Analysis of Automatic Identification System Data for Maritime Safety

by Philipp Last

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Abstract

The Automatic Identification System (AIS) has been globally introduced to increase the maritime safety. When introducing AIS two very high frequency (VHF) channels have been reserved worldwide allowing maritime entities to transmit individual data. Usually, AIS systems are installed on vessels. Nevertheless, AIS systems are nowadays installed on all different kinds of maritime entities such as oil rigs, sea marks, life vests, helicopters or search and rescue (SAR) planes. AIS data are sent in form of different types of AIS messages which are autonomously exchanged between nearby AIS systems. The automatically exchanged data provided by shipborne AIS may include the speed of a vessel, its course, heading, rate of turn or its Global Positioning System (GPS) position. Besides these dynamic data further static data are exchanged including, e.g., the dimension of a vessel, its worldwide unique Maritime Mobile Service Identity (MMSI) number or its call sign. In addition, vessels may also transmit information about their current port of destination and their expected arrival time. By providing such information AIS represents the first major improvement in maritime safety, especially with respect to collision avoidance, since the introduction of radar technology.

Modern bridge devices are connected to AIS allowing to decode and visually represent received AIS data. Vessel crew members mainly use available AIS data for collision avoidance. Compared to the past, AIS allows mariners to directly obtain the call sign of a vessel by selecting its visual representation on the bridge devices. Hence, to make agreements with respect to collision avoidance, AIS allows for directly contacting a specific vessel by using its call sign what decreases the required time for ship-to-ship communication since radio communication is exchanged between all nearby vessels. Besides manual collision avoidance AIS allows for predicting possible vessel movements based on the dynamic data. Vessel traffic services (VTS) and authorities such as the United States Coast Guard use AIS data to monitor and track vessel movements.

Due to the AIS data density, variety and the low effort required to obtain AIS data they have become a research object within the past years. Geospatial analysis of marine traffic based AIS data is performed to identify global vessel movement patterns. Within this context, satellites are recently used to monitor AIS traffic which is out of range for coastal AIS
receivers. The visualization of vessel traffic densities and movement patterns obtained from AIS data represents a complete research field. Furthermore, AIS data are used as a data source for vessel movement prediction and target tracking algorithms within the scientific community.

Because of the meaning of AIS data for the maritime field and related research this thesis evaluates AIS data for maritime safety. Within this context it has to be evaluated how reliable AIS data are and in how far AIS data can be used within different types of applications. Hence, a comprehensive analysis of AIS data is part of this work. This analysis gives an essential overview about how shipborne AIS systems are currently configured and used. AIS data attributes relevant for vessel movement prediction and their availability are evaluated and discussed. Furthermore, the AIS reporting intervals are evaluated in detail. The AIS reporting intervals play a crucial role for vessel movement prediction and also for the graphical representation on current bridge systems since they determine how often AIS targets are visually updated. With respect to the graphical representation of AIS data on radar systems so far not visually encoded AIS data attributes have been identified in this thesis. An expert group gave feedback about the relevance of these attributes with respect to maritime safety. In addition, visual encodings for these attributes are proposed which have also been judged by the expert group. Visually encoding these information allows for a better situation assessment for mariners. Besides the graphical representation of AIS data the AIS reporting intervals are also of interest when integrating real world AIS data into maritime simulation systems. Since human error has been identified as the main maritime incident reason a full mission bridge simulator has been used for an integration of live AIS data within this thesis. The integration of real AIS data allows for representing actual maritime traffic scenarios within the simulation process which aims at improving the maritime safety. Moreover, based on the AIS evaluations related to AIS data availability and AIS reporting intervals an interactive history-based vessel movement prediction algorithm is proposed within this thesis. The proposed algorithm is solely based on historical AIS data and allows to predict vessel movements even if AIS reporting intervals are not kept according to the official standard. The prediction outcome including uncertainty is visualized to the user in a way that mariners are supported in performing collision avoidance. Hence, the presented prediction algorithm and its visualization aim at a better situation assessment and improvement of the maritime safety.
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Chapter 1

Introduction

The work of this thesis has been carried out as a part of the SIMSS project which has been funded by the Federal Ministry of Education and Research (BMBF). The project goal of SIMSS was to increase the maritime safety by analysing Automatic Identification System (AIS) data and by integrating real world AIS data into ship handling simulators to improve the nautical education. AIS installed on vessels provide information to crew members about nearby vessels which cannot be obtained from conventional radar images. This includes, e.g., the vessel type or its call sign. Further information relevant for maritime safety are provided, including the GPS position and the vessel course and speed. Therefore AIS allows for a better situation assessment and supports mariners within the ship-to-ship communication, especially with respect to collision avoidance.

Within this work, AIS data are evaluated with respect to availability, correctness and according their specified reporting intervals giving an overview about how shipborne AIS are currently configured and used. Based on these evaluation results further improvements related to the visual representation of AIS data on bridge devices are proposed. Furthermore, the suitability of AIS data for vessel movement prediction in general as well as the usage of AIS data within maritime simulations in particular is evaluated within this work.

The research has been performed by the Jacobs University and the Institute for Maritime Simulation. The Institute for Maritime Simulation as part of the University of Applied Sciences, Bremen, operates two full bridge ship handling simulators used for nautical education.
1.1 The Automatic Identification System

The main systems used for navigation on board of professional operating vessels are the radar system and the Electronic Chart Display and Information System (ECDIS). To reduce vessel incidents based on failures of technical systems complete redundancy for these bridge devices is mandatory for professional operating vessels. The radar system uses an antenna to generate radar echoes which are displayed on the radar screen. The appearance of the radar echoes depends on the parameters configured by crew members and environmental conditions. The ECDIS systems show digitalized sea charts allowing to interactively retrieving information about water depths, navigational aids, etc. Furthermore the ECDIS provides route planning functionality. Both systems are usually connected to AIS whose data can be displayed as an additional overlay.

AIS is a relatively new maritime technology based on very high frequency (VHF) communication mainly used to track and monitor vessel movements. Thus, AIS represents an additional data source for radar and ECDIS. In total, 27 AIS message types exist which are transmitted between nearby AIS systems. Each AIS message type serves a specific purpose, e.g., message type one, two and three represent the dynamic data of Class A systems including the rate of turn, heading, speed over ground or the navigational status. A Self-Organized Time Division Multiple Access (SOTDMA) algorithm according to the international standard [1] is used to assign free message slots to vessels which intend to transmit data. Each vessel transmits its data autonomously and periodically by reserving these time slots. A base station used to organise AIS traffic is not required.

Compared to radar systems, AIS provides information about nearby vessels that would otherwise not be available, including the Global Positioning System (GPS) position, speed, course over ground, the vessel name and its dimension. Furthermore, depending on the AIS antenna height AIS signals may even be received over landmasses which are blocking radar signals. Besides installing AIS on vessels land-based AIS stations are in use, e.g., to extend the AIS range. Satellites are used to receive AIS data if vessels leave the coverage of coastal AIS receivers. Sea marks such as buoys are also equipped with AIS. Hence, formerly static sea marks such as Aids to Navigation (AtoN) are now additionally broadcasting their identification and position. Nowadays even life vest have an AIS transmitter sending emergency signals including the GPS position when in contact with water. However, not all vessels are equipped with AIS. In addition, vessels may switch their AIS off and receiving AIS signals may fail due to obstacles. Hence, it is not allowed to solely rely on AIS data for navigational purposes.
1.2 Maritime Safety

Despite the availability of different bridge devices and technologies supporting mariners such as AIS operating a vessel is nowadays still a complex task. Vessel incidents, especially within European waters, happen at a daily basis as shown within the latest annual overviews of marine casualties and incidents released by the European Maritime Safety Agency (EMSA) [2, 3]. The goal of the EMSA is to inform about vessel incidents as well as their causes and impacts. Maritime incident types and their reasons are manifold. Examples for maritime incidents are collisions, sinkings, groundings or damage to ship or equipment, also caused by fire and explosions [3].

Vessel incidents often involve a loss of human life and represent an economic damage, e.g. by losing cargo or whole vessels. From 2011 until 2014 over 10,000 vessels were involved in accidents [3, p. 23]. 3285 of these accidents happened in the English Channel and the North Sea and Baltic Sea [3, p. 65]. 178 vessels were lost, 1028 were reported to be unfit to proceed [3, p. 51, 53]. Hence, maritime safety is also an ecological and economic aspect for nations and shipping companies. Most vessel accidents occurred within internal waters, port areas and coastal waters where the vessel density increases [3, p. 63]. Within this context 908 vessel accident investigations have been evaluated by the EMSA with the goal to identify the main cause for vessel accidents. In approx. 67% of all cases human failure led to a vessel accident followed by equipment failure in 24% of all cases [3, p. 45]. Other factors barely play a role. This confirms studies which already evaluated maritime incident reasons and conclude that the main reason for maritime incidents is human failure [4–9]. Decisions errors made by crew members are, e.g., caused by environmental factors such as poor visibility and the misuse of instruments or deficits in the ship-to-ship communications [4]. Therefore decision errors are a result out of, inter alia, a lack of experience of crew members.

1.3 Research Goals

Presented numbers of Section 1.2 show that there is a need for research to improve the maritime safety. Due to the AIS data importance, density, variety and the low effort required to obtain AIS data these data have become a research object within the past years. Examples are the following PhD theses: Scheepens [10] and Willems [11] developed visualization approaches for vessel densities and vessel movements based on AIS data. Hsu [12] evaluated AIS with respect to manual bridge lookout in his PhD thesis. Zaman [13] recorded the sea traffic conditions of a part of the Malacca Straits to perform risk analysis based on AIS data. Jakub [14] used shipborne AIS data to estimate ocean currents. Eucker [15] used
AIS messages to characterize the spatial and temporal variability of surface vessel traffic in relation to sea-ice conditions on the Arctic Ocean. AIS as a research object itself has been part of Dembovskis’ [16] dissertation. He analysed the problem of overlapping AIS signals when using satellites to monitor AIS traffic from space and proposes approaches for satellite-based (SAT-AIS) AIS message extraction. Jaskólski [17] analysed AIS, e.g., with respect to the availability of base stations in his PhD thesis. The relevance of AIS, especially within the maritime field, leads to the main research question of this work:

**How do current shipborne AIS configurations affect the maritime safety?**

To answer this research question different problems have to be addressed. To actually use AIS data for improving maritime safety, it has to be evaluated how reliable AIS data are and in how far AIS data can be used within different types of applications. Hence, to answer the research question, a general evaluation about how shipborne AIS are currently configured and used with respect to maritime safety is required and therefore part of this thesis. Besides evaluating actual data transmitted by AIS the AIS reporting intervals, which have so far not been evaluated, are additionally evaluated since they play a crucial role for maritime safety in general.

