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The Autosea project: Developing closed-loop target tracking and collision avoidance systems

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

NTNU, Department of Engineering Cybernetics, 7491 Trondheim, Norway

E-mail: edmund.brekke@ntnu.no

Abstract. Autonomous surface vehicles and maritime autonomous surface ships must rely on sense-and-avoid systems for navigating safely among other ships. The main objective of this paper is to present examples of such systems, and their verification in full-scale collision avoidance experiments as part of the research project “Sensor fusion and collision avoidance for autonomous surface vehicles” (Autosea). Lessons learned from the progression of experiments have led to increasing robustness of the methods, and provide a foundation for several important topics of further research in the near future.

1. Introduction

Autonomous ship technology has emerged as a nascent research area in recent years. Building upon successful demonstrations and commercial products in exhibiting high degrees of autonomy in aerial, underwater and automotive systems, it is hoped that increased autonomy in shipping can lead to cost reductions and improved safety. A key prerequisite for this is a trustworthy collision avoidance (COLAV) system.

COLAV is also known as sense-and-avoid. The systems must use onboard sensors to perceive obstacles in the surroundings. For several reasons, target tracking is an important part of this processing pipeline. The motion of other obstacles (ships) is in general non-zero and unknown, and must therefore be estimated. Furthermore, raw sensor images do not by themselves provide any temporal continuity. Tracking methods must perform data association in order to link detections from subsequent images, so that tracks can be established and their kinematic attributes can be estimated. Most established tracking methods are variations of multiple hypothesis tracking (MHT) or joint probabilistic data association (JPDA) [1]. In MHT, the method attempts to enumerate all association hypotheses with significant probability involving several scans, or to search more directly for the best hypothesis. In JPDA, the method merges all the association hypotheses into a single hypothesis after every scan is received.

As for the avoid part, methods range from variations of path planning [2], [3] to highly reactive methods which are tightly integrated with the control system [4]. In between these two extremes we find several popular methods such as the velocity obstacle (VO) [5] [6] and the dynamic window (DW) method [7]. The VO method searches for a safe and optimal linear velocity vector. In its plain-vanilla form it assumes that the ownship (i.e., the ASV attempting to avoid collision) immediate is able to achieve this velocity. The DW method searches for a safe and optimal pair of surge (i.e., forward velocity) and turn rate. In land robotics this means



that candidate avoidance maneuvers are circular arcs, while the resulting maneuvers must be calculated by simulation when the DW method is adapted to second-order nonholonomic vehicles such as ships [8].

Obstacle avoidance for ASVs has been a topic of active research since the mid 2000's. Early works such as [9] focused on adapting fundamental technology from the more mature field of unmanned ground vehicles (UGVs). The first comprehensive description of an ASV system in a journal publication dates from 2010 [10]. In this work, MHT with interacting multiple models (IMM) was used for obstacle tracking with input from several input sensors, including X-band radar and stereo vision. Few details of the motion control system were given; *waypoint navigation* and *replanning* were mentioned on a superficial level. A COLAV system more targeted towards low-cost applications was described in [11]. In this work, radar tracking by means of JPDA with IMM was used in the perception pipeline, while an A* search was used to find a collision free path.

When the research project ‘‘Sensor fusion and collision avoidance for autonomous surface vehicles’’ (Autosea) was commenced in 2015 there was hence a need for more in-depth and precise understanding of how *local* COLAV methods could be integrated with tracking systems. The focus of the Autosea project has been to design algorithms for target tracking and COLAV, and verify these in closed-loop full-scale experiments. The purpose of the present paper is to provide the reader with a bird-eye overview of these developments and experiments, which is not available from the previous publications of the project. The paper is written in a colloquial style, with absolutely no equations. Familiarity with ASV technology, motion control and sensor fusion is taken for granted.

