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Review

Survey on Multi-Source Data Based Application and Exploitation Toward Smart Ship Navigation

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Abstract

Maritime ship transportation is not only the core infrastructure of the global logistics system but also is closely related to national security and sustainable development. However, the human factor remains the primary source of risk leading to maritime accidents during ship navigation. In recent years, multi-source data has been recognized as an important means to improve the efficiency of ship operations and navigation safety. In this paper, the major research methods and technical pathways of maritime multi-source data in recent years have been systematically reviewed, and a comprehensive technical framework from data acquisition and preprocessing to practical application has been constructed. Focusing on the data layer, application layer, and system layer, this paper comprehensively analyzes the key technologies of maritime navigation based on multi-source data. At the same time, this paper also highlights the advantages and cutting-edge methods of multi-source data in typical application scenarios—such as track extraction, target recognition, behavior detection, path planning, and collision avoidance—and analyzes their performance and adaptation strategies in different usage contexts. Through the combination of theory and engineering practice, this paper looks forward to the future development of ship intelligence and water transportation systems, providing a theoretical basis and technical support for the construction of intelligent shipping systems.

Keywords: multi-source data; maritime video surveillance; ship trajectory identification and prediction; maritime traffic situation awareness; smart ship

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1. Introduction

With the continuous development of science and technology, shipping has become a key component of global logistics. Over the last decades, according to the United Nations, over 90% of world trade is carried by sea. As the foundation of global logistics, shipping plays an essential role not only in global resource circulation but also in national security and rational development strategies. Meanwhile, maritime accidents cause economic losses and environmental pollution. Relevant studies report that the main factor contributing to ship accidents is human error, which exposes a structural risk of over-reliance on manpower and insufficient responses to environmental changes in the current shipping navigation and decision-making processes [1].

Against this background, the role of data (like maps, coordinates (GPS), radar, and weather forecast, etc.) is becoming increasingly important. With the extensive deployment of the AIS (Automatic Identification System), radar, remote sensing imagery, video monitoring, meteorological detection, and other sensing systems, the types of data available for ship navigation have been continuously enriched, and the informational dimension has continued to expand [2]. The integration of multi-source heterogeneous data makes it possible to comprehensively depict the maritime traffic environment, providing ships with refined environmental perception, situational understanding, behavior-prediction capabilities, and environmental protection [3–5].

Especially in the context of the widespread adoption of artificial intelligence and big-data analysis methods, data-driven models have become a key technical pathway for improving navigation safety and enabling autonomous navigation. Since 2020, large-scale neural network models, also known as large models, have been developing rapidly. For example, recent popular deep learning methods based on CNN-KAN. These models are characterized by their ability to handle large datasets and have a large number of parameters. Compared to smaller models with limited data volumes and other dimensional scales, the unique "emergent capabilities" of large models have driven the development of various industries, including the shipping industry. In the shipping sector, large models are widely applied in areas such as target recognition and trajectory prediction, driving the industry toward intelligent and automated development. Additionally, the recent advancements in embodied intelligence have aligned with the broader trends of large models, further propelling the development of intelligent data. Real-time perception and comprehensive utilization of multi-source data not only help reduce the risk of human error but also lay a solid foundation for intelligent systems—such as abnormal-behavior detection, trajectory recognition, and route optimization—which have become the core drivers of modern intelligent shipping [6–8].

This article systematically constructs a comprehensive knowledge framework for shipping navigation, covering multi-source data from generation and preprocessing to practical application, with the goal of advancing more digital, networked, and intelligent operations [9,10]. First, we review the current mainstream maritime data types (e.g., AIS, radar, remote sensing imagery, meteorological data) and their corresponding processing technologies. Next, we analyze typical maritime application scenarios at multiple levels—including route planning, abnormal-behavior detection, and situational perception—demonstrating the potential of data-driven intelligent shipping [11–13]. Finally, this paper examines recent research trends and envisions the future integration of multi-source heterogeneous maritime data, providing theoretical and practical support to enhance the safety, intelligence, and sustainability of water-transportation systems [9,14].

In terms of specific technical implementation, after establishing relevant paper topics, we selected databases from Springer, MDPI, ScienceDirect, and IEEE covering the period 2020–2025. We conducted retrieval and filtering at both the application layer and data layer. Application layer keywords included image recognition, path planning, collision detection, and green shipping. Data sources encompassed images, AIS (Automatic Identification System), radar, and other multifaceted data types. From 500 articles, we selected relevant papers, categorized them by methodology and technical objectives, analyzed their common technical characteristics, and compared their accuracy. The methodological framework for the systematic literature review's execution is as shown in Figure 1.

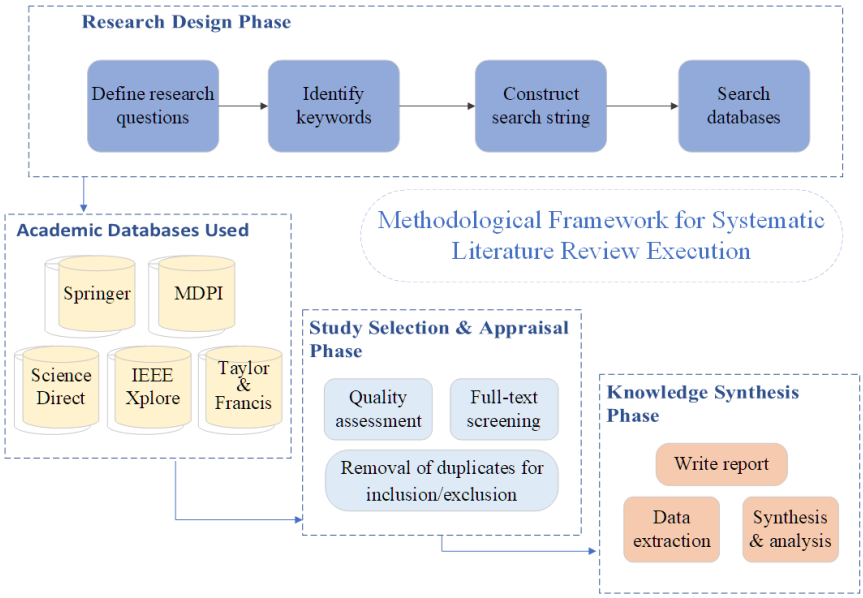


Figure 1. Methodological framework for systematic literature review execution.

This article analyzes the current opportunities and challenges of navigation technology for multiple-data driven shipping, providing the following contributions: (1) Analyzing the relevant research driven by maritime data in recent years, and analyzing the core data types of ship water navigation. (2) Focusing on ship water navigation, it has built a knowledge framework for maritime multi-source data from generation to pre-processing to application. (3) Conducting a multi-dimensional analysis of typical scenarios of ship navigation driven by multi-source data. (4) Based on existing relevant research, predictions and suggestions are given for the development of ship navigation with multi-source data.

2. Mainstream Maritime Data and Pre-Processing Techniques

2.1. AIS Data

The Automatic Identification System (AIS) is an electronic tracking system installed on ships that exchanges data with nearby vessels, AIS terminals, and satellites, enabling ship traffic management systems to identify and locate vessels. When a satellite detects an AIS signal, it displays S-AIS. AIS data can be provided to maritime RADAR to prioritize the avoidance of collisions in maritime traffic [15]. The AIS message includes a unique identification code, ship name, position, heading, and speed, and is displayed on the AIS screen or electronic chart. The AIS enables the officer on watch and maritime authorities to track and monitor vessel movements [16]. The AIS integrates standard VHF transmitters with position information provided by GPS or LORAN-C receivers, as well as other electronic sailing equipment such as magnetic compasses or rudder angle indicators. The AIS integrates a standard VHF transmitter with position information provided by GPS or LORAN-C receivers, as well as other electronic navigation equipment such as an electronic compass or rudder angle indicator. When a vessel is equipped with an AIS transceiver and interrogator, it can be tracked by an AIS shore station. When the vessel is too far from the coast, a vessel can be identified by a specially installed AIS receiver using a large number of satellites to identify its position from a large number of other signals [11].

