (IPDA) have been derived, both based on a Markov model for the detection probability. A marginalized particle filter was derived for more general models, for example constrained Gaussian distributions. The advantage of marginalization is that the position and velocity of the target does not have to be sampled, which reduces the required number of particles dramatically compared to a particle filter that samples the whole state.

This thesis also presents applications of target tracking to full-scale maritime COLAV experiments. The contributions are both on the tracking system input, i.e. the sensor data processing pipeline, and on the output, which is the interface to the COLAV methods. In particular, the work in this thesis describes the detection, coordinate transformation, land masking and measurement clustering performed on data from a typical consumer-grade maritime radar. With respect to COLAV, it describes a method for reducing the fluctuations in the state estimates, which is useful when the COLAV method is vulnerable to e.g. noisy course estimates.

1.4 Publications

The thesis consists of 7 papers, which are listed below in chronological order:

Paper 1 (Wilthil2016) **E. F. Wilthil** and E. F. Brekke, "Compensation of Navigation Uncertainty for Target Tracking on a Moving Platform", 2016 19th International Conference on Information Fusion (FUSION), Heidelberg, 2016, pp. 1616–1621.

Paper 2 (Wilthil2017) **E. F. Wilthil**, A. L. Flåten and E.F. Brekke, "A Target Tracking System for ASV Collision Avoidance Based on the PDAF", in Sensing and Control for Autonomous Vehicles, T. I. Fossen, K. Y. Pettersen and H. Nijmeijer, Eds., Springer, 2017, pp. 269–288.

Paper 6 (Eriksen2018) B.-O. H. Eriksen, **E. F. Wilthil**, A. L. Flåten, E. F. Brekke and M. Breivik, "Radar-based Maritime Collision Avoidance using Dynamic Window", 2018 IEEE Aerospace Conference, Big Sky, 2018.

Paper 3 (Wilthil2018) **E. F. Wilthil**, E. Brekke and O. B. Asplin, "Track Initiation for Maritime Radar Tracking with and without Prior Information", 2018 21st International Conference on Information Fusion (FUSION), Cambridge, 2018.

Paper 7 (Kufoalor2019) D. K. M. Kufoalor, **E. Wilthil**, I. B. Hagen, E. F. Brekke and T.A. Johansen, "Autonomous COLREGs-Compliant Decision Making using Maritime Radar Tracking and Model Predictive Control", 2019 European Control Conference (ECC), Naples, 2019.

Paper 4 (Wilthil2019a) **E. F. Wilthil**, Y. Bar-Shalom, P. Willett and E. Brekke, "Estimation of Target Detectability for Maritime Target Tracking in the PDA Framework", 2019 22nd International Conference on Information Fusion (FUSION), Ottawa, 2019.

Paper 5 (Wilthil2019b) **E. F. Wilthil**, P. Willett, Y. Bar-Shalom and E. Brekke, "Varying Detectability in Maritime Target Tracking", Draft, 2019.

Paper 4 received second place in the Tammy L. Blair student paper award at the conference. In addition to these, three papers that are not included have been coauthored during the work with this thesis:

Paper 8 (Brekke2017) E. F. Brekke and **E. F. Wilthil**, "Suboptimal Kalman Filters for Target Tracking with Navigation Uncertainty in One Dimension", 2017 IEEE Aerospace Conference, Big Sky, 2017.

Paper 9 (Eriksen2019) B.-O. H. Eriksen, M. Breivik, **E. F. Wilthil**, A. L. Flåten and E. F. Brekke, "The Branching-Course MPC Algorithm for Maritime Collision Avoidance", Journal of Field Robotics, 2019; 36: 1222–1249.

Paper 10 (Brekke2019) E. F. Brekke, **E. F. Wilthil**, B.-O. H. Eriksen, D. K. M. Kufoalor, Ø. K. Helgesen, I.B. Hagen, M. Breivik and T. A. Johansen, "Dynamic maritime collision avoidance in theory and practice", International Conference on Maritime Autonomous Surface Ships (submitted), Trondheim, 2019

The papers may be read in chronological order[1]. However, an alternative suggestion is given in Fig. 1.2. The papers on the top gives an overview of

[1]As most practical estimators, this thesis is a causal system.

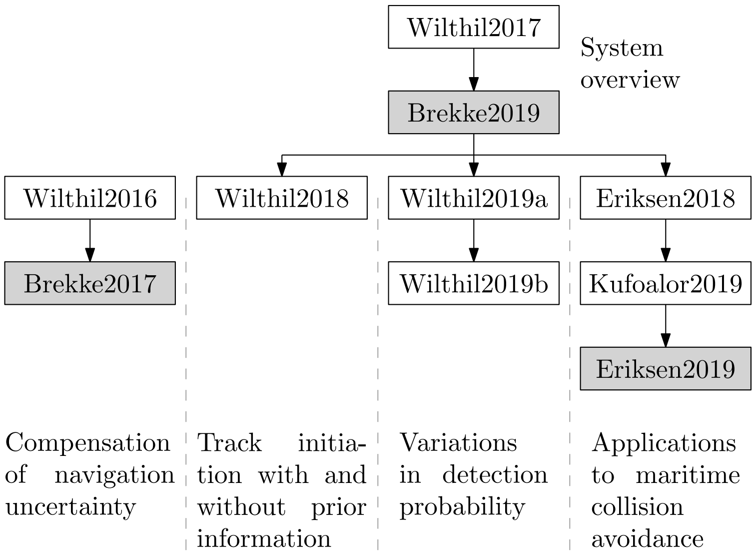

Figure 1.2: Recommended reading order for the contributions in the thesis. Gray indicate coauthored papers not included in the thesis, but are included in the figure to describe their relationship with the other papers.

the tracking system and its interface to COLAV algorithms. [74] in particular describes how the radar tracking pipeline is setup to fulfill the classical assumption of tracking methods. The tracking system has evolved since [74] was written. Some of these changes are described in [8].

The remaining papers can be divided in four categories. Three of them describes how a radar tracking system can compensate for varying sensor performance. The first is on compensating for uncertainty in the navigation sensor. As these papers does not contain experimental results, they may be read independently of the system design and radar pipeline. The second investigates the performance of track initiation methods. This is done in a detection-theoretic approach, since COLAV algorithms usually does not consider the target existence probabilities. The third addresses varying detection probability. The cause of variations in detection probability is considered, and methods for estimating the detection probability are derived. The last category is on maritime COLAV applications, and contains papers that describe how COLAV methods use the tracking system for situational awareness.

1.5 Outline

The rest of the thesis is structured as follows. Chapter 2 presents the background theory of target tracking. Chapter 3 presents the current state of the art of maritime target detection and tracking for COLAV. Chapter 4 presents the contributions of this thesis. Chapter 5 contains conclusions and suggestions for further work, and the original publications of the thesis is included in Chapter 6.

Chapter 2

Target tracking

2.1 Overview

Target tracking is the processing of measurements obtained from exteroceptive sensors in order to estimate the state of one or more moving objects. An exteroceptive sensor is a sensor that observes the environment remotely, and is therefore independent of communication links and infrastructure. In additional to filtering and state estimation, the problem of data association is a considerable hurdle in target tracking. The goal of this chapter is to provide a brief overview of the different approaches and mindsets for target tracking, and describe the most popular methods.

In general, the surveillance region of a sensor can be very large, up to thousands of square kilometers with a maritime radar. It may seem silly then, to research single-target tracking, as there are inevitably more than one target in such a large region. However, there has been an extensive research focus on single-target tracking, including the methods developed in this thesis, and we start off by defining singlet-target versus multi-target tracking.

The term single-target does not necessarily mean that the tracking system is only capable of tracking only one target in the surveillance region. Rather, the difference is that single-target methods calculate probabilities without considering the possibility that the measurement originates from other targets in the vicinity. If targets are well separated in the state space, the joint associations will be negligible. Consider the simplified examples shown in Fig. 2.1. On the left, the probability that measurement z^1 originates from target t^1 rather than target t^2 is much higher, and vice versa for measurement z^2. On the right, it is not immediately clear which target is the origin of measurement z^1. However, measurement z^2 is closer to target z^2 than target t^1, such that the most likely association is that measurement z^1 originates from target t^1, and measurement z^2 from target t^2. Missed target detections and false alarms, which is not considered in this example, complicate matters further. Missed targets and false alarms are also the primary complicating factor in single-target tracking; although there are no uncertainties in what target to assign measurements to, the absence of target-originated measurements and presence of clutter can be a major problem.

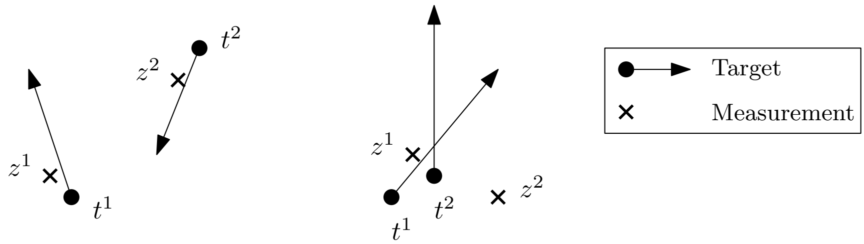

Figure 2.1: Two situations with multiple targets. The situation on the left is easily resolved, the one on the right is more ambiguous.

2.2 Sensors and sensor models

Measurements from several different sensors can be used to estimate the target state, and they may be classified as either active or passive. Active sensors sends a signal into the environment, and measures the reaction of the environment. Radar and sonar are examples of active sensors, as they transmit electromagnetic and acoustic signals, respectively, and measure the return signal strength. Passive sensors does not transmit anything, but receives signals that the environment itself transmits. Examples of passive sensors include cameras and microphones.

Regardless of the sensor type, a measurement model provides the relationship between the measurement and the target state. Such a measurement model is the fundamental requirement for state estimation, and the model depends on both the target state and the type of sensor. Many active sensors, such as radars, measure the position of the target, which may yield a linear measurement model. Other types of sensors may provide nonlinear measurements of the target state, such as e.g. the bearing angle to the target. In addition, sensors are affected by measurement noise which has to be modeled.

In addition to the measurement model, exteroceptive sensors are subject to missed detections and false alarms. This is because of the detection process in the sensor, which performs a hypothesis test on the return signal strength. If the detector declares a target present when it is not, a false alarm occurs. these measurements are also referred to as clutter. A missed detection occurs when the detector does not declare a target present when it is. Detectors are based on setting a threshold on the returned signal strength, often adaptively to avoid a large inflow of false alarms. For sensors with a large number of detection cells, the most common model for the number of clutter measurements is the Poisson model, where the expected number of clutter measurements is proportional to the sensor area/volume. This proportionality constant is

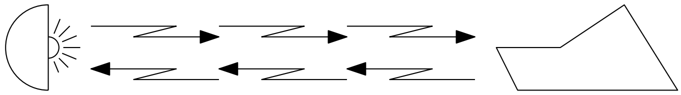

Figure 2.2: Working principle of the radar illustrated.

called the clutter density. See [57, 26] for more information on the detection process.

The most common active sensor for maritime target tracking is the radar, and it has been the primary sensor for work carried out in this thesis. The radar measures target range by measuring the round-trip time of an electromagnetic wave, illustrated in Fig. 2.2. The distance to the object can then be calculated. By restricting the beamwidth of the radar pulse in the receiver, the angle to the target can also be measured, which results in a polar position measurement of the target. Since the target state often is formulated in a Cartesian state with position and velocity, the polar measurement can be converted to a position measurement before updating the tracker [3]. The advantage of this is that the measurement model becomes linear, which simplifies the tracker design.

2.3 Target models

The most common state vector for tracking of point targets is the position and velocity of the target in a Cartesian reference frame, e.g. north and east coordinates. Although exteroceptive sensors measure the target in body-frame coordinates, the target motion model is best formulated in a world-fixed frame. It is possible to represent the target state in relative coordinates as well, but in this case the movements of the ownship enters the target state equations.

The simplest, and most common, target model is the nearly constant velocity (NCV) model. As the name implies, it models the velocity as a constant term plus a small increment given by a white noise term. Although true target maneuvers are not random, it is assumed that they can be described by the randomness of the velocity increment. The main advantage of this model is the simplicity, as the only parameter needed in addition to the sensor sample time is the covariance of the velocity increment. A large value will increase the space of possible target maneuvers, which means the tracking system is able to capture accelerations, stops and turns. However, this will lead to larger uncertainties in steady-state course and velocity estimates when the target is not maneuvering. The model is not suited for long-term prediction, as the covariance of the state will grow rapidly and unbounded. When predicting on a longer term, it is desirable to have a model that is at least bounded in the velocity uncertainty, and a tendency to keep the current speed and course.

Variants of the Ornstein-Uhlenbeck process [12] introduces feedback from a nominal position or velocity, and is better suited for long-term prediction [47]. Although this family of models may represent target motion better for maritime targets, they have more parameters than the NCV model, which must be estimated. Additionally, for short time intervals, the difference with the NCV model is negligible. If historic data of target motion in the surveillance data, such as historic AIS data, is available, this may also be used to perform long-term prediction [32, 13].

In addition to the position and velocity, it may also be desirable to estimate the turn rate of the targets. The coordinates of the targets become coupled [39], which may lead to more accurate state estimates. The turn rate is usually modeled as a first-order process, requiring an additional covariance parameter. Estimating target turn rate is covered in [3, 23].

Realistically, a target may change between models as it moves in the surveillance area. For example, ships mostly have a constant course and speed, but may maneuver when it closes in on its destination or to avoid collision. The preferred way of handling multiple models for a single target is the interacting multiple model (IMM) approach. The probability of being in each model based on the measurements is calculated, and the model states are weighted based on the probabilities to provide a total estimate of the target state.

Although this chapter encompasses the most commonly used model for maritime target tracking, several other models may also have their use. See the survey [39] for an overview.

2.4 Data association

As previously mentioned, the biggest challenge in target tracking is data association. The measurements from exteroceptive sensors are unlabeled, and the process of assigning measurements to clutter, existing targets or new targets must be done by a data association method. There is a vast literature on the subject, and it would be overly ambitious to cover them all. Note also that there may be methods that does not necessarily fit into the categories below.

Tracking methods may be categorized as single- or multi-scan methods. A single-scan method will associate the most recent measurements to targets, and the association will not be changed at a later stage. The advantage of this is simplicity, as once association probabilities has been calculated, there

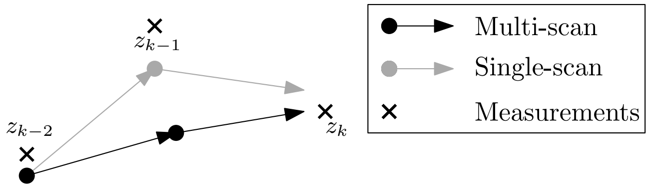

Figure 2.3: Both data association methods assign z_{k-1} to the target at t_{k-1}, but only a multi-scan method would reassign it as clutter at time t_k.

is no need to recalculate them at later scans. The advantage of a multi-scan method is that it has the opportunity to discard measurements that previously looked like a good choice. This is illustrated in Fig. 2.3. The measurement z_{k-1} is a clutter measurement, and causes a large state estimation error when it is associated to the target at time $k-1$. When the measurement z_k is associated to the target, a multi-scan method is able to infer that the target was undetected at time k, changing the association of z_{k-1} from the target to clutter.

Considerations like these can also apply to multi-target situations, where the possibility to reassociate measurements to different targets at later time scans can be invaluable. However, these methods naturally lead to a rapidly expanding tree structure of association hypotheses. The size of this hypothesis tree must be managed by merging similar hypotheses, or pruning the least likely hypotheses. However, care must be taken to still preserve the hypothesis diversity. An important parameter in such situations is the tree depth, which defines the number of scans the method can reassign the measurement.

