Scenario Identification for Safety Assessment of Autonomous Shipping using AIS Data

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Synopsis

While autonomy offers a solution to many issues facing the maritime and naval industry, assessing the safety and reliability of autonomous shipping is one of the key challenges. Established methods and standards for conventional ships are still relevant but do not account for the challenges that come with the application of Artificial Intelligence (AI) and cyber-physical systems for Maritime Autonomous Surface Ships (MASS). Such systems require specialised safety assessment techniques. Scenario-based safety assessment for autonomous systems is one of the potential approaches and represents the state of the art. In this research, we conduct a feasibility study on identification and classification of seafaring scenarios, as described in COLREG, from Automatic Identification System (AIS) data. Furthermore, the statistical distributions for the parameters of these scenarios are empirically determined. We illustrate the utility of our methods using real-life AIS data from the Strait of Dover. Results indicate that AIS data can be a rich data source for identifying real-life scenarios that can be used for safety assessment of MASS.

Keywords: Autonomous Shipping; Automatic Identification System; Scenario Identification and Classification; Scenario Based Safety Assessment

1 Introduction

The introduction of more (semi-) unmanned Maritime Autonomous Surface Ships (MASS) in the future has several potential benefits. Compared to conventional manned ships, they may become more sustainable (Rødseth and Burmeister, 2012), cost-effective (Kretschmann et al., 2017) and safer (Burmeister et al., 2014).

These autonomous ships should operate and interact safely in complex situations, and at the same time should also adhere to the International Regulations for Preventing Collision at Sea (COLREG) (IMO, 1972). However, these regulations do not provide detailed guidance to specific (multi-ship) encounters, nor do they specify how machines should be endowed with "good seamanship". Discussions on the regulation of these unmanned autonomous ships are still ongoing at the International Maritime Organization (IMO) (Ringbom, 2019). What is clear, is that these autonomous surface ships should at least be as safe as current conventional manned ships (Veritas, 2017), this is often referred to as being Equivalent Safe (ES). Therefore, the development of efficient safety assessment methods/techniques is essential to pave the way for autonomous shipping to become widespread and accepted by the maritime sector.

Scenario-based safety assessment for autonomous systems is one of the potential approaches and represents the state of the art. This approach proposes to create a scenario database from real-life data and utilise it in the assessment of the autonomous system. Extensive development efforts in this approach is being carried out by automotive companies and research institutions (Elrofai et al., 2018; Pütz et al., 2017; Enable-S3 et al., 2016). In addition, it is broadly supported by the automotive community (ISO, 2019; Staplin et al., 2018). This experience from the field of autonomous driving can be of great benefit for autonomous shipping.

Following the scenario-based approach, and to identify relevant scenarios for safety evaluation, we need to understand and find out, the real-life "complex" situations in which autonomous ships must deal with in daily seafaring traffic. These scenarios may include surrounding ships that might be in interaction of its course, sea status and weather conditions.

In this paper we conduct a feasibility study on the extraction and classification of seafaring scenarios from Automatic Identication System (AIS) data. The extracted scenarios include the encounters as defined in COLREG, namely crossing stand-on, crossing give-way, head-on and overtaking.

Analysis of AIS data has been done extensively in the past (Tu et al., 2017). For example, for the purpose of detecting anomalous behaviour in traffic patterns using machine learning (Coleman et al., 2020) or statistical analysis (Ristic et al., 2008; Rong et al., 2020). AIS data has also been used for the purpose of collision risk assessment (Mou et al., 2010; Qu et al., 2011; Silveira et al., 2013) and detecting near miss ship collisions (Zhang

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et al., 2015b). Similar methods have also been used to evaluate and compare ship behaviour at different restricted waterways (Xiao et al., 2015). However, only a limited number of studies look at the actual detection and evaluation of specific COLREG encounters using AIS data (Iperen, 2015; Lei et al., 2018, 2019). However, to the best of our knowledge, AIS data has not been used yet for comprehensive scenario identification and classification nor for the purpose of scenario-based safety assessment.