The paper is organized as follows. In Section 2 we present COLAV methods developed in Autosea, while Section 3 provides a fairly detailed description of the tracking system that was used in the experimental work, which again is summarized in Section 4. Topics for future research and suggestions for definitions of COLAV terminology are discussed in Section 5 before a brief conclusion follows in Section 6.

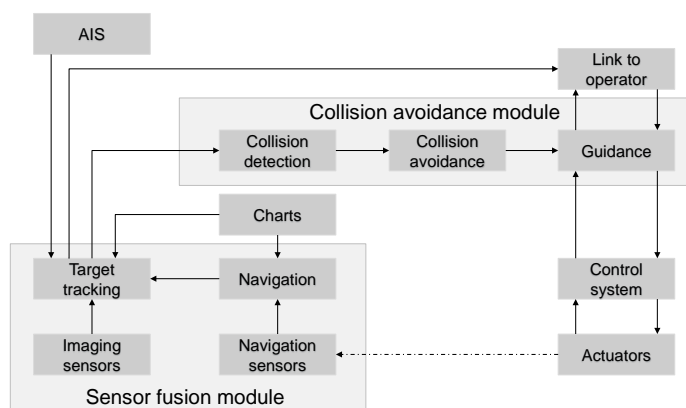


Figure 1. Block diagram of the system architecture for a COLAV system. The left-hand side represents perception, while the right-hand side represents control. The dashed arrow indicates that it is a closed-loop system. Both online AIS and imaging sensors such as radar may be used as data sources.

2. Variations of model-predictive control for collision avoidance

Model predictive control (MPC) is an approach to optimal control that works by searching for a control input, as a function of time up to a given prediction horizon, that will make the system behave as close to the desired behavior as possible. While MPC typically is associated with applications in process control, it appears to be less established in autonomous vehicle navigation. We will therefore provide a general overview of our perspective on MPC in general, before we delve into recently proposed MPC-based COLAV methods in greater detail.

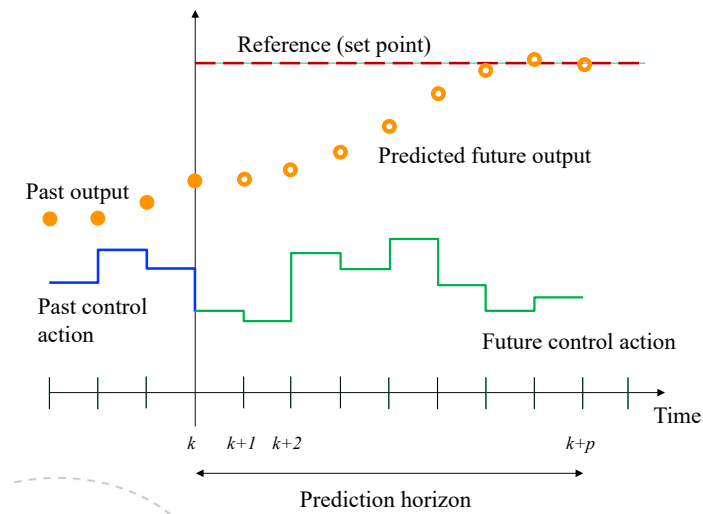


Figure 2. Basic principles of MPC. In the illustration, the goal is to reach a constant value of the reference. In a COLAV system this could for example be a particular course angle. The cost function depends on both the reference, the predicted trajectory and the control input. Penalties on, e.g., high values of derivatives may lead the algorithm to choose control inputs that give a slower convergence to the reference than theoretically possible.

Key design choices in the development of an MPC method include the parametrization of the control input, the parametrization of the cost function and the search technique. Regarding the control input, the MPC method may search for a good sequence of low level actuator controls, or it may search for higher-level trajectory descriptions, which then are fed to the low level controllers. As for the cost function, it may include a variety of measures derived from both the desired reference, the predicted trajectory and the control input. Examples of such measures can be deviation between reference and prediction, risk measures derived from the prediction, fuel costs derived from the suggested control input, etc. Finally, a key distinction goes between MPC methods that perform a gradient-based search for optimal control input, and MPC-methods that search for a good control input over a discrete search space.