Methods may be either classified as hard or soft. Hard methods will associate measurements without any uncertainty. Soft methods will not assign a measurement directly to a target, but calculates an association probability for each measurement-to-target match. Although the definition for single- and multi-scan methods differs from soft and hard association, they are often related. To increase the resilience against missed detections and clutter, a data association method typically needs to either hedge on several measurements as soft methods, or reassign measurements to the target at later times as multi-scan methods. Historically, these combinations (single-scan with soft association and multi-scan with hard association) have been the most common approaches to target tracking.

More recently, finite set statistics (FISST) has been introduced as an approach to treat both targets and measurements as random finite sets (RFSs) [45]. In principle, this expresses the prediction and update steps as a single set-valued prediction and update equation, respectively. However, this Bayes-optimal multitarget filter has no practical uses due to computational

Figure 2.4: Although some of the targets are close to each other, two clusters can be formed and data association is done independently.

complexity [43], and suitable approximations must be made. Many consider FISST incompatible with the classical multi-target tracking approaches, but it has been shown in [5] that the Possion multi-Bernoulli mixture (PMBM) filter, which is based on RFS theory, generalizes the classical multiple hypothesis tracker (MHT).

Validation gates are also commonly used to reduce the number of measurements that are assigned to the track. A gate is setup around the position of existing targets based on the covariance of the measurement innovation. Any measurements inside the validation gate is associated to the track, and measurements outside this gate is allowed to be associated with other tracks, or form new tracks. The measurements inside the gate are not necessarily assigned to the tested track only, as the main goal of gating is to reduce the number of measurements that may be target-originated, before more computationally demanding methods are used to e.g. calculate association probabilities. This coarse sorting can be used inside in multi-target trackers as well, in order to group tracks into clusters that can be tracked independently, as shown in Fig. 2.4.

2.5 Track initiation

Track initiation is the process of associating measurements to a new target in the surveillance region. Many tracking methods assume that tracks are established on targets in the surveillance region, or track initiation may be implicit in the tracking method. In either case, the track initiation need a new target model, i.e. a description of how likely undetected targets are in the surveillance region. The most common model for this is to assume that the number of new targets in the surveillance region has a Poisson distribution, with the expected number of new targets proportional to the surveillance area volume. This mirrors the number of clutter measurements in the surveillance region as previously described, and the density is called the new target density.

Methods that only consider the possibility of a single target in the validation gate may use a Markov chain for modelling new targets, with a specified transition probability from the no-target state to the target-present state.

There are two main ways to view track initiation. The first is as a detection process, where the goal is to declare whether a sequence of measurements originate from a previously undiscovered target or not. The second is an estimation process, where the goal is to calculate the probability of a sequence of measurements originating from a target or not. This mirrors the hard and soft data association methods from the previous section. Note that the detection process can be added to the estimation process by setting a threshold on the estimated existence probability, and confirm targets that exceed this value.

2.6 Filtering and track extraction

After measurements have been assigned to the target, filtering methods are applied to obtain the state estimate. If the linear models previously discussed applies, and the measurement noise has a Gaussian distribution, the Kalman filter (KF) [34] is the workhorse of the estimation problem. Hard methods will have at most one measurement associated to the track, and the KF can be applied directly to update the state estimate of the track. If no measurement is associated to the track, the filter simply does not perform an update step. If the target or measurement model is nonlinear, a nonlinear estimator must be used. The extended Kalman filter (EKF) [3] is the most common, but particle filters [58, 29] can also be used if the nonlinearities are severe.

Soft methods may have more measurements associated to each track, and the resulting state estimate is typically a weighted sum based on the estimates depending on each of the measurements. The same applies to multi-scan methods, as the different sequences of associated measurements have a different state estimate. In this case, track extraction is needed to obtain the total target state estimate. This may be the maximum a posteriori (MAP) estimate, or moment-matching may be used to calculate the minimum mean square error (MMSE) estimate, also known as expected a posteriori estimate.

2.7 Common tracking algorithms

Some popular tracking methods are summarized in Table 2.1, and a brief description follows.

The simplest tracking method that could possibly be derived is the nearest-neighbor standard filter (NNSF) [3]. As the name implies, it performs data

Table 2.1: Overview of common target tracking methods.

Method	Targets	Scans	Association	Existence probability
NN	Single	Single	Hard	No
PDA	Single	Single	Soft	No
IPDA	Single	Single	Soft	Yes
TSF	Single	Multiple	Hard	No
GNN	Multiple	Single	Hard	No
JPDA	Multiple	Single	Soft	No
JIPDA	Multiple	Single	Soft	Yes
TO-MHT	Multiple	Multiple	Hard	No
HO-MHT	Multiple	Multiple	Hard	Yes
PHD	Multiple	Single	Soft	Yes
PMBM	Multiple	Multiple	Soft	Yes

association by selecting the closest measurement to the estimated target position, and uses a standard KF to estimate the target state. As it does not consider the possibility of an undetected target, it is very susceptible to track loss. This makes it only somewhat suitable for applications with very high signal-to-noise ratio (SNR).

The probabilistic data association filter (PDAF), a single-target, single-scan soft tracking method, was developed in the early 1970's [2] and is to this day a very common tracking method in use in practical systems. Contrary to the NNSF, the PDAF is an "all-neighbor" filter, and calculate the association probability for each of the measurements in the validation gate, as well as the probability that no measurement is target-originated. Additionally, it assumes that the posterior estimate of the state can be represented by a single Gaussian, which makes the computational burden only slightly higher than a KF, and the hedging on all the measurements in the validation gate greatly improves the robustness of the PDAF compared to the NNSF.

An extension of the PDAF to also calculate the existence probability of the target is presented in [49], called the IPDA. This means it can be used as a measure of track quality, which in turn means it can be used to confirm or terminate tracks automatically.

Another approach to improve the mediocre performance of the NNSF is to split the track and estimate the state with each measurement in the validation gate independently of each other. This is called the track split filter (TSF). If the track is split at consecutive timesteps, the resulting structure is a tree. The likelihood of each sequence of measurements can be calculated, and sequences with a low likelihood can be removed from the structure to keep the computational complexity manageable.

The thought process of the NNSF can be extended to multiple targets, and we applied it to the scenario in Fig. 2.1 as an example of single-target versus multi-target methods. This is the global nearest neighbor (GNN) tracker, which finds the optimal solution to a 2D assignment problem based on e.g. distance, and update the track estimates by applying the selected measurements with a KF. As with the NNSF, it is simple to implement but susceptible to track loss.

If the validation gate of two or more targets overlap, the PDAF will calculate the association probabilities of the measurements in common without considering the presence of another target. This results in a higher association probability for the measurements in common, increasing the risk of track coalescence. This can be remedied by using a bona fide multi-target tracker. The joint probabilistic data association filter (JPDA) [24] is the multi-target version of the PDAF, and calculates the joint association probabilities of the measurements. However, since the JPDA is still a single-scan method, the target-originated measurement associations are not reevaluated for later scans, and track coalescence can still be an issue [4]. Similarly to the IPDA, the joint integrated probabilistic data association filter (JIPDA) [48] calculates the existence probability based on the joint association probabilities.

Instead of calculating the state estimate based on the joint associations as in the JPDA, it is possible to explicitly associate the measurements to existing targets and clutter, and calculate the likelihood of this hypothesis. These hypotheses can then be stored, and the most probable hypotheses can be expanded on as new measurements arrive. The result is the MHT [56], which traditionally has been considered the gold standard of multi-target tracking.

There are several ways to structure the hypotheses of an MHT. The hypothesis-oriented MHT (HO-MHT) maintains a number of global hypotheses. The track-oriented MHT (TO-MHT) maintains the hypotheses as a track tree for each target. Global hypotheses are found from solving a multidimensional assignment (MDA) problem, often by means of integer linear programming (ILP) [65]. Regardless of the hypothesis structure, the number of hypotheses will increase exponentially as new sets of measurements are used to expand the hypotheses, which makes computational complexity a significant hurdle in practical implementations of the MHT. Pruning, both with validation gates and removing the least likely hypotheses are a common technique. Merging similar hypotheses would also reduce the tree size, but is nontrivial and still an active research topic [1, 70].

The probability hypothesis density (PHD) filter is the most common solution to approximate the FISST-based multitarget Bayes filter [43]. It only propagates the first-order moment, similar to the constant-gain KF. It has gained significant popularity, but suffers from cardinality issues. This was later improved by the cardinalized PHD (CPHD) filter [44]. It was shown in in [69] that the output of the multitarget Bayes filter can be factored into a Poisson and a multi-Bernoulli component, which leads to hypotheses similar to the MHT.

The most popular track initiation methods for tracking methods that does not calculate the track existence probabilities are the logic-based M/N method [3] and the SPRT [64]. The M/N method is the simplest, and only counts the number of scans the validation gate of the target contains measurements. If the number is greater or equal to M after N scans, a target is declared present. The SPRT branches out like the MHT, and declares a target present when the likelihood ratio (LR) of the target-present versus clutter-only hypothesis is larger than a selected threshold. The threshold can be set according to the desired probabilities of obtaining a true or false track.

Once again, this is just a brief overview of the methods. For further reading, see [3, 46, 65, 10, 55].

Chapter 3

Maritime situational awareness

3.1 Exteroceptive sensors

Today, there are several aids available to navigators. Radars, mentioned in Section 2.2, were introduced on ships shortly after their invention during the second world war, and have been a key component of maritime situational awareness ever since. Ships of 300 gross tonnage or above, and passenger ships irrespective of size are required by the international convention for the safety of life at sea (SOLAS) to have a radar mounted[1].

Many radars comes with an automatic radar plotting aid (ARPA) system that automatically estimate the position and velocity of targets in range. However, many of these are so-called minimal ARPA, which means that the user has to select, i.e. initiate, the targets of interest on the track display. For the true ARPA with built-in track initiation capabilities, the output is often restricted to the track itself, which prevents measurement-level fusion of sensor data. It is possible to fuse the tracks from a tracker, and measurements from another sensor with the information decorrelation approach [11]. Additionally, the ARPA systems often provides only the position and possibly velocity of the objects, not the covariance of the estimate. To the authors best knowledge, algorithms for track fusion require the covariance of the state estimate as well.

AIS transponders are also frequently used. It broadcasts the state of the vessel based on the onboard positioning system over a standard very high frequency (VHF) transmitter, possibly along with information such as vessel size and voyage details. This is also mandatory under SOLAS for the same vessels that are required to have a radar. Since the transmitted state is based on the navigation system of the target, often the GNSS-indicated position as detailed in Section 3.2, the expected accuracy of a fully working system is very high. However, the system is based on several links, all of which can deteriorate or cut off the availability of the service. First, GNSS may be faulty. Although there is a very low probability that the satellites themselves or the ground station stops working, the receiver onboard the ship may be out of order. Second, the AIS transmitter may be off, either due to malice or negligence. Third, the transmit rate of the AIS is very variable, and extrapolating old data can be disastrous if the target has maneuvered since the last message was received. Depending on AIS as the only tool for situational awareness is therefore not recommended [30]. Although this thesis focuses on ASVs, radars and AIS are the main sensors for maritime situational awareness for

[1]The SOLAS also allows for any other "means to determine and display the range and bearing of radar transponders and of other surface craft, obstructions, buoys, shorelines and navigational marks to assist in navigation and in collision avoidance". Applying the duck test, radars can be expected to be found on most ships.

human mariners as well.

In addition to the radar and AIS, cameras are often used on ASVs [15]. Cameras are in particular useful for classification of objects, but depends on the natural lightning of the environment, unless using infrared cameras. Cameras only measure the bearing of the target, and the range is also needed to fully resolve the target position. This means georeferencing, stereo vision or other sensors must be used to obtain the full position of the target. Detections in the image frame are typically extracted using deep learning methods, such as the single shot detector [41].

Although cameras and radars are both exteroceptive sensors, they have some nice complementary properties which justifies the use of both on ASVs. Radars have a long range that allows for early detection of an object, and the feature-rich camera images can give great details at short range. Additionally, classification is important to comply with the international regulations for preventing collisions at sea (COLREGs). It is primarily the range that makes radar the backbone for maritime situational awareness, whereas cameras can play a larger role when the required range are shorter, for example in autonomous cars [63].

3.2 Navigation systems

In order to utilize both a radar and the AIS system, the tracking system will depend on a good navigation system to transform data from one of the systems into another. Depending on the audience the term “navigation” has two meanings. One is the task, of directing a vessel from one place to another. Thus, it includes planning and maneuvering, in addition to the situational awareness presented in this chapter. This is the meaning used by mariners. In this thesis, however, navigation is defined as the process of determining the state of a ship, i.e. the position, velocity and attitude. This is the definition often used by researchers on state estimation.

The sensor package of maritime navigation systems are often comprised of an inertial measurement unit (IMU) and a GNSS receiver with at least two antennas. Their popularity can be attributed to their complementary properties. IMUs measure the acceleration and angular rate of the object they are fastened to. They have a high update rate, and the measurements can be integrated to obtain the attitude, velocity and position of the ASV without external references. However, measurement errors leads to an unbounded estimation error. By integrating the GNSS signals, which provides measurements of the target position in a world-fixed reference frame, the state estimates are corrected and the measurement error sources, such as the

IMU bias, may be estimated. Error state EKFs [28] or nonlinear observers [27] are the most common methods used to fuse IMU and GNSS measurements.

The general assumption in this thesis is that the ASV is equipped with a navigation system, that may or may not have a significant uncertainty associated with it.

3.3 Collision avoidance

As described in Section 1.2, the motivation behind the work of this thesis has been target tracking for maritime COLAV. The goal of this section is not to provide a comprehensive review of COLAV, but rather to give insight into the requirements and desired properties of these methods with respect to the target state estimates, and then give an overview of recent advances in sensor-based COLAV. For more thorough references on maritime COLAV, see [17, 61, 59].

Very few algorithms will cover the entire scope of ASV path planning from port-to-port travel to emergency maneuvers. One way of separating the responsibility is to divide the planning hierarchy into several layers based on the time horizon. An example of this strategy is covered in [18], where a three-layer architecture is used. The top layer is a path planner, which only considers static obstacles, i.e. maps, and possibly long-term information such as weather forecasts. The middle layer attempts to follow the path from the path planner, but also considers the COLREGs, and aims to avoid collisions in a controlled and predictable manner. The bottom layer performs safety maneuvers for when the top two layers fail, e.g. if a target fails to follow COLREGs. We will consider this form of layer structure in the following. Note that other architectures may also be used, and examples are given in e.g. [42, 9, 60]. However, the methods discussed below will fit into most architectures. Additionally, the importance of a good tracking system based on exteroceptive sensors are increasingly important as the time horizon is reduced, regardless of the chosen architecture.

Optimization-based methods, such as model predictive control (MPC), may be used for all layers in the described architecture. The flexibility of MPC lies in the objective function, which can take a large number of variables into account. For long prediction horizons, the optimization problem typically takes static information, such as nautical charts, and possibly slowly-varying information, such as weather forecast, into account. The resulting path can be optimized for e.g. the fuel and crew costs under the constraint of reaching the goal port within a certain timeframe.

For the middle layer of the architecture, typical information is data from

AIS and radar, and the prediction is usually done by assuming that targets in the vicinity will comply with the COLREGs, and possibly includes long-term prediction methods as previously discussed in Section 2.3. These methods usually ensures the ASVs maneuvers will comply with COLREGs, and can be considered normal behavior at sea. Optimization-based methods can be applied in this layer as well, see [21] for an example.