In section 2, we explain the methodology developed for scenario extraction using AIS data, including the assumptions used, the identification of the scenarios and the calculation of the scenario parameter distributions. In section 3, we show a case study in which we extract give-way crossing scenarios in the Strait of Dover and calculate their parameter distributions. The conclusions and future work are discussed in section 4.

2 Identification of Seafaring Scenarios using AIS Data

A scenario can be designed by test engineers to assess the safety of autonomous ships both during design and prototype phases. In our framework, we aim to extract scenarios from AIS data for the same purpose. These scenarios are then called real-life scenarios. A scenario is generally defined as a sequence of events. In our framework a scenario for testing an autonomous shipping system is defined as the sum of all relevant events and conditions, under which this system is examined during the test. Main elements of the scenario include: the Own Ship (OS), surrounding Target Ships (TSs), navigational information, sea status, sea depth and weather conditions.

In this section we describe our methodology using AIS data to automatically detect COLREG encounters (e.g., give-way crossing, head-on) and identify specific scenarios. Thus we focus on the interaction between the own ship and the target ships. Other scenario elements such as sea status are not addressed in this study. Furthermore, we generate the statistical distributions for the parameters of these scenarios (e.g., angle and speed of approach).

2.1 COLREG Encounters and Assumptions

All encounters specified in the COLREG regulations are illustrated in Fig. 1, namely crossing stand-on, crossing give-way, head-on and overtaking. The angles used for each region are similar to those used in existing literature (Zhang et al., 2015a; He et al., 2017) and correspond to the visible white sternlight and green and red sidelights as defined in the COLREG. Some automated collision avoidance methods use different regions in which for instance the angle of the head-on region and crossing regions are wider (Campbell and Naeem, 2012).

Although we use discrete encounter regions here in our research, one should note that in practice the interpretation of the encounter is subjective and depends on many other factors (such as environmental conditions and the types of ships involved). Furthermore, it often relies on what in the COLREG is referred to as “good seamanship”. The latter is especially hard to evaluate for autonomous ships (Porathe, 2019a), which may encounter both manned and unmanned ships along its route (Porathe, 2019b). This motivates our approach for using empirical AIS data in order to synthesise realistic scenarios for safety assessment.

Similar to existing work (Zhang et al., 2015a), we use different assumptions for the Ship Domain, Action Range and Visible Range relevant for the interpretation of an encounter (see Fig. 1):

1. *Ship Domain:*
   The ship domain is defined as the free space around a ship in which no other ship or object should enter. Many definitions of this ship domain exist (from circular, elliptical to polygonal shapes) and often depend on characteristics of the ship and the situation at hand (He et al., 2017). AIS data has been used in the past to derive an empirical ship domain from the behaviour of surrounding ships (Hansen et al., 2013). For sake of simplicity, we use the same ship domain as defined in (Zhang et al., 2015a), namely a circle around the ship with radius of $1500m$ (approx. $0.8NM$).

2. *Action Range:*
   The action range is the range between the own ship and other ship targets at which it is believed that the ship will most likely take action according the COLREG rules. Experiments show that in most cases the officer on watch typically take actions around $5NM$ (Lin, 2006). As such, we use the same action range as used in (Zhang et al., 2015a), namely a range of $6NM$ (approx. $11.11km$).

3. *Visible Range:*
   The visible range is the range at which other ships are visible, but no action is taken. Although in real life situations this range is typically larger (depending on the available information from AIS, radar and eyesight), we limit the visible range to $13.5km$ (approx. $7.3NM$) which corresponds to the upper limit of the action range as empirically found in (Lin, 2006). This range is limited in order to reduce the scope of the scenario.

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Figure 1: Encounter diagram illustrating the different regions relevant for the COLREG encounters (stand-on, give-way, head-on and overtaking). The inner circle represents the Ship Domain, the outer circle represents the Action Range of the Own Ship (OS). See text for more details.