2.2. Image Data

The main image data in maritime applications includes Optical Images, Infrared Images, Synthetic Aperture Radar, and LiDAR Point Cloud Images. In maritime operations, the primary tasks of imagery involve target identification and tracking, traffic situation

analysis, and determining target distance and size. Optical images primarily originate from unmanned aerial vehicles (UAVs), shore-based cameras, and satellite remote sensing equipment. They generally offer high resolution but are susceptible to weather conditions such as rain and fog during acquisition, which can degrade image quality. Infrared imaging equipment is primarily deployed on ship-based and shore-based thermal imaging systems, as well as infrared satellite devices. It enables nighttime imaging and the detection of fire sources or other heat sources. SAR imagery serves as a primary data source for vessel identification and maritime traffic flow analysis. Possessing strong anti-interference properties, it is deployed on satellites and shore-based SAR systems, playing a crucial role in intelligent vessel navigation. Unlike the aforementioned data, LiDAR imagery provides three-dimensional point cloud data, making it particularly suitable for range measurement and object behavior extraction.

In terms of image data management, file-based approaches are technically mature and easy to implement; however, they suffer from limitations in security, scalability, and content-based image retrieval. In contrast, database-based management has become the mainstream for large-scale image datasets, such as those used in remote sensing. This approach supports structured, distributed, and metadata-integrated management. Image processing includes geometric transformation, arithmetic operations, image enhancement, restoration, recognition, and other tasks. Image enhancement techniques aim to improve image quality, contrast, and detail expression. Image segmentation, a fundamental step in image understanding, focuses on extracting meaningful regions or edges. Edge detection, used to localize contours by identifying grayscale discontinuities, often incorporates optimization algorithms—such as dynamic programming—to achieve globally optimal detection results [17].

2.3. Radar Data

The Synthetic Aperture Radar (SAR) ship detection dataset is part of the SAR sample dataset, which uses remote-sensing sensors to receive reflected or radiated information from objects on the Earth's surface in different bands, record it in the form of electromagnetic waves, and form image data that can be observed and analyzed by humans [18]. These images are of various types and can be categorized according to the different imaging bands. This type of image is commonly used in crop classification, water identification, and other refined analyses. Hyperspectral remote sensing emphasizes the combined performance of spectral resolution, spatial resolution, radiometric resolution, and temporal resolution, and is at the forefront of scientific research in remote sensing. Infrared remote sensing images can capture information about features at night and under the cover of smoke, and are suitable for forest fire monitoring, heat source detection, and other scenarios, but their image clarity and contrast are low, as with another type of active remote sensing technology, and utilizes microwave band imaging, which has the advantages of strong penetration and all-weather imaging capabilities, but due to the complexity of the imaging mechanism, its images are often accompanied by strong noise, which requires interference and filtering processing.

Image correction is one of the core steps of SAR image processing, including geometric correction and radiometric correction. Geometric correction is mainly used to eliminate the image distortion caused by sensor attitude, orbital perturbation, curvature of the Earth, or terrain undulation, etc., so that the image can correctly correspond to the geographic coordinates. Radiometric correction is used to calibrate the sensor response or eliminate atmospheric effects, so that the remote sensing image can truly reflect the radiometric properties of the ground. In the display and interaction of remote sensing images, large data volume, high resolution, and various formats become the main challenges. In addition

to radar image data, there are point data and track data acquired by the radar. Point data is the information that the shipboard radar extracts from the target (obstacle or ship) such as its relative azimuth, relative distance, and reflection intensity. Trajectory data includes target identifier, target distance, bearing, speed, heading, nearest time, and space. The two different types of data depend on the different radars selected for different ships [19]. Also, we focus on all the main types of ship data in recent years and classify the extracted data. Figure 2 shows the classification framework for maritime multi-data types. Fine granularity refers to the resolution of data in terms of time or space. Availability refers to whether the data is easily accessible, with the main reason for inaccessibility being privacy concerns.

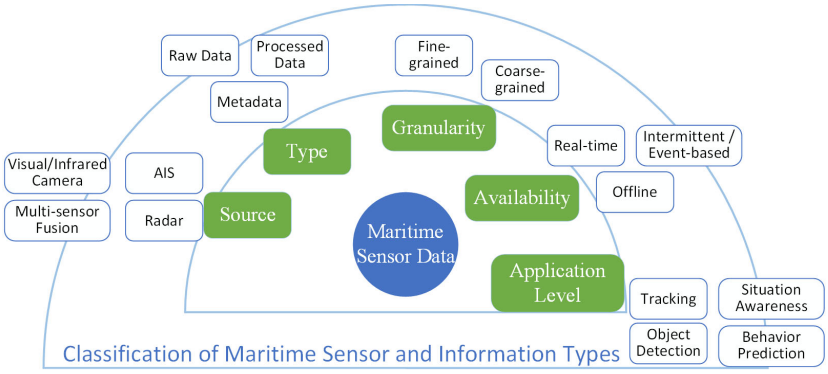


Figure 2. Classification of maritime sensor and information types.

2.4. Maritime Data Processing Techniques

2.4.1. Data Imputation

Due to human or technical factors, AIS data may be incomplete or corrupted during the collection and transmission process. Such data issues can lead to deviations in ship route planning, risk assessment, and traffic modeling, ultimately affecting the accuracy of analysis and the reliability of decision-making. Therefore, imputing abnormal or missing AIS data is essential to ensure the reliability of waterborne traffic systems. In this study, we analyze recent research on maritime data imputation and compare various approaches across different dimensions.

Chen et al. proposed an innovative hybrid strategy to separately handle long-term and short-term trajectory data. For short-term trajectories, the AKI method is applied to project the trajectory onto a Mercator plane. Intermediate trajectory points are estimated using uniformly accelerated linear motion equations, and speed-weighted error adjustment is performed for imputation. For long-term trajectories, a historical migration approach is used to select and align similar historical tracks. The method performs proportional time-axis adjustment to correct trajectory anomalies and repair both short- and long-distance gaps. While there remains room for improvement in deep learning method comparisons and real-time performance, as in a paper published in Ocean Engineering, it holds significant value in integrating theory with practical applications [18].

For traditional machine learning approaches, Szarmach and Czarnowski applied initial screening and clustering to classify AIS anomalies into two main types [20]. For isolated AIS points, the k-nearest neighbor (KNN) classifier is used to infer the most likely corresponding vessel. Anomalous features are extracted using wavelet transformation and standard deviation change analysis. Then, Random Forest or XGBoost classifiers are employed to predict the specific corrupted fields. If more than half of the AIS fields are identified as anomalous, the message is considered misdetected.

For fine-grained anomaly detection within message clusters, dynamic field feature vectors are predicted using multi-class Random Forest/XGBoost models, while Isolation

Forest is applied to static fields for single-field anomaly detection. Finally, each AIS message is independently assessed and trained with multi-label outputs for comprehensive anomaly monitoring.

In deep learning-based approaches, Zhang et al. proposed a multi-stage correction framework that incorporates a Generative Adversarial Network (GAN) for AIS trajectory imputation [21]. Bidirectional Temporal Convolutional Networks (TCNs) and Bidirectional LSTM are first used to extract shallow and deep features. A self-attention mechanism is applied to fuse features across layers [22]. The GAN model is then trained to generate plausible trajectory segments to supplement the AIS data. In addition, a second-stage smoothing is performed using Savitzky–Golay filtering for linear segments and cubic exponential smoothing for curved trajectories, enabling more natural and accurate recovery of missing AIS points.