Based on these general evaluations different aspects are considered to answer the research question. At first, it is evaluated how decision making during navigation can be supported by enhancing the radar display with visualizations of AIS data attributes relevant for navigation. Within this context the challenge is to identify relevant AIS attributes and to visually encode them in a way such that the visual encoding provides additional information while reducing misinterpretations by crew members. A further aspect of maritime safety is the nautical training of mariners. With respect to the human error and also based on the general AIS evaluations, this thesis evaluates how AIS data can be used to extend maritime simulation systems used to train mariners. The goal is to integrate real world traffic scenarios into maritime simulations to enhance the simulator-based nautical education and therefore to improve the maritime safety, since human error has been identified as the main incident cause. A further maritime safety related aspect is the usage of AIS data for vessel movement prediction. Based on the general evaluations of this thesis, it is evaluated how vessel movements can be predicted by using AIS data. Within this context, the prediction outcome needs to be visualized in a way that supports mariners in performing collision avoidance. This includes the development of an appropriate uncertainty visualization.
1.4 Research Structure

At the beginning of this work and as a starting point for all further research a general evaluation of AIS data has been performed. The results of this evaluation are presented in Chapter 2. The aim was to evaluate how shipborne AIS systems are currently configured and used. AIS systems have to be initially configured by authorized personnel. This initial configuration includes setting important attributes such as the Mobile Maritime Service Identity (MMSI), which is a unique vessel identification number, or the vessel’s call sign which is important for ship to ship communication. This data cannot be altered by the crew at a later time point. In addition different sensor systems are expected to be connected to the AIS. This includes, e.g., the GPS receiver allowing transmitting the vessel’s position. Hence, one would assume that at least the unalterable data are available and error free and that the vessel’s GPS position is transmitted. However, the general AIS evaluation presented in Chapter 2 shows that this is not necessarily true. Within this context especially the dynamic AIS data have been evaluated concerning their availability and suitability for vessel movement prediction. Differing to existing studies which evaluated AIS data on a daily or weekly basis AIS data had been recorded over a time period of two months at German North Sea coast. Furthermore, compared to existing studies which evaluated AIS data manually a database management system has been used to store received AIS data allowing formulating and performing repeatable database queries. Using a database-based approach allowed for performing vessel related queries and evaluations instead of message related evaluations as done in other studies. Thus, Chapter 2 provides a comprehensive analysis of how shipborne AIS systems are currently configured and which data can be expected from them.

The evaluation presented in Chapter 2 also shows that the AIS reporting intervals do often not accord to the official AIS standard. However, AIS reporting intervals play a crucial role, not only for displaying and updating AIS targets on bridge devices but also for predicting vessel movements. Typical prediction algorithms rely on short update intervals while switching between a prediction and correction step. Examples are the Kalman Filter and the Particle Filter. Hence, a detailed evaluation of the AIS antenna setup and the AIS reporting intervals has been performed. The results are presented in Chapter 3. The aim of this evaluation was to identify possible reasons for a potential AIS message loss resulting in not kept reporting intervals. A further goal of this study was to show which receiving behaviour can be expected by crew members from an AIS system under realistic but almost perfect environmental conditions. For this study AIS data have been recorded on vessels of the German Search and Rescue service (DGzRS) which use high quality AIS systems whose
technical installations do comply with the official International Maritime Organization (IMO) guidelines.

AIS data are visually encoded and represented on current bridge devices such as the radar system or the ECDIS. However, evaluating the general availability of AIS attributes in Chapter 2 showed that not all AIS attributes are yet visually encoded. Within Chapter 4 so far not visually encoded AIS attributes have been identified. With respect to the usage of bridge devices by crew members the work of Chapter 4 aims at reducing misuse and misinterpretations while working with radar systems and activated AIS overlay. Hence, potential visual encodings in form of glyphs for so far not encoded AIS attributes have been developed and presented to an expert group solely consisting of mariners. The expert group judged the relevance of the so far not encoded AIS attributes. Furthermore, they gave feedback on the proposed glyphs. Within this context challenges were to develop glyphs which keep the concept of familiarity and which can be represented on radar systems which are typically embedded systems with low processing power to improve the maritime safety.

Based on the evaluation results of Chapter 2 and Chapter 3 a software architecture allowing to integrate real world AIS data into maritime simulation systems is presented in Chapter 5. In particular a full mission bridge simulator of type Advanced Nautical Simulator (ANS) 6000 has been used for this purpose. The University of Applied Sciences, Bremen, maintains two of these ship handling simulators to educate nautical students and pilots. The presented software architecture extrapolates vessel states during the time of missing AIS updates to compensate not kept AIS reporting intervals. The presented work was a main part of the SIMSS project and allows for representing actual maritime traffic scenarios based on real world AIS data within a simulation process. Real world incidents can be analysed and more realistic simulator exercises can be created what directly aims at improving maritime safety. Since a full mission bridge simulator has been used the 3D representation respectively mapping between incoming AIS data and available 3D models plays an important role and is therefore also discussed.

Within Chapter 6 a vessel movement prediction algorithm is presented which is solely based on AIS data. To overcome the mentioned problem of not kept AIS reporting intervals the presented approach uses historical AIS data for prediction. The algorithm presented in Section 6 allows for both long and short range predictions. Long range predictions aim at identifying the most likely path chosen by a vessel and estimating its likely Estimated Arrival Time (ETA). In addition, the proposed long range prediction can be used as more sophisticated dead reckoning approach when integrating live AIS data into maritime simulation systems as presented in Chapter 5. Using the proposed algorithm for short range predictions allows
visualizing likely vessel movements within a restricted time interval aiming at collision avoidance. The short range prediction outcome is visualized with uncertainty bands. The aim of the presented work is to provide an approach of predicting and visualizing vessel movements which leads to a better situation assessment and improves the maritime safety.
Chapter 2

Comprehensive Analysis of AIS Data in Regard to Vessel Movement Prediction

The contents of this chapter have already been published in:

Chapter 3

How AIS Antenna Setup Affects AIS Signal Quality

The contents of this chapter have already been published in:

Chapter 4

Visual Encoding of AIS Data for Radar Systems

The contents of this chapter have already been published in:

Chapter 5

Generating Real-time Objects for a Bridge Ship-handling Simulator Based on AIS Data

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Chapter 6

Interactive History-based Vessel Movement Prediction and Visualization

Vessels are the main transportation medium for global trade. Vessel movements are of interest, e.g., for collision avoidance and logistics planning. We support this with a novel approach for short- and long-term vessel movement prediction and visualization based on prior knowledge provided by historical movement data. All professional operating vessels are required to have the Automatic Identification System (AIS) installed which allows for vessel tracking. To handle the large amount of AIS data, we present a novel real-time compression scheme for AIS data targeted for use in prediction and visualization. We propose a prediction model where compressed AIS data build a background model for estimating the probabilities of possible vessel movements. The predicted movements and their uncertainties are visualized with an interactive system which allows for visual inspection of relevant vessel movements within the above-mentioned scenarios.

6.1 Preface

Over 90% of the global trading is executed by using vessels to transport goods. Within this context, mariners, shipping companies as well as public authorities are interested in where a specific vessel is currently located and also where it might be located in the future and at which time an arrival can be expected. Also, collisions between vessels need to be avoided.

Even though a vessel might theoretically use a freely chosen path to its target, shipways and traffic separation schemes are used to direct and organize vessel traffic. For that reason almost all vessels follow specific itineraries. Exceptions are, e.g., search and rescue operations (SAR) or other vessel traffic caused by law enforcement or surveying vessels which are
allowed to violate traffic rules if required. Furthermore, depending on the vessel type, vessels might be additionally restricted in their maneuverability when using these shipways such that large container vessels most likely operate in the middle of seaways due to the waterway depth and vessel draught.

Within this paper we make use of these restrictions and present a prediction algorithm based on historical Automatic Identification System (AIS) data. AIS data allow for tracking vessel movements where the vessels AIS broadcast spatiotemporal data including Global Positioning System (GPS) information in short intervals ranging typically from two seconds up to three minutes. The data are received by nearby vessels, satellites, and land-based AIS stations. Due to the reporting intervals and the high vessel density on sea a huge amount of data is continuously generated which needs to be efficiently stored and prepared for an analysis.

We present an algorithm capable to extract and compress trajectories from a live AIS data stream. The algorithm’s output is used to create a historical background model. The actual prediction for a selected vessel is performed by sampling this background model and using probability density functions to estimate possible vessel movements. Within this context we distinguish between a short range prediction indicating possible vessel movements within the next minutes and a long range prediction which aims at estimating which itinerary a vessel will most likely follow and how much travel time will be needed. A visual analysis system has been developed to interactively trigger and evaluate predictions and to visually inspect the prediction outcome. We document how this approach can be used for analyzing vessel traffic as done at Vessel Traffic Services (VTS) and for supporting decision making with respect to collision avoidance as done by mariners.

6.2 Background and Related Work

6.2.1 Vessel Tracking

Related to vessel movement prediction and collision avoidance current prediction approaches mainly rely on at least one of the following three data categories:

- Laser or Radar data
- Image or Video data
- AIS data

Radar systems are mandatory for professional operating vessels. VTS stations also operate radar towers. A vessel prediction approach based on laser and radar data has been
presented by Ruiz and Granja [91]. Further similar publications use the Extended Kalman Filter (EKF) in combination with laser and radar data aiming at improving collision avoidance [34, 92, 93]. However, laser and radar data are less freely available than both other data sources and are in general difficult to interpret.

A further data source for predictions is video input. Jinhai et al. used video data in combination with the Extended Kalman Filter [35]. Single images instead of a video stream have also been used for prediction by Bustos et al. who estimated vessel trajectories while using radar data and satellite images [94].

With respect to mentioned data types it is not uncommon to use sensor data fusion as described in [95] to improve the prediction. Within this context Kang et al. performed a study about sensor data fusion with regard to maritime collision avoidance [96]. Sensor data fusion approaches with respect to the prediction of marine targets are presented in [28, 97, 98]. A common combination is the usage of AIS data and radar data to track vessel movements as presented in [99–105].