2.2 Trajectory Generation using AIS Data

Many AIS data mining methods are roughly divided into two approaches, point-based approach and trajectory-based approach (Cazzanti and Pallotta, 2015). Our method presented here is a trajectory-based approach since it first determines the trajectories of all vessels before mining scenarios from them. The fact that AIS data can be very noisy and is it sent asynchronously and irregularly, makes it very challenging to get smooth synchronised trajectories from different vessels. To generate smooth synchronised trajectories from AIS data we apply the following steps.

1. *AIS Data Loading and Filtering:*
   At first, raw AIS messages that are previously collected from AISHub (AISHub, 2020) are loaded and filtered. Data filtering is based on the region of interest both in terms of the specific area (defined as a longitudinal and lateral range) and specific period in time (defined as a period between two dates). From each ship (identified by its unique Maritime Mobile Service Identity (MMSI)) relevant information such as its GPS location, Speed over Ground (SoG) and Course over Ground (CoG) are collected.

2. *Extracting Trajectories:*
   For each ship, trajectories are extracted based on continuous sequences of position updates as received by the AIS messages. A position datapoint is assumed to be part of the trajectory if its time interval between itself and the last datapoint is no longer than 5 minutes. Trajectories with less than 20 datapoints are ignored.

3. *Coordinate Projection:*
   The longitudinal and lateral positions of the trajectory are projected on x and y coordinates of the specified area. Our method uses the EPSG:3857 Web Mercator projected coordinate system (Battersby et al., 2014).

4. *Interpolation to Fixed Timeframe:*
   The x, y, SoG and CoG values of the valid trajectories are interpolated in fixed time intervals of 10 seconds. This compensates for small gaps in the data and synchronises the time of AIS message updates between different ships. The method uses cubic spline interpolation which has shown to perform better over other AIS interpolation methods such as piecewise cubic Hermit interpolation (Zhang et al., 2017).

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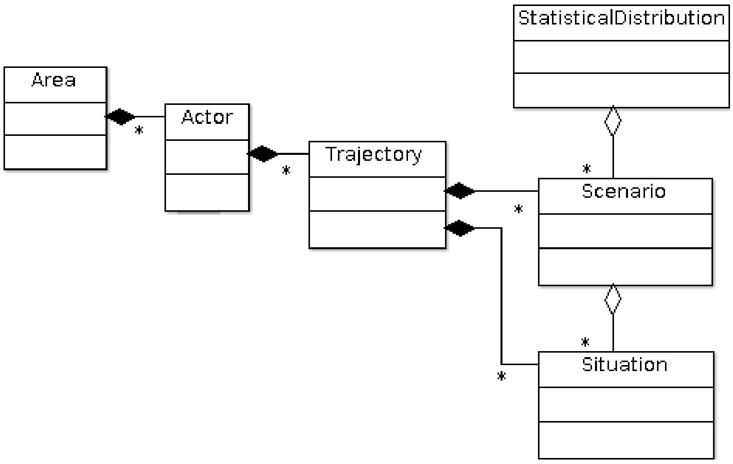

Figure 2: Class diagram of all scenario components extracted from the AIS data. A statistical distribution for each scenario parameter is calculated from multiple mined scenarios. Each scenario consists of multiple encounter situations. Each situation represents a single moment in time in which all relative positions and speeds of each target are known.

5. *Finding Overlapping Trajectories:*
   Once interpolation is complete, overlapping trajectories between a given ship and all other target ships, are found with the use of the same timeframe. Trajectories outside the visible range of the ship are ignored.

6. *Local Polar Coordinate Projection:*
   Each trajectory is converted to the local polar coordinate system (as shown in Fig. 1) of the corresponding ship. The relative positions of the target ships within the visible range of the ship are also projected in this space. This results in a series of situations (in which all relative positions of all targets are known) with a time interval of 10 seconds from which the COLREG encounters can be detected.

The above mentioned steps decompose the data into the components as illustrated by the class diagram in Fig. 2.

2.3 Scenario Detection

Fig. 3 illustrates the procedure for detecting different COLREG encounters using the same polar coordinate system as shown in Fig. 1. A COLREG encounter (give-way, stand-on, head-on and overtaking), for a specific target ship, is detected from a series of situations the moment it enters the visible range (position 1) and continue to the enter encounter zone (position 2, see the different colours in Fig. 1). The scenario corresponding to these situations ends the moment the target ship exits the encounter zone (position 3). Encounter detection is not triggered if the target ships enters a zone from another zone within its action range.

