Ship Voyage Analysis: Unraveling the Dynamics of Turning Maneuvers using AIS Data

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Declaration

I, **Shahnoor**, declare that the work in this dissertation titled *"Ship Voyage Analysis: Unraveling the Dynamics of Turning Maneuvers using AIS Data"* is carried out by me. This work is submitted to Åbo Akademi for the award of a degree or educational qualification. I also declare that the information published in this dissertation has been obtained and presented in accordance with academic rules and ethical conduct. Any information obtained from other sources has been properly referenced.

Acknowledgement

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Acronyms

AIS Automatic identification system

IMO International Maritime Organization

GNSS Global Navigation Satellite System

VTS Vessel traffic services

SOLAS safety of life at sea

ECDIS Electronic Chart Display and Information Systems

SOG speed-over-ground

ROT rate-of-turn

OECD Organisation for Economic Co-operation and Development

PPO Proximal Policy Optimization

LIME Local Interpretable Model-Agnostic Explanations

LMTs Linear Model Trees

MMSI Maritime Mobile Service Identity

VHF Very High Frequency

GPS Global Positioning System

COG Course over ground

UTC Coordinated Universal Time

ETA Estimated Time Arrival

OOW Officer on Watch

DBSCAN Density-Based Spatial Clustering of Applications with Noise

MSP Maritime Spatial Planning

TR Turning Radius

nm nautical mile

LOA Length Over-all

POI Point-of-overcoming the inertia

NAVSTAT Navigation Status

POSACC Position Accuracy

RAIM Receiver Autonomous Integrity Monitoring

COT Center of Turn

WOL Wheel Over Line

WOP Wheel Over Point

GRT Gross Register Tonnage

ARPA Applied Research Platform for Autonomous Systems

CSV Comma-Separated Values

Abstract

The analysis of ship voyages using Automatic Identification System (AIS) data plays a crucial role in enhancing our understanding of maritime behavior and improving navigational safety. In this study, we focused on elucidating ship voyages by applying the elastic trend filter to AIS data and analyzing turns using circle-fitting techniques. Our primary objective was to gain insight into a ship's navigational characteristics and decision-making processes during turning maneuvers.

To achieve this, we identified turns in the ship's trajectory, approximated their radii by fitting circles to the data points, and extracted the underlying route using the elastic trend filter. The consistent turn radii observed in the results indicated the presence of a common navigational strategy. However, variations in turn radii were also observed, suggesting instances of sharper turns made to avoid obstacles or navigate through constrained spaces.

To assess the accuracy of our circle fitting method, we compared its precision to manual measurements and previous investigations, demonstrating its reliability. These findings have important implications for autonomous ship control systems, navigational regulations, and marine safety. Recognizing ship maneuvers and their associated radii can contribute to enhancing navigation procedures and optimizing route planning.

By leveraging the analysis of AIS data, our study contributes to advancing transparency and providing novel insights into the navigational behavior of ships. The acquired knowledge holds significance in understanding and explaining ship voyages, making a valuable contribution to this field of study.

Chapter 1

Introduction

1.1 Overview

Shipping is one of the backbones of today's globalized economy that is highly interconnected. Over 70% of goods will be transported by sea by 2050, which is expected to double the demand for freight transportation [4]. Passenger ships, ferries, fishing vessels, and recreational boats also sail the world's oceans in addition to commercial transport ships. To ensure the continued operation of the increasingly globalized market economy, as well as the health and safety of passengers and marine ecosystems, it is necessary to ensure the safety and security of diverse maritime traffic. Automatic identification system (AIS), designed by the International Maritime Organization (IMO) in the 1990s to increase safety and security at sea, is complementary to high-frequency radars [5]. A ship that is equipped with an AIS transceiver broadcasts its position to nearby vessels and authorities on a periodic basis based on the Global Navigation Satellite System (GNSS). On-shore Vessel traffic services (VTS) rely on the AIS to guide and plan traffic as adjacent vessels use positional data that aids the vessel in collision avoidance [6]. Ships that use AIS transponders transmit regular information, such as their location, course, speed, destination, and ship identifier, as required under the international convention for safety of life at sea (SOLAS) [7, 8]. It is possible to collect this information over time and analyze it in order to identify normal patterns of behavior [9]. The behavior of a ship could indicate that it is being used for illicit activities if it exhibits anomalous behavior. Tens of thousands of ships traveling between thousands of ports every day, however, make it impossible to manually monitor the potential threat. Therefore, a priority list for further investigation must be created using efficient and robust automatic data processing. In recent years, a variety of methods have been developed to explain ship voyages and automatically detect anomalies in maritime AIS tracks [10, 11, 12, 13, 14, 15]. Detecting anomalies within confined local areas is possible through anomaly detectors developed in mentioned papers because vessel traffic is to some extent predictable. The physical constraints of sea routes or mandatory sailing routes also prevent vessels from acting arbitrarily. This makes such detectors capable of detecting anomalies in vessel traffic patterns, like accidents or criminal activities, and marking them as anomalies. Developed methods can also contain a high number of false alarms, one of the common challenges in detecting anomalies in a maritime environment.

Traditionally, before the era of Electronic Chart Display and Information Systems (ECDIS), route planning for ships was done with a ruler and compass. While a voyage involves drawing lines on a chart, critical decisions have to be made throughout. When navigating, a number of factors must be considered, such as weather conditions, sea state, currents, traffic separation schemes, depths of water, and maneuvering characteristics of the vessel.

Most of the studies have focused on using techniques to detect and restore the anomaly AIS data based on route planning of a particular vessel, calculated from machine learning models but several existing works ignored the changes in the vessel's direction in confined constraints due to the impact of size, speed or weather conditions [16, 17, 18, 19]. To reduce the environmental impact and ensure the efficiency, effectiveness, and safety of maritime transport, it is vital to understand current maritime transport patterns, from how a single ship operates within a narrow geographical context to how many ships operate within a wider geographical area. Consequently, route plans can be decomposed into straight lines, circle sections, and a few points of reference using simple rules and logic. This means reconstructing the route plan and explaining the critical decision-making in an executed voyage might be possible, given navigational AIS data. Taking into consideration the ship's ability to turn within a constrained space such as a narrow channel or harbor is something that should not be overlooked, especially during route planning. Factors such as a ship's size, speed, and shape affect its maneuvering characteristics, including its turning circle and stopping distance. It is imperative to understand these factors in order to ensure safe and efficient navigation of ships in confined waters.

This study delves into the significance of understanding the underlying reasons behind ship maneuvers, addressing a crucial gap in the current understanding of vessel behavior. Even while data from the AIS is useful for learning about ship operations, it largely focuses on what a ship is doing rather than the reasons for its particular maneuvers. This research intends to uncover insights that can help to a more thorough understanding of maritime operations by examining the reasons underlying ship motions. Moreover, the development of automated methods for extracting voyages and key maneuvers from AIS data has the potential to facilitate the creation of meaningful datasets for researchers. When enormous amounts of AIS data are generated during a journey, it is crucial to simply record the pertinent navigational points in order to prevent needless data storage. The availability of stored "typical voyages and key maneuver" data can be a useful resource for route planning in educational contexts and developing hands-on training exercises for training simulators, which is especially pertinent to institutions like Aboa Mare. Additionally, having access to the 'normal' maneuver patterns for a specific route makes it easier to spot anomalous maneuvers, potentially improving Vessel Traffic Services (VTS) capabilities.

For research purposes, AIS data is extracted from "The Finnish Transport Infrastructure Agency". The data was collected using a web socket API on Google Cloud. The thesis consists of four main chapters. Chapter 1 gives an introduction to the general research area, previous research done in the same area, the problem statement, the research aims and the scope. Moreover, it also gives an overview of AIS data and its workings. Chapter 2 reviews the historical context and methods already in use from earlier studies to explain ship maneuvering. Chapter 3 gives a review of the methodology used on AIS data. Moreover, it explains the research framework which includes raw data acquisition, data wrangling and preprocessing, feature analysis, dataset and the methods used to analyze the turning points in a vessel's journey. Chapter 4 shows the results obtained from methods implemented on the AIS dataset. Chapter 5 discusses a more general and holistic picture of the thesis and how it contributes toward the fulfillment of the research gap. Chapter 6 attempts to summarize the critical findings of the results and gives a holistic overview of the nature of the research. Furthermore, it also explains the problems and challenges that were faced during development and then provides suggestions related to some future work in this field.

1.2 Problem Statement

According to the Organisation for Economic Co-operation and Development (OECD), over 70-90% of the trade goods traded in the world are transported by ships [20]. As a result, maritime traffic and ship sizes are increasing. Because of high investment costs and geographical constraints, the infrastructure at ports and terminals restrains the growth in the size of ships along waterways. Since both human and environmental impacts are involved in maritime logistics, the margin for error becomes very small. An example can be taken by the grounding of the Ever-Given ship in the Suez Canal in 2021 illustrating the severe consequences of human error in maritime transport. The cause of maritime collisions has been evaluated statistically by engineers using historical collision data [21, 15]. In each area over a given period of time, there can only be a limited number of incidents collected on which statistical analysis can be performed. With the help of land-based and satellite-based stations, the AIS collects a large amount of maritime traffic data [22]. Insights into maritime traffic behavior and route estimation can be gained from the existing AIS data, as well as anomalous behavior can be detected.

Examining a voyage entails a thorough review of all the data points in the AIS dataset that have been assigned to a specific ship. The research is guided by the following questions: Based on the historical AIS data, how can maritime routing patterns be discovered automatically and efficiently? To discover patterns and create a network that represents maritime traffic, what algorithms might be applied? In order to efficiently process huge amounts of maritime information, how can we design and implement methods that can process huge amounts of maritime information? By answering these questions, researchers will be able to derive valuable information from the detailed analysis of voyage data, that helps advance maritime analytics, optimize routes, and improve decision-making in a variety of areas, including vessel traffic management, transportation planning, and maritime safety.

1.3 Research Aim

Explaining the voyage of a vessel can benefit a number of people in several ways. Ship navigator officers plan the voyage manually which can be a time-consuming and tiresome job, and sometimes human errors can be involved which can result in disastrous events. With the help of my research, voyage planning can be autonomous, and navigators who are unfamiliar with a sea area, and who don't have information about past experiences, would be able to plan a voyage easily due to the availability of vessel routes taken in the past. This way they will be able to know what would be the best practice in the considered area. In addition, avoiding technical disasters can also help the global economy as a single canal blockage due to a vessel can cost up to $9.6 billion of global trade [23].