Several short-term methods have been developed to handle immediate collision risk, e.g. when other vessels do not comply with the COLREGs. Because of this, they are typically fast and takes limited input, usually in the form of position and velocity of targets in the immediate vicinity. A typical property of these methods are that they are local, i.e. finds a collision-free path in the near vicinity of the ASV without verifying that the path leads to the destination. This is typically mitigated by the above layers, which can replan after avoiding collision.

The velocity obstacles (VO) method [22] is a very popular short-term method, which can be attributed to its experimental validation in [37]. It calculates the set of admissible velocities that guarantees avoidance of all the targets, given that they keep their current speed and course. Another example of a short-term COLAV method is the dynamic window (DW) algorithm [25]. The advantage of this is that it considers the dynamics of the ASV, such that the desired yaw rate and velocity are achievable. It has also been adapted for nonholomic vehicles [16]. It is also possible to design control laws that will ensure the target always have a safe distance to the obstacle, see [67].

Common for these methods is that they require the speed and course of the targets to predict the future trajectories. If these are estimated in a tracking system, the performance may decrease significantly. For example, if the chosen velocity vector in the VO is always chosen such that it lies on the edge of the set of admissible velocities, changes in the target course will lead to constant changes in the reference velocity of the ASV. The branching-course MPC (BC-MPC) algorithm [19] developed in the Autosea project seeks to mitigate these effects. It uses a discrete input space, and use hysteresis to favor the chosen control input at later timesteps. This results in maneuvers that clearly shows the intent of the ASV, and maneuvers that are robust to noise in the target estimates.

Chapter 4

Contributions

4.1 Research objectives

The material covered so far in the thesis is an overview of target tracking and situational awareness. In this chapter, the specific research goals of the thesis will be presented. Many of the goals were set based on results from experimental work.

The first research question was "what is the impact of navigation uncertainty on target tracking?". The reason for this was that it was, at the time, not sure what navigation system would be used, and a low-cost navigation system could have a significant impact on target tracking.

The sensor package was determined to be a Navico Simrad 4G radar, shown in Fig. 4.1, and a Kongsberg Seapath 330+, shown in Fig. 4.2. Additionally, an AIS receiver was used to get the true target states. Data acquisition tests were conducted in 2015 and 2016, and based on the data from these tests, the following research question was proposed: "what is the simplest tracking system that can be used for closed-loop collision avoidance?". The notion that it should be as simple as possible, but not simpler[1] is important. Although a simple system is desirable in order to proceed with closed-loop experiments, the insight gained and improvements made should be applicable to more advanced trackers. Due to this, the choice fell on the PDAF with the M/N method for track initiation.

Even with conservative tuning, the M/N-method confirmed a lot of false tracks. The research focus shifted to track initiation, and several methods were compared. In addition to comparing the methods with respect to their true track confirmation and false track rates, the goal was also to compare the methods with and without clutter and new target densities, which are

[1] by the words of Prof. Yaakov Bar-Shalom, quoting Einstein.

Figure 4.1: The Navico Simrad 4G radar, with and without the dome.

Figure 4.2: The Seapath 330+ navigation system, which consists of a processing unit, an interface unit and an IMU, in addition to cabling and GNSS antennas not shown in the photo.

seldom known in practical tracking systems.

Track loss due to e.g. reduced detection probability can lead to dangerous situations, and the research focus shifted to track maintenance, as this issue emerged in experimental data. The temporal detection probability could vary greatly from target to target, and the goal was to determine if the cause could be identified and develop tracking methods that could estimate the detection probability.

For an ASV running in the real world, multiple sensors in addition to radar are necessary for both detection and tracking of all the potential targets along the planned route, as well as for redundancy in case of sensor failure. Tracking with AIS, cameras and lidar data, as well as multi-sensor fusion, have been covered by other work within the Autosea project; see e.g. [40, 62, 31, 13, 51, 52].

4.2 Tracking with navigation uncertainty

One of the earliest hypotheses of the Autosea project was that target tracking from a moving platform instead of a fixed sensor location could have a significant impact on the state estimates. When both the ownship and stationary landmark states need to be estimated, simultaneous localization and mapping (SLAM) [14] is the most widespread solution. This is viable in an urban environment, where there are many stationary landmarks such as buildings and signs. Out at sea, there is a lower amount of stationary landmarks. There have been some research on including moving targets in the SLAM-based solution [66, 38]. Such a system would also be able to integrate navigation sensors such as an IMU and a GNSS receiver. However, there are two main objections against using a SLAM-based solution as a joint tracking and navigation module.

First, such a tight coupling between the navigation system and the tracking system means that the measurements from the navigation sensors must be integrated with the exteroceptive sensors in the SLAM module. A looser coupling facilitates the use of existing methods and technology for navigation systems.

Second, implementing a full SLAM solution means that the ownship state would be affected by the measurements from exteroceptive sensors. This makes the ownship state estimation vulnerable to faulty data association. This is of course also the case for other SLAM implementations [50]. In GNSS-denied environments, like indoor and underwater, this may be the only solution. However, out at open sea, GNSS are often available. Additionally, due to the low amount of stationary landmarks, the ownship state estimate would rely heavily on moving targets, which has the additional uncertainty of the motion model. The ideal solution for an ASV would be to account for the uncertainty in the navigation system, without letting the target estimates affect the navigation solution.

For these reasons, two methods for compensating for navigation uncertainty in the tracking system were derived in [72]. The first method uses the covariance from the navigation system to increase the measurement covariance, without maintaining correlations between the navigation and the tracking state. By linearizing the measurement equation, an expression very similar to the standard polar-to-Cartesian conversion of measurements [3] was obtained, where e.g. the heading error covariance was accounted for in the same way as radar bearing measurement covariance. The second method, a Schmidt-Kalman filter, maintains correlations between the navigation system error and the target state vector in order to more precisely account for the navigation error. This resulted in a more consistent filter, which is an important property of tracking systems.

In [7], several more variants were tested on a one-dimensional system, including body-parametrized filters. The body-parametrized filters had the best performance measured by the error in the relative distance between the target and the ownship, which is important for collision avoidance. However, the world-fixed Schmidt-Kalman filter had the best consistency results, as in [72]. This resulted in better tracking results when data association was introduced.

4.3 Tracking system overview and sensor processing pipeline

The next contributions of the thesis are on radar data preprocessing, described in [74]. The Simrad radar outputs raw data continuously on a spoke level. A spoke consists of all the detections from a single azimuth angle. There are 1024 detections cells per spoke, and the radar outputs 2048 spokes per revolution. At short range, this makes even small targets occupy hundreds of resolution cells, violating the “one measurement per target” assumption. The data is received in a body-fixed coordinate frame and in order to use nautical charts to mask out large pieces of land, they are transformed into a earth-fixed Cartesian reference frame. This is done using the Seapath navigation system. Then, the detections were clustered together to obtain one measurement per target. Additionally, the PDAF was implemented, and the process and measurement noise covariance matrices were found from experimental data. Because of this, [74] also describes the first iteration of the tracking system that could be used for closed-loop experiments.

Since [74] was written in the fall of 2016, the tracking system have been continuously improved for each round of experiments. Some of these changes have been detailed in [8], and the most important changes to the sensor pipeline and tracking architecture are summarized as follows.

To close the loop between target tracking and collision avoidance, it was necessary to design an interface that could provide tracks to the collision avoidance methods. Although the tracking methods only require the most recent estimates, it may be necessary to keep track of older estimates as well. Also, one of the goals for the Autosea project was that several collision avoidance methods should be able to use the tracking system for situational awareness. This necessitates a flexible tracking interface. The chosen design consist of both a robot operating system (ROS) service, and a network interface.

A service is ROS’ implementation of a request/response model. The tracking system organizes the estimates from the PDAF into tracks, i.e. sequences of estimates belonging to the same target. The collision avoidance requests estimates of targets at given timestamps. The tracks are then interpolated to the requested timestamps and sent in response. This ensures interpolation and prediction is contained in the tracking system. Thus, collision avoidance methods that are implemented in ROS should use this service as it provides up-to-date estimates at the requested times. Collision avoidance methods that are not implemented in ROS may receive obstacle estimates by connecting to the TCP network service, which sends target estimates on a specified rate.

In [74], a Cartesian measurement model was used. This worked well at close range, but when the target range exceeded approximately 1km the effects of the high beamwidth of the radar became more prominent, and it was found that a polar measurement model was needed. The values of these covariance parameters was estimated using data from targets with a high-rate AIS. Additionally, a radar angle offset was also calculated, as the radar is not necessarily mounted with the zero angle aligned with the navigation system reference frame.

4.4 Track initiation with and without prior information

The biggest issue with the tracking system described in [74] was the amount of false tracks, in particular near land. Much of this can be attributed to the logic-based M/N track initiation method, which does not take into account that the measurements in the validation gate may be clutter. It was speculated that other track initiation methods would perform better than the M/N-method, and this hypothesis was investigated in [73]. In addition to the established IPDA [49] and SPRT [64] methods, a Bayesian SPRT were derived. It is very similar to the SPRT of [64], but takes the new target density into account, if known. This leads to an initial likelihood ratio that is independent of the initial size of the validation gate. A lower new target density means the method has a lower initial likelihood ratio, which is reflected in a lower false track confirmation probability. In addition to the new target density, the impact of known clutter density were investigated as well, as this is an additional parameter that is seldom known in real applications. The clutter density was nonuniform, to mimic the challenges seen in the real data. Unknown clutter density reduced the performance of all the methods, but to a lesser extent for the IPDA.

To the knowledge of the author, this is currently the only comprehensive analysis of IPDA and SPRT for track initiation in terms of standard measures for detector performance. The results show that all the methods can be tuned to have a high probability of detecting the target. However, the IPDA and SPRTs outperformed the M/N method significantly with respect to false tracks. For example, to obtain a 99% target detection probability, the M/N method has a false track probability of 7%, meaning that approximately one out of fourteen tentative tracks will be confirmed even though no target-originated measurements are present in the data. The other methods are able to obtain false track probabilities in the range of 10^{-4} or less and still detect the target more than 99% of the time. The IPDA performed very well with respect to both target detection and false track probabilities, despite being a single-scan instead of a multi-scan method. It seems the largest benefit of using an SPRT is reduced track initiation time, at least for the conditions presented in [73].

4.5 Estimation of detection probability

As the nonparametric IPDA was a significant improvement over the M/N-method, it was selected for the next round of closed-loop COLAV experiments. These experiments, conducted in September 2018, involved several targets. Both the ocean space drone (OSD) of Kongsberg Seatex and Mukholmen II of Trondheim harbor, shown in Fig. 4.3, were involved as targets. The targets had a considerable difference in the observed detection probability, with the OSD being significantly less detectable than Munkholmen II. Investigations started to see if the difference could be accounted for by considering the target state, such as the aspect angle, which was considered in [71]. The varying detection probability can in part be explained by the aspect angle to the target. However, the impact of the aspect angle varies from target to target, and it is suspected that there are other factors that contribute to the variations as well, e.g. the range to the target.

Instead of having a state- or measurement-dependent detection probability, it was modeled as a random process with a finite number of known detection probabilities. Two methods were developed for estimating it in [71]. The first uses a hidden Markov model (HMM) to estimate the detection probability given the presence of a target, and this detection probability is then used in a regular IPDA to estimate the existence probability. This means the tracking method is unchanged with the exception of a parameter update, which may be a constraint in some systems. The second method jointly calculates the existence and detection probability, and provides a generalization of the IPDA equations.

The empirical detection probability as observed from the September 2018

Figure 4.3: The Kongsberg OSD (left) and Munkholmen II of Trondheim harbor (right).

experiments in [71] seems to follow a continuous model instead of having discrete values. A remedy to this is derived in [75], namely a marginalized particle filter (MPF). Particle filters have previously been used for estimating the target detection probability [53], but they require a lot of particles in order to represent the full state estimate. Instead, a MPF employ a computationally tractable solution to parts of the state, and sample the remaining variables. In this case, the position and velocity of the target can be estimated by the PDAF, which means only the detection probability needs to be sampled. Initial simulation results indicate that the MPF performs similarly to the IPDA of [71] with the discrete detection probability model using as few as 50 particles. As the PDAF is used for the kinematic state estimate, the kinematic tracking results are similar even with as low as 5 particles. With a continuous detection probability model, the MPF outperforms the IPDA.

Other approaches for handling varying detection probability can be found in the literature. In [68], the detection threshold is adjusted based on the measurement innovation. This means the detection threshold will be lower for radar reflections close to the predicted position of targets. This allows weaker signals to pass through the radar detector, and can mitigate effects that would cause lower detection probabilities with a constant gain detector. In [54], the aspect angle is used to adjust the SNR of the targets, which yields similar results. Both of these approaches assumes that the lower-level functionality in the radar, i.e. adjusting the detection threshold or knowledge of the SNR value, which is not possible with the Simrad radar.

4.6 Applications to maritime collision avoidance

The first closed-loop application of the tracking system with maritime collision avoidance is reported in [20]. These tests were conducted in May 2017, and the tracking system was nearly the same as the one reported in [74]. The main difference, as explained in [20], is the addition of a retrodiction method to improve the state estimates of the target. It had been found from previously recorded datasets that the course estimates of targets varied considerably. The retrodiction procedure smoothes the output of the tracking system by not only using the latest state estimate, but also the previous state estimates by assuming a constant velocity over the last timesteps. This is only applied to the state estimates that are sent to the collision avoidance system, and the tracking system still uses a NCV model, in order to prevent track loss.

The IPDA were tested in closed-loop experiments during autumn 2017 and 2018. The first published paper that shows the IPDA-based tracking system with collision avoidance is [35]. It also reports on the results using the improved measurement noise model, as reported in Section 4.3. This collision avoidance approach is based on [33].

In addition to the two methods described which is included in the thesis, the tracking system has also been tested with the BC-MPC [19] and the dynamic reciprocal velocity obstacles (DRVO) method [36].

Chapter 5

Conclusions and further work

5.1 Conclusion

This thesis presents a target tracking system for maritime COLAV. The tracking system, based on the PDAF, is modified in several ways to account for the varying performance associated with low-cost sensors. The performance of filtering, track initiation and track maintenance are all improved. The methods are validated both in simulations and full-scale COLAV experiments.

The tracking system may have to compensate for the uncertainty in the navigation system. The estimated covariance with an uncompensated tracker will be lower than with one that accounts for the navigation uncertainties, which can lead to over-optimistic results. This impacts the target tracking not only in the estimated covariance in the tracking estimates, but also in data association where e.g. the validation gates may be too small. Two methods for compensating for navigation uncertainty were developed in [72]. A desirable property was that the navigation uncertainty should affect the tracking estimates, but not the other way around as in e.g. SLAM. Results show that maintaining correlations between the target state and the navigation results can be important for consistency in the tracking estimates.

Track initiation methods were tested in [73], which includes the M/N-method, the IPDA and SPRTs with both known and unknown new target density. As most COLAV systems do not use the probabilistic estimate of target existence in their evaluation of different candidate maneuvers, target existence must be determined as a detection process. Because of this, the methods were tested by comparing the true track confirmation rate to the false track confirmation rate, using different thresholds for track confirmation. The resulting performance shows that the M/N-based method is greatly outperformed by the other methods. The impact of unknown clutter density was also investigated. Generally, nonparametric methods set the clutter density based on the number of measurements in the validation gate. The IPDA in particular was able to maintain a low probability of false alarms, even without knowledge of the clutter density. The advantage of using the SPRT is lower track initiation time than the other methods. Overall, the IPDA performed very well compared to the SPRTs, even though the computational cost is significantly lower.