2.3.1 Scenario Parameters

For each scenario different parameters are calculated for the Own Ship (OS) and and the Target Ship (TS) as described in Table 1. These parameters describe the interaction between the OS and TS inside the encounter zone during the entire period of the scenario. In particular we are interested in certain moments during a scenario, this includes:

1. *Start of a scenario:* The moment the TS enter the OS encounter zone, i.e. position 2 in Fig. 1.

2. *End of a scenario:* The moment the TS exits the OS encounter zone.

3. *Closest Point of Approach (CPA):* The moment in which the distance between the OS and TS is minimal.

The CPA is closely related to the Distance at Closest Point of Approach (DCPA) and the time remaining to reach this point (TCPA) as often used in existing collision avoidance systems (Vujičić et al., 2017; Szlapczynski, 2006).

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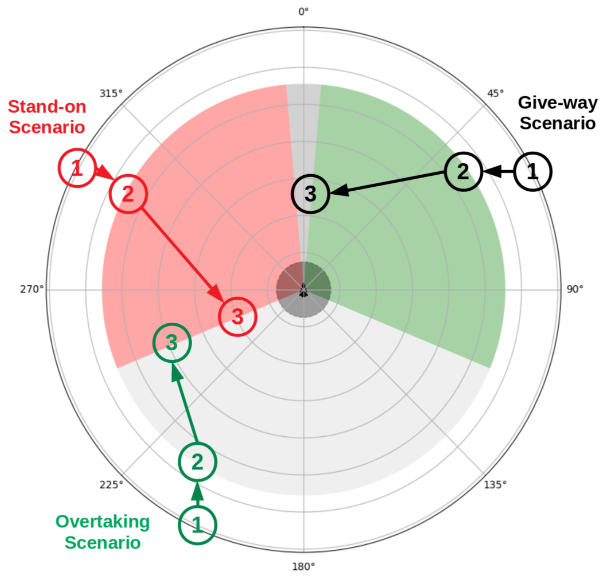

Figure 3: Examples of different encounters being detected. The numbers indicate the order of relative positions in which a target ship should be present in order to trigger a specific encounter detection. A valid scenario ends only if all 3 positions are present. See text and Fig. 1 for more details.

Category	Name	Description	Unit
Generic	Duration	The duration of the scenario.	seconds
Own Ship (OS) (min, max, mean, std)	CoG	Course over Ground	degrees
	SoG	Speed over Ground	knots
Target Ship (min, max, mean, std)	SoG	Speed over Ground	knots
	rCoG	Course over Ground relative to OS	radians
	AP	Angular position relative to OS	radians
	x	X location relative to OS	meters
	y	Y location relative to OS	meters
	Distance	Distance relative to OS	meters
	RV	Velocity relative to OS	m/s
At Approach (position 2 in Fig. 1)	rCoG	Course over Ground relative to OS	radians
	AP	Angular position relative to OS	radians
	SoG	Speed over Ground	knots
Closest Point (between position 2 and 3 in Fig. 1)	rCoG	Course over Ground relative to OS	radians
	AP	Angular position relative to OS	radians
	RV	Velocity relative to OS	m/s

Table 1: The calculated parameters extracted for each mined scenario.

2.4 Statistical Distributions

Once multiple scenarios are detected, statistical distributions in the form of Probability Density Functions (PDF) of their parameters can be calculated. The PDF provides for each random value of the parameter the corresponding likelihood of this value. In our method we use Kernel Density Estimation (KDE) to estimate the PDF. For the kernel we have used the Gaussian function and its bandwidth, which influences the width of the Gaussian for each contributing datapoint to the PDF, is calculated using the Scott method (Scott, 2015).

3 Case Study

3.1 Dataset and Region of Interest

In our case study we have used data already collected by AISHub. The dataset consist of one month period of AIS data at the Strait of Dover for two different ships (OS), including all target ships that these two ships encountered. The region of interest (at the Strait of Dover) included in the dataset is shown in Fig. 4.