I am trying to solve the problems explained in Section 1.2. Gaining a thorough grasp of how ships react and function throughout various maneuvers is the goal of ship maneuverability analysis. Researchers, naval architects, and maritime experts can accomplish the following goals by studying ship maneuverability:

1. Safety Assessment: When evaluating the safety of ship operations, especially during crucial maneuvers like turns, ship maneuverability is examined. Understanding a ship's moving capabilities and limitations can help in identifying potential dangers and risks, allowing for the formulation of safer navigational plans and the application of appropriate safety precautions.

2. Port and Waterway Planning: Planners of ports and waterways must consider ship maneuverability. Planning professionals may provide the best possible de-

sign and layout for port infrastructure, including navigation channels, berths, and turning basins, by examining how ships maneuver in constrained areas like ports, canals, or locks. By doing this, congestion and delays are reduced, and safe and effective vessel movements are guaranteed.

3. Collision Avoidance and Traffic Management: Systems for traffic management and collision avoidance depend on an understanding of ship maneuverability. Researchers can create advanced algorithms and models for assessing collision risk, predicting trajectories, and optimizing traffic flow by studying ship behavior during maneuvers. This makes it possible to implement efficient traffic management plans and create smart navigational systems to avoid collisions and raise overall maritime traffic safety.

4. Environmental Impact Assessment: Assessing ship maneuverability aids in determining how vessel operations impact the environment. Researchers can assess the impacts of ship movements on sensitive coastal areas, marine ecosystems, and air quality by observing turning behavior and maneuvering patterns. The development of sustainable shipping practices, coastal zone management, and environmental impact assessments all benefit from this information.

Overall, the goal of studying ship maneuverability is to increase marine safety, enhance port and waterway planning, create collision avoidance systems, and evaluate how vessel operations affect the environment. Gaining knowledge of ship maneuverability will help stakeholders in the marine sector make informed decisions, implement effective measures, and guarantee the efficient and safe movement of ships.

1.4 Research Scope

While the goal of this research is to offer insightful information on a ship's movement during turning maneuvers and to discover maritime routing patterns automatically and efficiently, it is crucial to recognize the study's inherent limitations. These restrictions are caused by various factors, such as data availability, methodology constraints, and contextual considerations. Contextualizing the results and ensuring a fair interpretation of the research findings depends on being aware of these limitations. When generalizing the findings and assessing the application of the findings in realistic marine contexts, it is imperative to take the following constraints into account.

1. Data Availability: AIS data quality and availability are crucial to the research scope. In this study, the spatial and temporal limitations of the dataset used may limit the analysis and findings. Moreover, the usage of specific dataset can constrain the generalizability of results.

2. Turning Point Extraction Methods: In this research, turning points from AIS data are extracted using trend-filtering techniques. Even though trend filtering can be an effective technique, choosing the right algorithm and parameter settings can ensure improved accuracy and robustness. However, this research does not cover alternative methods for identifying turning points or comparing multiple algorithms extensively.

3. Limited Contextual Information: Positioning and navigation information are primarily provided by AIS data, but certain contextual details may influence ship behavior during turns. In the analysis, factors such as vessel cargo, intended route, and navigational conditions are not directly taken into account. Rather than looking at comprehensive contextual data, the research scope focuses on ship trajectory analysis.

4. Simplified Turning Analysis: The research mainly focuses on identifying turning points and turning radii to characterize ship-turning behavior. The analysis may not include all aspects of ship maneuvering during turns, such as acceleration profiles or particular turning methods used by different vessel types, even though these measures offer insightful information.

5. Generalizability: The dataset and vessels used in the study could have influenced the research findings. Different vessel types, sizes, or operational circumstances might demonstrate different turning behaviors that aren't entirely covered by the defined scope. Only three ships' behavior is taken into account in this study. Further validation and the use of a more varied dataset could be necessary in order to generalize the results to the entire marine industry.

In conclusion, the main contributions of this thesis are summarized as follows:

1. Generate a benchmark route plan based on standard navigational rules and practices.
2. Develop methods for reconstructing the route plans from historical AIS data.
3. This paper proposes different trends on AIS data using Trend filtering methods such as Elastic Filtering.

1.5 AIS Data

In this study, as a first step towards explaining voyages and calculating radius, we will develop methods for reconstructing the route plans from historical AIS data. Before developing, it is necessary to know the AIS data and its guidelines. Moreover, it is also important to have knowledge about wheel over point and turning radius of a ship because when planning a passage, it is imperative that a ship adjusts its course correctly and follows the new intended course precisely.

1.5.1 What is AIS Data?

A short-range coastal tracking system known as the Automatic Identification System (AIS) is used by ships today. It serves both vessels and shore stations by providing identification and positioning information. Navigation safety has been improved by AIS since radar was introduced [24]. The system operates in the Very High Frequency (VHF) maritime band and provides digital positional awareness. The system provides additional information to assist situational awareness and assists with identifying ships, target tracking, search and rescue operations, and simplifying information exchange [25].

With the AIS, vessels continuously send their identities, positions, speeds, and courses, as well as other relevant information, to all AIS-equipped ships in their range. In addition to managing maritime traffic and reducing marine navigation hazards, the system works in conjunction with a shore station to enhance maritime safety. Figure 1.1 different routes AIS data can be transmitted [1].

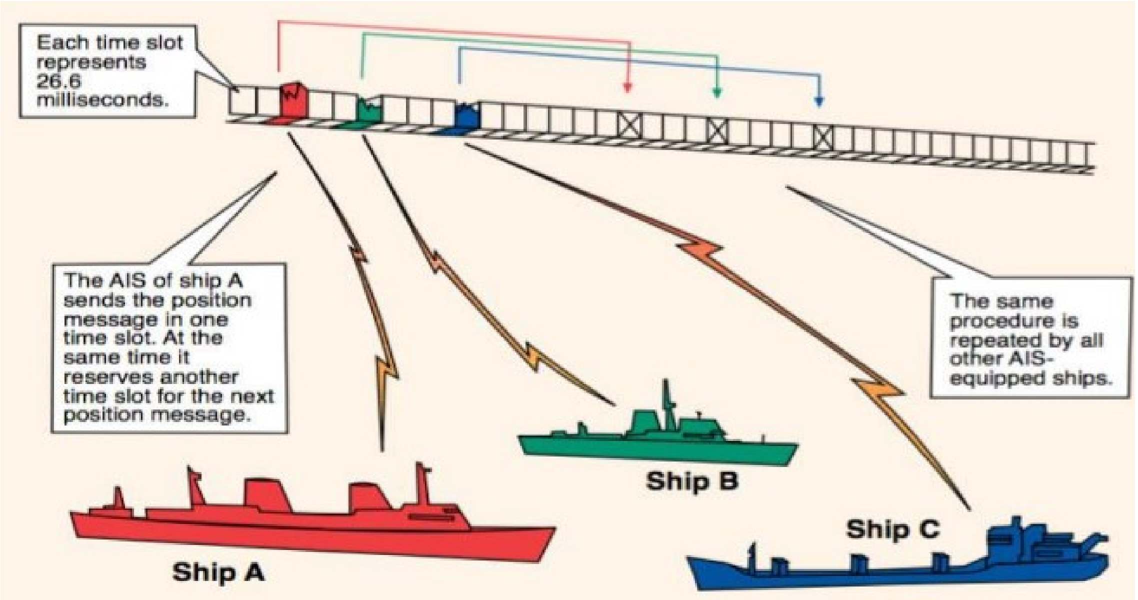


Figure 1.1: An example of AIS System Overview [1]

1.5.2 Working of AIS

In an AIS unit, automatic location and movement data are obtained by using the vessel's Global Positioning System (GPS) system or an internal sensor. A combination of this information and programmable information from the AIS unit (such as Maritime Mobile Service Identity (MMSI) number, the name of the vessel, the destination, and the cargo type) is then transmitted regularly at regular intervals while receiving AIS information from other vessels. There is the option of using an antenna splitter instead of the antenna that transmits from the VHF radio for the AIS unit. It is important to use an active antenna splitter that is suitable for AIS and VHF radios.

SOLAS requirements: Under the IMO Convention for SOLAS [26], all ships with a gross tonnage over 300GT engaged on international voyages as well as all passenger ships, regardless of size, must be equipped with AIS.

There are two types of classes in AIS:

1. **Class A:** This requirement applies to all passenger ships and vessels with a displacement of 300 GT or more engaged on international voyages.

2. **Class B:** Designed for vessels that are not SOLAS-compliant and provides

limited functionality. A pleasure craft is the most common vessel to use this type of propeller.

There are two dedicated VHF channels or frequencies that AIS operates on [27]:

1. **AIS 1:** Works on 161.975 MHz- Channel 87B (Simplex, for the ship to ship)
2. **AIS 2:** 162.025 MHz-Channel 88B (Duplex for the ship to shore)

There are four different types of data that AIS devices exchange and transmit, i.e. static, dynamic, voyage-related, and short safety-related messages.

1. **Static Information**

   The data presented in Table 1.1 is broadcast every 6 minutes and on request by a competent authority.

2. **Dynamic Information**

   The data presented in Table 1.2 depends on speed and course alteration. This data, typically, can be seen on the chartplotter. The AIS transceiver sends the dynamic information every 2 to 10 seconds depending on the vessel's speed while underway, and every 3 minutes while the vessel is at anchor.

3. **Voyage-related information**

   The data presented in Table 1.3 is broadcasted every 6 minutes when data is amended or on request.

4. **Short safety-related messages**

   These messages are in the form of free-format text messages which are addressed to one or many destinations or all stations located in the area. These messages can be related to content like iceberg sightings, buoy missing, etc.

Information	Description
MMSI number	Vessel's unique ID
IMO number	Company issues a unique seven-digit number to each vessel and it can refer to the ship owner or company.
Name and Call Sign	Name: Name of the vessel, max 20 characters. Call Sign: International radio call sign is assigned to each vessel during the process of its registration
Dimensions of ship	Length and Beam are measured in meters
Type of ship	Ship is categorized on the basis of the cargo it transports and its size. The type of ship can be passenger, reserved, cargo, tanker, etc.
Location of position fixing antenna	Location of positioning system's (e.g. GPS) antenna onboard the vessel

Table 1.1: Static Information in AIS

Information	Description
Navigation Status (NAVSTAT)	It indicates the status of the vessel "at anchor", "under way using engine" or "not under command"
rate-of-turn (ROT)	It indicates the vessel's position with respect to right or left, 0 to 720 degrees per minute.
speed-over-ground (SOG)	It indicates the speed of the vessel with respect to 0.1 knot resolution from 0 to 102 knots - vessel moving relative to the surface of the Earth
Position Accuracy (POSACC)	Ship's position with accuracy indication
Geographical Coordinates	It indicates the vessel's location with respect to: Longitude – to 1/10000 minute Latitude – to 1/10000 minute
Course over ground (COG)	Relative to true north to 0.1 degree
True Heading	0 to 359 degrees calculated using gyro compass
Position Timestamp	It is measured in Coordinated Universal Time (UTC)

Table 1.2: Dynamic Information in AIS

Information	Description
Ship's draught	0.1 meter to 25.5 meters
Type of cargo	Types can include dangerous goods, harmful substances, marine pollutants, etc.
Destination and Estimated Time Arrival (ETA)	Destination – max 20 characters ETA at destination – UTC month/date hour:minute
Route plan (Waypoints)	Route plan consists of waypoints and legs. A waypoint is a single coordinate within a route, at which a vessel stops or changes its course.