2.1. The Simulation-Based MPC (SB-MPC) method

The simulation-based MPC (SB-MPC) method was developed in [12] as a sample-based method that aims to find an optimal combination of desired surge speed and course. For each such surge-course combination, the method simulates how the ASV would behave if that combination was given to its guidance system. The simulation outcomes are analyzed and quantified into several performance measures which are used in the objective function. In [12], terms representing collision risk, collision cost, COLREGs compliance, nominal path deviation and grounding risk were included.

Key benefits of this approach are flexibility, scalability and ease of implementation. The cost function can be expanded to include terms related to vessel dynamics, weather conditions, uncertainty in the prediction of other vessels, etc. It is capable of handling a large number of target vessels since each vessel enters the objective function as just another term to minimize cost over, and because the method automatically gives priority to avoiding nearby vessels over vessels further away. The combination of all the hazard measures into a single cost function means that there is no need for multi-objective optimization. Also, the use of a single cost function mitigates the need for additional logic in the form of if-else-clauses. The method can be tuned to prefer course changes over speed changes or vice versa. Typically, course changes are preferred to produce ASV behaviors that are clear to observing operators/vessels [13].

In a more recent version of SB-MPC, transition costs were included in the cost function to penalize control behaviors that will cause the ASV to pass an obstacle on a different side than what is predicted with the current control behavior [14]. The transition costs play the same role as hysteresis does in standard VO implementations [6].

2.2. Mid-Level COLAV and the hybrid architecture

In [15] a hybrid architecture for maritime COLAV has been proposed, building upon ideas that were first formulated in [16]. The hybrid architecture consists of three layers: Energy-optimized path planning, mid-level COLAV and short-term COLAV. Both these COLAV methods are based on MPC. The mid-level COLAV method searches for a trajectory with clear maneuvers and otherwise mainly straight motion that avoids collision with other ships. The method is gradient based and calculates derivatives by means of automatic differentiation in the CASADI framework. The cost function accounts for deviation from the desired path, deviation from desired velocity and COLREGs compliance. Moving and static obstacles are avoided by means of hard inequality constraints, and velocity limitations of the ownship are also modeled by inequality constraints. The mid-level method adheres strictly to COLREGs. In a situation where the maneuvering aspects of COLREGs must be ignored to stay safe, the short-term COLAV method takes over.

2.3. The Branching Course MPC method

The Branching Course MPC (BC-MPC) algorithm [17] is also a sample-based MPC method, especially designed to be robust with respect to noisy obstacle estimates. As part of this, the method is designed without discontinuities or logic, which reduces the sensitivity to noise in obstacle estimates. The search space is constructed based on a set of motion primitives, generating trajectories with continuous acceleration, which can provide the vessel controllers with acceleration feedforward information. The trajectories consist of maneuvers and straight-line segments, representing common maritime maneuvers. Each trajectory consists of multiple maneuvers, making the algorithm able to plan for future maneuvers which can be necessary to find suitable solutions in complex situations. In [18], the BC-MPC algorithm is extended to also consider static obstacles.

The algorithm is used as a short-term algorithm in the hybrid architecture. Therefore, it is designed to comply with the maneuvering aspects of COLREGs when possible, although with the possibility of ignoring them in emergency situations. Emergency situations include situations where obstacles violate COLREGs, such as not maneuvering in a crossing situations where the ownship is the stand-on vessel, requiring the ownship to maneuver even though it has a stand-on obligation. Having a numerically robust sample-based algorithm at the bottom layer allow for using less numerically robust algorithms at the higher levels of the hybrid architecture, such as the gradient-based mid-level algorithm.

2.4. Dynamic reciprocal velocity obstacle method

Other COLAV methods such as DW and VO can also be viewed as simplifications or special cases of the MPC paradigm, by re-phrasing the methods in terms of objective function, constraints, search strategy and input parametrization. For example, the plain-vanilla VO assumption of immediate velocity change can be viewed as a rather simplified kind of simulation.