Just like radar systems, AIS systems are also mandatory for professionally operating vessels. AIS data include geospatial data such as the vessel’s position. In addition further data attributes describing the vessel are transmitted, including the vessel type or its Speed over Ground (SOG) and current Course over Ground (COG). The usage of AIS data with respect to manual collision avoidance done by crew members has been evaluated in [23, 20, 106]. Research related to the availability of AIS data attributes and the AIS reporting intervals has been performed by [22, 19, 27]. Their studies show that only a few AIS attributes provide a high availability and reliability. E.g., the COG or the SOG values are available in most cases whereas the Rate of Turn (ROT) information of a vessel is barely available. This has to be considered when using AIS data attributes for predictions. Further studies such as [31, 77] evaluated the reception performance and reporting intervals of AIS data in detail. There is no guarantee that an AIS update for a specific entity might be received within regular time intervals. Nonetheless, compared to laser or radar data, AIS receivers are comparatively cheap and can be installed without any permission.

Within this paper we present a prediction approach solely based on AIS data. With respect to existing vessel movement prediction approaches we present a novel approach which does not only consider dynamic attributes such as geographical positions and COG values but also further static information such as the vessel type for prediction. Moreover instead of using complete trajectories for prediction we use the local vessel environment allowing detecting typical movement patterns in specific situations to overcome the problem of not kept AIS reporting intervals.
6.2.2 Visual Analytics of Movement

Since AIS data are movement data, the work by Adrienko et al. covers several aspects related to our work such as transformations of movement data [107, p. 73]. This includes the derivation of new thematic attributes out of existing AIS data or extraction of spatial events and trajectory simplification. With respect to movement data simplification in general and AIS data in particular the usage of the Douglas-Peucker-Algorithm (DP) is currently a common approach to simplify data sets [107, 108]. Several publications related to AIS data compression using the DP algorithm exist [109–111]. When using a DP-based algorithm the user specifies a spatial threshold. By connecting the first and the last point of a complete trajectory to a line the maximum distance of the remaining trajectory points to this line is calculated. If this maximum distance exceeds the specified threshold, a respective point is stored as a split point and being connected to the current first and last point resulting in two lines. The algorithm iterates until no further split point is detected. Thus, if a vessel travels almost on a straight line only the information of the start and end points of this line are stored, information in between are lost. In addition the complete trajectory needs to be known beforehand to perform a simplification based on DP. Further problems with respect to the usage of DP for trajectory simplification are mentioned in [110].

Patroumpas presents a different approach to reduce live AIS data using events. His approach is based on detecting significant changes within a vessel’s behavior. This includes events such as stop, turn, smooth turn, or speed change. His algorithm allows a faster compression and a better compression rate than DP while keeping a tolerable approximation quality [112]. Similar approaches are the trajectory simplification using the Simple Event Model (SEM) [113] or the model-based approach presented by van Hage et al. [114].

Related to vessel data compression and also prediction, Etienne et al. present a data mining approach to handle a huge quantity of information generated by moving vessels including their geographical positions. Their approach allows for identifying a main itinerary which is used by nearby vessels by calculating median positions which are ordered according to a normalized time and also by using the DP algorithm. To identify whether a vessel is late or in time temporal zones can manually be defined by the user to perform appropriate calculations [115]. All these compression methods reduce data based on a path information only. They do not consider additional movement information such as Speed Over Ground (SOG) available in AIS data that is relevant for precise prediction. Hence, we propose a novel compression approach that maintains better the relevant information. Moreover, our approach operates on streaming data.

Related to vessel movement prediction based on AIS data, Scheepens et al. performed a history-based prediction and visualization [39]. The prediction outcome is visualized using
halos. However, they do not give further information about how their history-based model is being used with respect to AIS data attributes and their availability. Scheepens et al. and also Lampe et al. implemented AIS trajectory visualization based on density plots [36, 116]. To enable a more interactive visualization Scheepens et al. proposed a method to interactively explore multiple attributes in trajectory data using density maps [38] also in combination with a particle system visualized on top of the density map [117]. Jiacai et al. presented an AIS data visualization model which allows indicating dangerous shipping areas [118]. Similarly Feixiang presented an approach to statically visualize high traffic densities while using AIS data [119]. Goerlandt and Kujala presented an approach to create static ship collision probability plots based on AIS data as presented in [120]. Our approach is not based on static information, but on the visualization of prediction results. We are interested in seeing all paths within our history so that aggregated information like density plots are not suitable. Visual clutter is not an issue as we are investigating individual paths, which are highlighted accordingly.

Our system dynamically visualizes live AIS data streams, historical AIS trajectories forming our background model as well as the prediction outcome. Visualizing the prediction outcome is related to the concept of contour boxplots [121]. We use uncertainty bands to visualize the prediction outcome similar to the work of [122]. Furthermore we added the possibility to load sea charts and to interactively visualize the prediction debug data to give a better understanding of the algorithm’s decisions for each prediction step.

6.3 Data Description and Preprocessing

Within this section we give a brief overview about the used AIS data. Afterwards we present our AIS compressing algorithm allowing creating a background model which is used as a data source for performing the vessel movement prediction. Finally, the background model itself is presented which consists of the compressed AIS data. Our work is solely based on real world AIS data.

6.3.1 AIS Data

AIS allows for transmitting data between AIS devices, which can be installed on vessels, base stations like harbor authorities, marks such as buoys, or on search and rescue airplanes. Two VHF channels are used to transmit AIS data. The AIS reporting intervals vary depending on the AIS message types and may also change for a specific message type itself depending on
a vessel’s state such as being moored. The AIS data which are exchanged are divided into three different types [18]:

- Static data (e.g., vessel name, vessel type and the dimensions of the vessel)
- Dynamic data (e.g., vessel position, course over ground, and heading)
- Voyage-related data (e.g., current draught, description of cargo, and destination).

With respect to the static data the vessel type information is included in AIS message type five and stored in a byte. According to the official AIS standard, this byte has a valid value range of [0-99] [1]. Each value describes a specific vessel type such as *Fishing*, *Pilot Vessel*, *Military Ops* and *Tug*. Furthermore, some types are represented by additional categories such as *Tanker* with and without Hazardous category A-D. Those vessel types occupy 10 values in total. Value 0 indicates that a vessel type is not available which represents the default value. To reduce the amount of different AIS vessel types we group AIS vessel types only differing in specific attributes. E.g., all ten AIS vessel type ids ranging from 80 to 89 which describe tanker vessels have been concluded to a single tanker category. The same applies for passenger vessels, cargo vessels, etc. Vessels can be directly identified by using the transmitted unique Maritime Mobile Service Identity (MMSI) number.

In general AIS information are included in different AIS message types. In total 27 different AIS message types exist, of which some are only used to organize the AIS communication, e.g., by reserving time slots during channel access by using the Self-Organized Time Division Multiple Access (SOTDMA) method [1]. The typical usage of AIS data by vessel crew members is manual collision avoidance since AIS data are represented as an additional overlay on radar or ECDIS screens. VTS operators use AIS as a data source for traffic control.

### 6.3.2 AIS Data Compression and Representation

The main reason for research effort in compressing AIS data results out of the high amount of transmitted AIS messages. E.g., under specific circumstances a vessel might transmit AIS data each two seconds. Hence, storing AIS data for large areas or areas showing a high density of vessels will result in a large amount of raw data which needs to be handled. Depending on the considered area and the time span of recording the raw AIS data size easily exceeds several gigabytes. Such an amount of data can currently not be used for real time computations within an application. In addition the raw data include information which are not required for our prediction. For these reasons AIS data need to be compressed in a sense of a lossy data reduction while keeping the application relevant details.
We define a Trajectory $T$ as an object including the unique MMSI and the static data of a vessel derived from AIS data. The static data includes the vessel type, if available. The static data of each unique vessel is only stored once. In addition to the MMSI and static data each trajectory includes an array of tuples which represent the dynamic data forming the actual trajectory. In our case each tuple $m$ contains dynamic data attributes extracted from the AIS message types 1, 2 and 3 whereas $T_p$ is a pointer which references the trajectory to which tuple $m$ belongs to. ROT values are not used for the prediction since they are mostly not available and depending on the AIS reporting intervals not reliable [27].

$$m = \{T_p, \text{lat}, \text{lon}, \text{COG}, \text{SOG}\}$$  \hfill (6.1)

Since we intend to save trajectory tuples at regular intervals common compressions approaches based on the DP algorithm presented in Section 6.2 are not suitable for us. Even though DP based algorithms are common to compress AIS data they have specific drawbacks. For instance, if a vessel is driving a straight line only the data of the first and last geographical positions are kept after the simplification. This means that all transmitted information in between are not available for vessel movement prediction. E.g., the different Speed Over Ground (SOG) information are lost which allow identifying areas where vessels might typically slow down or speed up. In addition DP based and also event based algorithms will compress and keep any given trajectory including unwanted trajectories such as situations where a vessel is not travelling but floating around at a specific position for a longer period of time.

Consequently, we are introducing a basic compressing algorithm which compresses data in a way that it can be used for our vessel movement prediction. The presented structure allows deriving specific information at runtime, if required. This includes the identification of trajectory start or end points which can be determined by their position in the trajectory array. Our AIS data compression algorithm creates appropriate trajectory and tuple objects while using the following 5 parameters:

1. Minimum spatial distance $d_{\text{min}}[m]$ between two geographical positions
2. Maximum spatial distance $d_{\text{max}}[m]$ between two geographical positions
3. Minimum temporal distance $t_{\text{min}}[s]$ between to position reports
4. Maximum temporal distance $t_{\text{max}}[s]$ between to position reports
5. Minimum total length $l_{\text{min}}[m]$ which generates a trajectory
The input to the algorithm is a stream of AIS data. First the static data have to be received for a vessel. For each received AIS message type 1, 2 or 3 it is tested whether the geographical position and the COG and SOG attributes are available. To only consider moving objects we evaluate whether the SOG value of a vessel exceeds 3kn what is a common approach while working with AIS data. If no trajectory exists for a given MMSI, a new trajectory object is created and a new tuple is appended based on the information included within the received AIS data. This newly created trajectory is inserted in a pool of incomplete trajectories whereas each MMSI will only have one assigned incomplete trajectory at the same time.

If an incomplete trajectory exists which matches the MMSI of the received AIS position report the minimum thresholds \( t_{\text{min}} \) and \( d_{\text{min}} \) are considered to ensure that the vessel has travelled a specific distance between the last AIS message and that enough time between the last stored and the latest AIS message has elapsed. If this is the case, \( T \) is updated by creating and appending a new tuple based on the received AIS data what increases the total length of \( T \). If the minimum thresholds are not exceeded, the current AIS message is neglected.

If the maximum thresholds \( t_{\text{max}} \) or \( d_{\text{max}} \) are exceeded, it is tested whether the trajectory’s total length is longer than \( l_{\text{min}} \). If true, the trajectory is considered as complete and removed from the pool of incomplete trajectories. Otherwise, the trajectory is too short to be useful for our prediction algorithm and is deleted. In both cases a new trajectory is created, if further AIS data with the same MMSI are received.