Beyond data-driven approaches, Serra-Sogas et al. [22] introduced an alternative method that systematically employs Unmanned Aerial Vehicles (UAVs) to compensate for missing AIS data. Aerial cameras are used to collect and transmit synchronized video and AIS signals in real time. AIS targets are then extracted, labeled, and evaluated using a standardized Effort Index (EI). Spatially Predicted Usage Effort (SPUE) metrics are computed per grid cell by ship type, AIS, and non-AIS classification, providing a novel method for threat assessment and maritime traffic management.

2.4.2. Data Fusion

In the era of big data, intelligent ships rely on a wide range of data types collected and processed by onboard sensors, such as AIS data reflecting positioning information, radar data detecting surrounding targets and obstacles, weather data, nautical chart data, communication data, and more. In the context of water transportation, the effective fusion of these heterogeneous data sources can significantly enhance the navigation and control capabilities of smart ships. This study investigates recent major implementation methods of multi-source data fusion in water transportation.

In terms of AIS and communication data fusion, Chen et al. integrated maritime Very High Frequency (VHF) communication data with AIS information [23]. VHF refers to radio frequencies between 30 MHz and 300 MHz, with maritime VHF radios typically operating in the 156–174 MHz range, supporting two-way voice communication over distances of 30–50 km. VHF can transmit voice calls, digital selective calling (DSC), emergency signals, navigation information, and collision avoidance messages. In their approach, VHF audio is first converted into text, denoised, and key information is extracted using speech recognition techniques. AIS data is then extracted and filtered based on the spatio-temporal features aligned with the VHF data. For fusion, ship names are matched across two dimensions—Pinyin and numeric representations—using a similarity threshold. When the matching score exceeds the threshold, VHF information (e.g., ship name, intent, position, timestamp) is fused with AIS data (e.g., trajectory, MMSI, ship type), producing a fully integrated dataset.

Wang et al. utilized the fusion of multiple LiDAR units and a millimeter-wave radar to analyze berthing and de-berthing characteristics, such as bow and stern distances, speeds, and angles, during docking operations [24]. LiDAR sensors generate three-dimensional point clouds around the ship to calculate distance and angular data, while the millimeter-wave radar captures speed information, compensating for LiDAR's insensitivity to velocity. Multiple solid-state LiDARs are positioned at the bow and sides of the ship to achieve wide-area sensing and are calibrated for spatio-temporal synchronization. Temporal synchronization uses timestamps from low-frequency sensors as a reference to unify all sensor outputs, while spatial synchronization constructs rigid transformation matrices from each

sensor to the ship's coordinate system, enabling accurate alignment in dynamic environments. Radar data undergoes multi-frame clustering to eliminate invalid points based on angular thresholds, velocity intervals, and coordinate constraints. Each sensor independently computes berthing parameters such as vertical distance, relative speed, and berthing angle. A weighted fusion algorithm is then applied: distance values rely on LiDAR, speed values on radar, and angle values are fused with assigned weights. The final fused parameters assist in intelligent berthing and support autonomous docking decisions.

Image and AIS data fusion also continue to be a research hotspot, particularly in the areas of lightweight modeling and visual integration. Liu et al. proposed a lightweight YOLOX-s network combined with AIS spatio-temporal information for ship detection and fusion [25]. The model adopts transfer learning and data augmentation (e.g., low-light, haze conditions) to enhance detection performance in complex environments. For AIS data, key features such as latitude/longitude (Lat/Lon), speed over ground (SOG), and course over ground (COG) are used for position prediction and camera calibration, projecting the AIS data onto the image frame via the pinhole camera model. A custom fusion matching loss function is designed to match the detected ships in the image with the AIS-predicted targets. Pairwise costs between all image bounding boxes and AIS vessels are computed, and the optimal pairing is determined using a greedy algorithm or Hungarian matching. This method ultimately enables an augmented reality (AR) navigation interface by overlaying visual and AIS identity information, realizing multi-source ship recognition.

The above different fusion strategies are summarized in Table 1 below. As shown in the table, the first paper imposes corresponding hardware requirements and achieves moderate accuracy. The second paper demonstrates high precision and adaptability in specific aspects of parking tasks. The last paper implements multimodal processing on edge devices, representing the most complex and multi-source hybrid approach among the three methods, thus requiring greater computational resources. Regarding data fusion research, ensuring data accuracy, greater data diversity, reduced hardware requirements, and improved processing speed represent promising avenues for advancement in this field.

Table 1. Summary of different fusion strategies.

Ref	Article	Fusion Method	Task Objective	Method Type	Performance Metrics	Latency/ Complexity
[23]	Chen et al. (2024)	AIS + VHF speech	Ship behavior recognition and maritime traffic surveillance	Speech recognition + AIS trajectory matching	Accuracy: 89.2%	Medium (requires speech-to-text processing)
[24]	Wang and Zhang (2022)	Multi-LiDAR + MMW radar	Estimation of berthing parameters	Multi-sensor synchronization + filtering + weighted decision-level fusion	Mean error $\leq$ 0.52 m/1.3°	High (real-time computation required)
[25]	Liu et al. (2022)	Image/AIS/Radar/ Multi-source data	Autonomous surface vehicle	Edge computing + CNN feature fusion + attention mechanism	Accuracy: 93.5%, F1-score: 91.2%	Medium–High (optimized edge deployment)

3. Muti-Source Data Application in Maritime Traffic

3.1. Traffic Trajectory

Vessel traffic trajectories constitute an indispensable component of maritime transportation. Through real-time, accurate, and error-free trajectory data, researchers can effectively manage and plan maritime navigation channels and zones, thereby enhancing commuting efficiency. Simultaneously, planning vessel routes enables optimization of port cargo and logistics while boosting port scheduling capabilities. Beyond this, vessel trajectories also play a crucial role in fleet planning, energy management, and maritime search and rescue operations. This paper discusses vessel traffic trajectories from the perspective of both trajectory generation and prediction.

Ship traffic trajectory clustering refers to the process of identifying groups of data with multifaceted similarities through data preprocessing methods such as cleaning and compression when multi-ship AIS data is chaotic. Similarity encompasses attributes like the morphology of individual AIS data points, vessel movement patterns, and spatial locations, enabling classification and grouping. This section examines recent vessel trajectory extraction approaches through the lens of trajectory clustering, near-port zones, and global maritime trajectory extraction. Huang et al. innovates DP parameter selection by applying the Douglas–Peucker algorithm to compress trajectories [26]. The introduction of a new Average Compression Score (ACS) enables automatic compression rate adjustment, achieving efficient dimensionality reduction while preserving trajectory conformality. This addresses the reliance on manual DP algorithm parameter settings in traditional methods. Additionally, a key innovation lies in enhancing DBSCAN's adaptability to diverse data environments during clustering, improving robustness. Compared to traditional methods, this approach incorporates AIS dynamic data for modeling trajectory similarity. The model employs Hausdorff distance to analyze spatial shapes, integrating dynamic data-related "Key Point Heading Difference" (KHD) to form the improved clustering algorithm MD-DBSCAN. During clustering, it can set different feature thresholds based on heading and spatial distance differences to reduce weighted distortion. Finally, it utilizes a triangulation network to extract the centerline of the flight path and generate the trajectory.