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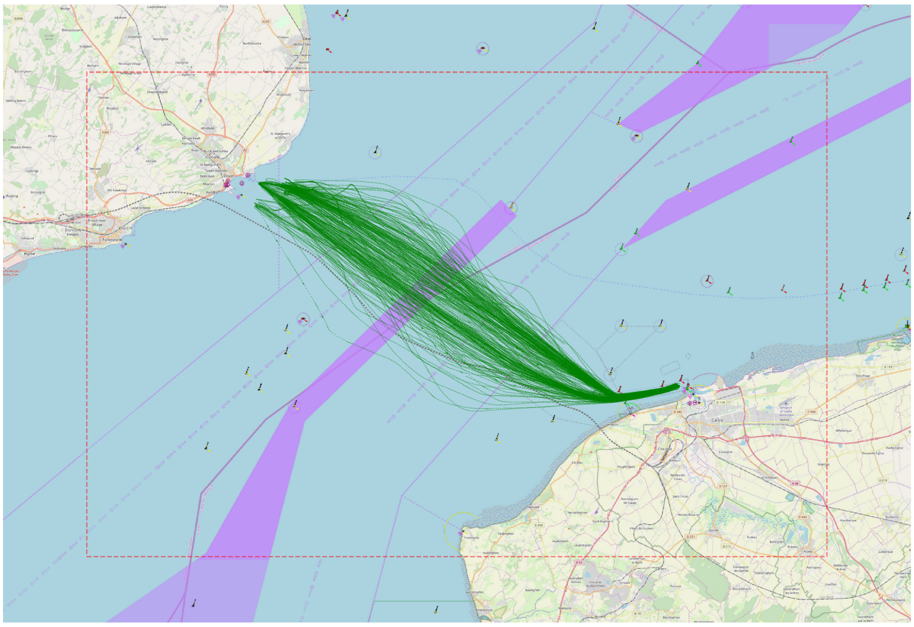

Figure 4: The region of interest (marked with the dashed red line) at the Strait of Dover from which AIS data was collected using AISHub. Only data from one ship (a ferry) for one month is shown here. The green dotted lines indicate the interpolated trajectories of the Own Ship (OS). For sake of clarity the positions/trajectories of the relevant target ships are not shown in this figure. Trajectories were ignored at harbours (in this case Dover, Calais and Dunkirk). Maps from OpenStreetMap (Haklay and Weber, 2008) and OpenSeaMap (OpenSeaMap, 2009) were used for visualisation.

As an example a snapshot of a single frame for a give-way crossing scenario is shown in Fig. 5. This scenario represents the interaction between a single target ship (indicated in red) and the own ship (indicated in black). Considering the other target ships in blue (see Fig. 5), multiple scenarios can be detected from this scene. This is a scenario representing multi-ship encounters.