Table 1.3: Voyage related Information in AIS

1.5.3 Limitation of AIS Data

As AIS is a relatively new technology (circa 2000), long-term records are rarely kept because the transmitted messages require so much physical space. In spite of the fact that AIS only represents received data, the greatest limitation is what is not received. Following are some of the key points to which AIS data is limited.

- AIS information may not be accurate. It is possible for ships to display the wrong destination. They might have forgotten to enter their final destination after leaving a port. It's possible that they overlooked updating their navigational status as well. Due to the fact that it depends on active input from a human, it is far too simple for this ”voyage data” to be incorrect.
- The AIS information could be misinterpreted. It is now the responsibility of the receiver to appropriately interpret the data, assuming that the information being transmitted by another vessel is accurate.
- Officer on Watch (OOW) could become over-reliant on AIS. The information on the screen can appear uncomfortably reliable when utilized on an ECDIS.
- AIS is not available on all smaller ships. AIS is only required on the following vessel categories (depending on Gross Register Tonnage (GRT)), according to SOLAS:
    1. Cargo ships >300 GRT on international voyages
    2. Cargo ships >500 GRT on all voyages

3. All passenger ships

- OOW should be aware that AIS may be disabled on certain ships, thus negating any information they might receive from them if AIS is installed.
- OOW should not assume that the information received from other ships might be inaccurate or not of the same precision as information available on their vessel.

However, collision avoidance should not solely be dependent on AIS information. A vessel's AIS system is merely a source of additional information for the OOW, and it only serves to assist in navigating the vessel. Human expertise on bridges can never be replaced by AIS and radar is the most reliable way to identify moving vessels.. In summary, AIS only contributes to better navigation safety through its assistance to OOW/VTS. The installation of a standalone AIS system is just a matter of plugging in a few cables and turning it on, since AIS is typically integrated with ship bridge systems or multi-functional displays.

Chapter 2

Literature Review

In the past decades, AIS data has been extensively utilized in maritime research. Since AIS is based on VHF signals, which have a limited range, rather than satellites, most research has focused on narrow and congested waterways. It has been identified by vessel operators that route planning sometimes involves long journeys which can cause inappropriate cost estimation [11]. As a result, it is considered a bad voyage plan. In [28], a data-driven methodology is proposed that can develop an optimized route considering the ship's dimensions, weather, and load conditions. This method divides the voyage into open and local sea passages. On the basis of speed, these passages are simplified to pattern nodes. After this process, two types of algorithms are applied to the dataset i.e. K-Means algorithm for the classification of pattern nodes on the basis of routes in the open sea and Density-Based Spatial Clustering of Applications with Noise (DBSCAN) algorithm for the identification of connection points on the basis of routes in the local sea. It is possible to determine the most navigated routes between two ports through a combination of representative routes in open sea passages as well as link points in local sea passages. Additionally, research based on the usage of AIS data to produce adequate information for Maritime Spatial Planning (MSP) is currently being conducted at the European level [29]. Integrating AIS with MSP offers a promising perspective for European Marine Strategy Framework although AIS data was originally applied to navigation safety; as data accessibility improved, it was used for diverse purposes.

These purposes include vessel traffic management, fisheries management, and informed decision-making. The application of AIS data can be divided into three stages, i.e., basic, extended, and advanced [2]. Approximately two to three application fields are present in each stage, totaling seven (refer Figure 2.1). Furthermore, a most recent application that has become famous, is whale-watching operations. To estimate whale-watching efforts in areas with cetacean populations, big data analysis based on AIS messages can be useful [30]. It is recommended that the responsible authorities promote the installation of AIS transponders at least on all vessels authorized to conduct whale-watching activities since the proposed methodology relies heavily on the number of vessels equipped with AIS transponders.

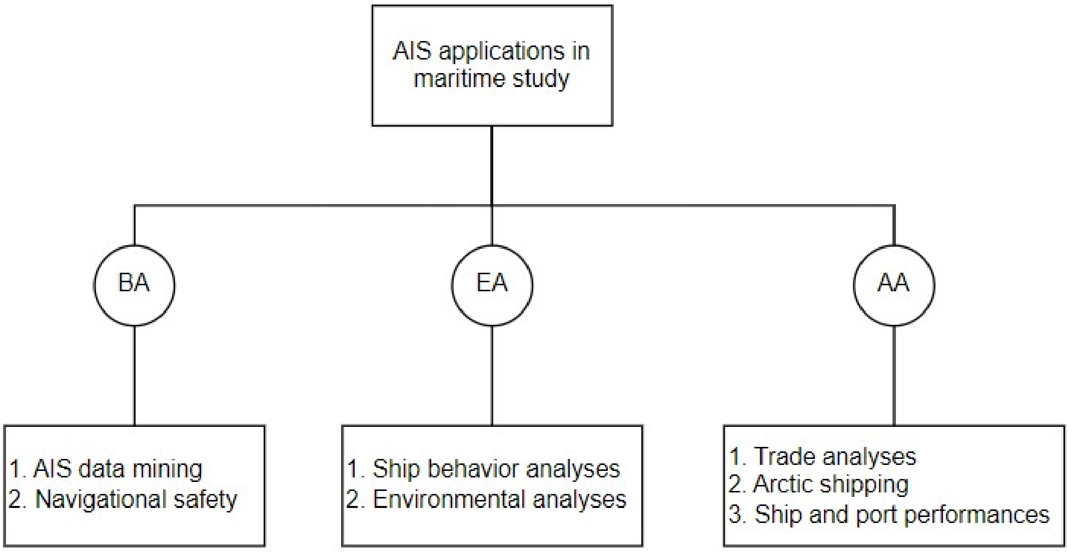


Figure 2.1: Application of AIS data in different areas [2]

The system that learns the normal behavior of vessels, detects anomalies and predicts the motion using an artificial neural network trained with AIS data is explained in [31]. The researchers have taken a few steps to analyze data which includes performing data mining to extract motion patterns and then defining those motion patterns. To simplify things, motion pattern is defined by kinematic and attribute information with only one variable i.e., its origin. The kinematic information will include the ship's location and velocity, both of them in two dimensions. The training data used for anomaly detection is partitioned into two regions, one region corresponding to the hypothesis (normal behavior) and the other to the anomaly. The anomaly detector is proposed for vessel motion which is based on adaptive kernel density estimation.

A novel approach to detect anomalies in AIS data based on the ship's position is introduced in [32]. To identify anomalies in AIS data accurately, parameters like longitude, latitude, and speed have been taken into account [32]. In order to satisfy the subsequent research and application based on trajectory, it is necessary to delete the abnormal points in the raw data. The proposed method classifies AIS abnormal points and processes them separately according to the longitude and latitude, speed, acceleration, and direction information in AIS data. It is worth noting that the proposed method only needs the AIS data of the ship itself and does not need the support of the historical track data. In addition, the cubic spline interpolation method is used to repair the trajectory after eliminating the abnormal points, which further improves the continuity and integrity of the trajectory. The results of processing actual ship trajectories show that the method proposed in this paper can identify all kinds of trajectory abnormal points in AIS data effectively.

Another research paper gives an insight into the process going on behind black box predictors by reasoning the solution to the automatic docking problem [33]. This problem includes guiding the vessel from the open sea towards a particular designated point in a harbor area by taking into account the environmental factors, non-linear motions, speed limit, and distance to other ships and obstacles. Researchers have explained that in trajectory and collision avoidance, deep reinforcement learning agents perform well. The agent was trained using Proximal Policy Optimization (PPO) and Local Interpretable Model-Agnostic Explanations (LIME) is applied to each data point once for every action. LIME is used to make approximations related to the behavior of the predictor for a single prediction. Another model Kernal SHAP is used, which is built on LIME framework and provides the functionality of removal of features by sampling the background data and replacing the missing features with random samples because setting the value to 0 is not helpful. Moreover, Linear Model Trees (LMTs) were also applied to the dataset and later advantages and disadvantages were calculated for each algorithm.

With the help of an unsupervised approach that can work on real-time systems,

[34] explain a framework that can learn AIS maritime traffic patterns automatically. In addition to data collected by terrestrial AIS receiver networks, the proposed methodology is also effective in situations where information is highly disrupted due to spatial gaps in coverage or significant temporal differences due to satellite revisits. By using Bayesian inference, the approach could be used to detect low-likelihood behavior in real-time.

An overview of the AIS system is presented in [35], along with an assessment of data quality and vulnerabilities for decision-making in maritime situational awareness scenarios. In addition to improving safety and security at sea, AIS data quality assessment would help detect AIS problems earlier. This would increase decision-makers situation awareness, and improve AIS data quality assessment.

#	Author	Method Description	Pros	Limitation
1	**B. Ristic**	This study uses adaptive kernel density estimation to build anomaly detector for vessel motion.	Successful prediction of motion of vessel using Gaussian sum tracking filter	Limited to the historic data analyzation
2	**Shuguang Chen**	Construction of anomaly detector on the basis of different variables like speed, distance etc.	Abnormal data can be easily detected.	It is a possibility that the detector only works on several ships.
3	**H. Rong**	Critical analysis is done on automatic docking problem by considering the processes happen behind black box.	Easy navigation guide for vessels	The detection method of ship behavior is only limited to one factor i.e. distance.
4	**Michele Vespe**	Unsupervised learning of AIS maritime traffic patterns automatically using Bayesian inference method.	The tool supports route planning, surveillance technology and vessel position prediction.	The method utilizes only AIS historic or real-time data.
5	**C. Iphar**	Data quality assessment on the basis of false and spoofed messages.	Increased situational awareness of decision makers and improved maritime safety and security.	Risks model is not defined in-case if the assessment fails on some data, that model can be followed to avoid further damages.
6	**Jie Cai**	Data-driven methodology is introduced to identify most navigated routes between two routes using K-means and DBSCAN algorithms.	Reliable routes can be provided to support decision-making at pre-fixture stage.	Solely relying on AIS data can make predicted methods less reliable.
7	**Le Tixerant M.**	AIS data processing and analysis can be used to produce adequate maritime traffic density information.	Incorporating AIS data into maritime spatial information systems can provide a clear way to facilitate dialogue in MSP	Requires specialized knowledge of hardware and software to handle high volume of raw data.
8	**Dong Yang**	A review on usage of AIS data and its applications.	Future research applications are explained that can be implemented on AIS data.	No novel approach is introduced.
9	**Dong Yang**	Analyzing AIS data to make whale-watching operations more sustainable.	Methodology can be used to estimate seasonal and annual trends in whale-watching effort.	Sufficient AIS terrestrial stations need to be installed for achieving complete coverage and maximum reception of broadcasted messages.