The impossibility of reaching the avoidance velocity instantaneously, combined with lack of cooperation between ownship and target ship, may lead to oscillatory behavior for the plain-vanilla VO method. When this happens, both ships make avoidance maneuvers simultaneously, and as collision appears to have been avoided, they both go back to their nominal velocities, and so on. Variations of so-called Reciprocal VO (RVO) have been developed to mitigate this problem, see e.g., [19]. In RVO, both ships share the responsibility for avoiding collision. A variation of RVO that takes COLREGs into account was developed in [20] as part of the Autosea project. This method, known as Dynamic Reciprocal VO (DRVO) also includes a dynamic assessment of whether the target ship is cooperating, which is used to control the degree of reciprocity.

3. Variations of probabilistic data association for obstacle tracking

In this section we describe the tracking system that has been used in the Autosea experiments. The system is a further development of the track system originally described in [21]. To provide context, we will first take a look at underlying assumptions and rationale for the design choices.

3.1. A very brief review of target tracking

Most established tracking methods, including MHT and JPDA, are based on the following at-most-one assumptions:

O1 *Point target assumption*: Any target generates at most one measurement.

O2 *No merged measurement assumption*: Any measurement comes from at most one target.

Tracking methods typically make use of a process model, a measurement model and also models for detection probability, clutter intensity etc. Both MHT and JPDA can employ several different process models in parallel, using the IMM framework. For example, such an ensemble can include a low noise constant velocity (CV) model, a high noise constant velocity (CV) model and a constant turn rate (CT) model [11]. Both MHT and JPDA are *multi-target* tracking methods which have the capability to resolve *measurement contention*, i.e., when it is unclear which of several targets a measurement originates from. *Single target* tracking methods do not possess the same awareness, but can still be used to track multiple targets in parallel, with a potential loss of optimality if the targets are close to each other. The single-target versions of the JPDA is known as the probabilistic data association filter (PDAF). Another key topic is existence modeling. JPDA and PDAF assume a fixed number of targets, and track confirmation and termination are typically performed by *M-out-of-N* logic. In contrast, the integrated probabilistic data association (IPDA) models target existence as a binary random variable that evolves according to a hidden Markov model (HMM) [22]. Track confirmation and termination can then be performed by setting thresholds on the existence probability.

3.2. Design choices

The tracking system is tuned for optimal performance on medium-size vessels such as Munkholmen 2 (MH2), the Ocean Space Drone 1 (OSD1) or FF Gunnerus (see Figure 3). Since the distance between ships tends to be fairly large, measurement contention was not deemed to be a main issue, and single-target tracking methods were used in the experiments. PDAF was chosen instead of MHT-based methods because of its simplicity and modest computational complexity. The tracking system uses a single process model instead of multiple models. The rationale for this choice has partly to do with simplicity, and partly with limited expectations regarding the performance gain from IMM methods. See Section 4.1 for further discussion about this.

False tracks and misdetections were considered to be the most serious challenge in the early stages of the tracker development. For this reason the original PDAF tracker described in [21] was converted into an IPDA tracker. The IPDA tracker can utilize detailed information about clutter intensities through clutter maps [23] and also estimate the detection probability [24].

3.3. Tracking pipeline description

The tracking system is processing data from a Simrad 4G broadband radar and a navigation system, and provides tracks to the COLAV system. An AIS receiver is included for ground truth reference. All these sensors communicate with the processing unit (PU). The PU implements all the methods described below, and handles the tracking interface for the various COLAV methods, which may be implemented on both the PU or on a built-in on-board computer (OBC). The radar pipeline is implemented in the robot operating system (ROS) and consists of steps