We empirically found the following parameter values to produce a good trade-off between memory consumption and information content: Spatial thresholds have been set to \( d_{\text{min}} = 30m \) and \( d_{\text{max}} = 1000m \). Temporal thresholds have been set to \( t_{\text{min}} = 10s \) and \( t_{\text{max}} = 900s \). The required minimum trajectory length has been set to \( l_{\text{min}} = 40.000m \).

Using these parameters we compressed 2 months of AIS data using our presented algorithm. Approx. 20 gigabytes of AIS raw data have been reduced to approx. 1.8 gigabytes of data resulting in a compression ratio larger than 10 : 1. Depending on the amount of incoming AIS data presented parameters may be adjusted resulting in a different compression ratio. E.g., setting \( l_{\text{min}} \) to a smaller value will lead to more but also shorter trajectories which will be stored resulting in higher memory consumption. When comparing to other algorithms, our method typically maintains more data points, which on the other hand allows for better prediction outcome. Moreover, by using \( l_{\text{min}} \), we discard vessels not useful for prediction such as non- or barely moving vessels as well as vessels with no continuous data transmission.
### 6.3.3 Background Model Usage

All identified trajectories form a background model which is used for prediction. Within this context the compressed data can be stored in any database management system such as PostgreSQL or MySQL. Even though we are working with a compressed data set still millions of tuples have to be stored and accessed in a fast way. We deploy a quadtree, which is a common data structure for storing geospatial data [123]. Figure 6.1 shows a visualization based on a background model with approx. 10,000 trajectories which consist of approx. 5.5 million tuples in total. Magenta points indicate start and end points of a trajectory.

AIS data have been recorded with several AIS receivers at the German North Sea coast. For orientation purposes different sea charts are additionally overlaid showing the coast line. Five points of interest are described from left to right: The left rectangle shows the port of Emden (purple rectangle). The large amount of magenta tuples close to the coast represents vessels which are anchored in the roadstead (orange). These vessels wait for low tides so that they may enter their desired port such as the port of Hamburg. The third rectangle shows the port of Wilhelmshaven (green), the fourth the port of Bremerhaven (blue) including the river Weser, which leads to the Bremen ports located in the back country. The yellow rectangle shows the port of Cuxhaven as well as a part of the North Sea coast including the river Elbe which directly leads to the Kiel Canal and the port of Hamburg. Our background model covers an area of approx. 22,500 square kilometers. Related to the memory consumption approx. 1.8 gigabytes RAM are sufficient to store the background model.
6.4 Prediction Cycle

Our main contribution is a prediction algorithm and its visualization which is solely based on historical AIS data. The idea is to predict the path of a currently selected vessel based on background knowledge obtained from preceding journeys of vessels. This includes the exploitation of information generated by the same and similar vessels in the past. The prediction algorithm itself consists of a prediction cycle which includes five steps as shown in Figure 6.2. This prediction cycle is repeatedly executed until a termination condition is detected. This section gives a brief overview about the five prediction steps. Detailed explanations follow in appropriate sub sections.

Fig. 6.2 Prediction Cycle

The main principle of our prediction algorithm is to sample data from our background model which are located close to the current vessel position. The aim is to identify movement patterns in local tuple subsets. Thus, as the first step we take the current real vessel state including the geographical position as well as the COG and SOG information as a starting point. As an initial assumption this vessel state already includes a valid COG value. By using the geographical position we query all tuples from the quadtree which are spatially located close to the current real vessel location. We restrict this area by defining a square whose side length can be specified by a parameter named window size. The window size should allow covering substantial parts of the waterways included in the background model. However, a too big window size value may result in wrongly sampled tuples which may affect the prediction in a negative way. For instance a waterway might sampled which is currently not reachable based on the currently predicted position. For our data set the window size parameter has been set to 0.016 degrees or approx. 1.8 km, respectively.

The first step of the prediction cycle also includes a peak detection which is based on the extracted data. The relevant information within this context is the COG information
which indicates the direction a vessel is driving to. Performing a peak detection on COG values allows us to identify directions and therefore itineraries that have been used by nearby vessels. Identified peaks are used as start parameters to cluster extracted tuples which is done in the second step Clustering. Clustering is performed by using expectation maximization whose output is a number of probability density functions (PDFs) which equals the amount of identified peaks. Making use of the PDFs allows calculating the probabilities of each tuple and therefore to determine to which PDF respectively cluster a considered tuple is assigned to.

In step three identified clusters are used to perform a matching between the current vessel state and the clusters. The matching process includes the calculation of a probability for each cluster by using a weighting function. The weighting function takes into account whether the vessel has been driven in the direction of a specific cluster before, whether specific vessel types such as tankers are most likely driving in the direction of a specific cluster and finally to which cluster the majority of tuples has been assigned to. The last case describes the most frequently chosen itinerary within the sampled data.

After the current vessel state has been matched to a specific cluster step four determines a mean object which includes tuple information of the matched clusters. This object allows us to obtain new COG and SOG values which are assigned to the current vessel state. Finally, the motion model is performed by using these values to predict the next geographical position. Afterwards, the prediction cycle repeats but now uses the currently predicted position as the new starting point.

6.4.1 Sampling and Peak Detection

The sampling is done by querying data from the quadtree which lies within a square specified by the search window size. To identify local itineraries the COG information of each sampled tuple is considered. Figure 6.3 shows the histogram of COG values for a typical situation of a waterway. Each COG value is specified in degrees and is element of \([0°, 359°]\). Most COG values are given as integers, only few are with higher precision \([27]\). Hence, we round each COG value to the nearest number.

We evaluated COG values on different waterways within our data set and can confirm earlier observations \([124, 26]\) that normal distributions with appropriate \(\mu\) and \(\sigma\) values can be used to characterize AIS data attributes. Figure 6.3 shows two separated peaks with \(\mu\) values of approx. 117° and 298° since data has been sampled from a waterway with two opposite itineraries indicating two Gaussian distributions with low variance. The shown situation represents a simple case, where the peaks in the histogram are clearly separated. In most cases the sampled data include Gaussian mixture models (GMM) with several peaks.
Next we implemented a peak detection algorithm which is based on the mean histogram value and standard deviation of the peaks. We first consider only peaks, where the size of the peak is above the histogram’s mean value. For evaluating different areas including branches and crossings we introduced the parameter $\sigma_e$ which describes the expected default standard deviation for COG peaks. Throughout the peak detection $\sigma_e$ is set to 4° since separated COG clusters show a low uncertainty resulting in a spiky representation as shown in Figure 6.3. While identifying peaks we ensure that the distance between two peaks is at least $3\sigma_e$.

To detect peaks our algorithm iterates from 0° up to 359° while recognizing monotonically increasing values and storing the currently highest detected value if above mean. If a possible peak position is detected, it is tested whether there is no higher peak within the next $3\sigma_e$ values. In this case the stored peak position is kept as part of the result. A special case has to be considered if peaks are close to 0° and 359°, where a peak may be split. Thus, we operate modulo 360° within the presented work.

Using the mean histogram value allows us to identify the local main itineraries within the current search window. Nonetheless, some waterways are less frequently used than the main routes resulting in differing traffic densities. In extreme cases branches are not detected since COG peaks of less frequently used waterways may be located below the calculated mean. Figure 6.4 gives an example by showing a branch of waterways with differing traffic intensities. All blue points represent in total approx. 67,000 sampled tuples whose COG values are used for peak detection.
It can be observed that the density of blue points belonging to the itinerary leading from South to North and vice versa is much lower than the density of the main waterway. To detect and cluster less frequently used waterways we introduced a parameter *Peak Mean Divider* with a value of 6. This parameter is used to divide the calculated mean for the sampled area allowing to detect and separate peaks above and below the mean value. Figure 6.5 shows our peak detection outcome for the branch of Figure 6.4, where the black circles mark peaks above the mean and the red circles mark further peak candidates below the mean.

![Fig. 6.5 Peak Detection Outcome Example](image-url)
For each further peak candidate it is tested, whether it should be added to the list of peaks. To do so, we have to check whether this peak represents one of these low traffic itineraries. We introduce an additional search window that is shifted into the COG direction of the peak candidate. If the peak COG value is a local maximum within the shifted search window, then the peak candidate should be considered as peak. The concept of shifting the search window is exemplary shown in Figure 6.7. The final peak list is used as start parameters for the subsequent clustering algorithm.

### 6.4.2 Clustering by Expectation Maximization

Clustering of trajectory data allows detecting and interpreting groups of objects with similar properties [107]. Within this context two common clustering approaches are k-means and Expectation Maximization (EM). For instance, a variation of EM has been used by Wang et al. to cluster weather data [109]. Within our work we use EM which is an iterative algorithm assigning data to clusters by calculating probabilities. Hence, the COG values of the sampled tuples are assigned to clusters whereas each cluster is represented by a Probability Density Function (PDF) described by respective mean and standard deviation values. GMM occur if the \( \mu \) values of different PDFs are located close to each other or if the variance is high. Figure 6.6 shows COG data obtained from tuples which were sampled within an area where vessels may switch from on itinerary to another.

EM performs a soft clustering meaning the probabilities calculated for a COG value located between two \( \mu \) values can be similar since the uncertainty is high within this interval. Thus, EM allows detecting situations where a COG value might match several PDFs. Compared to other clustering approaches such as k-means, EM does not require an even cluster size which allows clustering sampled data from itineraries with different densities.

Before executing the EM algorithm, a threshold is used to remove COG values with low frequencies which are considered as noise. In Figure 6.6b, this is most likely the case for all COG values smaller than 60° and bigger than 120°. Using the threshold prevents a wrong \( \mu \) determination. In addition, the EM variance calculation may be highly affected by outliers when not using a threshold. We identified a threshold value of \( \text{COG}_{\text{mean}}^{16} \) as suitable.