Table 2.1: Literature review summary

Chapter 3

Methodology

3.1 Overview

The approach used in this research to examine ship maneuverability during turning maneuvers is described in this chapter. To get insights into ship behavior, the methodology includes data collecting, preprocessing, turning point extraction, turning analysis, and statistical tools. To analyze turning points in a vessel journey, an analytical approach using elastic trend filters [36] is proposed. This approach is particularly aimed at constructing a system that reflects vessel traffic. Additionally, this approach aims to improve the practice of maritime voyage planning, which is typically done manually by a ship's navigation officer, because there are no methods available for detecting critical maritime waypoints efficiently based on the analysis of large amounts of historical data.

The purpose of this chapter is to provide an overview of how to prepare data for applying an Elastic Trend Filter. The chapter is divided into four main sections: raw data acquisition, data wrangling and preprocessing, feature analysis, and dataset and evaluation metrics. In section 3.2, the process of collecting and obtaining data from various sources is discussed. It is crucial that the data collected in this stage is of high quality in order for the algorithm to be accurate and useful. In section 3.3, the process of cleaning, transforming, and organizing the raw data is presented. Trend Filtering applications require high-quality data, which is a time-consuming and complex process. The accuracy and reliability of the data are ensured through techniques such as data imputation, normalization, and outlier detection. In section 3.4, the most relevant variables or features are taken into account and it also discusses the feature selection technique used for this study. In section 3.5, information related to the dataset that has been used in this study is described. In section 3.6, the methods used on the data to explain the vessel's journey are explained in addition to how they are applied and why they are chosen for analyzing ship's turns.

3.2 Raw Data Acquisition

The dataset is provided by the Novia University of Applied Science in collaboration with Aboa Mare and Turku University of Applied Sciences (Turku AMK) which I have used throughout my thesis. The data is extracted and saved every minute and data in this study is based on historical AIS records spanning from October 2022 to December 2022, which included more than a hundred thousand positional records. The data is downloaded in Comma-Separated Values (CSV) format using API developed by ARPA project by Novia and Turku AMK. In Original Data, there are 12 variables. Those variables are MMSI, Longitude, Latitude, SOG, COG, NAVSTAT, ROT, POSACC, Raim, Heading, Timestamp, Timestamp external. To illustrate the vastness and coverage of the historical AIS dataset, Figure 3.1 shows 200 million AIS positional records. Analyzing vessel journeys requires taking into account the time and feature variables. An important consideration when analyzing multiple vessels' journeys is their time frame. It can also help identify areas of congestion and other issues due to patterns and trends in vessel movement. It is also possible to gain valuable insights into a vessel's journey by analyzing its specific features in addition to its time variables. Under certain conditions or in certain areas, a vessel's size, speed, maneuverability, and draft can all have an impact on its ability to navigate. Focusing on a specific vessel's journey during a particular time frame can help to provide a more detailed and focused analysis. Regarding the journey of the ship 'M/S Viking Glory', focusing on its movements during the months of October to December can provide a more focused analysis of its journey. This time frame may be significant for several reasons, such as the weather conditions during this period or specific events or activities in the area.

Figure 3.2 shows the real-time vessel tracking information. With the help of this website, through AIS data, it is possible to monitor the location of ships, boats, and other vessels at any time and anywhere in real-time. To explain vessel voyages, this thesis incorporates vessel segmentation as part of its proposed approach. Another important factor of this website is that it provides users with real-time vessel traffic so that the fastest and safest maritime routes can be identified. This has helped me analyze voyages critically. Blue markers in Figure 3.2 indicate ship location in real-time, by clicking them further information related to the ship is shown, for example vessel information, past track, route forecast, navigational status, speed/course, draught, etc.

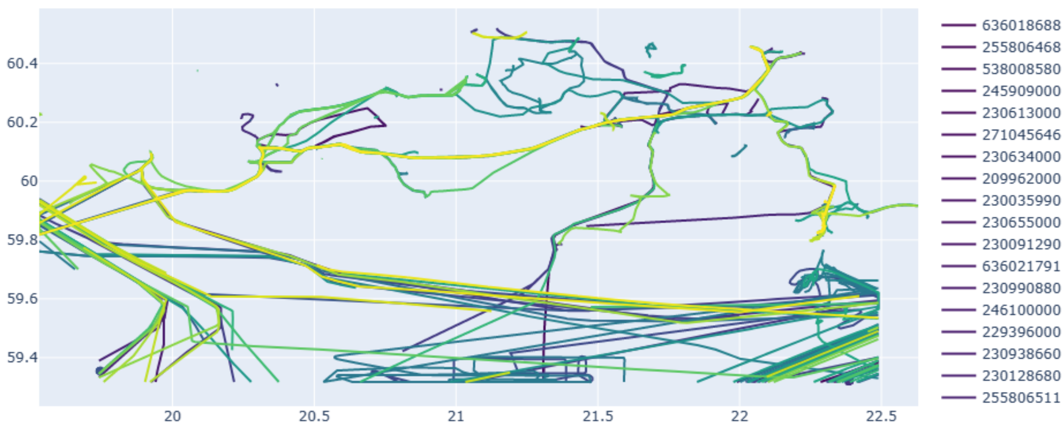


Figure 3.1: The historical AIS dataset is enormous, as illustrated by a visualization of around 200 million potential records.

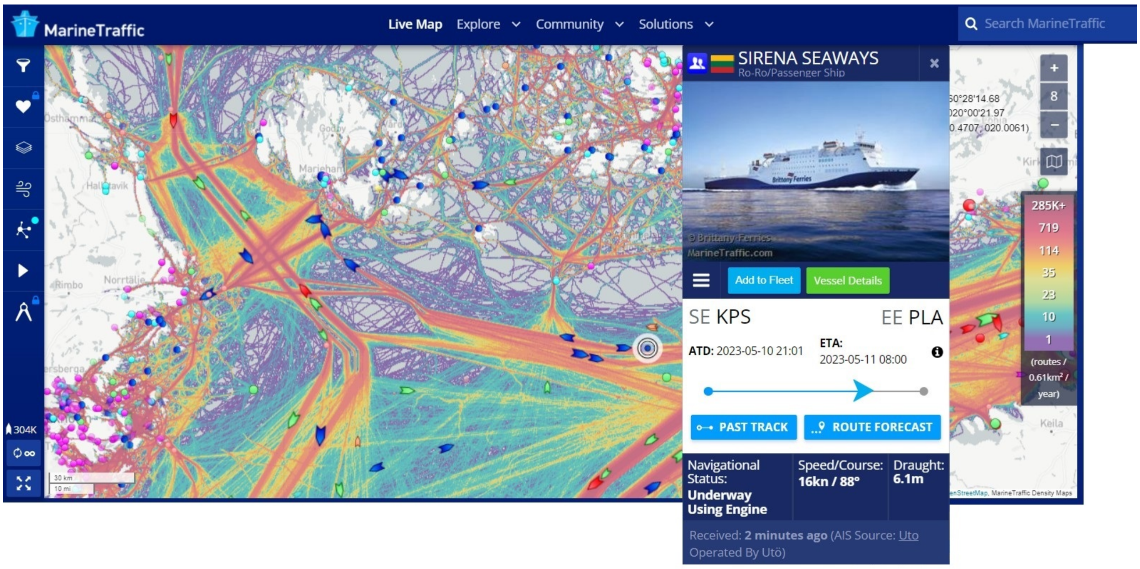


Figure 3.2: On Marine Traffic website selection can be made according to vessel segments and sub-segments [3]

3.3 Data Wrangling and Preprocessing

First of all, duplicates and missing values are removed from the data so that suitable results can be extracted. After that, three ships are selected for the analysis i.e. FINN Sky (Cargo ship), Viking Grace, and Viking Glory. To obtain the data of the related ships, the data is filtered out on the basis of their MMSI numbers. When this step is done, normalization and feature engineering are applied to the dataset. To analyze the position of the vessel and the rate at which it takes the turn, longitude, and latitude variables are taken into account.

3.4 Feature Analysis

Figure 3.3 shows the position of three ships of interest using the longitude and latitude variables obtained from AIS data, i.e. longitude and latitude. The longitude and latitude variables are used to identify the location of ships and to visualize ship routes and patterns. In Figure 3.4, each ship's position is represented by a green marker point on the map, and the lines connecting these points show the path taken by each ship. Figure 3.5 shows a closer look on a 10min journey of a vessel and pop-up indicates the MMSI belonging to that vessel. A detailed analysis of AIS data can provide useful information about ship behavior, such as speed, course, and destination. Using this data, shipping routes can be optimized, maritime safety and security can be improved, and the environmental impact can be reduced.