Near the port area, AIS data is abundant. Liu et al. similarly employ a method analogous to Huang et al. for extracting trajectories in port approach waters [26,27]. For similarity calculation, an improved Hausdorff distance was employed alongside principal component analysis (PCA) to extract the top-contributing components as the number of clusters. Subsequently, K-means trajectory clustering was performed using Hausdorff distance as the metric. Inbound and outbound vessel movements were divided into two subsets, with the Soft-DTW method generating central routes for each subset. An observation line is then defined to record intersection points with the central route. For these intersections, the optimal distribution is selected from 13 options (e.g., normal, gamma, extreme value, log-normal) for fitting, and its cumulative distribution function (CDF) is used to determine left and right boundaries. When addressing the same port problem, Lee et al. employ a recent approach similar to the preceding work: Hausdorff and DP algorithms for trajectory similarity analysis and dimensionality reduction clustering [28]. However, differing from the two prior methods, this approach introduces a kernel density estimation (KDE) probabilistic model to automatically generate different route levels tailored to audience preferences and diverse route requirements.

Beyond attempting to extract vessel-related paths from "straight lines" and "point-like" features, relevant studies also sought to build upon previous innovative approaches. They considered the inherent width of vessel passage and continued applying innovative thinking to extract vessel trajectories from the perspective of "polygonal tracks." Kim et al. quantified vessel navigation time occupancy through the spatio-temporal analysis

of time occupancy within 1 km grids [29]. This method employs ArcGIS algorithms to merge, smooth, and simplify vessel network boundaries before extracting trajectories for a similarity assessment. Polygons undergo CRITIC analysis combining centroid distance, shape index, and overlap ratio to calculate average similarity, thereby identifying authentic navigation corridors.

Different scholars have also sought solutions from multi-source data beyond the AIS. Currently, the primary challenge in extracting waterborne traffic trajectories from images lies in the fact that if occlusions occur during vessel image recognition or if the recognition algorithm fails to identify vessels continuously, it leads to interruptions in trajectory extraction. To address these challenges in vessel trajectory extraction, Chen et al. proposes PYEDS, an end-to-end deep learning framework spanning image recognition to trajectory extraction [30]. It incorporates SE attention mechanisms and HyperColumn aggregation to enhance YOLO's vessel recognition accuracy. To address discontinuities in frame extraction between images and trajectories, EDS (Enhanced Deep SORT) was designed. This includes algorithmic processing for low-concentration images, Kalman filtering, the Hungarian algorithm, and an IOU matching mechanism to enhance multi-object consistency and trajectory continuity. Chen et al. pioneered the integration of traffic trajectory and vessel state semantics at the image level. First, the Dark Channel Prior (DCP) model enhances vessel clarity. Simultaneously, vessel image trajectory interpolation smoothing and anti-jitter processing are applied to construct high-fidelity image trajectory lines through frame-by-frame matching. For traffic timing determination, trajectories extracted from images establish a three-dimensional coordinate system of time and pixel X/Y values, enabling the recognition of three typical vessel behaviors: overtaking, tailgating, and passing [31].

Recently, relevant studies have also explored the entire maritime domain. The key feature of extracting global trajectories lies in modeling approaches oriented toward the entire ocean. The focus of AIS data extraction and clustering shifts toward optimizing the "global" perspective at sea and enhancing robustness across all maritime areas, including port regions. Bläser et al. first addressed the issue of lacking navigational logic in grid generation results from traditional methods [32]. When determining node positions, representative navigation "stop datapoints" and "turn datapoints" were incorporated. During network node construction, these points were clustered to generate nodes, and directed edges were established between nodes using candidate sequences and sliding window pruning algorithms based on adjacent nodes. Subsequently, preprocessing steps including DAISTIN interpolation and loop detection are applied to the processed AIS data. Addressing the fitness issue related to data density in coastal and offshore regions, the paper innovatively combines the Adaptive Neighborhood Radius (ANR) algorithm and Directional Variance Indicator (DVI) algorithm to simultaneously optimize AIS density and berthing distance during clustering, while discussing the Traditional Shipping Zone (TSS) during clustering. For final path fitting and visualization evaluation, the method introduces SPD distance metrics and proposes a new quantitative metric, Trajectory Discretization Error (TDE), to assess visualization inaccuracies. This method is also scalable for extracting global ports and sea areas, making it suitable for modeling global maritime path networks. Unlike the previous approach, this study focuses on trajectory generation during vessel movement from its origin to intermediate nodes to its destination, constructing a three-tier network structure comprising a PLSN (Port-Level Shipping Network), an NLSN (Node-Level Shipping Network), and an RLSN (Route-Level Shipping Network) [33]. First, for each vessel trajectory's endpoints, port identification and port-level shipping networks utilize the CLIQUE algorithm to identify anchorage and berth locations while extracting their interconnections. Simultaneously, the DP compression algorithm (Adaptive Douglas–Peucker) extracts critical turning points in trajectory point-dense regions. The Node-Level

Shipping Network (NLSN) identifies major turning points and diversion points at sea. After conducting trajectory flow cross-section analysis on each edge within the NLSN, the RLSN generates grid projections and density heatmaps to achieve Gaussian fitting for trajectory structure generation. Testing demonstrated effective coverage in Singapore, Rotterdam, and Shanghai. For bulk carriers, a comprehensive track extraction model was developed using AIS data. This involved encoding global historical AIS tracks into low-dimensional feature vectors [34]. Low-latitude data undergoes density-based clustering (HDBSCAN), which resolves clustering issues across varying density regions. Geospatial smoothing averages extract a stable central track. Trajectory edges are established based on point-to-nearest-neighbor relationships, while trajectory endpoints serve as nodes to construct maritime traffic networks. Testing confirms this method operates globally on AIS data without manual intervention and exhibits strong universality.

Vessel trajectory prediction involves processing historical trajectory data (typically AIS data) using mathematical models, machine learning, or deep learning algorithms to forecast the temporal and spatial characteristics of a vessel's future path. The output comprises trajectory curves or their features over specified time intervals. Traditional ship trajectory prediction methods incorporate both machine learning and conventional mathematical approaches. However, due to limitations in prediction accuracy and temporal scope (e.g., machine learning requiring manual feature extraction), current research in trajectory prediction has shifted toward deep learning techniques such as LSTM. Consequently, this study focuses on categorizing and analyzing approaches within the deep learning domain.

For the problem of maritime multi-source AIS data asynchrony affecting the trajectory prediction of maritime traffic behavior. Xiao et al. proposes an ADF model design structure integrating the multi-source data from shore-based satellites for ship trajectory prediction, using MLP to extract the linear features of the shore-based AIS, using BiGRU modeling to process the satellite AIS data with bidirectional timing dependency, and finally splicing the shore-based data with the satellite AIS data and the original data [35]. Trajectory prediction experiments are conducted on the data, and the results significantly optimize the effect of multi-source ship trajectory prediction.

As mentioned earlier, the recent focus of ship trajectory prediction has been on machine learning or even more on deep learning. Li et al. systematically evaluate the current mainstream prediction algorithms (e.g., Kalman, LSTM, etc.) in different scenarios based on this research background [36]. The methodology selects Chengshan Cape, the Zhoushan Islands, and Caofeidian harbor as three typical oceanic sea areas. Different machine learning (five kinds) and deep learning methods (seven kinds) are selected to predict the ship trajectory at the next point using the same division inputs Poi, Poi+1, Poi+2, Poi+3 data, respectively, and the adaptive scenarios and the superiority of different methods are explored, which provides important support for the prediction of trajectories on the water.