Table 1. List of experiments

#	When	Where	COLAV	Data	Tracker	Target	Pub.
1	May 2017	Trondheimsfjorden	DW	Radar	PDA	Motorboat	[25]
2	May 2017	Trondheimsfjorden	SB-MPC	AIS	None	MH2	[14]
3	Oct. 2017	Trondheimsfjorden	BC-MPC	Radar	PDA	OSD1	[17]
4	Nov. 2017	Den Helder	SB-MPC	AIS	None	RIB++	[26]
5	Sept. 2018	Trondheimsfjorden	SB-MPC	Radar	IPDA	MH2 OSD1	[13]
			BC-MPC				[24]
			DRVO				[18]
6	June 2019	Trondheimsfjorden	SB-MPC BC-MPC	Radar	IPDA	MH2 Gunnerus	

for detection, projection, land filtering, clustering and target tracking. A detailed description is given in [21].

Key tasks of the pipeline are synchronization and measurement extraction. Radar data are timestamped on the arrival in the PU, synchronized with the navigation system and transformed to Cartesian world coordinates, before measurement extraction by means of clustering. The clustering procedure uses a single-linkage approach. A cluster consists of a centroid and its footprint, which is based on the convex hull of the points in the cluster. Every cluster in a scan is given the mean timestamp of the scan. Notice that the footprint information is not used in the tracking system.

The current version of the tracking system is based on a non-parametric IPDA with CV process model as described in [22]. New tracks are initiated on all measurements that are not associated with existing tracks. In the COLAV experiments from October 2017 and later the value $(0.05\text{m/s}^2)^2$ was used for the continuous-time process noise covariance. The probability of existence is initiated at a fairly low value, and tracks are not confirmed until the existence probability is close to unity.

3.4. Tracking interface

The tracking system outputs tracks in two main ways. For the ROS-based COLAV systems, a ROS service is provided. Instead of passively listening to tracks, the COLAV system requests tracks at specified timestamps, and the tracking system handles prediction and interpolation. For other systems, a TCP-based publisher/subscriber interface is provided, and tracks will be output on the network at the specified rate.

4. Lessons from full-scale collision avoidance experiments

Table 1 summarizes most of the COLAV experiments conducted as part of the Autosea project.

4.1. Experiment 1: Modified DW with PDAF radar tracking [25]

This very first closed-loop COLAV experiment had the goal of testing purely reactive COLAV, to be used as a last resort if more advanced and proactive methods fail. The hypothesis was that the modified DW method [25], by directly controlling the yawrate, would give a fast and strong response suitable for a last resort reactive method. As ownship, Maritime Robotics' dual manned/unmanned sport vessel Telemetron was used in autonomous mode, while a small



Figure 3. Some of the ships used in Autosea experiments: Telemetron, Munkholmen 2, Ocean Space Drone 1 and FF Gunnerus.

motorboat equipped with a radar reflector was used as target ship. The tracking system as described in [21] was used to process the radar data.

The biggest surprise in these experiments was that the course estimates (i.e., direction of estimated velocity vector) from the PDAF fluctuated significantly more than anticipated from purely theoretical considerations. With a typical error of approximately 20° , and occasionally exceeding 45° , the COLAV system had a hard time choosing sensible trajectories. The direct control of yawrate made the ownship react very strongly to these noisy course estimates. This could both result in wobbling and failure to make any evasive maneuver at all, or it could lead to evasive maneuver so strong that they would pose a significant safety threat. Another weakness of this COLAV system was that it did not include any COLREGS compliance. Thus, the ownship would chose to pass on whichever side of the target ship that was most convenient.

A possible solution to the challenges with course estimation could have been to replace the standard PDAF with an IMM-based tracking method. This direction was, however, not followed for two reasons. For IMM methods to give significant improvement over a single Kalman filter, the so-called maneuvering index should be larger than 0.5 according to [27]. For tracking of civilian aircraft, where IMM is known to work well, it will typically reach values of 2 or higher. For maritime target tracking, where velocities are significantly lower, typical values may be around 0.2. Second, while IMM enables better estimation of the velocity vector, it does not prevent sudden and large jumps in the course estimate. We have observed occasional errors up to 40° also when using an IMM tracker similar to the one used in [11].