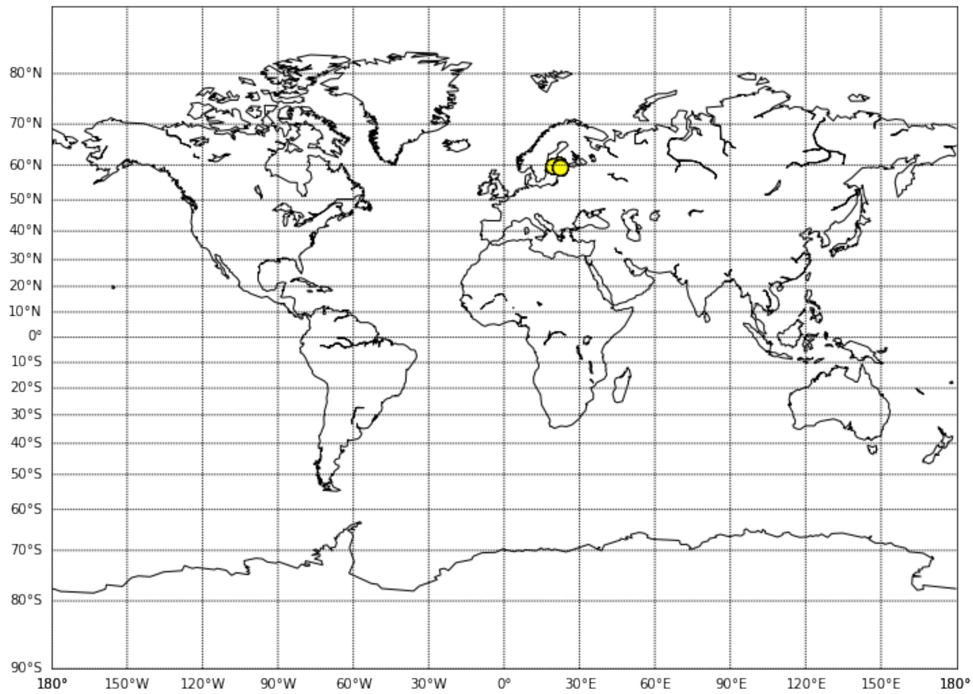


Figure 3.3: Basemap

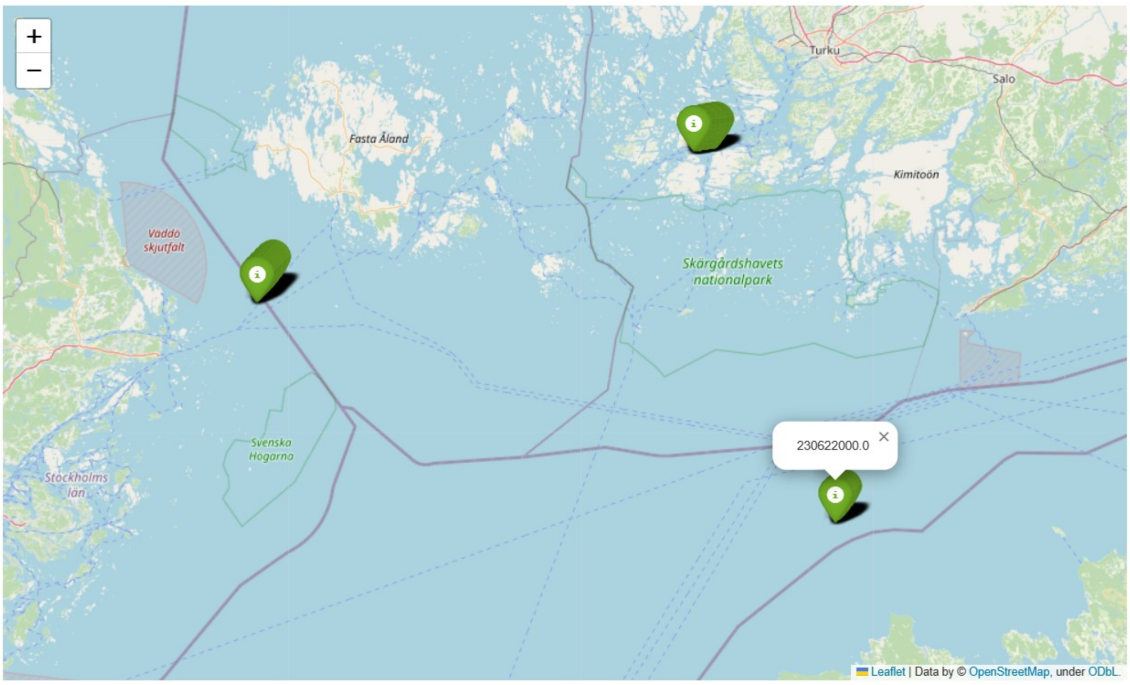


Figure 3.4: Location of Selected Vessels Journey

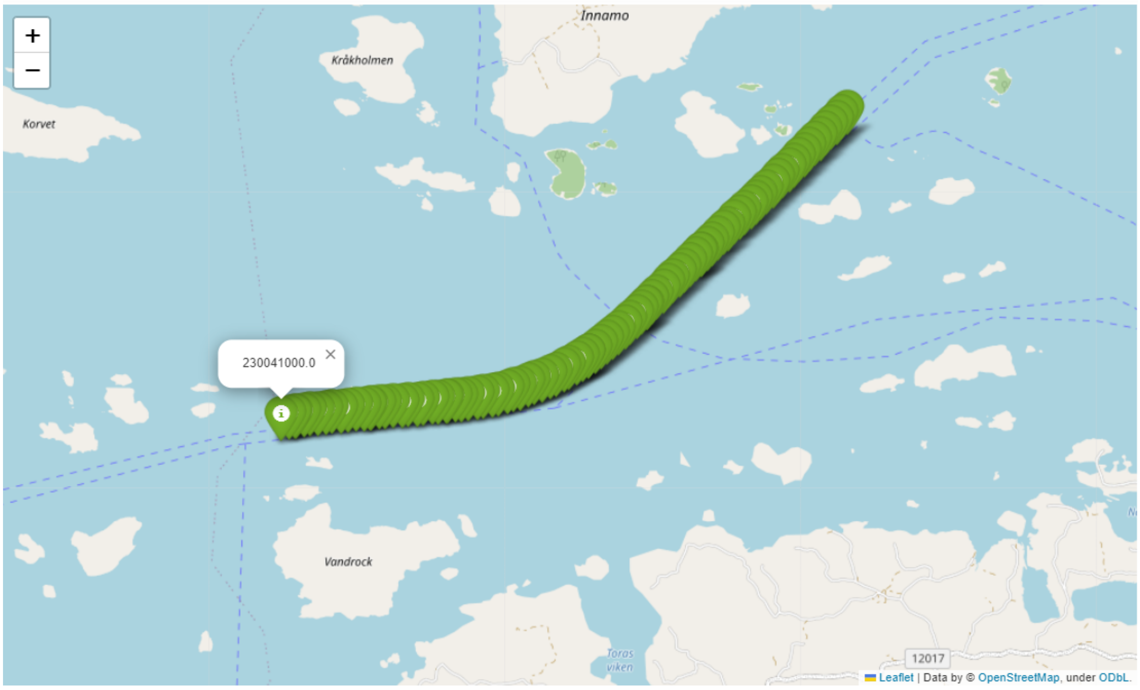


Figure 3.5: 10-min detailed Vessel Journey and its location on Folium

3.5 Dataset

A ship's position, speed, and other information can be shared with other ships and shore stations through the Automatic Identification System (AIS). Ground stations collect AIS data and is available for companies who can pay for the data. Tracking the movement and behavior of ships can be done by analyzing this data. The dataset is provided by the Novia University of Applied Science, located in Turku and Vaasa, Finland. The university acquires AIS data from the nearby sea areas where ships are regularly passing through. The original size of the data is 84MB and it comprises of 12 variables: mmsi, longitude, latitude, sog, cog, navstat, rot, posacc, raim, heading, timestamp, timestamp external. Table 3.1 describes the above-mentioned variables in AIS data with respect to its definitions.

Variables	Description
MMSI	It is a unique 9-digit identification number that is assigned to every vessel by the IMO. It is used for identifying and tracking ships through AIS.
Longitude	It's a geographic coordinate that specifies the position of a ship on the Earth's surface. It refers to the east-west position.
Latitude	It's a geographic coordinate that specifies the position of a ship on the Earth's surface. It refers to the north-south position.
SOG	It is the speed at which the ship is moving relative to the Earth's surface.
COG	It is the direction in which the ship is moving relative to the Earth's surface.
NAVSTAT	It is the status of the ship, such as "underway using engine", "at anchor", "moored", etc.
ROT	It is the rate at which the ship is turning.
POSACC	It is the accuracy of the position reported by the ship's GPS system.
Receiver Autonomous Integrity Monitoring (RAIM)	It is a system used to ensure the integrity of the GPS signal.
Heading	It is the direction in which the ship is pointing.
Time stamp	It is the time at which the position data was recorded.
Time stamp external	It is the time at which the AIS signal was received by a ground station.

Table 3.1: AIS data used throughout thesis

3.6 Data Analysis Methods

To decompose voyage data into simple, explainable segments, we propose the following two approaches:

1. Defining a ship navigational model based on information available in fundamental navigational rules.
2. Represent voyages in a small latent feature space: Represent the route in terms of maneuvers (turn rudder, increase engine power etc.)

Motivated by the fact that traditional navigation consists of decomposing the route into straight lines and circles segments, we propose to formulate the problem as a piecewise regression problem where the goal is to decompose the realized path in terms of interconnected circle arcs and straight lines.

The decomposition of a route into piecewise linear and arc segments can be seen as a trend-filtering problem. Linear Detection of non-stationary components such as outliers, level shifts, and measurement trends have been studied extensively in the time-series analysis literature [37]. Trend estimation has been applied in a variety of different fields, including macroeconomics[38], finance [39], and in biological and medical sciences [40, 41]. Furthermore, in system identification, trend filtering has been used to remove trends, outliers, level shifts, and slopes that would otherwise deteriorate the identification accuracy [42, 43].

Several trend estimation techniques have been studied in the literature, including Hodrick-Prescott (H-P) filtering [38], ℓ_1 trend filtering [44], empirical mode decomposition [16], smoothing splines [45], moving average filtering [46] and linear programming with a fixed number of kink points [17]. However, if an underlying dynamical system has generated the measured time-series, standard trend filtering methods may produce poor results since they do not distinguish trends in data from effects of the system dynamics or input signals [43]. Thus, if the data depend on a known input signal, the input and dynamics of the system should be accounted for when estimating the trends.

In signal processing, elastic trend filtering is used to extract smooth and sparse trends from noisy data. In short, elastic trend filtering approximates a noisy signal x with $\hat{x}$ by solving the convex optimization problem [36]

$$\underset{\hat{x}}{\text{minimize}}\ \|x-\hat{x}\|_2^2+\lambda_1\|D^2\hat{x}\|_1+\lambda_2\|D^2\hat{x}\|_2^2,$$

where $\lambda_1, \lambda_2 > 0$ are scalar parameters tuned to determine the sparseness and smoothness of the estimate $\hat{x}$, and $D^2\hat{x}$ denotes the second difference of $\hat{x}$. The elastic trend filtering is a generalization of the H-P trend filter (when $\lambda_1 = 0$) and the ℓ_1 trend filter (when $\lambda_2 = 0$).

In applications where we want to remove high-frequency noise from a signal whilst preserving its low-frequency features, trend filtering is particularly useful. In this research, AIS data is analyzed using elastic trend filtering to extract the underlying trajectory of a vessel from noisy position data. There are many sources of noise in AIS data, including measurement errors, missing data, and other sources that can obscure the true path of a vessel. These issues are addressed by elastic trend filtering, which smooths the data while preserving the essential characteristics of the vessel's trajectory. A basic principle of elastic trend filtering is to minimize a cost function based on both squared differences between the filtered data and the original data and second-order differences between the filtered data (i.e., the curvature). As long as these two terms are balanced, elastic trend filtering can extract the underlying trends of a signal while avoiding overfitting.