As for each optimization algorithm the initial assumption determines if and how fast the algorithm terminates. Thus, the execution of the EM algorithm directly depends on our peak detection presented above. Accordingly, each detected COG peak is assumed to be an inertial \( \mu \) value of a PDF for the first EM iteration. Again, we are using \( \sigma_e \) as an inertial assumption for each PDF. In the following we will refer to the PDFs as clusters.
The first step of each EM iteration is to calculate likelihoods for all sampled COG values. Thus, the amount of clusters equals the amount of probabilities to be calculated for each data point. The probability $P$ of COG value $x_i$ belonging to a cluster $c_j$ is computed by

$$P(x_i|c_j) = \frac{1}{\sqrt{2\pi\sigma^2_{c_j}}} \exp\left(-\frac{(x_i - \mu_{c_j})^2}{2\sigma^2_{c_j}}\right)$$

Based on this background knowledge, the posterior probability $b$ is calculated. Again, this is performed for each $x_i$ and each cluster $c$ resulting in a matrix of size $m \times n$ whereas $m$ represents the amount of clusters and $n$ represents the amount of data points. The posterior probability of a given COG value $x_i$ belonging to a given cluster $c_j$ is calculated by

$$b_{c_j,x_i} = P(c_j|x_i) = \frac{P(x_i|c_j)P(c_j)}{\sum_{k=1}^{m} P(x_i|c_k)P(c_k)}$$

We assume that $P(c_k)$ is equal for all $k$. Hence, the equation can be simplified by removing these factors. By multiplying each data point $x_i$ with its individual posterior probability.
calculated for $c_j$ the new mean value is computed by

$$\mu_{c_j} = \frac{\sum_{i=1}^{n} (b_{c_j,x_i} \cdot x_i)}{\sum_{i=1}^{n} b_{c_j,x_i}}$$

Thus, $x_i$ values with a low posterior probability for a cluster $c_j$ barely affect the cluster’s $\mu$ estimation. Finally new variances for all clusters are estimated. The variance for a cluster is calculated using its estimated $\mu_{c_j}$ by summing squared deviation of $x_i$ to $\mu_{c_j}$ weighted by the respective posterior probability $b_{c_j,x_i}$ and dividing the sum of the posterior probabilities:

$$\sigma^2_{c_j} = \frac{\sum_{i=1}^{n} (b_{c_j,x_i} \cdot (\mu_{c_j} - x_i)^2)}{\sum_{i=1}^{n} b_{c_j,x_i}}$$

The EM iterations are continued as long as a significant change (any $\mu_c$ difference > 0.001) has been detected between the last and current iteration and less than 100 iterations have been executed. As a result of the EM algorithm each cluster $c$ can be described by its $\mu_c$ and $\sigma_c$ estimations.

These PDF parameter estimations are finally used to cluster the sampled tuples by identifying the most likely cluster for each tuple. In cases where only one peak has been identified the EM algorithm is not necessary and consequently not executed. For instance, a vessel could drive on a waterway which is part of a traffic separation scheme.

Figure 6.7 shows exemplary situations where data has been sampled and clustered using our EM implementation for a given area restricted by the window size parameter. Each identified cluster is indicated by a different color.

Fig. 6.7 EM clustering result. (a) Bi-directional Waterway restricted by navigational aids. (b) Search window shift and clustering at a branch. (c) Complex situation with 8 identified clusters at the port of Bremerhaven.
Figure 6.7a shows the clustering result of the sampled data of Figure 6.3. Figure 6.7b shows a shifted search window to the North created within the peak detection to verify whether a specific cluster of COG values is actually existing in the estimated direction. Both waterways have a width of approx. 2km. Three clusters have been detected. It can be observed that some vessels were using the opposing lane which is indicated by green tuples located within the red cluster. Hence, by comparing live vessel traffic with the results of our clustering approach, maritime safety and security applications such as presented in [125] might be extended. Figure 6.7c shows the port of Bremerhaven (Figure 6.1: zoomed area of second rectangle from the right). Still, magenta points indicate trajectory start or end points. The situation in Figure 6.7c is a difficult one since eight different clusters which partially overlap have been identified. The waterway width is approx. 1km. Figure 6.7 shows that our proposed clustering algorithm is capable of detecting COG clusters in different and complex situations.

Correct peak detection is crucial for the clustering approach. E.g., if the peak detection identified only one peak instead of the existing peaks, EM with only one start value would result in a PDF with a wrong mean and a high sigma value and the overall vessel movement prediction step would have a large error. We detect a potentially failed clustering by evaluating the sigma values of the clusters. If a sigma value exceeds a defined threshold of 45°, it can be suspected that the peak detection has failed. In such cases the values of the last predicted vessel state are used to predict the next one, i.e., the steps Matching and Creating Mean-Object are skipped and the motion model is directly executed with current COG and SOG values.

6.4.3 Matching

Matching means that the current vessel state is being assigned to one of the identified clusters. This assignment allows using information from the chosen cluster such as the COG value to predict the next vessel state. Clusters which represent an opposite direction to the current vessel course are removed beforehand. To do so we are storing the last three used COG values in a queue to avoid U-turns. If only one cluster is left after removing opposite clusters the probability for the remaining cluster is 1.0. Otherwise identifying the most likely cluster is achieved by calculating the probability value $p_c$ for each remaining cluster to determine $p_{\text{max}}$ while using the following weighting function

$$p_c = w_a \cdot \frac{c_c}{c_a} + w_t \cdot \frac{t_c}{t_a} + w_M \cdot \frac{M_c}{M_a}$$

(6.2)
All fractions represent the percentage of tuples which belong to the currently considered cluster $c$, where $c$ stands for the total amount of tuples which have been assigned to cluster $c$ with the appropriate $\mu_c$ and $\sigma_c$ values. $t_c$ stands for the unique amount of vessels included in $c$ having a similar vessel type as the currently predicted vessel, $M_c$ stands for tuples which have been generated by the same MMSI, i.e., the same vessel, in the past. All denominators represent the total sums of respective tuples extracted within the search windows. The most important ratio is $\frac{M_c}{M_a}$. If not zero, the vessel has driven in the direction of the cluster $c$ before what is a strong indicator that the vessel is likely to choose this direction again. A value of 1.0 indicates that the vessel was in the area before and has always driven in the direction of cluster $c$. The ratio $\frac{c_c}{t_a}$ includes the total amount $t_a$ of vessels having a similar vessel type and the amount $t_c$ of these vessels which have been assigned to cluster $c$. Related to the AIS data description of Section 6.3.1 we implemented a function $\text{isVesselTypeSimilar}$ which takes two bytes as input parameters. If these bytes do not contain not available or reserved values it is checked whether both values are equal or belong to the same of the defined AIS groups and are therefore considered as similar. Each unique vessel included in cluster $c$ which is similar to the currently predicted vessel increases $t_c$. Thus, $t_a$ is the total amount of unique vessels within the search window which have a similar type as the predicted vessel. The ratio $\frac{c_c}{t_a}$ specifies the total amount of tuples assigned to a cluster. Therefore, $c_c$ also includes the tuples $t_c$ and $M_c$, if available.

Recorded real world AIS tracks allowed us to perform different predictions runs with differing weighting factors. By varying mentioned weighting factors we evaluated whether the predicted path was similar to the ground truth path. Additionally we evaluated how smooth the predicted trajectory looked like and whether the predicted positions were located within the waterways since varying the weighting factors may result in in unexpected turns or simply in choosing a wrong but existing path. For the weights, it is intuitive that $w_a \leq w_t \leq w_M$, as more weight should be given to the same vessel than to other vessels and to similar vessels than to dissimilar vessels. We empirically determined suitable weights as

$$w_a = 0.2 \quad w_t = 0.3 \quad w_M = 0.5$$

Areas may be sampled where the vessel is traveling for the first time. Then, Equation 6.2 is not well-defined, as $M_a = 0$. Simply neglecting the last term would result in a maximum probability of $w_a + w_t$. In such a case the value of $w_M$ is distributed to $w_a$ and $w_t$ such that $w_a + w_t = 1.0$ and $\frac{w_a}{w_t}$ stays constant. For our choices, the weights would increase to $w_a = 0.4$ and $w_t = 0.6$. The same applies if no tuples with a similar vessel type have been found with the cluster. This might be the case if the vessel has a very rare type such as Anti-pollution equipment or Medical Transport or if the vessel does simply not provide a valid vessel type.
If neither the vessel has been in the area before nor similar types exist in the area $w_a$ is set to 1.0, i.e., the next predicted vessel state leads in the direction of the most frequently used itinerary. It is important that the sum of the weighting factors equals 1.0, since they are used within the mean-object creation step.

6.4.4 Creating Mean-Object

With respect to the weighting factors three mean objects are computed for the most likely cluster. The first mean object is composed of all cluster tuples belonging to the predicted vessel if this vessel has been in the area before. This allows for calculating mean values for the position as well as COG and SOG values which are directly related to the vessel and its past behavior in this area. The second mean object is composed of all cluster tuples which belong to a vessel with a similar type. This allows distinguishing between, e.g., high speed boats and cargo vessels since the SOG most likely differs. The predicted arrival time is expected to be more accurate when using SOG values of similar or identical vessels, since a speed boat is most likely driving faster than a tanker. Moreover, the geographical position of similar vessels is relevant since a cargo vessel is probably driving in the middle of a waterway whereas a pleasure boat might drive at the borders. The third mean object takes all cluster tuples into account thereby forming an actual mean object. Using these mean objects and the same weighting factors as described above allows for calculating new COG and SOG values. These values are used when performing the motion model.

6.4.5 Performing Motion Model

The next vessel prediction state $x_t$ is based on the current vessel state $x_{t-1}$. A vessel state consists of the current geographical position and a COG and SOG information, i.e.,

$$x_{t-1} = \{\text{lat}, \text{lon}, \text{COG}, \text{SOG}\}$$

To calculate $x_t$ a motion model needs to be defined and executed. Since within AIS position reports the geographical information are encoded in decimal degrees and the SOG information is specified in knots conversions are necessary. These conversations are exemplary shown within the following unit equations which can be used to calculate a new latitude value in nautical degrees:

$$\text{lat}_t = \text{lat}[\degree] + \Delta t[s] * \cos(\text{COG}) * \text{SOG}[\text{kn}]$$

Since $\text{kn} = \frac{\text{NM}}{h}$:
\[ \text{lat}_t = \text{lat}[^\circ] + \Delta t[s] \times \cos(COG) \times \text{SOG}^{\frac{NM}{h}} \]

Since 60NM are approx. 1° and 1h equals 3600 seconds:

\[ \text{lat}_t = \text{lat}[^\circ] + \Delta t[s] \times \cos(COG) \times \text{SOG} \times \frac{1}{3600 \times 60}^\circ \]

Finally the time unit can be cancelled so that a result in geographical degrees is calculated. Arc minutes stay only constant for longitude values. For that reason the calculated movement distance for the longitude value has to be divided by a value based on the current latitude leading to the motion model \( f_M \):

\[
x_t = f_M(x_{t-1}, \Delta t) = \begin{pmatrix}
\text{lat} + \Delta t \times \cos(COG) \times \text{SOG} \times \frac{1}{3600 \times 60}^\circ \\
\text{lon} + \Delta t \times \sin(COG) \times \text{SOG} \times \frac{1}{3600 \times 60}^\circ \\
\text{COG} \\
\text{SOG}
\end{pmatrix}
\] (6.4)

As mentioned in Section 6.3.2 we do not make use of the ROT information since ROT values are mostly not available and depending on the AIS reporting intervals not reliable. Instead by sampling our background model and creating mean objects we obtain current COG values for a given area. Hence, it is not necessary to derive and apply ROT values manually within the motion model.