Varying detection probability was considered in [71], and methods for estimating the target existence and detectability mode probabilities were derived. One of the methods was based on the IPDA, with a Markov chain for the joint existence and detectability mode. The closed-form expressions are of a general nature similar to the Markov chain 2 IPDA. Although allowing reduced detectability leads to longer false track termination time, the trackers that compensate for varying detection probability are able to maintain tracks on targets that have sudden changes in the detectability. For detection probability variations that does not follow a known Markov model, a marginalized particle filter was derived in [75]. Instead of sampling the entire state vector as in a regular particle filter, only the detection probability is sampled, and each particle estimate the position and velocity of the target with a PDAF.

Although there are several research results on maritime COLAV with exteroceptive sensors reported in the litterature, few has detailed the interactions between target tracking and COLAV as extensively as the Autosea project. In particular, the radar pipeline is extensively described in [74], which also describes how the process and measurement noise covariances can be estimated. In [20], the impact of varying course estimates on the COLAV is described. Varying course estimates can lead to frequent changes in the planned trajectory, and the ASV will not be able to complete a maneuver. The impact of lost tracks is described in [35], where tracks persisted in the cost function of the MPC some time after termination. By scaling the weight of the terminated track by the time since the last detection, tracks from the tracking system still had priority over the predicted position of terminated tracks.

5.2 Further work

As in any research project, there are open questions and room for improvements on the results of this thesis. In the following, some research topics are suggested, ranging from direct extensions to broader suggestions.

The filtering methods for target tracking with navigation uncertainty developed in [72] have not been tested with data association. Results from [7] indicate that body-parametrized tracking filters performs better with respect to relative error, and the Schmidt-Kalman filter is better with respect to consistency in a one-dimensional tracking scenario. It remains to be seen if this is the case for ASVs as well, when attitude uncertainties are present.

The performance of the track initiation methods in [73] are evaluated in simulations. It remains to be seen if theoretic limits on the success rates can be found, similar to the ones found in [6]. Both SPRTs investigated in [73] had a larger performance decrease from the parametric to the nonparametric methods compared to the IPDA. This may indicate that there are room for improvements on nonparametric tracking and clutter estimation for multi-scan methods. Clutter maps have previously been used to estimate the clutter density in a IPDA framework. These methods could in principle be applied with hard association methods as well, such as the SPRT and MHT. However, this leads to a clutter map for every association hypothesis, which is an additional computational burden. Research on clutter maps for multi-scan association methods is therefore, to the author's knowledge, still an open research area.

As this PhD, and the Autosea project, is wrapping up, several research projects on ASVs are starting. The Autoferry project[1] will develop new concepts and methods for autonomous ferries. The Autosit project aims to develop methods for increased situational awareness based on machine learning, fusion of radar and AIS data, and pose estimation using cameras. It is the author's hope that these projects can benefit from the results and experience of this PhD thesis and the Autosea project, and the following paragraphs describe some research suggestions for these projects, as well as other research projects on ASVs.

Throughout this thesis, a single NCV model has been used as the target model. It would be advantageous to have multiple models for targets, to make more accurate predictions and prevent track loss during maneuvers. The most common way of achieving this is by means of the IMM method. The additional models does not necessarily have to be more complicated and require a lot of parameters. It is possible to run several NCV models with different covariance values in paralell in an IMM. As the targets observed in [74] were observed to mainly have two different covariance values, another NCV model with higher covariance would make the tracking system handle a wider variety of targets of opportunity in addition to the targets present in the experiments. It would also allow the tracking system to capture target maneuvers. Additionally, extending the target state model to include the turn rate would also be beneficial, in particular for prediction. Although a NCV model with a sufficiently high covariance will capture a maneuver, a turn rate estimate would help in identifying the target intent, e.g. that the target is turning to avoid collision.

A natural extension of the system is to track multiple targets by calculating the joint association probabilities. As the current IPDA is performing very well, it is natural to consider the JIPDA as a followup. In addition to the classical multi-target problems like track coalescence and undetected targets, the detectability estimation methods of [71, 75] are likely to have reduced performance when other targets in the vicinity are not accounted for. If the JIPDA is not powerful enough, a PMBM is the next step up in complexity, from which the JIPDA can be derived. Although the PMBM may be required to obtain adequate performance in congested areas such as harbors and rivers, it also has additional computational requirements. Ideally, the tracking system would be able to evaluate by itself when to use an IPDA, JIPDA or PMBM, respectively.

[1] `https://www.ntnu.edu/autoferry`

The tracking system presented in this thesis is based on radar data only. Although radar is an important sensor for maritime target tracking, there are several other sensors that must be included to obtain good situational awareness. To detect smaller objects in close proximity, cameras or lidars are beneficial. They are also important in order to classify objects. To get the most optimal result, the sensors should be combined in a multi-sensor tracking system. Preliminary results on multi-sensor fusion in the Autoferry project are presented in [31]. An additional reason for having several sensors is redundancy. If a sensor is faulty or obstructed, the system should still be able to have an acceptable situational awareness level. Ideally, the system should be able to determinte itself that the sensor is faulty, due to changes in the sensor model.

Although several full-scale maritime COLAV experiments have been conducted, there is still much to be explored in the interaction between situational awareness and COLAV. In a fully autonomous scenario, the COLAV system must be able to interpret the uncertainty in the tracking results, in order to fully ensure that the chosen maneuvers are safe.

Chapter 6

Original Publications

Paper 1 Compensation of Navigation Uncertainty for Target Tracking on a Moving Platform

E. F. Wilthil and E. F. Brekke, “Compensation of Navigation Uncertainty for Target Tracking on a Moving Platform”, *2016 19th International Conference on Information Fusion (FUSION)*, Heidelberg, 2016, pp. 1616–1621.

Paper 2 A Target Tracking System for ASV Collision Avoidance Based on the PDAF

E. F. Wilthil, A. L. Flåten and E.F. Brekke, "A Target Tracking System for ASV Collision Avoidance Based on the PDAF", in *Sensing and Control for Autonomous Vehicles*, T. I. Fossen, K. Y. Pettersen and H. Nijmeijer, Eds., Springer, 2017, pp. 269–288.

Paper 3 Track Initiation for Maritime Radar Tracking with and without Prior Information

E. F. Wilthil, E. Brekke and O. B. Asplin, "Track Initiation for Maritime Radar Tracking with and without Prior Information", *2018 21st International Conference on Information Fusion (FUSION)*, Cambridge, 2018.

Available at https://doi.org/10.23919/ICIF.2018.8455260

Paper 4 Estimation of Target Detectability for Maritime Target Tracking in the PDA Framework

E. F. Wilthil, Y. Bar-Shalom, P. Willett and E. Brekke, "Estimation of Target Detectability for Maritime Target Tracking in the PDA Framework", *2019 22nd International Conference on Information Fusion (FUSION)*, Ottawa, 2019.

Estimation of Target Detectability for Maritime Target Tracking in the PDA Framework

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***Abstract*—The detection probability of maritime vessels may change over time, either slowly or more abruptly, due to effects such as sea state and varying aspect angle. If the varying detectability is not accounted for in the tracking system, tracks may be terminated or lost. The undetected targets may cause dangerous situations in applications such as maritime collision avoidance. In the following, we propose two methods for tracking targets with varying detection probability, both in the integrated probabilistic data association (IPDA) framework. One method uses the number of validated measurements to estimate the detectability of the target, while the other calculates the joint detectability and existence probabilities based on the measurement association likelihoods. Both methods show significant improvements over the conventional Markov chain 1 and 2 IPDAs.**

I. Introduction

With increased autonomy in the maritime domain, reliable situational awareness and collision avoidance capabilities are needed to ensure the safe operation of vessels. Although many vessels are equipped with automatic identification system (AIS) transponders, a good object detection and tracking system is also needed to track targets without AIS, such as kayaks and leisure craft, or as a backup to the AIS system.

The main priority of tracking systems for collision avoidance is the capability to quickly and reliably track targets, as an undetected target is a direct threat to safety. This is also the case when confirmed tracks on targets are terminated, as the collision avoidance system may decide to steer into the now untracked target's path. However, false tracks may induce unnecessary maneuvers from the collision avoidance system and cause dangerous situation from other ships, and the system should also be able to terminate false tracks quickly.

The literature on track management for fluctuating detection probability is sparse. In [2], it was found that a Shiryaev test can greatly improve track termination performance when the detection probability is varying. In [10], the authors use a particle filter-based approach to estimate the detection probability, where the particle filter handles the nonlinearities that arise when the detection probability is constrained to a limited interval. Ref. [12] presents an adaptive tracker that is able to estimate the detection probability using a belief propagation message passing scheme. A method for extending random finite set (RFS) filters to include the detection probability in the state vector is presented in [6], with results in [7]. The resulting filters performs well with a constant, but unknown, detection probability.

The first contribution of this paper is an experimental investigation of whether the variations in small vessel detectability can be adequately modeled by varying aspect angle, based on a dataset from a collision avoidance test. The motivation for using a Markov model as in e.g. [2], [10] is that it is difficult to identify the primary contributing factor to the detectability variations, and we will investigate if this is the case for this dataset as well.

The second contribution of this paper is the extension of the integrated probabilistic data association (IPDA) to handle varying target detectability. The first extension estimates the detectability based on the number of validated measurements, and the second calculates the joint detection and existence probability. We have chosen the probabilistic data association (PDA) framework for two main reasons. The first is that the PDA has proven to be an efficient tool for object detection and tracking in short-range maritime collision avoidance, see e.g. [16], [5], [4], [11]. The other is that the IPDA is a special case of the joint integrated probabilistic data association (JIPDA) [8], which in turn can be derived from Poisson multi-Bernoulli mixture (PMBM) filters [14].

The rest of the paper is structured as follows. Section II contains assumptions and motivation, Section III describes the modifications made to the IPDA in order to account for varying detectability, Section IV presents the results, and the conclusion follows in Section V.

II. Motivation and problem formulation

A. Definitions

The goal of the system is to estimate the state of the target at time k, which consists of a kinematic component x_k with target position and velocity, and the detection probability d_k. Measurements are denoted z_k^i, $Z_k = \{z_k^i\}_{i=0}^{m_k}$ and $Z^k = (Z_{k_0}, \ldots, Z_k)$ for measurements, sets of measurements and data (sequence of sets) at time k, respectively.

Assumption 1: The target moves according to

$$p(x_{k+1}|x_k) = \mathcal{N}(x_{k+1}; F_k x_k, Q_k) \tag{1}$$

independent for all k, and $\mathcal{N}(x; \hat{x}, P)$ is the probability density function (PDF) of the normal distribution of x, with expected value $\hat{x}$ and covariance P, respectively.

Assumption 2: The target is assumed to have time-varying detectability, chosen from a discrete set of N_d states. Let E_k^j be the event that the target is in detectability mode j at time k, i.e. that $d_k = P_D^j$. Further, assume that the values of P_D^j are known, and that d follows a random process according to

$$P(E_k^j | E_{k-1}^i) = \pi_{ij} \qquad i, j = 1, \ldots, N_d \tag{2}$$

Assumption 3: The target-originated measurement is distributed according to

$$p(z_k | x_k) = \mathcal{N}(z_k; Hx_k, R_k) \tag{3}$$

independently for all k, and independent of Assumption 1. The target is detected with probability P_D^j, according to the current detectability mode.

Assumption 4: The number of false alarms in the surveillance region follows a Poisson distribution, with probability mass function (PMF)

$$\mu_F(m) = \frac{(\lambda V)^m}{m!} e^{-\lambda V} \tag{4}$$

where V is the area of the surveillance region, and λ is the clutter density. The spatial distribution of clutter measurements is assumed to be uniform.

Assumption 5: Target existence at time k is denoted $\mathcal{H}_k$, and $\bar{\mathcal{H}}_k$ is defined as the complementary event, namely that the target does not exist at time k. It is assumed to follow a Bernoulli random process according to

$$P(\mathcal{H}_k | \mathcal{H}_{k-1}) = p_s \tag{5}$$

$$P(\mathcal{H}_k | \bar{\mathcal{H}}_{k-1}) = p_b \tag{6}$$

where p_s and p_b are the probability of survival and birth, respectively.

B. Track initiation with constant detectability

As one of the assumptions of PDA is that it cannot begin before a track has been initialized, some form of track initialization is needed. Fundamental to the PDA approach is the calculation of the association probabilities for the validated measurements at the current time based on a single prior. For the m_k validated measurements, let θ_k^i be the event that measurement z_k^i is the target-originated measurement for $i = 1, \ldots, m_k$, and that none of the measurements are target-originated for $i = 0$. One of the first attempts at handling track initiation in the PDA framework can be found in [3], where an additional association event is added, the event that the target is unobservable. This causes tracks that have a low probability of being observable to have low association probabilities for measurements in the validation gate, reducing their impact on the posterior state estimate. However, the probability of detection is still considered constant in [3] when the target is detectable.

Other approaches to track initiation are logic-based track formation [1] and sequential tests [13], [15]. This includes the popular M/N-logic, which requires M detections in N scans in order to confirm the track. This approach only accounts for the detectability of the target implicitly by the choice of M and N. As explored in [2], this may have a significant impact on performance when the detectability of the target changes. The detection probability also appears in the likelihood ratio in the sequential probability ratio test (SPRT) of [13].

In the following, we will focus on the IPDA described in [9]. As opposed to [3], where the PDA association probabilities are modified with an extra event, the evaluation of the association event probabilities are the same as in the original treatment of the PDA, and the existence probability of the target is calculated by

$$P(\mathcal{H}_k | Z^k) = \frac{\mathcal{L}_k P(\mathcal{H}_k | Z^{k-1})}{1 - (1 - \mathcal{L}_k) P(\mathcal{H}_k | Z^{k-1})} \tag{7}$$

where $\mathcal{L}_k$ is the likelihood ratio of the target-present versus the clutter-only hypotheses, based on the measurements in scan k. Under the PDA assumption, this is given by

$$\mathcal{L}_k = 1 - P_D P_G + P_D \lambda^{-1} \sum_{i=1}^{m_k} p(z_k^i | \theta_k^i, Z^{k-1}) \tag{8}$$

where P_G is the validation gate probability and $p(z_k^i | \theta_k^i, Z^{k-1}) = \mathcal{N}(\nu_k^i; 0, S_k)$. The innovations are given by $\nu_k^i = z_k^i - H\hat{x}_{k|k-1}$, with corresponding covariance S_k. The time update of the existence probability is given by

$$P(\mathcal{H}_k | Z^{k-1}) = p_s P(\mathcal{H}_{k-1} | Z^{k-1}) + p_b P(\bar{\mathcal{H}}_{k-1} | Z^{k-1}). \tag{9}$$

This variant is denoted the Markov chain one (MC1) IPDA in [9]. It is also derived with another Markov chain, named the Markov chain two (MC2) IPDA. In addition to the target-present and no-target state, it also includes an undetectable-target state. The likelihoods of undetectable targets cannot be distinguished from the clutter-only hypothesis in the MC2 IPDA, which means that erroneous tracks will have a high existence probability several scans after the track is lost.

The one-point initialization procedure [1] is used for forming preliminary tracks, with existence probability ε_I. If the existence probability exceeds a threshold ε_C, the track is confirmed. Tracks with existence probability below ε_T are terminated. Established tracks are gated according to known techniques, with gate probability P_G [1]. Any measurements that are gated by confirmed tracks are not used to update preliminary tracks, and new preliminary tracks are formed only with measurements that are not gated by confirmed or preliminary tracks.