It is important to know that there are many different algorithms and implementations of elastic trend filtering, each with its own strengths and weaknesses [47]. There are several popular approaches, such as variation regularization or basis pursuit denoising. A preprocessing step is typically required to remove missing values, outliers, and other sources of noise from AIS data before applying elastic trend filtering. Using this filtered trajectory, one can estimate the vessel's speed, course, and turn rate, as well as predict its future trajectory. Three ships are chosen to apply an elastic trend filter so turning points in the whole ship journey can be observed. After getting smooth trends by applying a trend filter to the vessel's trajectory, the second difference of that trajectory is taken. The second difference of the position refers to the acceleration. The rate of change (first difference) of a position x(k), at time instance k, is

$$\Delta x(k) = x(k) - x(k-1) \tag{3.1}$$

and the second difference is

$$\Delta^2 x(k) = \Delta x(k) - \Delta x(k-1) = x(k) - 2x(k-1) + x(k-2). \tag{3.2}$$

Significant changes in acceleration often accompany turning points or changes in the ship's movement, which is what explains the connection between the second difference and turning points. By analyzing a ship's second difference in position, we can detect when it changes direction and experiences a change in acceleration. It is possible to identify peaks or valleys in the ship's acceleration data by examining the second difference over time. A peak or valley indicates a significant change in acceleration rate, thus indicating a potential turning point and zero acceleration means that the ship is moving with constant velocity. A large positive/negative peak or valley may represent a sharp turn or maneuver, whereas a smaller peak or valley may indicate a smooth change. Analyzing the second difference of a ship's acceleration data can, therefore, guide the detection and characterization of turning points, providing insights into the ship's navigation and movement patterns.

The radius of turning points in a vessel's journey is calculated using Circular arcs. The radius of the turn can be estimated by fitting a circular arc to a portion of the vessel's trajectory. For estimation, the vessel's trajectory is analyzed in segments in order to find the turning points. It is important that these segments contain the relevant data prior to, during, and after the turn. Essentially, this involves measuring how far the vessel's trajectory deviates from a circular path. To calculate the radius, a circular arc is fitted to each turning point segment. This is done by using the Equation 3.3 of a circle with radius r centered at (x_0, y_0)

$$r^2 = (x - x_0)^2 + (y - y_0)^2 \tag{3.3}$$

or equivalently in parametric form

$$x = x_0 + rcos(\theta) \tag{3.4}$$

$$y = y_0 + rsin(\theta) \tag{3.5}$$

An accurate representation of a vessel's trajectory during a given turn is represented by its radius. Calculating the radius of the vessel's turns and fitting circle arcs provide insight into its maneuverability and navigational behavior.

3.7 Wheel-Over Point and Turning Radius

Route planning is influenced by a ship's ability to turn tightly after altering the course and stay on the new intended course. Due to the inertia of the ship, it typically takes some time for a ship to react when the wheel is turned. Therefore, the wheel must be spun before the turning point of the ship. It is often referred to as "the wheel over the position". A ship must initiate a turn at the wheel-over position in order to arrive safely on the new track.

Turning around at one point is impossible for large vessels. Due to this, it is important not to overlook the ship's ability to turn within constrained spaces. Making a turn requires a vessel to know its wheel-over position.

3.7.1 How to Determine the Wheel-Over Point

In order to come onto the desired new track safely, a ship needs to commence a turn at the Wheel Over Point (WOP). It becomes critical to determine the wheel-over point if the cross-track error is minimal in narrow channels or confined waters. Ship size, water depth, and speed all factor into determining the wheel-over point. Other factors include the deadweight and speed of the ship. The most significant component is likely the ship's speed, which dictates how much inertia must be overcome before the ship starts to turn. Following are the examples that should be considered when determining the position of the wheel:

- Current course: 90-degree turn - It means that the ship is traveling in a direction that is due east.
- Next course: 45-degree turn - It means the ship will make a turn to the right and travel in a direction that is northeast considering the current course of the ship 90 degrees True.
- Speed Over the Ground (SOG): 12 knots - It means the ship is traveling at a speed of 12 nautical miles per hour relative to the surface of the Earth.
- Turning Radius (TR) (TR = SOG/ROT) = 1.0 nm - TR of a vessel is a measure of the minimum radius of the circle that it can turn while maintaining

a constant speed and ROT. If the TR is calculated as TR = SOG/ROT and is equal to 1.0 nautical mile (nm), then it means that the vessel requires a minimum distance of 1.0 nm to complete a turn of 360 degrees.

- Length Over-all (LOA): 235 meters - LOA describes the maximum length of a vessel, including any protrusions or extensions. This measurement is taken from the tip of the bow to the end of the stern and includes any extensions such as the anchor, bowsprit, or bulbous bow. Knowing the LOA of a vessel is important for a variety of reasons, including determining the vessel's docking requirements, cargo capacity, and ability to navigate through certain waterways.
- Point-of-overcoming the inertia (POI): 1.5 x LOA = 352.5 meters also known as the execution point wherein the ship starts to turn. (Such info is posted in the wheelhouse poster [3] (see Figure 3.7 for reference)).
- Wheel Over Line (Wheel Over Line (WOL)): It refers to a navigational maneuver carried out by a ship. In order to bring the ship's heading or course precisely over a given line or track, the ship's wheel (helm) must be turned. The ship can securely sail along planned paths or through limited spaces by performing a WOL maneuver. It aids in keeping the ship on course and enables it to navigate around any dangers or obstacles that may be present on either side of the desired line.

Calculating the trajectory for a constant-radius turn consists of determining the Center of Turn (COT) point and the WOL and WOP illustrated in Figure 3.6. The resulting theoretical ship trajectory consists of piece-wise linear trajectories and circle segments when the ship turns.

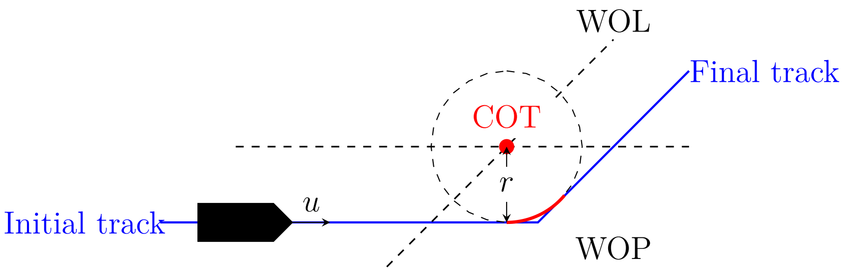


Figure 3.6: Illustration of how the WOL, COT for a constant radius, turn can be determined

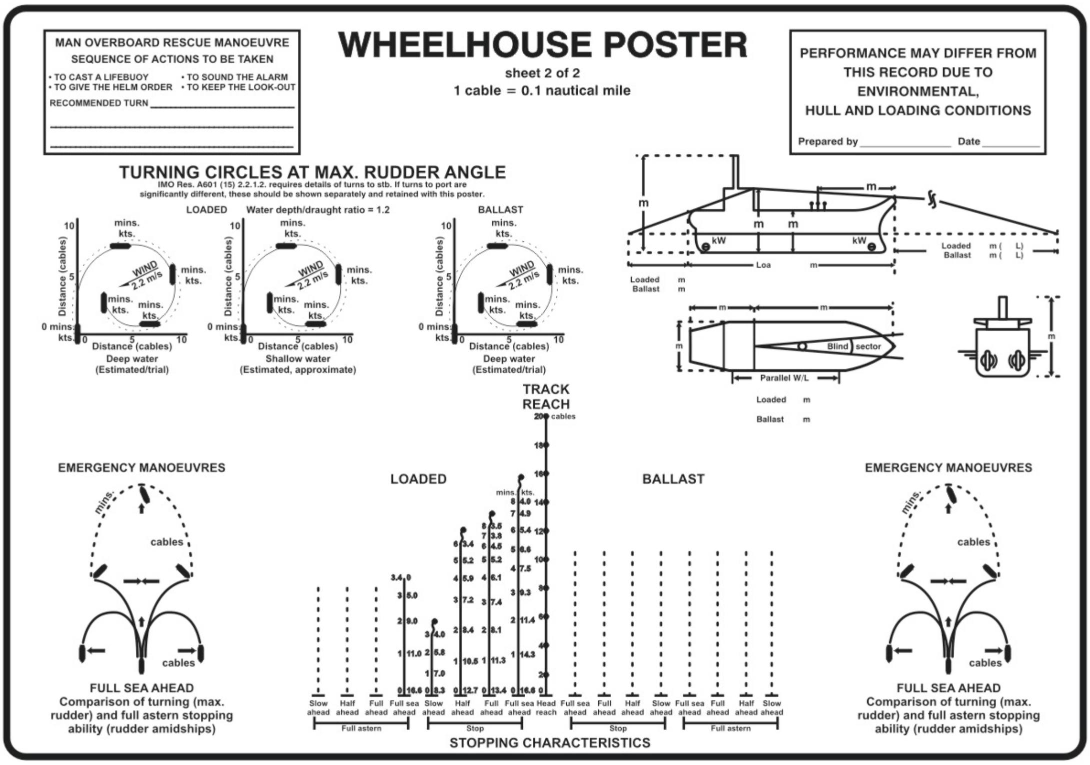


Figure 3.7: Wheelhouse Poster [3]

3.7.2 The Turning Radius of a Ship

A vessel's pivot point follows roughly a circular path when the ship is turning with a constant rudder angle. A ship's turning radius is determined by the radius of this circle. As the ship is moving, it is affected by the depth of the water, and by the length of the ship. The general rule is that the turning circle of a long ship will be larger. This rule means that a longer ship will typically need a larger area to make its full turn. A ship's final diameter is determined by the type of rudder and the steering effect it produces, with the distance between the rudder and the hull also playing a significant role. It is more efficient for the rudder to turn a boat when the clearance between the rudder and hull is smaller. As a result, the turning circle and turning radius will be affected by the following factors:

- Structural design and length of the ship.
- Draught and trim of the ship.
- Size and motive power of the main machinery.
- Distribution and stowage of cargo.
- Even keel or carrying a list.
- Position of turning in relation to the available depth of water.
- Amount of rudder angle required to complete the turn.