The SOG and COG values are directly taken from the weighted mean object of the most likely cluster to update \( x_{t-1} \). If two or three mean objects have been calculated while predicting and the current predicted vessel’s position is far off the mean object positions, the COG value of the most likely cluster used in Equation 6.4 is modified. This correction is based on the assumption that the mean objects indicate where the current vessel and similar vessels were mostly located on the waterway in the past. For instance the highest trajectory density for vessels with a heavy draught is in the middle of a waterway whereas vessels with light draught may use border areas of a waterway. Within this context using the last two mean object positions \( m_t, m_{t-1} \) allows for calculating the minimum distance between a line formed by \( m_t, m_{t-1} \) and the current predicted position. If the minimum distance exceeds a threshold, in our case \( 10^{-3} \)° (approx. 110 meters), we adjust the current COG value before executing the motion model by adding or subtracting the variance value \( \sigma \), calculated for the chosen cluster depending on whether the vessel is currently located left or right of the line. Yet, the correction is always performed within the interval \([\sigma, 3\sigma]\).

It is well-known from numerics (cf. Euler scheme) that the prediction time \( \Delta t \) used in Equation 6.4 is a parameter which highly affects the computation time and prediction
outcome. Low values for $\Delta t$ result in high computation times since the whole prediction cycle including the EM algorithm is more often executed. High values on the other hand might result in missed areas which are not sampled since executing the motion model with high $\Delta t$ values significantly changes the current geographical position. Missed areas might include crossings or branches which are not considered in this case. In addition, the predicted travel time depends on reliable SOG values meaning the time between sampling updates should not be too big. Within our evaluations we identified a value of 60s for $\Delta t$ as suitable when executing long term predictions. Related to short term predictions, we suggest using smaller values such as $\Delta t = 20s$ to increase the influence of the local environment.

6.5 Interaction Mechanisms and Visual Encoding

The prediction cycle estimations are embedded within an interactive visual system that allows for the analysis, exploration, and investigation of the trajectories from the background model and the predicted trajectories including uncertainty. The interaction mechanisms and visual encodings support different application scenarios.

This software prototype has been developed in C++ and consists of two windows. The first window is an interactive navigation window which uses OpenGL to render sea charts, vessel trajectories, and prediction results. Hence, this navigation window represents the world view and is the main input window. Standard user operations such as position translation and zooming are supported. The navigation window is not restricted in its size and is mostly used maximized on an additional screen. The second window is the control window. This window is a typical GUI containing controls to load data, to change prediction parameters or to start evaluation tests. According to our proposed prediction algorithm, mainly two application scenarios are covered by our software prototype.

6.5.1 Application Scenarios

One application scenario is the visual inspection of vessel movement data. The user is able to select individual AIS trajectories within the navigation window by using the mouse. Each tuple of the selected trajectory may additionally be highlighted and is also selectable. The geographical world position, tuple and trajectory information such as COG and SOG values, timestamps or the vessel’s static data such as MMSI and vessel type are displayed within the navigation window. Of course, panning and zooming is supported, as well. Further controls allow for filtering trajectories by length or by vessel types. The world navigation is performed by using keys, the mouse or by directly entering a world position in the control
window. Point of interests consisting of a geographical position and the current zooming factor can be saved and loaded. Further interaction mechanisms allow the user to load sea charts with different scalings. The usage of nautical charts provides a better understanding of the background model data and the prediction results. E.g., overlaying the background model with the nautical sea charts allows for analyzing traffic densities at specific locations. It also supports the in-depth analysis of the prediction steps to support their understanding. This user interface has been used to create Figures such as Figure 6.9 and Figure 6.7.

Other application scenarios target long- or short range prediction for a selected AIS target. Appropriate user controls allow setting prediction parameters such as $t_{\text{max}}$ or defining target zones. Predictions may be started for live AIS targets and for each tuple included in the background model. The latter was relevant for our evaluations, where we removed the selected trajectory from the background model while running the prediction. Selecting tuples from the background model allow comparing the outcome of different prediction parameters since the temporarily removed trajectory represents ground truth data in this case.

With respect to the user interaction an important aspect is the termination of the prediction cycle and therefore stopping the motion model execution. We defined three criteria when to stop predicting. The first criterion is the elapsed time $t_{\text{max}}$ related to a vessel’s movement prediction. This means that the algorithm stops if a vessels itinerary has been predicted over a user specified amount of time, e.g., $t_{\text{max}} = 10h$. The second criterion is the reaching of an area that can be defined by the user, e.g., a port area or a section on a waterway. Lastly, our prediction cycle automatically terminates if the end of a path has been reached. This is recognized if the current predicted position does not have any further neighbor tuples which can be queried from the quadtree. After the prediction has finished, the prediction result is visually encoded and represented in the navigation window. Debug controls allow retracing each performed prediction step. E.g. the user may directly jump to a specific prediction step and view the clustering result, calculated probabilities or the currently predicted position.

### 6.5.2 Visual Encoding

In general our visual encoding uses a geo-spatial representation where geometric objects in form of polygonal lines represent the background model trajectories. Predicted vessel paths are overlaid with geographic maps. For the background model trajectory visualization we decided not to make use of aggregated visualization approaches such as density plots as presented in [36, 37] or dynamic glyphs related to vessel data [126], as we are interested in seeing all trajectories and allowing the user to select any point on any trajectory. The visual clutter that trajectories produce in high-density areas is desired in this context and not an issue when observing individual trajectories, as they are visually highlighted.
The visual encoding of the prediction outcome depends on the analysis task. With respect to the long-range prediction, we visualize the most likely path to the user while showing additional information such as the estimated arrival time. The uncertainty in the predicted arrival time is visually encoded by coloring the predicted trajectory. Given the estimated arrival time (mean of predictions), we estimate positions within one and two standard deviations and use different colors for those intervals of the trajectory. The colors indicate positions where the vessel is after the estimated time with 68% and 95% probability.

When starting a short-range prediction, the goal is typically collision detection. Hence, one is not only interested in the most likely path, but also in the uncertainty of the prediction. We address this by computing an uncertainty band and visualize it to indicate the area that will likely contain the path of the predicted vessel. To calculate and visualize the uncertainty band we are considering possible future movements of the selected vessel for a given $\Delta t$ and $t_{\text{max}}$. To determine different movements we create a parameter set consisting of different weighting factors variations, where the weighting factors are varied for one decimal place. As a necessary condition the weighting factor sum of each variation equals 1.0. Thus, our parameter set consists of 66 variations including our default weighting factors presented in Section 6.4.3. Partial weightings such as $w_a = 0.0, w_t = 0.0, w_M = 1.0$ are included. Finally, for each variation of parameter settings a prediction cycle is started. Since the presented prediction algorithm requires only read access to the background model we use threading to distribute these predictions to reduce computation times. As a result we obtain a set of predictions for each prediction step, where each prediction has the same starting point which is the current geographical position of the selected vessel.

To calculate the uncertainty band we take the starting point and all predicted results. Since SOG and COG values change slowly over time all time step prediction positions are located relatively close to each other and can be parameterized along a line. Hence, to calculate the median and appropriate variance values of the next time step, we project all predicted positions onto a line orthogonal to the previously predicted movement direction as shown in Figure 6.8.

After projecting, statistical values such as mean, median, and variance can be estimated in 1D along the line. Afterwards we are projecting the calculated results back into 2D space using the mean distance between the orthogonal line and the projected points. We repeat these steps for each prediction step. Finally, we visualize the uncertainty band by using lines to connect the calculated medians. Transparent layers are used to indicate the area which will most likely include the vessel movements, where darker colors indicate a higher likelihood, see Figure 6.14. The predicted trajectory based on our default weighting factors...
6.6 Evaluation and Results

With the help of the developed software prototype test cases have been automatically generated for each trajectory belonging to the background model. The first tuple of each trajectory has been used as a prediction start point. A target region has been created around the last tuple of each trajectory. Within this context each test case has two stop criteria. It either stops if the target area has been reached (success) or if 1.2 times the original trajectory length has been exceeded while predicting (fail). Since our prediction algorithm relies on background model sampling we made two restrictions. First, the start area must contain at least 5 other data points. Secondly, the target area must be reachable, meaning the target area must include at least 25 data points which is a low value compared to a normal sampling step which extracts hundreds or thousands of tuples from the background model.

Since a test case has been generated for each trajectory of the background model instead of manually selecting a specific amount of trajectories, there is no bias towards picking simple cases. In total, 10,224 test cases have been generated. 367 test cases have not been executed due to the lack of background information within the start or target region. Thus, 9,857 test cases have been executed. 2,670 test cases failed (approx. 27%). Hence, 7,187 (approx. 73%) of all test cases succeeded. While executing a test case, the original trajectory has been removed from the background model to avoid any influence caused by ground truth data.
Each test case prediction can be viewed with the user interface and is additionally serialized to the hard disk for later access. The succeeded test cases do not simply represent successful decisions between two available paths but represent a chain of many correct decisions made by our proposed prediction algorithm. The overall evaluation result shows that our proposed prediction algorithm is capable of finding the most likely itinerary for a given start point in the majority of cases. Since our prediction algorithm can be used for long- and short-range prediction, evaluation results are presented in appropriate sub-sections.

6.6.1 Long-range Prediction

The goal of the long range prediction is to identify the most likely itinerary and arrival time for a given vessel. This information is of interest for pilots, VTS, port authorities, shipping companies and companies offering mooring services since proper personnel and logistic planning have to be performed. Within this context estimating the expected arrival time (ETA) of vessels is an important research topic, cf. [127, 128].

The operator of a vessel or the vessel shipping company must inform the port authorities of the destination port and - if applicable - the appropriate pilot station about the ETA 24 hours in advance or at the latest at the time the vessel leaves the origin port if the voyage time is expected to be less than 24 hours [128, p. 28]. However, it is not uncommon that the destination port is not known or changes during the voyage. In such cases, the port authorities of the destination port must be notified about the ETA as soon as the destination port is known to the vessel crew [128, p. 28].
Predicted vessel itinerary located in the German North Sea starting at the port of Bremen (South East) leading to the Netherlands (West). *White*: Trajectories forming the background model. *Dark blue*: Ground truth itinerary which has been predicted (not part of the background model). *Light blue*: Historical trajectories of the same vessel which generated the ground truth itinerary (part of the background model). *Magenta*: Predicted itinerary by our algorithm (partially occluding light blue trajectories). The ground truth itinerary has a length of approx. 220 km and the vessel needed approx. 9h for traveling this distance. With respect to the ground truth data our prediction has a time error of 15 minutes. Spatial deviations between ground truth data and our prediction are caused by the historical trajectories which have significant impact on the prediction.
With respect to cases where the destination port of a vessel is currently not known we present two exemplary successful long-term predictions in addition to Figure 6.9. In both Figure 6.10 and Figure 6.11 the high density of magenta points represents vessels anchored in the roadstead (Figure 6.1: second rectangle from the left). Again, the dark blue trajectory represents the ground truth data whereas light blue trajectories indicate historical AIS data generated by the same vessel in the past which are part of the background model. For clarity reasons only the relevant excerpts are shown.