C. Forensic analysis of recorded data

Varying target detectability may have many sources, such as target aspect angle, range and varying sea state. A scenario where target detectability is an issue is shown in Fig. 1, which shows data from a collision avoidance experiment conducted in the Trondheimsfjord in September 2018. There are three targets present in the tests, two boats and a stationary seamark[1]. The target moving east-to-west is a tugboat with

[1]A seamark is an aid to navigation for passing ships, typically a board or a buoy attached to the sea floor.

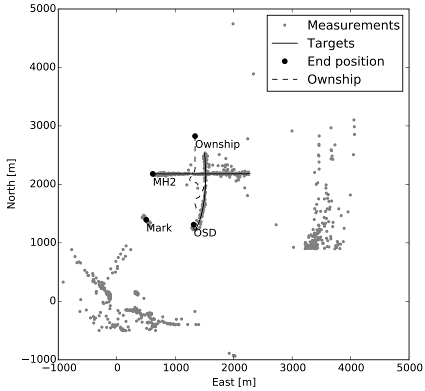

Fig. 1. Scenario overview. The grey dots are radar measurements, the black lines are AIS position trajectories, and the dashed line is the ownship position trajectory.

Fig. 2. The targets present in the experiments. Top left: The Ocean Space Drone. Bottom left: Munkholmen II. Right: The seamark.

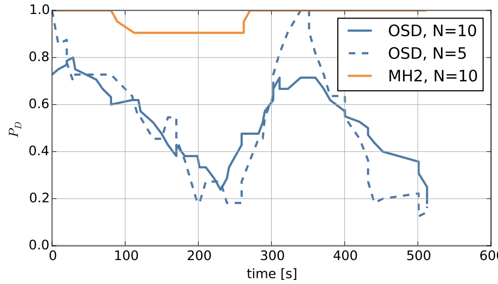

Fig. 3. Empirical detection probability for the two boats in Fig. 1, calculated by (10), where the values close to the start and end of the dataset have been calculated by truncating (10).

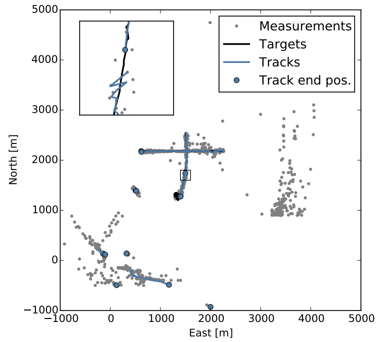

Fig. 4. Resulting tracks after running the IPDA tracker described in Section II-A. The track from the OSD target is terminated due to the assumed high detection probability, as shown in the inset.

callsign Munkholmen II (MH II), which has a steel hull. The target moving north-to-south is a lifeboat, repurposed into an autonomous test vessel, with callsign Ocean Space Drone (OSD). It has a fiberglass hull. A radar is mounted on the ownship, which successfully avoids collision with both targets. The targets are shown in Fig. 2. The dataset has a low amount of clutter, with the exception of near-shore areas close to the origin and to the east.

In the following discussion, the ground truth is based on the AIS-indicated position of the targets, and the measurements recorded during the experiments. Although the AIS system is based on satellite navigation with its own flaws, we believe it to be of sufficient accuracy to discuss the issues presented in the rest of this section.

Both targets have frequent detections for the most part, but there are some periods with more sparse detections. By assuming the AIS-indicated position is sufficiently accurate and a low clutter density, a validation gate can be set up around the reported position. Let δ_k be a measurement indicator, which is 0 when the validation gate is empty at time k, and 1 otherwise. Then, the moving average detection probability can be calculated by

$$P_D(k) = \frac{1}{2N+1} \sum_{n=k-N}^{k+N} \delta_n. \tag{10}$$

Fig. 3 shows the detection probability for each of the targets with different values of N.

The MH II has very good reflective properties and has a high detection probability throughout the experiment, but the detection probability of the OSD varies a lot. Keeping a continuous track on the OSD is hard, and Fig. 4 shows a set of tracks resulting from running an IPDA described in Section II-A with a detection probability of 0.8. The track on the OSD is lost and regained during the experiment.

In addition to the dataset shown in Figures 1 and 4, an additional 15 datasets have been analysed. These datasets comprise 3554 radar scans of the targets from 2 hours and 50 minutes of data, collected the same day as the previously discussed

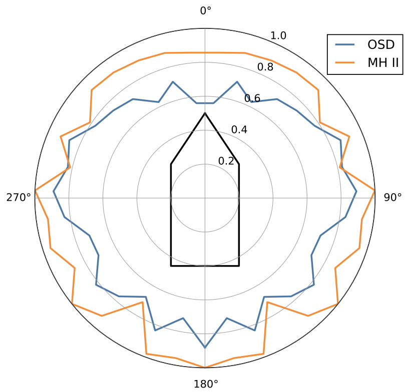

Fig. 5. Empirical detection probability based on the AIS-indicated aspect angle. Zero degrees is the bow. Symmetry about the centerline is assumed, and the range to the targets have not been accounted for.

scenario. The goal is to investigate whether the aspect angle is a main contributing factor to the varying detection probability. For every timestep k, a validation gate is set up around the AIS-indicated position, and δ_k is evaluated. Additionally, the aspect angle is calculated based on the velocity information of the target, also given by the AIS system. The aspect angle α can be found from the angle between the vectors from the target to the ownship and the velocity of the target, and is given by

$$\cos\alpha_k = \frac{p_k^{to} \cdot v_k^t}{\|p_k^{to}\|\|v_k^t\|} \tag{11}$$

where p_k^{to} is the vector from the target to the ownship position, and v_k^t is the target velocity. The accumulated aspect angle and detection indicators are then used to evaluate the aspect-dependent detection probability by dividing the ship aspect angle into discrete bins, and the detection probability for each bin is calculated by

$$P_D = \frac{\sum_{\ell=1}^{N}\delta_\ell}{N}. \tag{12}$$

The results based on all the datasets are shown in Fig. 5, where it has been assumed that the target is symmetric about the centerline to increase the number of samples per bin. The steel hull of MH II has good detectability from all aspect angles, around $P_D = 0.9$. The OSD is slightly less detectable, usually about 0.8 and as low as 0.6 from the front. However, there are no aspect angles with a detection probability which is as low as the ones indicated in Fig. 3. This example shows that it can be hard to model the detectability by a single parameter, and justifies the use of a random process as in Assumption 2 for these datasets.

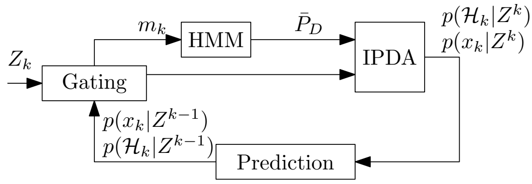

Fig. 6. The cascade form HMM and IPDA estimators.

III. Extensions to the IPDA

In the following two sections, we introduce two extensions which accounts for varying target detectability.

A. *Cascade form HMM and IPDA*

This method consists of a hidden Markov model (HMM) to estimate the detectability of the target based on the number of measurements in the validation gate, and the actual measurements Z_k are not used. A MC1-IPDA is used to estimate the target existence probability based on the detectability estimate $\bar{P}_D$. This structure is shown in Fig. 6.

To estimate the detectability of the target, the number of measurements in the validation gate m_k and the gate area V_k are evaluated when the validation gate is setup. Under the Poisson clutter assumption and detectability mode E_k^j, m_k has the distribution

$$P(m_k|E_k^j, \mathcal{H}_k) = \mu_F(m_k)(1 - P_D^j P_G) + \mu_F(m_k - 1)P_D^j P_G \tag{13}$$

where the first term is the probability of m_k clutter measurements and a missed detection, and the second term is the probability of $m_k - 1$ clutter measurements and a detection, respectively. Given a sequence of observations $m^k = (m_{k_0}, \dots, m_k)$, the probability of being in mode j can be calculated recursively by

$$P(E_k^j|m^k, \mathcal{H}_k) = \frac{1}{c}P(m_k|E_k^j, m^{k-1}, \mathcal{H}_k)P(E_k^j|m^{k-1}, \mathcal{H}_{k-1}) \tag{14}$$

where $c = P(m_k|m^{k-1})$ is a normalization constant. As the detections and clutter are independent over time, $P(m_k|E_k^j, m^{k-1}) = P(m_k|E_k^j)$, and

$$\begin{aligned} P(E_k^j|m^k, \mathcal{H}_k) =& \frac{1}{c}P(E_k^j|m^k, \mathcal{H}_k) \\ & \cdot \sum_{i=1}^{N_d} \pi_{ij} P(E_{k-1}^i|m^{k-1}, \mathcal{H}_k). \end{aligned} \tag{15}$$

The estimate of the detection probability is then given by

$$\bar{P}_D = \sum_{j=1}^{N_d} P_D^j P(E_k^j|m_k, \mathcal{H}_k) \tag{16}$$

which is then used in a regular IPDA, as described in Section II-B.

Although calculating the average detectability in this way is a heuristic technique, the following example illustrates how the approximation fits into the PDA framework. Consider the probabilities of the measurement association events $p(\theta_k^i|m_k, \mathcal{H}_k, Z^{k-1})$. By marginalizing over the detectability, this becomes

$$P(\theta_k^i|m_k) = \sum_{j=1}^{N_d} P(\theta_k^i|E_k^j, m_k)P(E_k^j|m_k) \tag{17}$$

where the conditioning on target existence $\mathcal{H}_k$ and past data Z^{k-1} has been omitted for brevity. The first term is the regular PDA association event probability with detection probability equal to P_D^j, and the second term is the HMM probability of being in mode j. For the nonparametric PDA, this gives

$$\begin{aligned} P(\theta_k^i|m_k) &= \begin{cases} \sum_{j=1}^{N_d}(1 - P_G P_D^j)P(E_k^j|m_k) & i = 0 \\ \sum_{j=1}^{N_d} \frac{P_G P_D^j}{m_k} P(E_k^j|m_k) & i = 1, \dots, m_k \end{cases} \\ &= \begin{cases} 1 - P_G \bar{P}_D & i = 0 \\ \frac{P_G \bar{P}_D}{m_k} & i = 1, \dots, m_k \end{cases} \end{aligned} \tag{18}$$

which are expressions from the prior PDA probabilities using the value $\bar{P}_D$.

B. Detectability-based IPDA

The estimation of the detectability state can also be integrated into the IPDA presented in Section II-B, such that the detectability is estimated based on the likelihood of the measurement association hypothesis. The goal of this extension is to estimate the joint probability of target existence $\mathcal{H}_k$ and detectability mode E_k^j, given by

$$P(\mathcal{H}_k, E_k^j|Z^k) = \frac{p(Z_k|\mathcal{H}_k, E_k^j, Z^{k-1})}{p(Z_k|Z^{k-1})} P(\mathcal{H}_k, E_k^j|Z^{k-1}). \tag{19}$$

where the dependence on the number of measurements m_k can be made explicit by

$$\begin{aligned} p(Z_k|E_k^j, \mathcal{H}_k, Z^{k-1}) =& p(Z_k|m_k, E_k^j, \mathcal{H}_k, Z^{k-1}) \\ & \cdot P(m_k|E_k^j, \mathcal{H}_k, Z^{k-1}) \end{aligned} \tag{20}$$

where the last term is given in (13) since it is independent of the past data Z^{k-1}. By considering the different data association hypotheses θ_k^i, we have

$$\begin{aligned} p(Z_k|m_k, E_k^j, \mathcal{H}_k, Z^{k-1}) =& \sum_{i=0}^{m_k} p(Z_k|\theta_k^i, m_k, E_k^j, \mathcal{H}_k, Z^{k-1}) \\ & \cdot P(\theta_k^i|m_k, E_k^j, \mathcal{H}_k, Z^{k-1}) \end{aligned} \tag{21}$$

where the PDF of the measurements can be found in e.g. [1], and are given by

$$\begin{aligned} & p(Z_k|\theta_k^i, m_k, E_k^j, \mathcal{H}_k, Z^{k-1}) \\ &= \begin{cases} V_k^{-m_k+1} P_G^{-1} \mathcal{N}(\nu_k^i; 0, S_k) & i = 1, \dots, m_k \\ V_k^{-m_k} & i = 0 \end{cases}. \end{aligned} \tag{22}$$

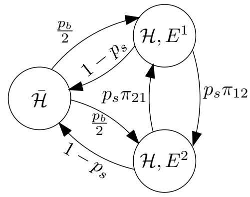

Fig. 7. The Markov chain with the nonexisting target-state, and two detectability states. The self-transition probabilities are not shown.

Conditioned on target existence and detectability, the prior association event probabilites can be found from the regular PDA equations, and are also found in e.g. [1]:

$$\begin{aligned} & P(\theta_k^i|m_k, E_k^j, \mathcal{H}_k, Z^{k-1}) \\ &= \begin{cases} \frac{1}{m_k} P_D^j P_G c_j^{-1} & i = 1, \dots, m_k \\ (1 - P_D^j P_G) \frac{\mu_F(m_k)}{\mu_F(m_k - 1)} c_j^{-1} & i = 0 \end{cases} \end{aligned} \tag{23}$$

where c_j normalizes the association events. (13) divided by c_j can be shown to be $\mu_F(m_k - 1)$, and summing and multiplying everything together into (20) gives

$$\begin{aligned} p(Z_k|E_k^j, \mathcal{H}_k, Z^{k-1}) &= \mu_F(m_k) V_k^{-m_k} (1 - P_D^j P_G) \\ &+ \mu_F(m_k - 1) V_k^{m_k - 1} \frac{1}{m_k} P_D^j \sum_{i=1}^{m_k} \mathcal{N}(\nu_k^i; 0, S_k). \end{aligned} \tag{24}$$

Inserting the clutter PMF from Assumption 4 into (24), cancelling and gathering terms yields

$$\begin{aligned} p(Z_k|E_k^j, \mathcal{H}_k, Z^{k-1}) &= \frac{\lambda^{m_k} e^{-\lambda V_k}}{m_k!} \Big[(1 - P_D^j P_G) \\ &+ P_D^j \lambda^{-1} \sum_{i=1}^{m_k} \mathcal{N}(\nu_k^i; 0, S_k)\Big] = C_k \mathcal{L}_k^j \end{aligned} \tag{25}$$

where $\mathcal{L}_k^j$ is the likelihood ratio of the measurements in scan k for the target present in detectability mode j versus the clutter-only hypotheses, as in (8).

The prior $P(\mathcal{H}_k, E_k^j|Z^{k-1})$ is calculated as follows. Since the detectability mode change conditioned on target existence is known from Assumption 2, it is rewritten as (omitting the dependence on the past data Z^{k-1} for brevity)

$$\begin{aligned} P(\mathcal{H}_k, E_k^j) =& P(E_k^j, \mathcal{H}_k|\mathcal{H}_{k-1})P(\mathcal{H}_{k-1}) \\ &+ P(E_k^j, \mathcal{H}_k|\bar{\mathcal{H}}_{k-1})P(\bar{\mathcal{H}}_{k-1}) \\ =& p_s \sum_{i=1}^{N_d} \pi_{ij} P(E_{k-1}^i, \mathcal{H}_{k-1}) + \frac{p_b}{N_d} P(\bar{\mathcal{H}}_{k-1}) \end{aligned} \tag{26}$$

These transition probabilities are equivalent to a Markov chain with the $N_d + 1$ states $\bar{\mathcal{H}}$ and $(\mathcal{H}, E^j)$ for $j = 1$ to N_d. An example with two detectability states is shown in Fig. 7.