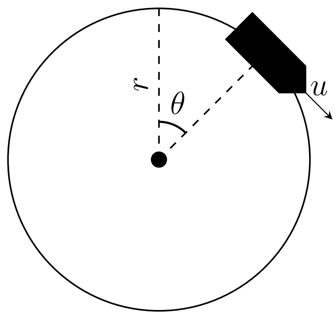
When examining a ship's maneuverability and how the ship handles different situations, it is important to consider both wheel-over-point and turning radius. It is difficult for a ship with a large turning radius to maneuver in tight spaces, for instance. Alternatively, ships with a small turning radius may be more agile in rough weather, but less stable. Watchkeepers can know at each waypoint the parameters they must maintain to correctly negotiate a course change by calculating and drawing wheel-over-points on charts. The OOW, for example, will know the correct parameters to use for negotiating the turn because he/she knows the ROT equals the ship's speed divided by its radius of turn.

Taking into consideration the ship's ability to turn within a constrained space is something that should not be overlooked. Traditionally, route planning was done with a ruler and compass pen. Given a fixed speed-over-ground u (SOG) and rate-of-turn $\dot{\theta}$ (ROT), the turning radius can easily be calculated. For a fixed u, the time t it takes to traverse a full revolution of a circle of radius r is $t = 2\pi r/u$. Likewise, for a fixed ROT, the time it takes to traverse a full revolution is $t = 2\pi/\dot{\theta}$ (assuming that $\dot{\theta}$ is given in rad/s). Combining the expressions gives the turning radius

$$r = \frac{u}{\dot{\theta}},$$

cf. Figure 3.8.

A ship must be maintained on the planned course during the course of a voyage in order to avoid a hazard or danger, especially when it travels through traffic lane separations, passes shorelines, or passes rocks. Because of the limited availability of sea room, cross-track distance should be kept to a minimum or zero. Using the ship's turning radius in conjunction with the wheel over position is a technique that ensures the ship stays on track during and after a course alteration in order to minimize cross-track distances and to keep the vessel safe from potential hazards while making course changes.



Circumference $C = 2\pi r$

Figure 3.8: Tuning circle of a ship/vessel

Chapter 4

Results

4.1 Overview

The examination of turns in the ship's course was made easier by applying the elastic trend filter to the AIS data. We learned more about the ship's navigational qualities and behavior by fitting circles to these turns. The findings from the analysis of turns using the circle-fitting approach are presented in this section, along with a discussion of their consequences.

4.2 AIS Data Analysis

In order to improve operations and ensure maritime safety, AIS data analysis plays a crucial role. As the Viking Glory ship navigated through the water, AIS data provided valuable insights into its navigation patterns. Applying an elastic trend filter to the data is one innovative method of analysis. AIS data is smoothed by using this filter, removing noise and irregularities to reveal the underlying trend. A more accurate representation of the ship's trajectory and movement is possible by applying this filter. The elastic trend filter is applied to all three ships separately and every ship's journey is analyzed individually. Figure 4.1 shows the original vessel trajectory in addition to the trend filter applied to the dataset. Figure 4.2 visualizes the second difference of the trajectory highlighting the positive peaks and sharp edges. A turning maneuver is the next step after the AIS data has been processed using the elastic trend filter. Calculating the radius of a turn is commonly done by using the circle equation method. As a result, the ship's path during a turn is approximated by a circular arc derived from this mathematical method. On the right of Figure 4.1, the red markers highlight the turning points in a vessel's journey, and these turning points are the main focus of the ship's journey. Using the circle equation, it is necessary to make certain assumptions in order to calculate the turn radius. The ship's speed during the turning maneuver is often assumed to remain constant throughout the maneuver. The filtered AIS data points corresponding to the turn are fitted to a circle based on this assumption (refer to Figure 4.3). The calculated radius value is 0.9977. It is important to note that the accuracy of calculating the radius when the ship takes a turn is dependent upon many factors, including the quality of the AIS data, the data point's time resolution, and the assumptions used. While this approach offers useful estimates, it can also be applied to analyze a ship's navigation performance and understand its maneuvering characteristics.

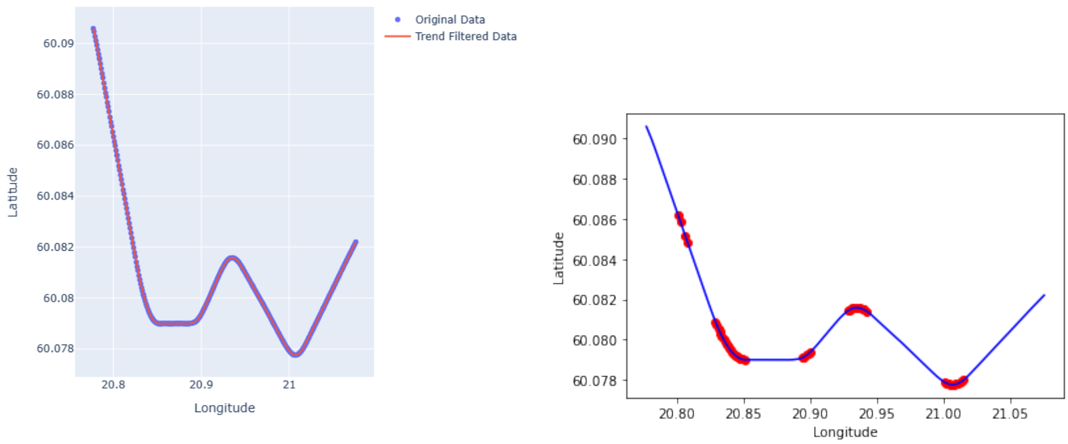


Figure 4.1: 800-1100 points taken from Viking Glory Journey present in AIS Data

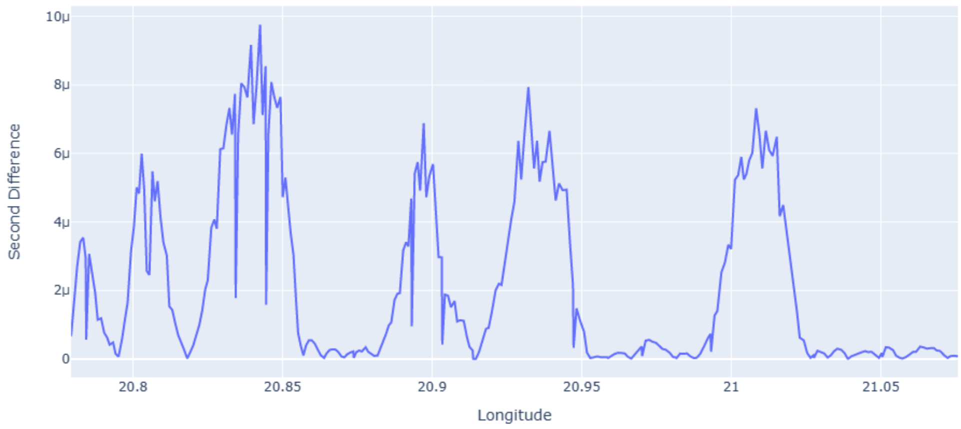


Figure 4.2: Second Difference of Viking Glory Journey

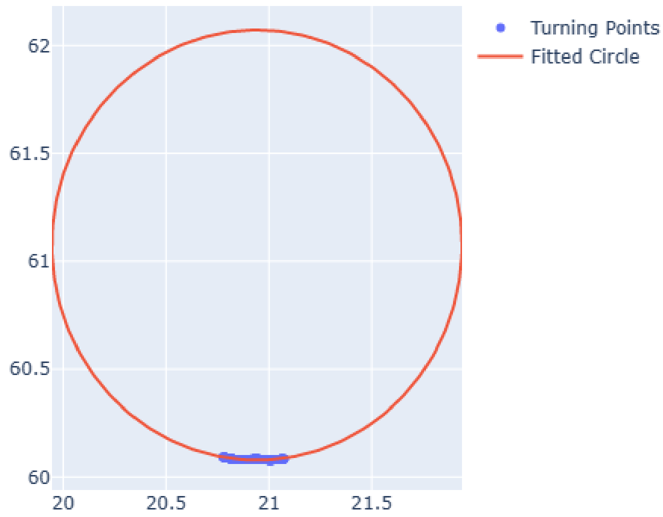


Figure 4.3: Fitted Circle when Viking Glory commences a turn

A similar approach is applied to two other ships in addition to the Viking Glory vessel using an elastic trend filter and the circle equation to calculate the radius when the ship commences the turn. Figure 4.4 shows the Viking Grace ship's trajectory along with the smoothing of the data, which is achieved using an elastic trend filter.

On the right side of Figure 4.4, red markers represent the turning points in the ship's journey. It is easier to notice the sharp turns in the ship's journey by taking the second difference of the trend-filtered data. Figure 4.5 shows large positive peaks which means a sharp maneuver. Moreover, it also indicates that the change in acceleration rate is significant. Now the radius of the turn can be calculated using Equation 3.3, and the calculated value of radius is 0.0392 (refer to Figure 4.6). Figure 4.7 shows the journey of a cargo ship i.e. Finn Sky Ship along with the filtered data that helps smoothen out the journey. In this journey, there are no such sharp maneuvers that could be considered to fit the circular arc. Figure 4.8 shows that the turn made in the journey is a rather smooth change indicating minor maneuvers.