LSTM is widely implemented in ship trajectory because trajectory is essentially a series of AIS data. LSTM is a neural network structure designed to model such temporal patterns and is capable of capturing complex navigational behaviors and trends and analyzing them for ship trajectory prediction. Wang et al. divides the spatio-temporal feature extraction into three parts [37]. The first part learns the motion trends between neighboring time frames using LSTM. The second part constructs a "ship-vessel" graph structure and uses GAT to aggregate the features of neighboring nodes to obtain the spatial interaction coding results. In the third part, the output of the above graph structure is modeled in time. The key variables are selected as intermediate variables to be fused with the spatio-temporal feature extraction module for prediction. The prediction is performed by modeling the encoded feature sequences with multi-layer GRU/LSTM layers or convolutional structures to achieve future multi-step trajectory prediction.

The cell state is an important component of LSTM, which is used to carry and retain key information in a long-time sequence. Wang et al. introduces a new Switching-Input Mechanism (SIM) when designing ship trajectory prediction using traditional LSTM [38]. The input gate i_t (input gate) and the candidate memory g_t (candidate memory) are fixed combinations in traditional LSTM. This article splits them, and both of them can act on the cell state individually and this introduces the two parameters p and a to select the input source according to the ship and other ship states, which is more generalized compared with the traditional prediction. In addition, the method also introduces negative feedback to the cell state to form a more dynamic forgetting mechanism to the cell state, which in turn better improves the propagation of the perceptual ability in complex and local trajectory features. Li et al. on the other hand, combines Density-Based Clustering (DBSCAN) and Geohash coding with the LSTM network, to optimize the accuracy and stability of ship trajectory prediction [39]. Meanwhile, four sub-views, Dimension Reduction, Prediction, Dimension Promotion, and Mapping, are designed to form a training layer to enhance the trajectory prediction transformation and prediction capability.

In addition to the above mainstream LSTM, other related research has also explored trajectory prediction methods from different aspects, for example, the graph structure has recently shown its advantages. Zhang et al. firstly applies the graph structure to represent the maritime traffic network and embeds the generative network into the prediction framework [40]. It also embeds marine meteorological data such as temperature, wind, wave height, etc., respectively, to form a multimodal time-series feature modeling to capture the long-range dependence of the time dimension and the interactions among different modes. Singh et al. adopt the graph-structured traffic pattern (GTRA) approach, which combines the graph representation (GTR) and the data association (GTA). The above traffic patterns are used for trajectory prediction using RNN-EDL to estimate the point prediction value, data uncertainty, and model uncertainty. Finally, EDL is used to classify quick turn (UT) detection and OOS detection [41].

The trajectory prediction method is not limited to the improvement of LSTM and other related popular methods; Xiao et al. innovatively propose a bidirectional trajectory prediction method to change the previous unidirectional prediction of future trajectories from historical data [42]. The forward network Encoder–Decoder sub-network is designed using LSTM as the encoder, and the directional Encoder–Decoder sub-network uses BiLSTM to capture the bidirectional correlation between the contexts of the trajectories, and this bidirectional trajectory prediction method is more accurate for dealing with the motion trend of the center-point trajectories (e.g., turns, decelerations, etc.). Finally, the MLP Decoder is used to map the encoder output to a sequence of future trajectory points, while supporting multi-step prediction of future position points and other regression outputs. Chen et al. developed a hybrid deep learning method that combines CNN, LSTM, Attention+, and iLSTM to achieve highly accurate prediction of complex ship trajectories [43]. Farahnakian et al. proposed a trajectory prediction system that combines TCN, kTSCV (time-series cross-validation), and dynamic window selection, ensuring model accuracy through a dynamic parameter-driven framework [44].

We conducted a methodological analysis of the above articles and summarized our findings as follows, with the methodology summary provided in the Table 2. Current main issues include parameter and density sensitivity: DBSCAN-based methods are sensitive to ε and minPts selection. Weak cross-domain transferability: frequent reconstruction is required after environmental adjustments. Inconsistent benchmarks and metrics: varying evaluation criteria across papers hinder cross-study comparisons. Moreover, domain shift poses significant challenges in trajectory extraction and prediction; when applied to different maritime regions (e.g., from coastal to open sea, or from port-level data to

global-scale data), the performance remains unstable. Future research on vessel trajectory analysis should explore more robust clustering methods with parameter self-tuning (e.g., HDBSCAN, multi-resolution graph clustering). Simultaneously, multi-scale and adaptive networks should be investigated for globally/regionally coordinated navigability. In congested ports, research should focus on enhancing multi-source data (cross-modal alignment of video and radar data).

Table 2. Summary of main approach of trajectory generation and trajectory prediction.

Trajectory Generation	**Main Characteristics**
Density-based Clustering (DBSCAN/MD-DBSCAN/HDBSCAN)	Clusters features (time, speed, heading) to extract main routes; good at handling noise but sensitive to parameters and uneven density.
Multi-scale Shipping Network Extraction	Builds shipping networks from "port–node–route" structures, ensuring scale consistency.
Environment-adaptive Network (MATNEC)	Converts AIS data into graphs to generate realistic routes, adaptable to different sea areas.
Shape Similarity/Polygon-based Route Representation	Uses shape similarity to find high-traffic areas; works well for stable, repeated routes.
Image Trajectory Extraction (Aggregated YOLO)	When AIS is missing, trajectories can be extracted from video tracking as a supplement.
Trajectory Prediction	Main Characteristics
RNN/LSTM/GRU Series	Backbone for short- to mid-term prediction; bidirectional models outperform unidirectional ones in turns and speed changes.
TCN (Temporal Convolutional Networks with Dilated Convolutions)	More robust to irregular sampling; new methods adapt window lengths to different horizons.
Spatiotemporal Graph/Graph + Sequence Fusion	Encodes maritime "road networks" (e.g., AISfuser) for constrained waterways, improving long-term prediction.
Regional Encoding and Clustering Priors (Geohash/DBSCAN + CLSTM)	Uses clustering or gridding before prediction to improve accuracy and reduce noise.
Multi-source/Multi-modal Fusion	Fuses AIS with environmental or multi-source data, reducing errors and improving generalization.

3.2. Maritime Target Recognition

The application of target recognition on water is promising and critical and is one of the core technologies to promote future intelligent navigation, unmanned ships, maritime safety supervision, and emergency response. Its current main data sources include various shipboard or shore-based cameras (the main types include high-definition, infrared, fish-eye cameras, etc.), radar (radar remote sensing images, lidar, etc.), and others.

The camera mainly performs ship identification including the process of data sensors acquired by different cameras, image data pre-processing, and finally, ship identification. Image data acquisition corresponds to different ways and different characteristics of the data. (e.g., a Fisheye camera can capture wide-angle images in different directions and at large angles, but its images are affected by a certain amount of edge distortion. Infrared cameras can sense the difference in target temperature in bad weather or at night, which is suitable for ship detection tasks at night and in foggy conditions, etc.). Image pre-processing is the process of enhancing, denoising, image correction, and background modeling of image data due to environmental interference caused by insufficient brightness of the original image data, foggy weather at sea, and so on. Previous conventional methods

include traditional methods and simple methods based on machine learning, etc. The mainstream methods are still deep learning-based methods, which generally use migration learning and fine-tuning for image processing for ship image datasets (e.g., SeaShips and MaritimeDrone). The main tasks of their target recognition include target detection, classification, segmentation, and partitioning. Accordingly, it will be developed according to the above-mentioned types. In ship identification, the dataset is a key factor in determining the accuracy of ship data training results. A good dataset is characterized by its specificity, high precision, and large data volume.