The denominator of (19) is a normalization constant which can be found by summing over the possible target hypotheses, given by

$$\begin{aligned} p(Z_k|Z^{k-1}) &= p(Z_k|\bar{\mathcal{H}}_k, Z^{k-1})P(\bar{\mathcal{H}}_k|Z^{k-1}) \\ &\quad + \sum_{j=1}^{N_d} p(Z_k|\mathcal{H}_k, E_k^j, Z^{k-1})P(\mathcal{H}_k, E_k^j|Z^{k-1}) \\ &= C_k \left(1 - \sum_{j=1}^{N_d}(1-\mathcal{L}_k^j)P(\mathcal{H}_k, E_k^j|Z^{k-1})\right) \end{aligned} \tag{27}$$

and the C_k cancels in (19) with the same term in (25). To summarize, the time update of the IPDA with detectability estimation is given by a Markov chain as shown in Fig. 7, and the measurement update is given by

$$P(\mathcal{H}_k, E_k^j|Z^k) = \frac{\mathcal{L}_k^j P(\mathcal{H}_k, E_k^j|Z^{k-1})}{1 - \sum_{i=1}^{N_d}(1-\mathcal{L}_k^i)P(\mathcal{H}_k, E_k^i|Z^{k-1})}. \tag{28}$$

The MC1- and MC2-IPDAs from [9] can be obtained from this general expression by assuming a single mode with detection probability P_D or two detectability modes with detection probabilities of P_D and 0, respectively.

IV. Results

The two trackers that account for varying target detectability will be compared with the Markov chain 1 and 2 IPDAs. The four trackers can be summarized as follows:

MC1-IPDA
: The Markov Chain 1 IPDA without detectability estimation. It has a single detection probability P_D^H.

MC2-IPDA
: The Markov Chain 2 IPDA that allows for undetectable targets. It also has a single detection probability P_D^H.

HMM-IPDA
: The Markov Chain 1 IPDA with detectability estimation provided by a HMM. The HMM has two detection probability values, P_D^H and P_D^L.

DET-IPDA
: The IPDA with joint detectability and target existence estimation, with two detection probability values, P_D^H and P_D^L.

Apart from the detectability models, the trackers use the same parameters, given in Table I. For the MC2-IPDA and DET-IPDA, the target existence probability is the summed existence probability of the two detectability modes.

All of the trackers use the same motion model, a white noise acceleration model given by

$$F_k = \begin{bmatrix} 1 & T \\ 0 & 1 \end{bmatrix} \qquad Q = q\begin{bmatrix} T^4/4 & T^3/2 \\ T^3/2 & T^2 \end{bmatrix} \tag{29}$$

independent for the north- and east dimensions with sample time T. Cartesian position measurements are used, with covariance rI_2, where I_2 is the identity matrix.

TABLE I
SIMULATION PARAMETERS

Parameter	Value
Sample time T	$3\,\mathrm{s}$
Detection probabilities P_D^H, P_D^L	0.8, 0.3
Clutter density λ	$1 \times 10^{-5}\,\mathrm{m}^{-2}$
Measurement covariance r	$100\,\mathrm{m}^2$
Process noise covariance q	$0.025\,\mathrm{m}^2\,\mathrm{s}^{-4}$
Survival probability p_s	1.0
Birth probability p_b	0
Detectability mode change probability π_{ij}	0.8, $i = j$ 0.2, $i \neq j$
Initial existence probability ε_I	0.2
Confirmation threshold ε_C	0.99
Termination threshold ε_T	0.1
Number of simulations N_{MC}	2500

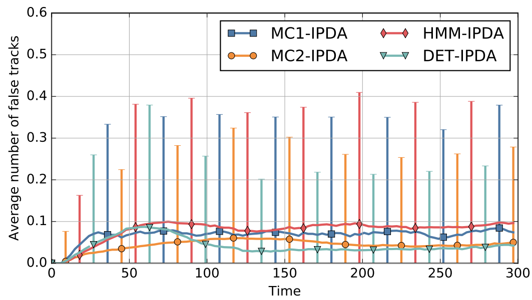

Fig. 8. Average number of confirmed tracks for the clutter-only scenario. Error bars correspond to one standard deviation.

A. False tracks

It is expected that allowing targets to have a lower detection probability in a surveillance area will increase the number of false tracks. In this section, we investigate if this expectation holds true, and to what extent it affects the tracking system.

To test the false track rejection capabilities of the trackers, a square surveillance area with edge length $2\,\mathrm{km}$ is set up, and clutter is generated according to Assumption 4 with clutter density λ given in Table I. No targets are present. Fig. 8 shows the average number of confirmed tracks over N_{MC} simulations.

The premise that the trackers with lower detectability are prone to more false tracks does not have merit as they all have a similar number of false tracks. The DET-IPDA and MC2-IPDA have a slightly lower number than the other two, but the results are still comparable when considering the sample standard deviation. The reason for this is that the trackers account for the lower detection probability in the update of the target existence probability. However, there is a large difference in the average duration of the false tracks, as summarized in Table II. The MC1-IPDA is very fast in both track initiation and termination, and the MC2-IPDA is very slow. When tracks persist for a long time, it will gate measurements that may have been used to confirm another

TABLE II
FALSE TRACK DURATION

Tracker	Avg. duration	Avg. conf. time
MC1-IPDA	10.0 scans	4.8 scans
MC2-IPDA	78.5 scans	15.8 scans
HMM-IPDA	29.3 scans	10.1 scans
DET-IPDA	30.4 scans	7.7 scans

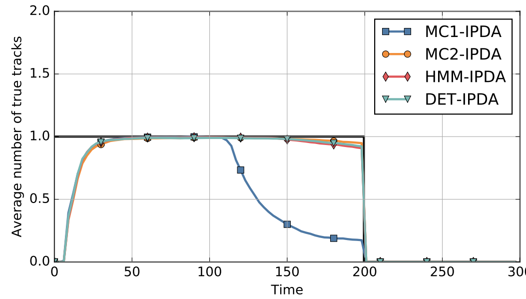

Fig. 9. Average number of true tracks with a single target present. The black line shows the ground truth. The detectability of the target drops at $t = 100\,\mathrm{s}$.

track, which in part may explain the lower average number of false tracks in the DET-IPDA and MC2-IPDA. These also have a slightly lower standard deviation in the number of false tracks.

B. Detectability estimation and lost tracks

To test the capability of tracking a target with varying detectability, a single target is added to the surveillance region previously described. It starts in the high detectability-mode, and changes to the low detectability-mode after $100\,\mathrm{s}$. After an additional $100\,\mathrm{s}$, the target disappears, and the scenario continues for an additional $100\,\mathrm{s}$. The purpose of the change in the detectability and track existence is to test both the ability to track targets with reduced detectability, and track termination capabilities, i.e. how fast the track is terminated when it is lost.

More precisely, define a true track as a confirmed track that has a position error of less than $100\,\mathrm{m}$. Further, a lost track is defined as a previously confirmed track that no longer satisfied this requirement. Consequently, a confirmed track that manages to track the target until it disappears will be considered lost until it is terminated. For each tracker, the average number of true tracks are shown in Fig. 9, and the average number of lost tracks are shown in Fig. 10.

As expected, the IPDA with constant detection probability struggles to keep track of the target when the detectability decreases. However, the fast track termination capabilities ensures the tracks are terminated rather than lost. The tracks that are maintained until the target disappears are also terminated very quickly. The other three trackers are much better at tracking the target until it disappears. The MC2-IPDA,

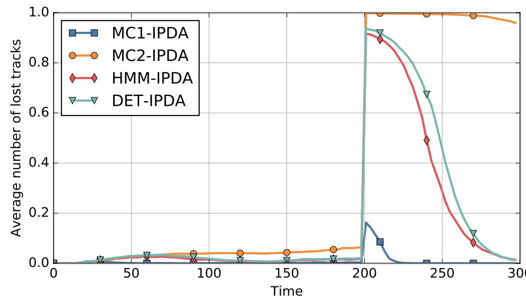

Fig. 10. Number of lost tracks with a single target present.

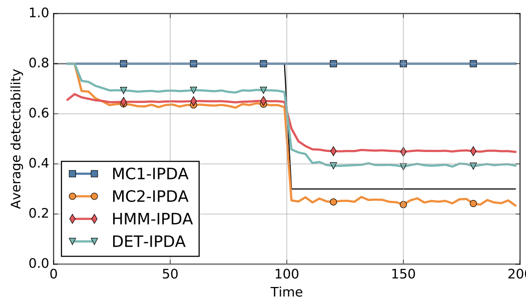

Fig. 11. Average mode of the detectability estimate of confirmed tracks when the target is present. The black line shows the ground truth.

however, still maintains over 90% of the lost tracks for more than 30 scans after the target disappears. The HMM-IPDA and the DET-IPDA terminates nearly all of the lost tracks before the end of the scenario.

The average mode of the detectability estimate is shown in Fig. 11. The DET-IPDA esitmates the detectability of the target slightly better than the HMM-IPDA. When the detectability is lowered, the MC2-IPDA is the closest, as one of the modes allows for detectability lower than the true value.

C. Real data results

We now test the trackers on the motivating scenario presented in Section II-C with 3 targets (OSD, MH II and the seamark). The tracking system parameters are the same as in Table I, with some exceptions. The sampling interval varies slightly according to when data is received, and the average is $2.88\,\mathrm{s}$. The clutter density is not known, and nonparametric tracking methods are used by substituting $\lambda = m_k/V_k$ where m_k and V_k are the number of validated measurements and the area of the validation gate, respectively. The Cartesian position measurement model is still used, but the measurement covariance is calculated by a polar to Cartesian conversion [1] with polar measurement standard deviations of $20\,\mathrm{m}$ and $2.3°$. Further details on the radar data processing can be found in

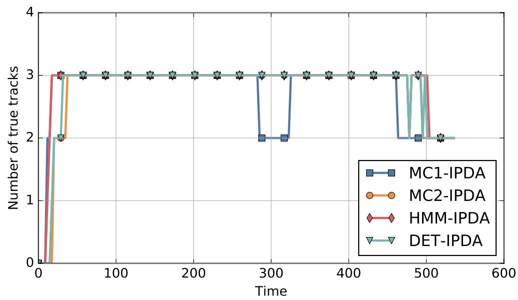

Fig. 12. Number of true tracks for the tracking methods in the real data scenario.

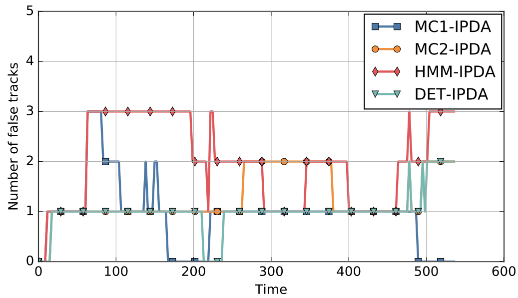

Fig. 13. Number of false targets for the tracking methods in the real data scenario.

[16], [15]. The limit for declaring a true track is now reduced to $60\,\mathrm{m}$.

The number of true and false tracks can be seen in Fig. 12 and Fig. 13, respectively. The MC1-IPDA loses the track of the OSD from $t = 280\,\mathrm{s}$ to $t = 320\,\mathrm{s}$, and the other trackers are able to keep track. The MC2- and DET-IPDA are slightly slower at confirming the track on the drone. Both the MC1- and HMM-IPDA rapidly confirms three false tracks, close to the island at the origin. The MC1-IPDA terminates these quickly, but the HMM-IPDA maintains them for a while longer. Both the MC2-IPDA and the DET-IPDA outperform the two other methods with respect to false tracks. At the end of the test, the OSD makes a $180°$ turn, and the trackers either lose or terminate the track.

V. Conclusion

Accounting for varying target detectability can significantly improve tracking performance when these issues are present. The detectability can be estimated with a HMM based on the number of validated measurements, or the probability of the joint detectability and target existence may be jointly evaluated using the based on the likelihood ratio of a target vs. clutter. Simulations shows that both of these methods are able to maintain the track when the detectability is lowered, and terminates lost tracks significantly faster than a Markov chain 2-IPDA. Tests on real data shows that the joint estimation of target detectability and existence probabilities reduces the number of false tracks, at the cost of slightly higher track confirmation time.

Acknowledgment

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Paper 5 Varying Detectability in Maritime Target Tracking

E. F. Wilthil, P. Willett, Y. Bar-Shalom and E. Brekke, “Varying Detectability in Maritime Target Tracking”, *Draft*, 2019.

This paper is awaiting publication and is not included in NTNU Open

Paper 6 Radar-based Maritime Collision Avoidance using Dynamic Window

B.-O. H. Eriksen, E. F. Wilthil, A. L. Flåten, E. F. Brekke and M. Breivik, "Radar-based Maritime Collision Avoidance using Dynamic Window", *2018 IEEE Aerospace Conference*, Big Sky, 2018.

Paper 7 Autonomous COLREGs-Compliant Decision Making using Maritime Radar Tracking and Model Predictive Control

D. K. M. Kufoalor, E. Wilthil, I. B. Hagen, E. F. Brekke and T.A. Johansen "Autonomous COLREGs-Compliant Decision Making using Maritime Radar Tracking and Model Predictive Control", *2019 European Control Conference*, Naples, 2019.

Autonomous COLREGs-Compliant Decision Making using Maritime Radar Tracking and Model Predictive Control*

D. K. M. Kufoalor, E. Wilthil, I. B. Hagen, E. F. Brekke, T. A. Johansen

***Abstract*— This paper addresses the challenges of making safe and predictable collision avoidance decisions considering uncertainties related to maritime radar tracking. When a maritime radar is used for autonomous collision avoidance, strategies for handling uncertain obstacle tracks, false tracks, and track loss become necessary. Robust decisions are needed in order to achieve clear and predictable actions according to the international regulations for preventing collisions at sea (COLREGs). We present robustness considerations and results of using an Integrated Probabilistic Data Association (IPDA) tracking method with a collision avoidance method based on Model Predictive Control. The results are from full-scale experiments that cover challenging multiple dynamic obstacle scenarios, including realistic vessel interactions where some obstacles obey COLREGs, while others do not.**

I. Introduction

Maritime collision avoidance is a challenging task that has been studied for many years, and the technology for safe navigation of marine vessels have evolved over the years. However, most of the existing technology is mainly intended as an aid to the human operator. The human operator makes a decision by evaluating the collision risk, using the information available about obstacles obtained from different sources, e.g. lookout, radar and nautical chart plotters, Automatic Identification System (AIS), and Vessel Traffic Service (VTS). Due to the reliance on a human operator, the reliability and accuracy of the existing automatic obstacle detection/tracking systems may not be the most crucial factors in the decision making process.

The existing "rules of the road" were also developed for the human operator, and therefore do not generally provide quantitative criteria for both the assessment of a potential collision situation and the actions needed to avoid collisions. Furthermore, COLREGs advocate "good seamanship" (see e.g. Rules 2 and 8 of [1]), probably due to the uniqueness of every situation and the characteristics of the maritime domain that make the collision avoidance task challenging. Specifically, the decision process needs to consider, among other factors, a large variety of obstacles, different sea states, dynamic motion in 2D space, and uncertainty in both sensor information and (intended) motion of obstacles in different environmental conditions. In view of the above observations, we acknowledge the difficulty of making the decision process autonomous, especially, based on existing technology and rules. An autonomous surface vehicle (ASV) must be able to rely on its sensors and should implement a decision strategy that is robust to uncertain information available for collision avoidance.