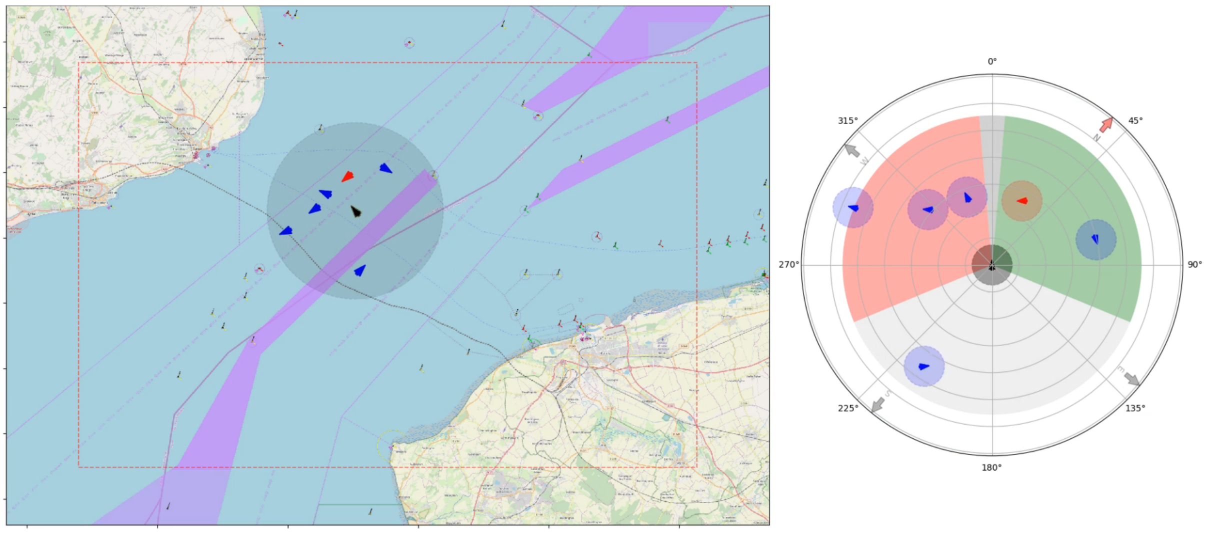

Figure 5: Example snapshot of a single frame for a given give-way crossing scenario between the own ship (indicated as the black ship in the centre) and the target ship (the red ship located in the green area).

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3.2 Results

In this section we show the results of give-way crossing scenarios (the green area as indicated in Fig. 3). In total 1498 incidents of this scenario were detected. In Fig. 6 we show as an example six probability distributions (out of a total of 43). The generated distributions show real-life situations and how ships interact in daily traffic. They also show the realistic ranges of these parameter values. This represents a great source of information that can be used to generate realistic scenarios for safety assessment of autonomous shipping.