Figure 6.10 shows an excerpt of a successful prediction of a vessel traveling from Cuxhaven to Bremerhaven (rectangles to the right of Figure 6.1) using $\Delta t = 60s$ for each prediction step. Decreasing $\Delta t$ might result in a smoother trajectory, but increases the computation time of the algorithm. Shown successful prediction has a length of approx. 100km and has a time error of less than 10 minutes between the real world data and the final predicted position. Figure 6.11 gives another example for a successful prediction.
It is visible that the predicted vessel is periodically traveling from the Netherlands to Cuxhaven and back. However, this vessel does not always use the same itinerary. We predicted the vessel itinerary for approximately 130 km with a time error of 20 minutes. Both figures show the relevance of historical AIS data for decision making. We conclude that more and more manifold background model data increase our proposed prediction approach accuracy.

With respect to the computation time the main influence factor besides $\Delta t$ is the used CPU. RAM usage is negligible. All evaluations have been performed on a system running with an Intel Core i7 5820K with 3.3GHz. Without using additional optimizations such as using different threads to shift search windows or to identify clusters or performing GPU operations the completion of the whole prediction cycle of Figure 6.11 takes approx. 15ms on average. In total 4.3s are required to perform the complete prediction. The most computation time is required for performing EM to cluster COG values. As mentioned in Section 6.4.2, in cases where only one peak has been detected, $\mu$ and $\sigma$ values of the sampled data points are directly calculated, which takes 0.01ms on average. In case of two or more peaks, expectation maximization is performed whereas two peaks require less than 1ms computation time on average for EM. Logically, the more peaks are detected the more computation time is required. E.g., areas with eight or more peaks require at least 50ms EM computation time. Thus, depending on the itinerary and chosen maximum prediction time the total computation time including sampling and executing the motion model ranges from a few seconds up to half a minute for predictions as shown in 6.9.

The uncertainty of a long-range prediction increases with each branch or crossing. After evaluating failed test cases we concluded common reasons for failed predictions when using our proposed prediction algorithm. One reason for failed predictions is the absence of historical data for a given vessel, see Figure 6.12.

Fig. 6.12 Prediction fail caused by missing historical and vessel type data

The vessel is traveling from East to West while switching to the northeast branch which is less frequently used than the other itineraries. In the presented case no movement data has been recorded for the vessel within the sampled location in the past. In addition the vessel
does not transmit its vessel type. Thus, our proposed algorithm chooses the most frequently used itinerary within the local environment and makes a wrong decision. The same might happen if the vessel transmits its vessel type but has a rarely occurring vessel type such as *Anti-pollution equipment* or *Medical Transport*. In such a case there is most likely no local background model information available for prediction.

Uncommon behavior of a vessel according to the background model might also result in failed predictions. For instance if all tanker vessels within a sampled area have chosen the same itinerary according to the background model and a tanker whose route is to be predicted and for which no background information exists chooses a different itinerary the prediction most likely fails.

Besides not transmitted or rare vessel types and missing background model data our presented weighting function might also indicate a wrong itinerary. Figure 6.13 gives an example for this.

![Fig. 6.13 Weighting factors causing a wrong prediction](image)

Within Figure 6.13 the prediction has been started for the point to the left. The shown waterway has a width of approx. 6km and is restricted to both sides by a traffic separation scheme which is visible at the upper and lower part of Figure 6.13. It is visible that one historical trajectory generated by the same vessel is available for the current area. As mentioned the dark blue trajectory is not part of the background model and therefore not influencing the prediction at any point. At some time step the branch between both visible waterways is detected by the prediction algorithm resulting in a course change according to the weighting factors. While performing the course change more and more data of the historical trajectory is sampled within the search window. Thus, at some point the probability of following the current itinerary instead of switching the itinerary is at least \( w_M = 0.5 \) since \( \frac{M}{M_e} = 1.0 \). Thus, due to the high weighting of historical trajectories a wrong decision is made at this point. A further common reason for failed predictions are vessels which are leaving the background model by ignoring traffic rules. This is especially the case for vessel types such as *Law Enforcement*, *Military Ops* or *SAR*. Our interactive visual systems allowed us to investigate all these cases and to detect the reasons for failure.
6.6.2 Short-range Prediction

Within the short-range prediction scenario, our system visualizes the possible movement radius of a vessel within a given period of time aiming to support decision making for crew members or VTS with respect to collision avoidance. In fact, the short range prediction is completely identical to our presented long range prediction algorithm. Only both time parameters $\Delta t$ and $t_{\text{max}}$ are adjusted. Smaller $\Delta t$ result in higher computation times but allow sampling the local area more often. $t_{\text{max}}$ restricts the prediction to a time window of interest, e.g. $t_{\text{max}} = 10m$. As shown in Section 6.5.2 we are using parameter variation to calculate different predictions to finally visualize possible movements with an uncertainty band. Figure 6.14 shows a short range prediction outcome.

![Short range prediction of a cargo vessel indicating high uncertainty. Background model data are additionally being shown.](image)

The situation of Figure 6.14 is at the same location as in Figure 6.13 using a different zooming factor. The starting point for all prediction runs is the selected tuple of the ground truth data to the left. Based on this point, 66 different trajectories have been calculated for a time window $t_{\text{max}} = 10m$ with $\Delta t = 20s$. The historical data show that the selected cargo vessel has been traveling the same itinerary twice in the past without changing the course at the visible branch. Since the majority of vessels as well as the selected vessel drove more close to the middle of the waterway in the past the calculated predictions lead into the appropriate direction. Within the first iterations the uncertainty is relatively low. After approx. half of $t_{\text{max}}$ the branch is detected as two clusters are continuously identified at this point. Since the vessel followed the direction of the first cluster two times in the
past whereas the majority of vessels as well as the majority of vessels with the same type located in this area switched their course at this point the uncertainty increases because it is ambiguous which path is the most likely with respect to the selected vessel. Hence, the prediction outcome is a cone which opens up a few iteration steps after starting the prediction indicating high uncertainty while covering a wide area including likely movements of the vessel. The green trajectory represents the median trajectory within this context. The purple trajectory corresponds to the prediction which is based on our proposed default weighting factors. The orange position located on the ground truth trajectory shows where the vessel was actually located after 10 minutes had passed. Figure 6.15 shows the same situation without showing the background model data.

Fig. 6.15 Short range prediction of a cargo vessel indicating high uncertainty

With respect to the broad waterway’s width it becomes apparent that our proposed uncertainty band visualization allows for a better situation assessment since the uncertainty band covers the area in which vessels are most likely located if they decide to take the branch at the current geographical location. Figure 6.16 shows another short range prediction outcome. This time the selected cargo vessel changes its course.

The parameter set predictions are started based on the selected ground truth tuple to the left, where the orange position located on the ground truth trajectory shows where the vessel was actually located after 10 minutes had passed. Since historical trajectories generated by the same vessel are located to the left and right of the ground truth data the uncertainty band visualization opens up to both directions. Similar to Figure 6.14 the uncertainty especially increases when both clusters are identified. However, in general the visualization shows a lower uncertainty compared to Figure 6.14 since within the local area most vessels and
most vessels with the same type as well as the selected vessel itself changed their course to the direction of the branch in the past. Hence, all calculated predictions are leading in the direction of the branch. After taking the branch the uncertainty slightly decreases since the traffic density differs. In addition, the historical trajectories of the selected vessel are getting close to each other except the trajectory leading to the South. However, the historical trajectory leading to the South is barely affecting the prediction outcome since no separate cluster is identified due to the uncommon COG value according to the background model.

Due to the weighting factor variations and the small $\Delta t$ value the required computation time for the short term predictions increases. Within this context the main influence factor for the computation time besides the chosen values for $t_{\text{max}}$ and $\Delta t$ is the local complexity of the background model. Depending on the local complexity the algorithm may need a few seconds up to 1 minute of computation time to terminate all parameter variation predictions when using the currently used $t_{\text{max}}$ and $\Delta t$ values. With respect to the latter case the middle rectangle (yellow) shown in Figure 6.1 shows an area which can be described as a key area within our background model network since the highest amount of itineraries meet here, where each itinerary might be chosen by a vessel. Hence, the computation times are especially high in this area. With respect to computation times both short range predictions shown in Figure 6.15 and Figure 6.16 finished in less than two seconds while using $t_{\text{max}} = 10m$ and $\Delta t = 20s$ in both cases.
6.7 Conclusion

Within this paper we presented a novel vessel movement prediction algorithm integrated in a software prototype which allows for visual inspection of prediction results and further maritime data. Historical AIS data have been compressed and stored as a background model which is used within the presented prediction cycle. The background model may be continuously updated with additional received AIS data. In general, our presented history-based approach may be used in any area that is covered by AIS receivers.

The user interface allows starting long-term predictions indicating the most likely path and arrival time of a vessel. Furthermore short-term predictions allow for the visualization of possible vessel movements within the near future aiming at collision avoidance. While developing the proposed prediction algorithm we considered the difficulty of not kept AIS reporting intervals. Thus, compared to different prediction algorithms based on the Extended Kalman Filter or Particle filter our proposed algorithm allows predicting the likely vessel itinerary based on a single received AIS message. Hence, the background model plays an important role and should include a sufficient amount of data covering existing vessel types and routes.

Our history-based prediction approach is also suitable for further maritime application fields. One example is vessel surveillance as done by VTS operators. Our background model allows detecting situations where a vessel or even a specific vessel type leaves a mandatory waterway restricted by navigational aids. Moreover, our background model allows detecting whether a vessel is driving against the direction of traffic, e.g., on the opposing lane of a waterway. Such situations respectively vessels could be automatically detected and highlighted for VTS operators increasing situation awareness.

6.8 Future Work

Related to additional application fields mentioned in Section 6.7 future work should evaluate existing visualization approaches such as [129] for encoding the background model trajectories for end users such as VTS operators who are only interested in selecting active targets. Currently, each background model tuple is selectable due to developing and testing reasons. If the background model is continuously updated with new data, further means should be taken to reduce clutter.