The maritime radar, which is a primary sensor for safe maritime navigation is useful in combination with effective obstacle tracking algorithms for autonomous collision avoidance if it produces accurate estimates of obstacle tracks, and has a low rate of false tracks and track loss. Different implementations and experimental validation of maritime target tracking algorithms are provided in [2], [3], [4]. A crucial aspect is to find a useful balance between false alarm rate and track initiation time in order to avoid detecting targets too late and also to reduce the risk of making wrong collision avoidance actions [2].

Earlier work that discuss the challenges of using maritime radar for autonomous collision avoidance include [5], [6]. While both focus on close-range situations, [5] assumes no track loss occurs, and the reactive method in [6] does not implement COLREGs compliance. Different methods that aim at COLREGs compliance are treated in [7], [8], [9], [10], [11], and some reviews of existing maritime collision avoidance methods can be found in [12], [13]. As noted in [8], different limitations in some of the existing collision avoidance methods motivate the use of ideas from optimization based control, which typically lead to a straightforward approach to specifying constraints and objectives.

In this paper, we explore the potentials of using the estimated maritime radar tracks from an Integrated Probabilistic Data Association (IPDA) tracking method in a Scenario-based Model Predictive Control (SB-MPC) decision framework. The main contributions include robustness considerations in the IPDA method, and the treatment of different uncertainties associated with maritime radar tracking in SB-MPC without using uncertainty estimates from the tracking method. The work in [8] and [14] is extended by introducing uncertainty adapted predictions of obstacle motion and a strategy for reducing the adverse effect of false/lost tracks. The overall collision avoidance system is suitable for both long-range and close-range encounters. Our approach leads to collision avoidance decisions that comply with COLREGs, by prioritizing deliberate early, clear, predictable actions. We also present full-scale experiments covering different dynamic multi-obstacle scenarios, using an ASV that implements the architectural components shown in Fig. 1.

The remainder of this paper is structured as follows:

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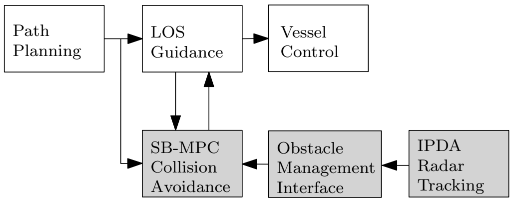


Fig. 1: ASV functional interface setup. The white boxes are existing functions, and the gray boxes are tracking, obstacle management, and collision avoidance functions presented in this paper.

Sections II–III describe the radar tracking method, the collision avoidance method, the uncertainties, and the related robustness considerations made in this work. Presentation and discussion of the experimental results follow in Section IV, and concluding remarks are given in Section V.

II. Maritime radar tracking

A. Radar tracking method

The backbone of the radar tracking system is described in [2], which implements a single-target tracking method. Through a parallel implementation of filters the tracking method is capable of tracking multiple targets when the targets are sufficiently separated in the state space. The tracking system uses one target motion model, a nearly constant velocity (NCV) model [15], which assumes that the target moves according to the linear Gaussian model

$$p(x_{j+1}|x_j) = \mathcal{N}(F_j x_j, Q_j), \tag{1}$$

where $\mathcal{N}$ is the probability density function of the normal distribution, $x_j = (p_N, v_N, p_E, v_E)$ is the state of the target at time j, consisting of, respectively, the North and East positions and velocities in a stationary North East Down (NED) reference frame. The state transition matrix F_j and the process noise covariance matrix Q_j in (1) are defined as follows:

$$F_j = \begin{bmatrix} F_1 & 0_{22} \\ 0_{22} & F_1 \end{bmatrix}, \quad F_1 = \begin{bmatrix} 1 & T_r \\ 0 & 1 \end{bmatrix},$$
$$Q_j = \begin{bmatrix} Q_1 & 0_{22} \\ 0_{22} & Q_1 \end{bmatrix}, \quad Q_1 = q \begin{bmatrix} T_r^4/4 & T_r^3/2 \\ T_r^3/2 & T_r^2 \end{bmatrix}.$$

T_r is the sampling time (i.e. the time between two radar scans), q is the process noise covariance parameter, and 0_{22} is a 2×2 zero matrix. The observation model used is

$$p(z_j|x_j) = \mathcal{N}(Hx_j, R_j), \tag{2}$$

where the matrix H extracts $z_j = (p_N, p_E)$ from x_j, and R_j is the measurement noise covariance matrix. The above model captures the typical straight-line motion of marine vessels.

The Integrated Probabilistic Data Association (IPDA) method presented in [16] is used for track initiation and track maintenance. The fundamental principle of the IPDA [17] is to calculate an existence probability for each track, based on the innovations of the measurements in the vicinity of the track, i.e. the difference between the measurements and their expected value based on the prior state estimate. Initially, tracks are categorized as preliminary tracks, which is only used internally in the tracking system. When the existence probability exceeds a given threshold P_C, the track is confirmed as a valid target. Tracks are terminated if the existence probability falls below another threshold P_T.

The output of the radar tracking system consists of a list of confirmed targets, each with an ID and estimates of the target's position (p_N, p_E), speed u, and course χ. The speed and course are, respectively, the magnitude and direction (angle) of the velocity vector (v_N, v_E). The estimates from the tracking system are considered as obstacle measurements used in the COLREGs-compliant decision method described in Section III. Every new track is given a new ID, which means that after a track is terminated, a new track that appears on the same target gets a new ID.

In this paper, we focus on the consequences of the assumptions made in the tracking system and the related uncertainties that a collision avoidance method needs to consider in its decision process. By not using uncertainty estimates computed by the tracking method in the COLREGs-compliant decision method, we obtain a collision avoidance system that does not depend on uncertainty representations specific to the implemented tracking method. We also avoid COLREGs-compliant method-specific representations in the tracking method that may lead to a more complicated (tightly-coupled) tuning procedure. For instance, prolonging the life of tracks in the tracking system based on their impact on collision avoidance decisions requires conservative tuning that produces many false tracks. Further details of the tracking system can be found in [2] and [16].

B. Radar track uncertainty

Radar tracking of obstacles introduces both data association uncertainty and state estimation uncertainty, i.e. position and velocity estimation errors, into a collision avoidance decision process.

The accuracy of data association in the tracking method is evident in the absence/presence of false tracks and the rate of track loss. In the IPDA tracking method used, premature track termination can be delayed by choosing a high value for the survival probability of the IPDA. This means that the existence probability will not be reduced below the threshold until several misdetections have occurred. This also increases the expected lifetime of any false track that appears. In practice, a useful balance is determined through tuning, and the collision avoidance decisions must be robust to both false tracks and track loss.

Due to the NCV model used in the tracking method, track loss may occur when the target is maneuvering. By choosing the process noise parameter q of the motion model process noise covariance properly, most of the typical maneuvers are captured by the NCV model. Additionally, the fast track initiation/establishment capabilities of the IPDA (see [16]) implies that the duration of track loss may not be significant in this case, since new tracks may appear, and may be used to trace the maneuvering path of the target. If the maneuvers are not sufficiently followed by the NCV model, an interacting multiple model (IMM) approach can be used [18]. Note that using an IMM does not necessarily avoid this issue entirely since one needs to deal with a more complex procedure that switches between models, and handling of cases where different models attain similar likelihoods (in a probabilistic framework) may not be a trivial task (see e.g. [5]).

The tracking system also influences the collision avoidance through fluctuations in the state estimate. In particular, the speed and course estimation errors can have a large impact on long-range collision prediction, as a small change of course may lead to a large change of position at the end of the prediction interval. This is remedied by representing the range-dependent measurement noise in the tracking system on a polar form, which is transformed into a Cartesian frame [18], instead of working directly with the uncertainty in the Cartesian frame as done in [2]. This provides less fluctuating estimates of the target course and speed when it is tracked from a long range.

III. COLREGs-compliant decision

In this section, we briefly describe our COLREGs-compliant decision method, and we propose different implementation strategies that enhance robustness to the radar tracking uncertainties discussed in Section II-B.

A. COLREGs-compliant decision method

The scenario-based MPC (SB-MPC) COLREGs-compliant decision method in [8] and the implementation of [14] is used in this work, with some extensions. The method solves the following optimization problem

$$k^*(t_0) = \arg\min_k \mathcal{H}^k(t_0), \tag{3}$$

where

$$\begin{aligned}\mathcal{H}^k(t_0) = \max_i \max_{t\in\mathcal{D}(t_0)} \big(&l_i(t_{\text{lost}}) \cdot c_i(u_m^k, \chi_m^k, t) \\ &+ \mu_i(u_m^k, \chi_m^k, t) + \tau_i(u_m^k, \chi_m^k, t)\big) \\ &+ f(u_m^k, \chi_m^k) + g(u_m^k, \chi_m^k),\end{aligned}$$

using the set $\mathcal{D}(t_0) = \{t_0, t_0 + T_s, \ldots, t_0 + T\}$, where T_s is the sampling time and T is the prediction horizon. We provide a brief description of the cost function components $l_i, c_i, \mu_i, \tau_i, f, g$ in this section, and we refer to [8] and [14] for their detailed specifications.

The cost function $\mathcal{H}^k(t_0)$ expresses the hazard associated with selecting a control behavior with index k and defined by course (χ_m^k) and speed (u_m^k) modifications that are applied to corresponding desired reference values, χ_d, u_d, for the course (χ) and speed (u), respectively. We use the following set of alternative control behaviors, which we assume to be fixed on the prediction horizon:

- course offset in degrees: $\chi_m^k \in$ {-90, -75, -60, -45, -30, -15, 0, 15, 30, 45, 60, 75, 90}
- speed factor: $u_m^k \in \{1, 0.5, 0\}$, which translates to 'keep speed', 'slow down', or 'stop'.

The function c_i denotes the cost of colliding with obstacle i, considering a collision risk that depends on the time and distance to the closest point of approach (CPA) and scales with the relative velocity of the obstacle and ASV. The allowed CPA is defined by a safety distance parameter d_{safe} and the obstacle's length (L_i). Specifically, $d_{\text{safe}} + L_i/2$ is used to define the radius of a circular safety region, which encloses obstacle i.

We introduce the track-loss factor $l_i(t_{\text{lost}})$, which reduces the relevance of the collision cost of obstacle i when its track is terminated by the tracking system. The track-loss factor becomes smaller, the longer the track-loss duration (t_{lost}) is, as specified in Section III-E. The cost of violating COLREGs is expressed by the function μ_i, and τ_i is a transitional cost that penalizes the termination of COLREGs-compliant maneuvers, in order to avoid unnecessary switching of control behaviors. The cost of maneuvering effort is specified by the function f, and g is a grounding cost that penalizes control behaviors that will result in collision with land or defined *no-go* zones.

The cost for each control behavior k at time $t \in \mathcal{D}(t_0)$ is calculated based on the predicted state of the ASV and each obstacle i, obtained from the simulation of their trajectories. We simulate the trajectory of obstacle i using a kinematic model:

$$\dot{\eta}_i = R(\chi_i)v_i, \;\; \eta_i = (x_i, y_i, \chi_i), \;\; v_i = (v_{x_i}, v_{y_i}, r_i),$$

and a 3-degrees of freedom (DOF) model for the ASV:

$$\begin{aligned}&\dot{\eta} = R(\psi)v, \\ &M\dot{v} + C(v)v + D(v)v = \tau_u,\end{aligned}$$

where $\eta = (x, y, \psi)$ denotes the position and heading in the earth-fixed frame, $v = (v_x, v_y, r)$ represents the velocities in surge, sway, and yaw specified in the body-fixed frame. The matrices M, $C(v)$, $D(v)$ are the vessel inertia matrix, Coriolis, and damping, respectively. $R(\psi)$ is a rotation matrix from body-fixed to earth-fixed frame, and τ_u is the vector of control forces from an autopilot (a control law), which accepts the commanded reference, $\chi_c = \chi_d + \chi_m^{k^*}$, $u_c = u_d u_m^{k^*}$.

If estimates of environmental disturbances such as wind and current are available, it is recommended to include their effect in the 3-DOF model as shown in [8]. In our experiments, we use a feedback-linearization controller for speed control and a proportional-derivative controller for course control. Both controllers are included in the prediction model to provide the control forces τ_u, which are used in the prediction of the ASV's trajectory for each scenario k.

B. Inherent properties and robustness

An important property of the above hazard evaluation criterion is that it seeks the least conservative solution according to the given constraints, by prioritizing solutions that result in tangential maneuvers w.r.t. the boundary of the defined circular safety region. This implies that the collision avoidance decisions inherently lead to straight-line motion, which is considered as predictable behavior in a maritime environment.

Due to the implementation of a COLREGs-transitional cost $\tau_i(\cdot)$, it is straightforward to prioritize COLREGs-compliant maneuvers in long-range encounters. Moreover, using a collision cost $c_i(\cdot)$ that scales with the collision time, range, and relative velocity, ensures that the SB-MPC strategy will choose an evasive maneuver if collision becomes imminent.

The main advantage of the SB-MPC strategy in terms of robustness to noise/uncertainty is the fact that the effect of all potentially uncertain variables that affect the collision avoidance decisions are evaluated in the cost function $\mathcal{H}^k(t_0)$ over a long prediction horizon T. In combination with an adequate choice of sampling time T_s and a scenario grid of alternative control behaviors, the cost function provides a filtering effect that ensures that changes in each variable must be significant enough to produce a change in the decisions. Moreover, the collision cost $c_i(\cdot)$ prioritizes avoiding collision hazards that are close in time over those that are more distant and usually more uncertain [8].

C. ASV guidance uncertainty

We assume that the ASV state is accurately known and the ASV's motion controllers are capable of achieving the desired references for course and speed, by compensating for disturbances (i.e. environmental forces). This assumption leads to a simple SB-MPC implementation, which relies on the hazard $\mathcal{H}^k(t_0)$ evaluation criterion in (3) in order to achieve safe decisions.

D. Obstacle motion uncertainty

In the nominal case where the obstacle state is accurately known, using a constant velocity model for predicting obstacle motion is sufficient to avoid collision in many cases (see e.g. [8],[14]). However, some cases may be difficult to capture with a constant velocity model, and collision avoidance decisions may become highly reactive.

We propose a few extra scenarios that branch on the nominal scenario, by defining the following uncertainty-adapted sets that are used to predict the region occupied by the obstacle in the future:

$$\mathcal{U}_i = \{\hat{u}_i - \bar{u}_{\mathrm{br1}} - \tilde{u},\ \hat{u}_i,\ \hat{u}_i + \bar{u}_{\mathrm{br2}} + \tilde{u}\},$$
$$\Psi_i = \{\hat{\chi}_i - \bar{\chi}_{\mathrm{br1}} - \tilde{\chi},\ \hat{\chi}_i,\ \hat{\chi}_i + \bar{\chi}_{\mathrm{br2}} + \tilde{\chi}\},$$

where $\tilde{u} = \min(\sigma_{u_i}, \bar{\sigma}_u)$ and $\tilde{\chi} = \min(\sigma_{\chi_i}, \bar{\sigma}_\chi)$ are limits for specifying the extent of uncertainty adjustment allowed for the estimated speed $\hat{u}_i$ and course $\hat{\chi}_i$, respectively. We consider obstacle speeds and course within one standard deviation (σ_{u_i}, σ_{χ_i}) around the mean, and we enforce the limits ($\bar{\sigma}_u$, $\bar{\sigma}_\chi$) to ensure that initial estimates are within acceptable limits. The estimated speed, course, and their associated variances are obtained through an obstacle management interface (cf. Fig. 1) discussed in Section III-E.