In any case, the results from the experiments indicated that the COLAV method should be made less sensitive to sudden course fluctuations. This could be achieved if the COLAV method to a larger extent was making a plan, and would stick to it unless there was sufficient evidence to do otherwise. This led to the BC-MPC method presented in Section 2.3.

4.2. Experiment 2: SB-MPC with AIS [14]

The first experiments with the SB-MPC method took place independently the same month. In these experiments, the focus was entirely on the behavior of the COLAV method itself, and AIS was therefore used as data source, instead of a radar tracking system with its many complexities. Again, the ownship was Telemetron while the tugboat Munkholmen 2 was used as a target ship. In addition to verifying the COLREGs compliance of the SB-MPC method, the experiments also verified that SB-MPC was capable of violating COLREGs when deemed necessary. The COLAV system gave satisfactory results even though the weather conditions were somewhat on the rough side, with wind speeds up to 15 m/s and wave height of about 1 m.

4.3. Experiment 3: BC-MPC with radar [17]

This experiment, performed during the Autumn 2017, was the first time the BC-MPC method (see Section 2.3) was tested. Again, Telemetron was used as ownship, and OSD1 was used as target ship. A PDAF-based radar tracking system was used as data source. Four scenarios were

repeated several times each: Head-on, crossing from starboard, overtaking and crossing from port. The BC-MPC algorithm solved the situations in accordance with COLREGs, and displayed good performance when coupled with the radar tracking system, demonstrating much better noise robustness than the modified DW algorithm. Occasionally, other vessels entered the test area. In one such situation, Telemetron was overtaken by the high-speed ferry Trondheimsfjord II, and the BC-MPC method was forced to make an unanticipated evasive maneuver. The biggest limitation of the BC-MPC method was perhaps its short prediction horizon, which caused the algorithm to drive alongside the obstacle in a crossing from port situation where the obstacle ignored its give-way obligation. This is less of a problem if the BC-MPC method is only used as a bottom layer in a hybrid architecture as described in Section 2.2.

4.4. Experiment 4: SB-MPC with AIS outside Den Helder [26]

The background for these experiments, in November 2017, was that authorities in the Netherlands, together with Deltares, invited selected companies to undergo a verification exercise in the Dutch North Sea in order to demonstrate and validate the capabilities of ASVs. Maritime Robotics was invited with Telemetron as ownship. Several target ships were involved. The most important ones were the Fast Raiding, Interception and Special forces Craft (FRISC) of the Royal Netherlands Navy and the Coastguard's Zirfaea. Both of these were equipped with AIS transmitters. The same SB-MPC method as was used in Section 4.2 was also used in these experiments. The scenarios progressed from simple head-on, crossing and overtaking scenarios via multi-vehicle scenarios combining overtaking and crossing, to scenarios that challenged the boundaries between different COLREGs regimes and scenarios with significant target ship intention uncertainty. Some scenarios were adapted on the fly by supervisors from the Navy with the aim of exploring challenging situations that may develop due to an unexpected change in behavior.

The main concerns identified in [26] had to do with AIS-latency and the challenges related to prediction when intentions are unclear. The latency of AIS data is up to 10 seconds. While this may be a negligible time in scenarios with long distances or low velocities, it can introduce significant delays for shorter distances and higher velocities, making the COLAV method behave in a more reactive manner than desirable. However, a tracking system using only the Simrad 4G radar also will need at least 10 seconds to discover that a maneuver has happened, because more than 3 scans are needed to confidently estimate a turn rate.