In terms of ship monitoring, Farahnakian et al. proposed WSA-YOLOv5s based on the lightweight target measurement model YOLOv5s, to which the Window Self-Attention (WSA) module, CBAM Attention module, and Focal Loss module were added [44]. While keeping lightweight, it reduces the computation of small target detection, mitigates the background interference, etc. Chen et al. on the other hand, faced with the detection of ship images in low-light environments with water visibility, designed the shallow attention enhancement and deep detail retention module [45]. The shallow layer extracts position information from DWConv, and the DRA self-attention module models the attention of the local window, and the MLP layer performs feature transformation to enhance the target contour and boundary information. The deep detail preservation block (DPBlock) is designed to increase the contrast in low light by using DSConv, MLP, BatchNorm, SiLU, etc. The feature fusion mechanism S-DHBlock is designed to increase the contrast in low light by using DSConv, MLP, BatchNorm, and SiLU. Finally, the feature fusion mechanism S-D HFFM is performed to integrate the deep and shallow features. Jia et al. uses the unsupervised contrast learning method MOC to extract high semantic visual features from the image, which is more robust than the traditional low-level features such as color and texture. After that, low rank sparse matrix factorization (LSMF) is used to extract saliency cues to construct saliency maps and perform target detection [46]. This article combines the GAN (generative adversarial network) with weighted BiFPN visual perception to restore images and detect ships at sea in low visibility weather conditions such as rain and fog [47].

For recognition, Chen et al. design employs a multi-scale feature extractor of a residual network based on esNet-50, which extracts different scale features at different layers of the backbone network (e.g., conv2_x, conv3_x, conv4_x), reflecting the shape contour, structural details, and global semantics, respectively; thus, solving the problem of weak fine-grained differences between ship shapes and the dominance of local features [43]. Finally, a multi-feature module is introduced to form a unified vector representation and assist the task learning module (e.g., scale-guided loss, discriminative subclassification task). It performs well in recognizing ship types with similar structure and appearance and improves the discriminative power and accuracy of the ship type classification task.

For segmentation, Sharma et al. propose a novel end-to-end single-stage ship instance segmentation network, MASSNet, combining a multi-scale attention mechanism with a lightweight design to efficiently recognize the pixel-level mask of each ship in complex maritime images [48]. Its MASS module combines channel attention (CA) and spatial attention (SA) to model the saliency of ships of different sizes and incorporates multi-scale context fusion to enhance target and background discrimination. Compared with the traditional FPN, it can better focus on the spatial distribution and boundaries at the instance level. Backbone chooses GhostNet (Lightweight Convolutional Network) to effectively reduce the computation and parameter scale, which is suitable for practical deployment in complex maritime vision systems.

Except for the processing of ordinary images, the SAR is an active remote sensing imaging radar system because it passes through microwave signals and receives reflected wave signals from the ground. Therefore, it is not affected by weather (cloud, fog, rain, etc.),

time, etc., and because of its high resolution and radar waves in the ocean and metal hulls of different reflectivity, so it occupies an irreplaceable role in the detection of marine vessels.

In practical applications, the main difficulty faced by SARs is that the SAR shows an outline of a ship that is small in the image due to the large distance scale. Meanwhile, sometimes when the waves are big, the wave reflections will be mistaken as ships in the SAR image. Next, when ships are congested in the harbor, many targets are also the difficulties of each water target recognition method. Through the study of current methods, identification by SAR includes the following.

First is the traditional statistical approach, Wang et al. innovatively introduce Poisson distribution statistical modeling into SAR image ship detection [49]. It is assumed that the appearance of ship targets obeys a non-uniform Poisson process and a hybrid PDP-CFAR detection method is constructed. Its method combines background noise with Poisson target modeling and adjusts the CFAR threshold, effectively improving the target detection rate and controlling the false alarm rate (FAR).

Machine learning and deep learning research in ship detection has become one of its most popular directions, Yasir et al. conducted a systematic review of deep learning-based SAR image ship detection methods in the past decade [50]. It categorizes the current deep learning methods on the SAR into CNN-based methods, Transformer-based methods, Anchor-Free methods, and hybrid model methods and discusses the current major challenges and mainstream datasets of deep learning methods for SAR ship identification. This study investigates the current main research on deep methods for ship recognition from CNN, Transformer, and other aspects.

Gupta et al. introduce an improved PSO algorithm to the initialization stage of CNN network convolutional layer parameters and the fully connected layer, and optimizes its initial weights and biases as well as improving the traditional CNN parameter ship detection initialization model, which is prone to fall into the problem of local optimum [51]. Zhou et al. designed the fusion of the Global Context Module, Multi-scale Feature Fusion Module, Spatial Fusion Module, and Spatial Fusion Module, which are the main backbone of the CNN network, Scale Feature Enhancement (MSFE), and Spatial Attention [52], in order to advance its accuracy in the field of ship detection. In addition to the network modification of CNN, the modification of the Transformer network is still of scientific significance in ship detection. Tian uses a CNN network as its backbone and designs a fusion of global context enhancement modules, multi-scale feature fusion modules, and spatial attention mechanisms to improve its accuracy in the field of ship detection [53]. The main architecture of the model includes a Multiscale Feature Extraction module for feature detection and extraction, a Reversible Column-Row Transformer for efficient dependency capturing, and an Adaptive Fusion module for fusing multiscale and column–row channel information, which can realize high-precision target recognition under different scales and complex backgrounds (e.g., near-shore, harbor, and cluttered sea surface). We have selected the relevant methods from the aforementioned papers for comparison in the Table 3.

This paper investigates relevant datasets for ship recognition in image recognition over the past five years, yielding the following results. SSDD, HRSID, and SeaShips constitute the primary datasets for maritime object detection. Among these, HRSID has been the most widely used and popular dataset in recent years. This reflects the mainstream role of SAR imagery in ship recognition. This paper compares these three dataset types. As shown in Table 4, self-collected data is also widely used. [54–57].

Table 3. Comparative efficiency metrics of representative ship detection models.

Method	Domain/Dataset	Parameters	FLOPs	Runtime/Speed	Notes
LH-YOLO (improved YOLOv8n)	SAR (HRSID, SAR-Ship)	1.862 M	−23.8% vs.YOLOv8n	—	Achieves mAP50 of 96.6% on HRSID while being extremely lightweight.
LD-Det (YOLOv8n variant)	SAR (SSDD)	24.4 M	8.1 G	312.1 FPS (↓15.7%)	Compared to YOLOv8n baseline (30.5 M, 8.4 G, 370.4 FPS).
SDNet (Lightweight Detector)	Visible-light maritime images	4.86 M	7.9 G	—	Reported to outperform other lightweight detectors in both accuracy and efficiency.
Lightweight Single-Stage Ship Detector (YOLOv5 variant)	Visible-light maritime images	−71% vs. YOLOv5s	−58% vs. YOLOv5s	—	Relative reduction compared to YOLOv5s, no absolute values given.

Table 4. Comparison of main used maritime target recognition database.

Dataset	Modality	Source	Resolution	Preprocessing	Train/Val/ Test Split	Reproducibility	Papers Using It
HRSID (High-Resolution SAR Images Dataset)	SAR	Gaofen-3, Sentinel-1	High (1–3 m)/~9000 images	Normalization, resizing, data augmentation (flip, rotate)	60%/20%/20%	PyTorch 2.0, CUDA 11.8, random seed = 42	[58–62]
SAR-Ship-Dataset	SAR	Multi-satellite SAR	Medium–High~40,000 images	Normalization, random cropping	70%/15%/15%	TensorFlow 2.9, fixed seed = 1234	[50,58,60]
SSDD/BBox-SSDD	SAR	Multi-satellite SAR	Medium~15,000 images	Histogram equalization, noise filtering	65%/20%/15%	PyTorch 1.13, random seed = 7	[58,60–63]
Seaship7000	Optical	HD cameras, optical sensors	High (1080p) 7000 images	Contrast enhancement, denoising, rotation augmentation	70%/10%/20%	PyTorch 2.0, deterministic training	[48,54,64]

3.3. Vessel Behavior Detection

Vessel traffic behavior detection refers to the extraction of specific behaviors of a vessel at the multi-source data level, and its commonly identified behaviors include vessel sailing, anchoring, yawing, turning around, wandering, and so on. Among them, ship behaviors that threaten safe water navigation such as wandering for a long time in a certain sea area, spoofing vessel identity, etc., are called abnormal ship behaviors. The identification of vessel behavior at the data level through multi-source data pairs is conducive to unmanned ship navigation (behavioral discrimination of other ships), ship safety management (whether the ship stays illegally, off-channel travel, etc.), port scheduling planning, and so on. In recent years, the main methods for the detection of ship behavior are mainly from the level of the AIS, image, AIS combined with image, and traditional machine learning aspects. Ribeiro et al. divide the behavioral inspection methods based on the AIS into four compositions of rule-driven, statistical methods, machine learning methods, and deep learning methods [65]. In this paper, we discuss the recent studies drawing on the similar classifications for normal traffic behavior detection and abnormal behavior detection for maritime traffic, respectively.