Future work should also evaluate approaches allowing terminating the prediction algorithm automatically. Currently our prediction algorithm stops if no further tuples exist in the search window, if $t_{max}$ is exceeded or if a user specified target area has been reached. This
could be improved by detecting harbor or mooring areas automatically. According to [130] density-based approaches perform best to identify and visualize clusters of start and end respectively stopping points and are robust to visual clutter. Hence, harbor or anchor areas as visible in Figure 6.1 could be automatically detected by using density-based approaches related to vessel movements such as presented by Willems et al. [131]. If the vessel had been moored in such an area this would increase the probability of stopping the prediction.

Related to the long range predictions future work should include AIS data from additional regions to evaluate prediction outcomes for even larger distances. With respect to the ETA users should be able to select an active target and to specify a desired path within the background model to calculate a desired ETA estimation independently from the actual prediction since the predicted itinerary might be wrong. Besides, further work should evaluate whether the usage of additional AIS information might result in a better prediction behavior. Considering the presented matching function currently only the vessel type is used to compare vessels using \( w_t \). Within this context further weighting factors could be introduced. For instance using the vessel’s draught and its dimensions which are included in the static AIS data instead of just comparing the vessel type might improve the matching process. With respect to the weighting factors a further factor might be the distance of the currently predicted state to the geographical means of the identified clusters whereas clusters close to the predicted state would have a higher probability.

Our presented prediction algorithm may also be improved by using a more detailed cluster evaluation. Currently, possible itineraries for a sampled area are identified using peak identification and clustering. Within the matching step the most likely cluster is identified by evaluating whether similar vessel types or even the same vessel was travelling in the direction of the cluster in the past. However, this approach does currently not consider whether vessels were actually switching the itinerary at this point. In fact it might be possible that switching is not allowed for the given context due to rules of navigation. Thus, within future work the matching step should additionally evaluate the amount of vessels belonging to the currently chosen cluster A which are actually switching to the itinerary represented by cluster B to make our algorithm more robust.

Finally a parameter optimization may improve the algorithm’s performance. Within this context the quality criteria to be optimized are the overall success rate of predictions and the total or average prediction time. Currently used parameters have been identified manually by making logical assumptions and evaluating test results. A possible approach for parameter optimization would be the definition of valid parameter ranges and the usage of a genetic algorithm since our proposed approach does not represent a traditional function for which deviations could be calculated.
Chapter 7

Conclusion and Outlook

Within this work different aspects of AIS with respect to maritime safety and its applications have been analyzed. At the beginning of this work the dynamic AIS data which are especially relevant for collision avoidance have been evaluated. It has been shown that for almost all dynamic data fields a high availability is achieved except for ROT and HDG. In addition, static attributes have been evaluated, e.g., showing that almost each vessel transmits its dimensions. With respect to the dynamic AIS attributes a motion model has been defined which has been used within exemplary extrapolation scenarios based on received real world AIS data. By using different examples it has been shown that a vessel movement prediction based on dynamic AIS data is difficult to achieve and that more sophisticated approaches are required. Especially missing or restricted ROT information make predictions difficult if a vessel performs a turning manoeuvre. Furthermore not kept reporting intervals increase the uncertainty of the predictions. With respect to the reporting intervals an additional evaluation has been performed showing receiving behavior of AIS systems under ideal circumstances in terms of maritime navigation. This evaluation shows that reliable respectively continuous vessel tracking based on received AIS data under mentioned conditions is not guaranteed since the official AIS reporting intervals are not always kept. Both evaluations presented in Chapter 2 and Chapter 3 are of relevance for all works which use dynamic and static AIS data for research.

Based on the AIS data evaluation of Chapter 2 AIS attributes which provide a benefit for users of radar systems in terms of maritime safety and which are currently not visually encoded have been identified in Chapter 4. New glyphs extending the current visual encoding of AIS data have been proposed and discussed with an expert group by evaluating different traffic scenarios. This includes, e.g., the proposed visual encoding of the draught value transmitted by vessels which gives hint about possible vessel movement restrictions. The
proposed visual encoding of AIS data as part of this work aims at increasing the maritime safety.

Furthermore, this work showed how real world AIS data can be used to extend maritime simulation systems. For this purpose the IEEE DIS standard has been used, which is well known within the simulation area. The AIS evaluations of Chapter 2 and Chapter 3 related to availability of AIS data and the AIS reporting intervals influenced the integration process presented in Chapter 5 significantly. With respect to DIS it has been shown that the AIS communication has not completely been standardized within the DIS standard at the time of this work. Hence, relevant DIS PDUs which can be used for an AIS data integration and their appropriate counterparts in case of using IEEE HLA instead of DIS have been presented. An approach has been presented allowing to match incoming AIS data with available 3D models of the simulator according to their size, vessel type and operating region. With respect to the reporting intervals, a dead reckoning approach has been presented and discussed allowing to control generated vessels based on real AIS data if the AIS update rate is not constant. The presented approach respectively its system architecture used to integrate live AIS data into a bridge ship handling simulator may have impact on further maritime simulation systems.

Finally, a new vessel movement prediction approach based on AIS data has been presented in Chapter 6. A background model consisting of historical AIS data is used for predictions to overcome the problem of not kept AIS reporting intervals as discussed in Chapter 3. Based on the local data of the background model and the current attributes of the vessel whose course should be predicted the most likely vessel path is identified. Within this context the vessel type, the vessel identity as well as the itineraries used by other vessels in the past affect the prediction outcome. Compared to other vessel movement prediction algorithms the presented approach does not necessarily require a correction step since the time between two AIS messages which include the dynamic data may exceed the official AIS reporting intervals as shown in Chapter 3. To interact with the proposed algorithm the user can specify different parameters. E.g., by setting different values for $\Delta t$ and $t_{\text{max}}$ the presented algorithm can be used for both short and long range vessel movement prediction. Besides visualizing the most likely prediction path including uncertainty visualization the user is additionally informed about likely arrival times derived from the historical AIS data stored in the background model. Especially when performing a short term prediction the presented algorithm including its uncertainty visualization increases the situation awareness for mariners.

In summary, this thesis shows how data of current shipborne AIS can be used to improve the maritime safety at different levels. The first level includes the improvement of manual decision making of crew members since a set of newly developed glyphs relevant for maritime navigation has been proposed. These glyphs enhance the visual representation of AIS targets
Conclusion and Outlook

...on radar screens with intuitive visualizations allowing for a better situation assessment. The manual level also includes the usage of AIS data to improve the simulator-based nautical education for mariners. The presented approach of integrating live AIS data directly aims at reducing the risk of human errors during navigation, since using AIS data allows for training exercise scenarios based on real vessel traffic within the simulator-based nautical education.

The second level describes the technical usage of AIS data in algorithms to increase the maritime safety. It has been shown that AIS data are a suitable data source for appropriate algorithms despite the fact that the general availability as well as the availability of mentioned AIS attributes should be increased. The presented approach of predicting and visualizing likely vessel movements including uncertainty visualization supports mariners in decision making with respect to collision avoidance. Moreover, it has been shown how AIS data can be used within logistics to predict arrival times based on statistical calculations.

Within this thesis the importance of AIS for maritime safety has been pointed out several times. Due to new satellites and related research projects which aim at providing the possibility of continuously tracking AIS movements also on the oceans, the role of AIS within the maritime field will be even bigger in the future. Some companies of the maritime industry already presented concept studies for new vessel bridges respectively bridge devices which make use of augmented reality. Presented concepts intend to merge different data sources to create a virtual overlay allowing crew members to see nearby vessels, obstacles, dangerous areas and navigational marks also during fog or at night. Hence, received AIS data of nearby vessels will definitely be a key part of these concepts. However, this thesis shows that current AIS configurations still lack availability and correctness. To be a reliable and useful data source for upcoming bridge technologies the correctness of AIS data attributes needs to be ensured and the availability needs to be increased in the future. This includes the correction of general information such as incorrect MMSI numbers, call sign and dimensional values as well as the installation of additional hardware to increase the availability of detailed ROT information, if applicable. The amount of vessels using AIS should be increased too, e.g., by including leisure boats which currently use AIS by choice. With respect to the presented study of Section 3 companies and authorities have to ensure the proper installation of shipborne AIS to additionally increase the reception rate. These steps are unavoidable when considering scenarios where, e.g., the received AIS vessel type and the vessel’s dimension provided by AIS are used within augmented reality or similar approaches to render a vessel model whose state is predicted by using received dynamic data. The German Federal Maritime and Hydrographic Agency already showed interest during the work of this thesis to start a project with the goal to correct misconfigured shipborne AIS. The idea of this project is to receive and analyze AIS data of all vessels which enter the port of Hamburg to identify missing or
invalid AIS attributes with respect to a vessel’s identity. If an AIS of a vessel is identified as misconfigured the vessel should be marked in a database and be informed by the authority. Additional vessel databases could be used to verify whether AIS information such as the transmitted dimensions or vessel names are actually valid.

Future research with respect to the presented vessel movement prediction algorithm should evaluate the role of the AIS-based background model. Since the background model allows for automatically detecting situations where a vessel or even a specific vessel type leaves a mandatory waterway restricted by navigational aids it should be evaluated in how far the background model can be used as a supportive unit within bridge devices or systems as used by VTS operators for vessel monitoring and tracking. Different applications scenarios which may be covered by the background model and with respect to maritime safety should be identified, including outlier detection. Examples may be the automatic detection of speeding vessels or the identification and tracking of vessels which are driving against the direction of traffic, e.g., on the opposing lane of a waterway. Especially the matching of radar data with an AIS background model might be of interest since suspicious behavior of vessels, e.g., caused by pirates or smuggling, might remain undetected since these subjects will likely turn their AIS system off, if they are using AIS at all. With respect to satellite-based AIS more reliable arrival time predictions may be possible in the future. Due to the continuous AIS coverage by satellites in the near future the presented prediction approach of this work may be extended and evaluated regarding its possibility to predict arrival times of vessels travelling between continents including uncertainty.

Future work related to the integration of real world data into maritime simulation systems should include the integration of further AIS messages such as message type 21 representing navigation aids such as buoys. Using further AIS attributes such as the vessel draught would allow to enhance the visual representation within the simulation process. Moreover, a user study should be performed to evaluate how the integration of real world AIS data affects the simulation-based maritime education. If upcoming bridge technologies make use of augmented reality the simulator-based education will also be affected. Additional user studies should be performed to identify a suitable visual encoding for augmented reality data.
Author’s Publications


References