4.5. Experiment 5: Several COLAV methods with IPDA radar tracking [13] [24] [18]

After the summer 2018 the IPDA-based tracking system described in Section 3 replaced the earlier PDAF-based tracking system from [21]. In September 2018, the BC-MPC method was tested with the IPDA-based tracking system, for avoidance of both static and moving obstacles [18]. The IPDA-based tracking system was also used as data source for a new version of the SB-MPC method with several robustness enhancements [13]. These were specifically designed to manage the additional uncertainties due to radar tracking that had posed challenges in the experiments reported in [25] and [17]. In particular, the following two robustness enhancements were central. First, an *obstacle management interface* was introduced to keep both obstacles currently being tracked, and obstacles whose tracks recently were terminated. A geometrically decaying track-loss factor was used to reduce the relevance of the latter kind of obstacles. This was done to prevent sudden changes in situational awareness due to track-loss events. Second, the predictions of obstacle motion were supplemented with branching scenarios representing possible changes of speed and course at the beginning of the prediction horizon.

The experiments again included several multi-vehicle situations, with both cooperating and non-cooperating obstacles, as well as static obstacles. The main target ships were Munkholmen II and the OSD1. The utility of the obstacle management interface was indeed verified during a

crossing-head on scenario where multiple tracks were established on Munkholmen II, which was in head-on situation.

4.6. Experiment 6: BC-MPC with IPDA radar tracking

During the final demonstrations of the Autosea project on June 14th 2019 the IPDA radar tracker was also used together with the BC-MPC method. Two scenarios were demonstrated for this combination: An overtaking scenario and a head-on scenario. Both involved FF Gunnerus as target ship. During the head-on scenario an additional complication arose as three very fast RIBs with so-called “water rafters” entered the test area, coming straight towards Telemetron, which was prompted to make a rapid evasive maneuver towards Gunnerus, before eventually making the main evasive maneuver to pass Gunnerus on the port side. See Figures 4 and 5.

5. Future research

5.1. Global, local, proactive and reactive methods

It is desirable to establish more precise terminology for categorizing the many different COLAV methods that exist. To provide some suggestions, we distinguish between global and local methods, and then we divide local methods into proactive and reactive methods. By global methods we mean methods that come up with a path or trajectory for an entire mission¹, such as crossing a fjord or traveling between two harbors. By local methods we mean methods that come up with a temporary deviation from a desired path, and which aim to return to the path as soon as it is considered safe. For maritime COLAV we generally want the local methods to be of a proactive nature rather than a reactive nature. While no agreed upon definition of proaction exists, we suggest that such a definition should include the ability to make and follow a plan according to situational awareness in a predictable manner. COLAV methods whose evasive control inputs depend directly on the state vector through a functional relationship (e.g., [4]) should automatically be considered reactive. It is also possible to divide local methods into long-term methods and short-term methods, where long-term methods utilize a more complete information picture, and short-term methods need a better understanding of the vehicle dynamics to provide more sudden evasive maneuvers. Short-term methods can be both proactive or reactive.

It is clear that both SB-MPC and the hybrid architecture/BC-MPC have huge potentials for further development. The SB-MPC cost function can be expanded to include more information sources, such as risk assessments [28]. It may sample candidate trajectories in a more deliberate manner than using a uniform grid, etc. The hybrid architecture has to be verified in experiments to evaluate its practical robustness and identify potential weaknesses to mitigate.

5.2. Heterogeneous multi-sensor fusion

It is clear that reliable COLAV systems must utilize a larger variety of sensors than the lone radar used in the Autosea experiments. Key reasons include the lower update rate and angular resolution of typically maritime radars, the limited feature information provided a radar, and the need for additional sensors for cross-validation.

The main research results on multi-sensor fusion from the Autosea project are reported in [29], where a multi-sensor version of the Joint IPDA (JIPDA) was used to track small vessels using radar, long-range lidar, optical camera and infrared camera. It was found that the inclusion of cameras, whether infrared or optical, prevented merged measurements from causing track coalescence. Lidar was found to be very useful for rapid track initiation, albeit at the expense of a significant increase in false tracks due to clutter caused by lidar returns from the sea surface.