3.3.1. Vessel Behavior Recognition

The main problems faced in water traffic behavior recognition engineering include the lack of systematic machine learning algorithms or ship traffic behavior systems, and inaccurate recognition of complex traffic behavior. Such as the inability to deal with low-speed form and anchored ship navigation behavior with high accuracy. Meanwhile, the bottom layer cannot avoid the inaccuracy caused by the impact of AIS data. In the face of waiting, berthing, anchoring, drifting, and such low-speed or near-shore ship traveling behavior, recent methods are mainly needle statistical methods or statistics combined with traditional machine learning methods. Ma adopts the traditional statistical methods to evaluate the ship behavior from the three dimensions of speed, position, and time to the ship waiting behavior. In the speed dimension, bimodal normal distribution and target point as the upper limit of waiting behavior speed are taken for three kinds of cargo ships: container ships, bulk carriers, and cruise ships. The position dimension and time dimension dimensions also take a similar approach to use the threshold value for judgment [66]. On the other hand, by analyzing the waiting time ratio, waiting characteristics and characteristics of different sizes of ships, the study achieves accurate identification and characterization of waiting behavior of ships outside the harbor. In addition, due to the easy migration nature of the statistical method, this method can be widely used in the analysis and decision-making of shipping companies and port management. Zaman et al. firstly adopt the OU model combined with the Generalized Likelihood Ratio Test (GLRT) to detect the abnormal behavior of ships and select the historical AIS trajectories to compute the DTWs between the trajectories and takes the "average distance minimum" as the reference trajectory [67]. Moreover, the method also combines the traditional machine learning method with the trained XGBoost to classify the multi-dimensional motion features of the ship's trajectory segments and identify its underway, berthing, anchoring, and drifting behaviors. The method is innovative because of this design and unlike other studies, this method can detect ship behavioral data online on ship data streams without relying on ship data labels and fixed heading.

With the same XGBoost, Ma et al. also similarly adopts the mainstream idea of ship traffic behavior recognition for the detection of sharp turning, drifting, and slow speed straight ahead behavior of ships [68]. Five-dimensional sub-trajectory feature parameters of position, direction, speed, and other rates of change are extracted for ship behavior. At the same time, UMAP behavioral clustering is adopted and replaced PCA/TSNE with spectral clustering to group the dimension reduction results. Each class is divided into a ship behavior, for each of the above behaviors are labeled and input into XGBoost for training. After the training is completed, it supports the automatic identification and prediction of new trajectories with high accuracy, strong generalization, and practical value.

For statistical methods for ship behavior identification, YongKyung introduces the Bayesian self-help method into ship trajectory modeling for the first time, which can be oriented to the detection of spatial anomalies and temporal anomalies of ships in large-scale sea areas. The main problem solved by this method is that the traditional grid method of AIS in large-scale sea areas generates a large number of grids and a large amount of computation. The method implementation process uses a small grid plus AIS clustering key points to extract multiple trajectory results. The Bayesian self-help method is introduced to quantify the uncertainty of path selection, and the AIS data is analyzed by constructing uncertainty distributions, setting confidence intervals, and defining spatial anomaly regions, so as to realize an interpretable, uncertainty-driven joint detection method of spatial and temporal anomalies. It is tested to be suitable to be deployed in intelligent maritime surveillance system in a large sea area.

Meanwhile, deep learning ship behavior recognition methods have also been advanced in recent years, Oh and Kim introduced a fusion graph attention network (GAT) to solve the problem of traditional methods finding it difficult to capture the ship speed, heading, and other ship behavior characteristics dependent on the perspective of deep learning [69]. The method selects a prediction model (GRU) to extract the dependency weights between nodes and capture the long-term dependencies before the GRU network and passes its output to the two branches of prediction and reconstruction. The authors combine the two models to extract anomalous eigenvalues and perform fusion to reason about ship behavior. Finally, to address the problem of relying on manually set anomaly values after quantization, the paper makes use of the Peak Over Threshold method in extreme value theory to model the dynamic distribution of anomaly inference scores and update the thresholds in real time.

Recent research on AIS ship behavior has expanded into ship behavior prediction in addition to online, computationally small, and deep learning. Murray and Perera propose a model that takes into account accuracy, generalization, and scalability in ship behavior prediction at the regional level [70]. The system slices, interpolates, and normalizes the historical AIS track data every minute and inputs it into a VRAE encoder to transform it into fixed potential vectors. The study is implemented as follows, data is input to HDBSCAN to discover clusters of behavioral patterns and remove noisy outliers. After that, the method employs Softmax output behavioral cluster probabilities to implement a soft classification process for ship behaviors while introducing a local prediction model based on RNN and attention mechanisms to train an independent sequence-to-sequence (Seq2Seq) model for each behavioral cluster. While model structure is designed as a bi-directional GRU encoder and attention decoder. It is realized to predict the next 30 min trajectory and achieve high accuracy regression.

In addition to single AIS data processing, deep learning methods for AIS trajectories combined with images have recently shown good innovation. After the trajectories are converted into a 2D image, the WGAN-GP and Encoder modules are employed to learn normal trajectories [71]. The authors define two functions ST(x)S_T(x), the pixel residuals of the original and reconstructed images, and SD(x)S_D(x), the residuals of the original and reconstructed images in the discriminator feature space, to calculate the pixel-level anomaly detection within the image area and identify the ship's navigational behavior errors. The method, with no annotation, visual localization, high robustness, and multi-class anomaly recognition capabilities, is an important solution that can be deployed and extended in the future maritime intelligent situational awareness.

3.3.2. Anomalous Behavior Detection

AIS abnormal data detection is the foundation of AIS application. Complete and error-free AIS data provides the basis for the intelligent maritime transportation of ships. In recent years, the abnormal detection of AIS data has been aimed at avoiding the occurrence of major dangerous behaviors of ships such as ship collision and the detection of abnormal behaviors of ships from the level of AIS data, especially for the detection of abnormal behaviors of using the AIS for ship identity deception and concealment.