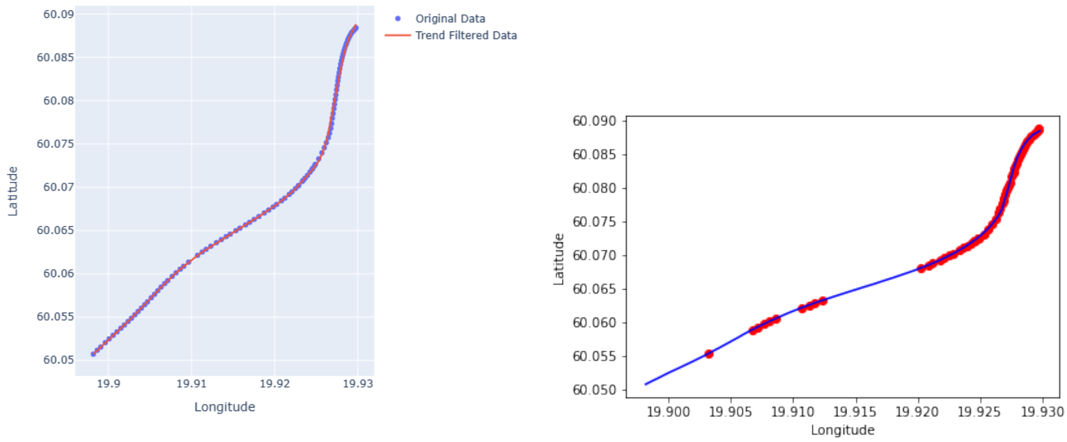


Figure 4.4: 800-900 points taken from Viking Grace Journey present in AIS Data

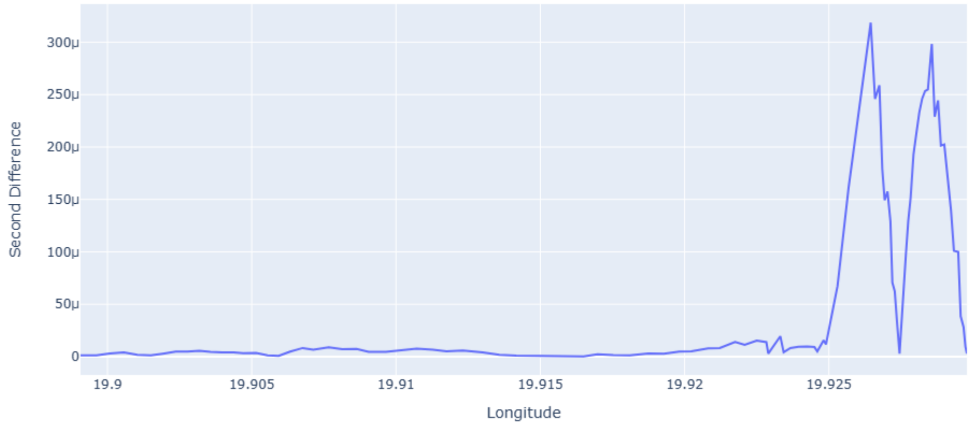


Figure 4.5: Second Difference of Viking Grace Journey

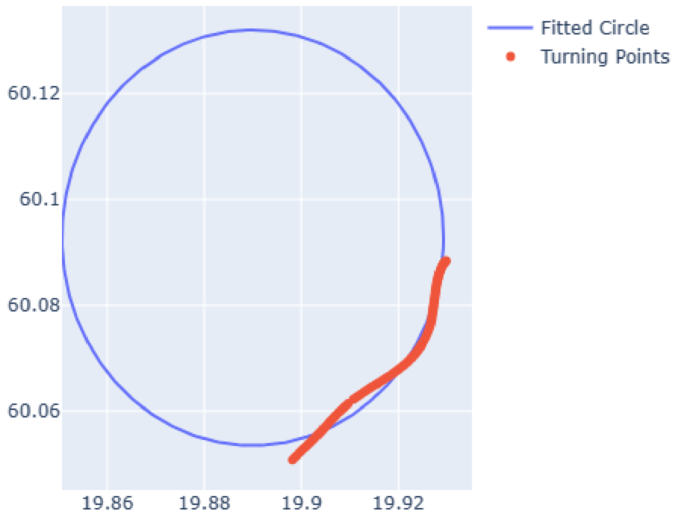


Figure 4.6: Fitted Circle when Viking Grace commences a turn

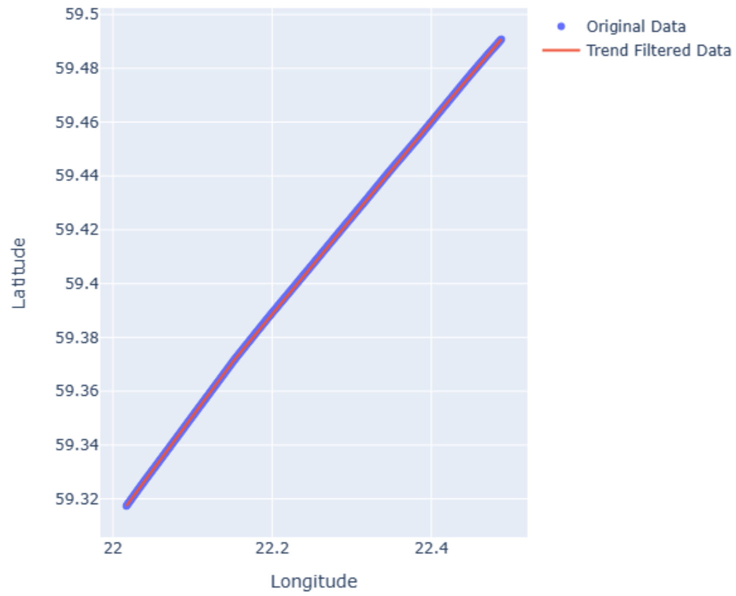


Figure 4.7: Finn Sky (Cargo Ship) Journey present in AIS Data

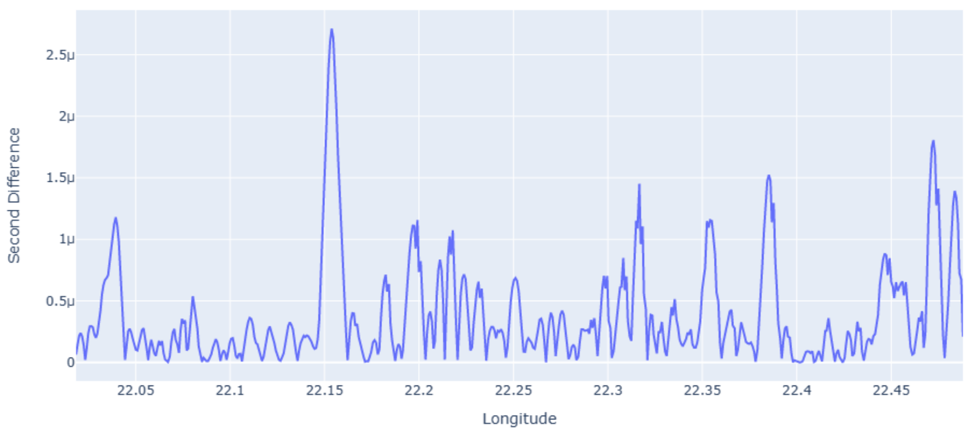


Figure 4.8: Second Difference

Chapter 5

Discussion

This thesis investigates AIS data's use in analyzing and explaining ship voyages. It has been possible to gain valuable insights into ship navigational behavior, including turning maneuvers, by applying techniques such as elastic trend filtering and circle equation calculations. This chapter discusses the study's findings, compares them with previous studies, and outlines its advantages and disadvantages.

As a result of applying the elastic trend filter to different ships in AIS data, the underlying trajectory of the ships were extracted, and turning maneuvers were detected. It provided crucial information about the vessel's navigational characteristics when the turn radius during these maneuvers was approximated using the circle equation method. The findings of my investigation provided crucial insights into the ship's turning behavior. It is observed that radii calculated during different maneuvers are consistent, for example, indicating a systematic approach to navigation by the crew. Furthermore, the study identified instances of steeper turns, which could be suggestive of avoiding obstacles or maneuvering in restricted regions.

I also compared my findings to other studies in the field of explainable ship journeys utilizing AIS data, I saw some commonalities as well as some unexpected findings. [18] examined vessel movement patterns in a similar manner, but utilized a different process, such as graph evolution analysis. This study focuses on topological voyage graph features to asses stationary behavior. Study [19], on the other hand, looked at ship voyages from a broader perspective, encompassing not only turning maneuvers but also the arrival and departure of ships from a Korean port. Their findings explained pattern analysis for speed over ground, course over ground, and ship position, which my study did not explore. As a result, combining the findings of our study with those of study [19] may provide a more complete knowledge of ship voyages and navigational decision-making. One of my approach's primary advantages is its simplicity and ease of implementation. The elastic trend filter and circle equation method are simple and efficient in computation, allowing for rapid AIS data processing. Furthermore, the results of our research provide useful insights into ship journeys, assisting in the study of navigational behavior and probable decision-making aspects. However, it is critical to recognize the limitations of my approach. To begin, the accuracy of the estimated turn radii is dependent on the assumptions established, such as maintaining constant speed during maneuvers. Deviations from these assumptions may cause radii to be calculated incorrectly. Furthermore, the resolution of the AIS data and any data gaps may have an impact on the precision of the results. Finally, our study was limited to turning maneuvers; a more thorough examination that included other characteristics of ship journeys could provide more comprehensive insight.

Several future directions can be identified based on the results and restrictions of this study. The accuracy of the results could be improved by using additional filtering techniques, such as the elastic trend filter, with varying settings or investigating other techniques like Kalman filtering. Second, including additional variables in the analysis, like speed, weather, and traffic volume, might give a more complete picture of the factors affecting ship journeys. Finally, utilizing machine learning and artificial intelligence approaches for anomaly detection and predictive analysis may lead to new insights into and explanations for ship voyages based on AIS data.

Chapter 6

Conclusion

In this study, we primarily focused on the analysis of turns through the fitting of circles and investigated the idea of explainable ship journeys using AIS data. We were able to derive the ship's underlying trajectory and locate turning maneuvers by using the elastic trend filter on the AIS data. We calculated the radii of these turns using the circle fitting approach, which gave us important information about how ships navigate and make decisions. My research has shown how important it is to comprehend ship turns and their radii in the context of maritime safety and navigational techniques. A standardized approach to navigation is suggested by the similar turn radii seen throughout numerous maneuvers, showing the existence of navigational standards and patterns. Insights on specific navigational issues encountered by ships, such as obstacle avoidance or maneuvering in crowded places, are provided by differences in turn radii, such as sharper turns with smaller radius. Circle fitting method's accuracy and dependability have been confirmed by comparisons with traditional measurements and previous investigations. This strengthens reliability when using circle fitting techniques and AIS data to analyze ship voyages and comprehend navigational behavior.

This study's implications go beyond the confines of academia. The creation of navigational rules can benefit from knowledge about constant turn radii, making maritime operations safer and more effective. Maritime authorities can use this data to recognize deviations from established standards and implement targeted measures to reduce risks and enhance security during navigation. The knowledge gathered from the analysis of turns can also be used to help create autonomous ship control systems. The agility of autonomous or semi-autonomous vessels can be improved, and safer and more predictable navigation can be promoted, by including standardized turning patterns in their algorithms. There are restrictions to take into account in any study. Turns were the only feature of ship travel that I examined; I did not include changes in speed or route optimization. By adding more variables and performing a more thorough examination of ship behavior based on AIS data, future studies may build on this investigation.

In conclusion, the use of elastic trend filtering with circle fitting algorithms to analyze turns and the analysis of explainable ship journeys using AIS data have both yielded substantial insights into ship navigational behavior. The results have ramifications for navigating rules, ship safety, and the creation of autonomous ship control systems. This study expands the realm of explainable ship journeys and shows how AIS data analysis has the potential to increase transparency and enhance navigational procedures in the maritime sector.

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