¹ In the sequel we will simply write path instead of the phrase “path or trajectory”. In other words, the path may or may not be time-parameterized. The word path may also refer to a path with a velocity assignment.

Notwithstanding its weaknesses, radar is ubiquitous in maritime collision avoidance. Key strengths include the fact that it works well on longer ranges than other sensors, and that radar data are significantly easier to interpret. While convolutional neural networks were used to extract detections from the cameras in [29], simple thresholding and clustering operations are sufficient to extract detections from radar images.

The sharper resolution of other sensors can also be a double edged sword, as it leads to violations of the standard at-most-one-assumptions. This may require novel methods for extended object tracking (EOT) [30].

None of the closed-loop experiments of the Autosea project used radar and AIS simultaneously. The scientific literature on this kind of fusion is rather scarce, encompassing only a couple of references such as [31] and [32]. Figure 4 illustrates some of the challenges involved in radar-AIS fusion: While it is straightforward to match the radar track of Gunnerus with its AIS track, it is not at all clear which of the 3 RIBs that the AIS track of Crazy Raven should be matched with. This is partly due to the fact that only one of the RIBs had AIS, and partly because of the poor quality of this AIS track.

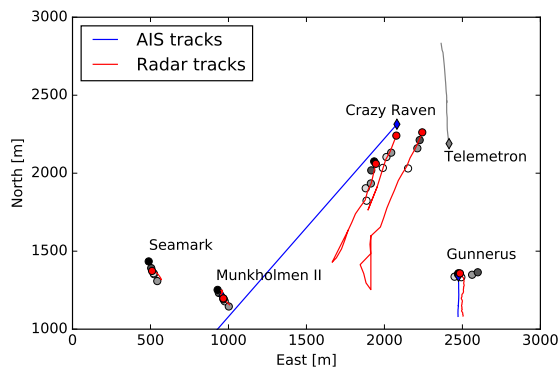


Figure 4. Radar tracking and AIS data from the Autosea final demonstration.



Figure 5. The same scenario seen from drone video.

5.3. Approaching the shore and harbors

EOT and *multi-target* tracking are of particular relevance in more confined and congested environments such as harbors or water canals, where the available space between different ship domains will be much smaller. Simultaneous localization and mapping (SLAM) or related localization methods are needed to prevent groundings and shore collisions. Shore constraints can also be included in the COLAV methods from existing electronic nautical charts (ENCs). This has been done for the SB-MPC method in [33] and for the BC-MPC method in [18]. When space is more limited, stop-and-go maneuvers may be preferred over the course changes that are preferred in open sea [34].

5.4. Elements of situational awareness

The overall challenge in developing a safe and reliable COLAV system is to ensure that the system itself is in possession of adequate situational awareness (SITAW). Sensor fusion and motion control are obvious building blocks in this, but several additional components are needed to realize good SITAW.

In particular, let us mention *risk assessment* and *intention prediction* as important research topics in SITAW. In order to act according to a complete risk picture, the COLAV system should utilize more of the uncertainties involved in the tracking methods, such as the probabilities of

the different association hypotheses or the covariances of individual tracks. A stepping stone towards such a system could be methods to calculate collision probabilities [28] [35]. Methods for intention prediction are another stepping stone for risk assessment. Prediction methods based on historical AIS data have been developed by MSc students affiliated with the Autosea project in [36] and [37]. There is a need for merging such data-driven methods with model-based methods such as the bridging distribution approach suggested in [38], and with online information from AIS or other communication protocols.

6. Conclusion

As part of the Autosea project complete COLAV systems for ASVs including target tracking and motion control have been developed and verified in full-scale experiments. Frequent interaction between researchers working on sensor fusion and researchers working on motion control has ensured that the tracking part of the the COLAV system is well adapted to the COLAV part, and that the COLAV part is well adapted to the tracking part. Strengthening SITAW and enabling ASVs to enter more congested and confined environments have been identified as broad topics for future research.

Acknowledgement

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