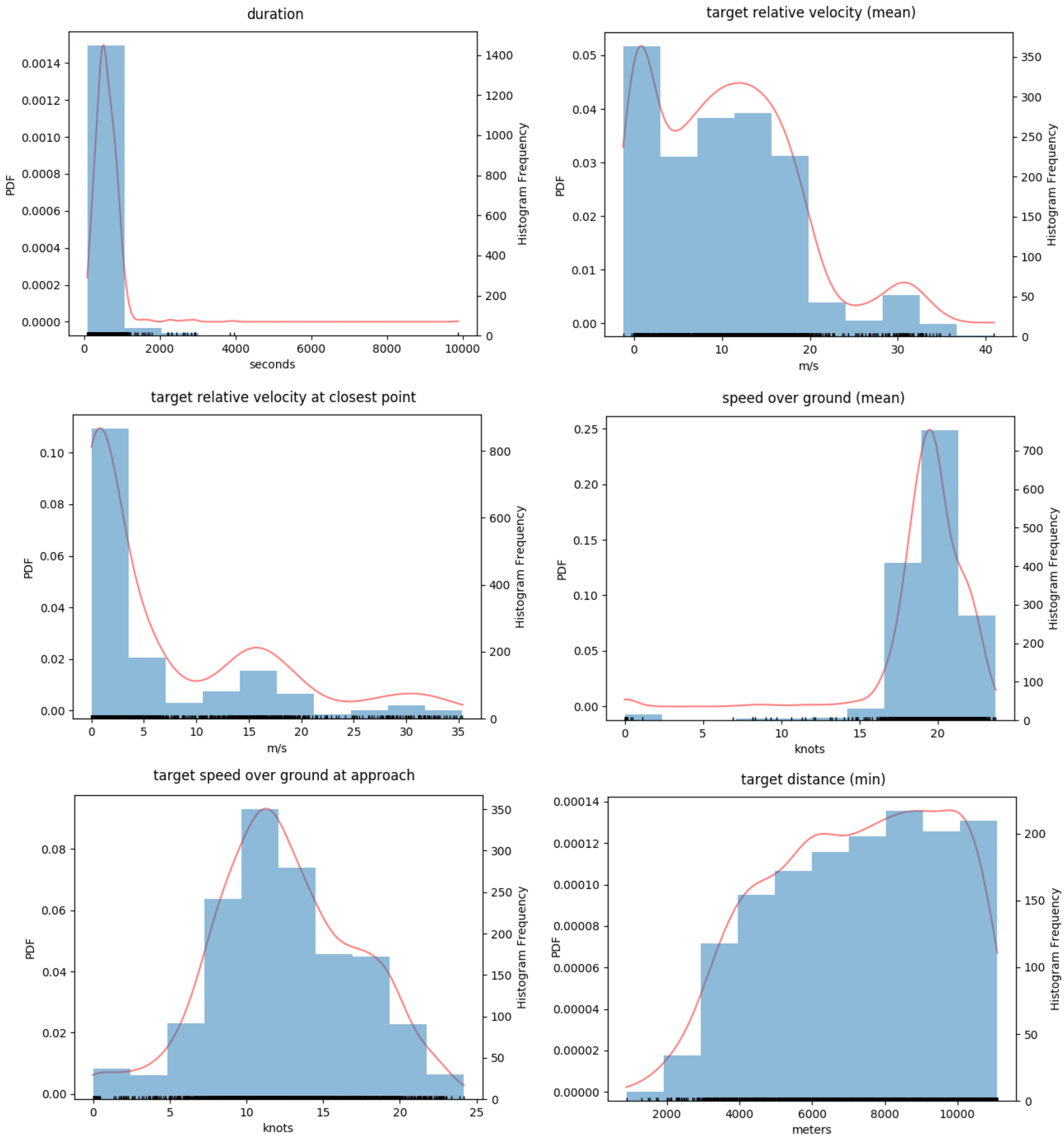

Figure 6: Examples of probability distributions of give-way crossing scenario parameters: scenario duration, mean relative velocity of TS towards OS, relative velocity of TS towards OS at CPA, mean speed over ground of OS, TS speed over ground at approach (position 2 in Fig. 3) and minimum distance between OS and TS. For each distribution, a total of 1498 datapoints were used to generate the histogram (indicated by the blue bars) and to estimate the PDF (indicated by the red line).

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4 Discussion and Conclusions

In this research we investigated the feasibility of using AIS data for the identification and classification of real-life scenarios. Furthermore, we have discussed how these real-life scenarios can be used for assessing safety of MASS, which represent an efficient approach, in addition to the field (physical) testing. The concept of a "scenario" and a "real-life scenario" were discussed in detail.

Results indicated that AIS data can be a rich data source for the detection of individual COLREG encounters. These encounters allow us to empirically estimate the probability density function of the relevant key parameters of these encounters. Beside the observed scenarios, the estimated PDFs can be used to sample new parameter variations and synthesise unseen, yet realistic, scenarios. These scenarios can be of great value to assess the safety of MASS in simulation.

For this research we collected AIS from a small region (the Strait of Dover) for a limited amount of time (see Fig. 4). Given the readily available AIS data over the whole world, our method can easily be scaled up and provide more reliable estimations for probability density functions for various locations and ship types. However this can be limited by the coverage of the AIS source being used (in our case AISHub (AISHub, 2020)) and the quality of the AIS data (Harati-Mokhtari et al., 2007; Eriksen et al., 2014). For instance, the coverage of the network in the middle of the North Sea was limited, which motivated our choice for using AIS data at the Strait of Dover instead.

Besides scenario based safety assessment, the identified scenarios could be applied in the field of maritime situational awareness and threat detection. These real-life scenarios can be used to train machine learning models and detect anomalous ship behavior. Which in turn can be of great use to detect illicit activities (Lane et al., 2010; Pallotta et al., 2013). Here, validation of the proper use of AIS data should also be investigated, for instance by detecting spoofing (Katsilieris et al., 2013) or hiding AIS signals (Mazzarella et al., 2016) by potential anomalous vessels.

In the future we aim to extend our work to include the analysis of more COLREG encounters with the use of a larger AIS dataset from different locations. Also, we would like to extend our scenario database with weather information, ship types and additional information from nautical charts. Beside COLREG encounters, we are planning to investigate multi-encounter situations and include the relevant identified scenarios to the database. Our final aim is to extend our framework with the actual synthesis and simulation of relevant scenarios. This framework would allow for the improved safety assessment of MASS.

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