The parameters $\bar{u}_{\mathrm{br1}}, \bar{u}_{\mathrm{br2}}, \bar{\chi}_{\mathrm{br1}}, \bar{\chi}_{\mathrm{br2}}$ specify asymmetric branching offsets in speed and course, which account for a possible change in speed and course at the beginning of the prediction horizon. Therefore, the predicted region possibly occupied by the obstacle becomes larger further into the prediction horizon. This does not pose feasibility issues in complex scenarios since the sets do not introduce hard constraints into the optimization problem (3). Moreover, branching the nominal (straight-line) predicted trajectory at the beginning of the horizon is still useful if the actual maneuver occurs later in the horizon since the predicted (conservative) region may still be valid. We choose asymmetric parameters, typically $\bar{u}_{\mathrm{br1}} = 1\,\mathrm{m/s}$, $\bar{u}_{\mathrm{br2}} = 0.1\,\mathrm{m/s}$, $\bar{\chi}_{\mathrm{br1}} = 1\,°$, $\bar{\chi}_{\mathrm{br2}} = 5\,°$, because we expect obstacles that intend to follow COLREGs in dangerous situations to prefer starboard maneuvers over port, and may reduce speed, instead of increasing speed.

E. Track loss and false tracks

We implement an obstacle management interface (see Fig. 1), which maintains a list of obstacles that have been previously used in the SB-MPC, and we manage this list separately from the obstacle list obtained from the tracking system. The intention is to be able to determine the impact of a track on the current collision avoidance decision based on its influence on previous decisions. The impact of a track depends on how long the track has been alive. This means that an obstacle that has been tracked for a while and suddenly terminated by the tracking system should not cause a (dangerous) abrupt change in behavior of the ASV.

Using a standard Kalman filter with relatively high measurement covariance values allows the SB-MPC algorithm to obtain position, speed, and course estimates that are close to the tracks received from the radar tracking system. The filter provides useful (open-loop) short-term predictions in case of track loss, without the need of keeping a long history of past states. If the track has been alive for less than a minimum tracking time $t_{\mathrm{min}}^{\mathrm{track}}$, it is immediately discarded when terminated by the radar tracking system. Tracks that are used for at least $t_{\mathrm{min}}^{\mathrm{track}}$ are still considered in the hazard evaluation criterion $\mathcal{H}^k(t_0)$ and the corresponding collision cost is reduced using the track-loss factor (cf. (3)):

$$l_i(t_{\mathrm{lost}}) = \frac{T_s}{(t_{\mathrm{lost}})^{q_l}}, \quad t_{\mathrm{lost}} \geq T_s, \tag{4}$$

where t_{lost} is the track loss duration and $q_l \geq 1$ is a tuning parameter. After a short duration $\bar{t}_{\mathrm{lost}}$, or if the Kalman filter's error covariance estimates grow beyond a defined threshold, the track is discarded. This decision is based on the observation that real tracks that are (falsely) terminated will be regained quickly with a new ID (within $\bar{t}_{\mathrm{lost}}$), while false tracks or tracks that leave the radar sensing range may not return.

At close range to an obstacle, it is important that t_{lost} is kept as short as possible since a lost target may return with a new track that deviates significantly from the lost track (e.g. due to a sharp turn). However, the track-loss penalty ensures that the effect of a lost track diminishes quickly, giving priority to any new track that may pose a greater danger to the ASV. The above strategy also influences the effect of false tracks in the collision avoidance decisions.

(a) Telemetron (ASV) (b) Munkholmen II (c) Ocean Space Drone I

Fig. 2: Vessels involved in the experiments.

TABLE I: Vessel data: Ocean Space Drone I (OSD. I)

	ASV	obstacles	
Parameter	Telemetron	Munkholmen II	OSD. I
Length [m]	8.0	14.0	12.0
Width [m]	3.0	6.0	3.0
Max. speed [kn]	~ 34	~ 10	~ 8

TABLE II: Radar tracking system parameters

Sampling time	(T_r)	2.8 s
Process noise covariance parameter	(q)	$(0.05\ \mathrm{m\,s^{-2}})^2 I_2$
Measurement noise covariance (range)	(R_r)	$(20\mathrm{m})^2$
Measurement noise covariance (bearing)	(R_θ)	$(2.3°)^2$
Confirmation probability threshold	(P_C)	0.95
Termination probability threshold	(P_T)	0.1

TABLE III: COLREGs-compliant decision parameters

Sampling time	(T_s)	5 s
Prediction horizon	(T)	300 s
Obstacle considered close	(d_{close})	1000 m
Safety distance to obstacle	(d_{safe})	185.2 m
Action initialization range	(d_{init})	1852 m

IV. Field Experiments

Experiments using the SB-MPC and the IPDA-based radar tracking system were performed in the Trondheimsfjord in order to evaluate the performance in both long-range and close-quarter scenarios. The test setup and results are presented and discussed in this section.

A. Test setup

The ASV used is called Telemetron, which is a Polar Circle 845 Sport vessel owned by Maritime Robotics. Telemetron is a stable and highly maneuverable Rigid Buoyancy Boat (RBB). The obstacle vessels are the Trondheim Port Authority's Munkholmen II tugboat and Kongsberg's Ocean Space Drone I. An overview of relevant vessel specifications are provided in Table I. The vessels were equipped with the Automatic Identification System (AIS), which transmitted their position, course, and speed information. However, the AIS data was not always accurate in our tests, possibly due to significant AIS signal delays, especially when the obstacles were maneuvering. Therefore, we do not consider the AIS measurements as ground truth in our discussions.

The ASV Telemetron is equipped with the Kongsberg Seapath 330+ navigation system, which has an accuracy of 0.1° RMS in roll/pitch/yaw estimates, and 0.1 m RMS accuracy in position estimates. This makes accurate navigation, guidance, and control of Telemetron possible. Using the existing mission/path planning, Line-Of-Sight (LOS) guidance, and low-level vessel control software installed on Telemetron (cf. Fig. 1), we are able to achieve desired high-performance motion control according to our assumptions in Section III-C. A C++ implementation of the SB-MPC collision avoidance method was installed as part of the onboard control system (OBS), which runs on an embedded computer in the Telemetron vessel. For obstacle tracking, we use the Simrad Broadband 4G™ Radar, the Seapath 330+ navigation system, and the real-time Global Navigation Satellite System (GNSS) corrections for positioning (known as CPOS) from the Norwegian mapping authority (Kartverket) [19]. The IPDA tracking algorithm is implemented in the Robot Operating System (ROS) installed on a separate computer, which has an Intel® i7 3.4 GHz CPU, running Ubuntu 16.04 Linux.

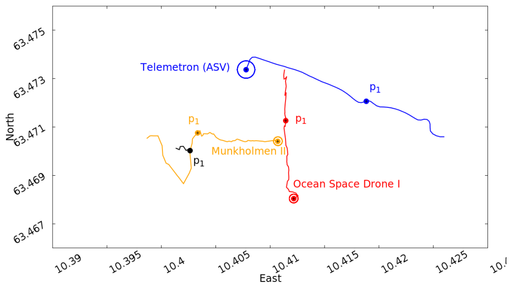
The main parameters used for both radar tracking and COLREGs-compliant decisions are shown in Table II and III, respectively. The SB-MPC method is tuned to prioritize changes in course over speed in order to produce ASV behaviors that are clear to observing operators/vessels.

B. Scenarios and Results

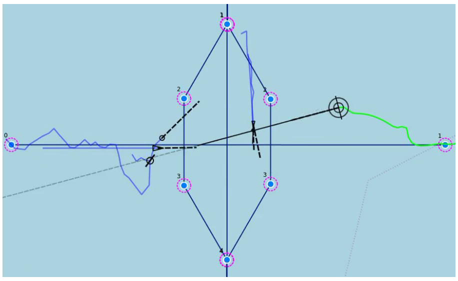
The scenarios cover both cooperating and non-cooperating obstacle situations, where the ASV is required to be proactive, but is allowed to choose reactive actions if necessary. We consider collision avoidance decisions that are made 1 nautical mile (NM) away from the target as long-range decisions, which must be COLREGs-compliant. We focus on the case where no communication exists between the ASV and the obstacles, meaning that the ASV uses only the IPDA radar tracking system installed for its collision avoidance decisions. Results from different scenarios are shown in figures 3–5.

In Fig. 3, a combined crossing and head-on situation is shown, where Fig. 3a shows the trajectories of the vessels involved, using the position estimates from the radar tracking system. The Ocean Space Drone I is well tracked from North to South, while the track of Munkholmen II is highly uncertain in the beginning. Both false tracks and track loss were experienced in this test run, with two 'competing' tracks (the long yellow track and the short black track) appearing for the same Munkholmen II vessel. For the COLREGs-compliant decision system, the radar tracks of Munkholmen II describe the motion of two different obstacles, and the COLREGs-compliant strategy must be robust to the uncertain motion of the obstacles.

We will use the snapshot of the vehicle control station (VCS) in Fig. 3b to discuss our observations. The VCS figure shows the planned waypoints and paths used throughout the experiments. Note that Ocean Space Drone I deviates



(a) Trajectories showing the ASV's measured position and position estimates from the radar tracking system. The end of a trajectory is indicated by the symbol ⨀ for the ASV and ⊙ for the obstacle vessels. The position of each obstacle is enclosed by a relatively large circular safety region (cf. d_{safe} in Table III).



(b) Vehicle control station (VCS) snapshot at position p_1 in Fig. 3a, showing planned waypoints, paths, and vessel trajectories obtained from both radar tracking (○) and AIS values (▷).

Fig. 3: Obstacle vessels Head-on and crossing from starboard.

significantly from its planned path from North to South. This is due to the waves and eastward currents experienced during the experiments. For Munkholmen II, it is easy to compare the radar tracks (cf. Fig. 3a) with the AIS track, which is a straight line in the West-East direction. The course and track status at p_1 are also shown in the VCS figure, where the symbol $\varnothing$ indicates that the short track is terminated at p_1. Before the short track was terminated it represented a significant hazard on the ASV's path, while the long track made a large deviation from the path. However, the large deviations did not lead to large reactive maneuvers by the ASV. The most critical event occurs at position p_1 when the short track is terminated. The long (surviving) track has an estimated course which suggests that Munkholmen II is crossing the path of the ASV. This drastic change in situation means a significant change in collision hazard, but this leads to only a slight reaction in the ASV's behavior due to the robustness considerations in the SB-MPC strategy.

The next scenario shown in Fig. 4 describes a situation with two obstacles that do not cooperate according to COLREGs. Munkholmen II was traveling with an average speed of 6 kn (∼3 m/s), while the Ocean Space drone's speed was about 5 kn (∼2.5 m/s). The reference speed (10 kn) of the

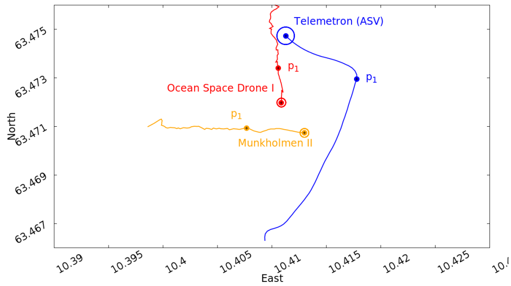


Fig. 4: Non-cooperating obstacles head-on and crossing from port. The end of a trajectory is indicated by the symbol ⨀ for the ASV and ⊙ for the obstacles. The position of each obstacle is enclosed by a relatively large circular safety region (cf. d_{safe} in Table III).

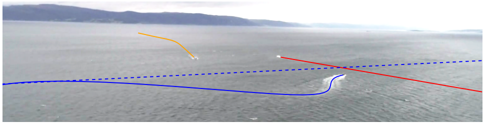
ASV allows it to make an early and clear starboard maneuver, which is adapted into a nearly straight path. The ASV's path is predictable according to COLREGs, and the ASV stays well clear of both obstacles, before heading towards its original path from position p_1. Note that both obstacles are well tracked by the IPDA tracking method, and the noise in the radar tracks does not have any significant effect on the behavior of the ASV.

We take a closer look at the course and speed estimates from the radar tracking method in the experimental results shown in Fig. 5. In Fig. 5, we test a situation where the ASV's path (from West to East) crosses the paths of both Munkholmen II and Ocean Space Drone I. An aerial photo taken during this test run is shown in Fig. 5a. Munkholmen II travels towards South, and after a while, it makes a starboard maneuver with the intention of taking partial responsibility in the head-on and crossing situation. Ocean Space Drone I on the other hand chooses a passive strategy by maintaining its course and speed. The ASV's challenging task is to understand the intentions of both obstacles based on their uncertain state estimates. The scenario is such that a wrong reaction of the ASV to Munkholmen II's starboard maneuver could easily lead to a close-quarter collision situation when Munkholmen II returns to its original (intended) course.

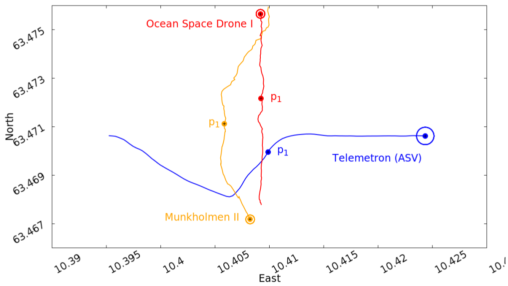
In Fig. 5c–5d, significant variations can be seen in the ASV's own course and speed measurements (partly due to the effect of waves) and estimates from the radar tracking system. The control modifications by the SB-MPC strategy show that the observed behavior of the ASV is not due to the noise in the estimates, but mainly the result of the changes in the actual collision situation and the corresponding assessment of collision hazard in the SB-MPC (cf. Section III-B).

V. Conclusions

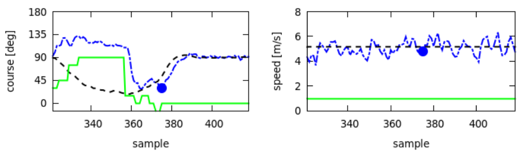
An autonomous collision avoidance system that uses an IPDA radar tracking method and SB-MPC was presented in this paper. The discussions focused on the robustness considerations made when using the SB-MPC and IPDA methods, and in particular, the case where no uncertainty estimates of obstacle tracks are obtained from the IPDA



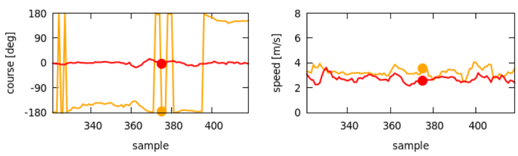
(a) Crossing situation, showing the planned (– – –) and actual (——) paths of the ASV, and the actual paths of Munkholmen II (——) and Ocean Space Drone I (——).



(b) Trajectories showing the ASV's measured position and position estimates from the radar tracking system. The end of a trajectory is indicated by the symbol ⨀ for the ASV and ⊙ for the obstacle vessels. The position of each obstacle is enclosed by a relatively large circular safety region (cf. d_{safe} in Table III).



(c) Desired value from LOS guidance (– – –), SB-MPC modification (——), and measured value (–·–). Compare SB-MPC modifications with desired values from LOS guidance. The points represent p_1 in Fig. 5b.



(d) Obstacle course and speed values from IPDA radar tracking. The colors correspond to the trajectories in Fig. 5b, and the points represent p_1.

Fig. 5: Obstacle vessels crossing from both port and starboard.

tracking method for making collision avoidance decisions. Results from full-scale experiments were discussed, and the results show that the IPDA radar tracking method produces obstacle track estimates suitable for collision avoidance, and the SB-MPC method is capable of handling uncertain tracks in its decision process in both close-quarter and long-range scenarios.

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