Among the main machine learning methods used, LSTM/GRU supervised neural network models, Transformer neural network training, and SVM classifiers, show utility in anomaly classification. Liu et al. use a data-driven approach to extract feature vectors for the target points LAT, LON (latitude and longitude positions), SOG, COG (heading and speed), (SOG change rate), (COG change rate), and CLP (turning strength criterion). After that, the above data is inputted into the sliding window method to generate three kinds of abnormal behavior datasets, namely SCA (speed anomaly), TA (heading change anomaly), and LA (wandering anomaly) of the ship. The authors select mainstream

machine learning models LSTM, GRU, LSTM-FCN, GRU-FCN for the training comparison of the dataset, and finally derive the Accuracy, F1-score, and Confusion matrix technical indexes of each response model, and filter the above data to generate the real-time anomaly detection system [63]. Bernabé et al. selected AISSat and NorSat satellite data provided by Norwegian Statsat, and applied the sliding window method and sub-supervised labeling to generate the dataset and divided it into two parts: historical trajectory (25 trajectory data) VH and recent position VL (the latest AIS) [72]. The two parts of the dataset are put into a self-supervised Transformer network for splicing to form feature vectors and for judging whether the AIS is received at time t, and then for judging whether it is an abnormal trajectory (suspected shutdown). Meanwhile, the method supports online AIS shutdown detection. In the work of Wei et al. the AIS data is mapped into an eight-dimensional feature space to fully reflect the spatial and kinematic characteristics of the trajectory by statistical mapping [73]. Based on the improved DBSCAN, the Euclidean distance in the feature space is used to measure the trajectory similarity to categorize the normal traffic patterns, and the adaptive SVM + Weighted Hybrid Kernel model is trained to determine the corresponding ships' deviation from the main route, abnormal operation, and illegal berthing. The average accuracy of the experimental results is about 99%, which is better than the single kernel SVM and traditional methods such as RF, ANN, and DT.H. Rong uses the method of sliding window and KDE probability density detection to set the probability of normal behavior, and make probability judgments on AIS data speed, heading, and lateral offset [74]. If a continuous abnormality occurs, it is recorded as a time period to continue the judgment. Afterwards, the speed fluctuation, heading difference, and yaw angle of each abnormal segment are extracted for subsequent cluster analysis. The clustering uses DBSCAN unsupervised clustering for abnormal behavior and uses Random Forest (Random Forest) classification and SHAP value the interpretation model to judge the influence factor to detect abnormal behavior.

Unsupervised learning methods are also attracting attention. For example, Nguyen et al. combined latitude, longitude, heading, and speed trajectory points into a four-hot vector [75]. Meanwhile, hidden variables are added to the VRNN to maximize the AIS log likelihood and model the trajectory generation. After obtaining the trajectory, it is modeled using small grids of local probability distribution regions. The Geo-A- Contrario method lies in the method of discriminating against AIS anomalies by calculating the probability of being in the grid where it is located and the binomial distribution test assistance, for each AIS point.

Among the non-machine learning methods, statistical methods have performed most effectively and received much attention in recent years [65]. The core role of statistical methods for anomaly detection is to judge anomalies based on statistical hypothesis testing. Louart et al. incorporates Kalman filter initialization to track the CFO position information of each transmitter and continuously monitors the difference between the observed and predicted values. Finally, the detection method of the chi-square statistical test is used to detect the judgment of identity forgery [76].

3.4. Maritime-Source Data-Based Maritime Collision Avoidance

Collision avoidance on water for ships is defined as a process of sensing, evaluating, and making decisions on objects encountered in ship navigation through data means, which is a core part of current water navigation safety. The study of water collision avoidance of ships can provide assistance for the safe driving of all types of ships including manual driving. More importantly, it will provide safety and technical support for unmanned autonomous ships on water. Currently, the research focuses on the water sensing of ships and its corresponding judgment. Sensing is based on a wide range of data sources,

including the AIS, radar, and image data to sense obstacles. Judgment is usually based on the International Collision Avoidance Rules at Sea (COLREGs), relevant standards of the IMO, and rules of intelligent systems (such as risk perception algorithms based on images, radar, and the AIS), etc., to make the corresponding avoidance measures such as turning direction, slowing down, and accelerating, etc., for the existence of the ship. This process is shown in Figure 3 (Black boxes indicate the detected ships in the image.).

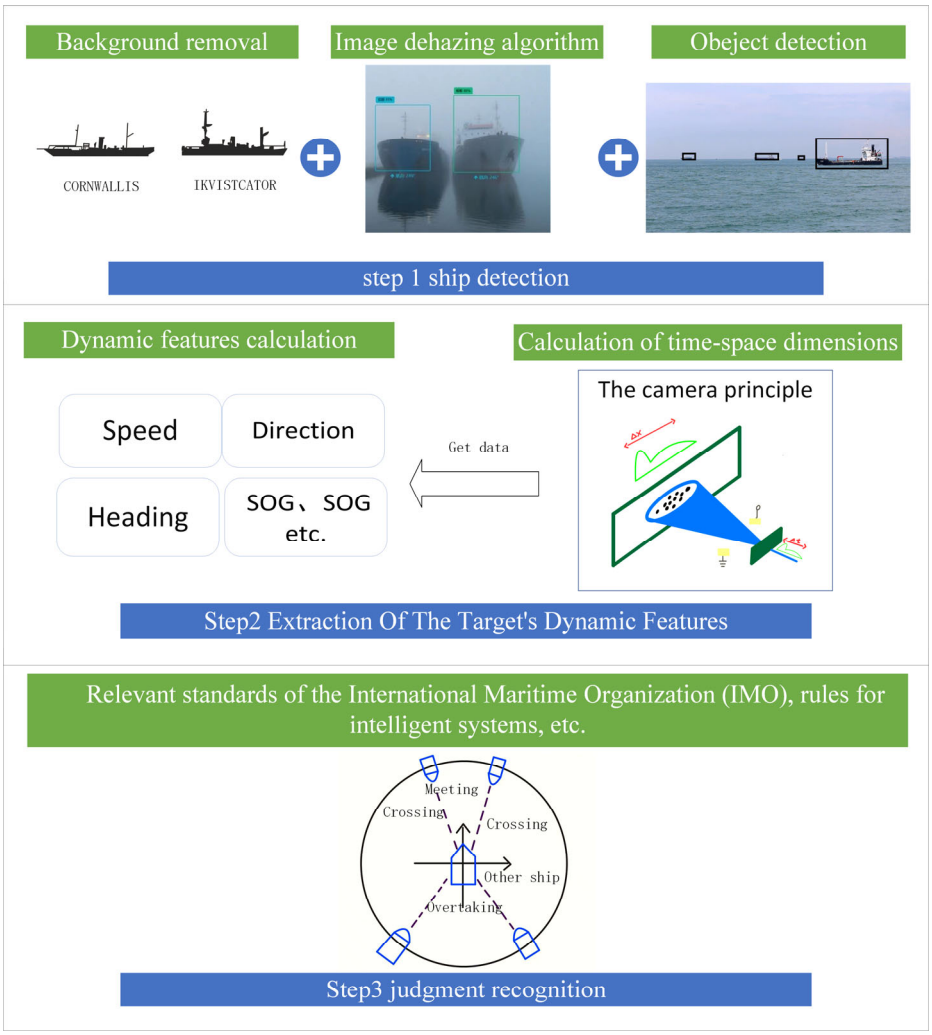


Figure 3. The framework of maritime collision avoidance.

In recent years, the main problems faced by ships in water collision avoidance focus on the perception level of water collision avoidance, such as the AIS level, when the AIS data is missing, unstable, and chaotic, it is impossible to accurately judge the ship's speed, heading, and other dynamic features. Radar can easily recognize the target when the data volume is large, easy to overlap, and other problems are difficult to judge. Based on the MetaFormer architecture, which integrates relative depth and metric depth information, distance values with metric depth are predicted from monocular camera images. The goal is to enable port systems to accurately measure the distance between ships and docks, as well as other facilities, for use in actual port monitoring or safety management [77].

Recent research on modeling keyword screening concluded that relevant ship collision avoidance is still based on radar and image as a starting point; image-based maritime collision avoidance research is largely based on 'accurate extraction of the target individual' (including de-fogging, removing the background, etc.), 'extraction of the target's dynamic features' (the camera principle to build a time–space dimension to calculate its speed,

direction, and other dynamic features), and judgment recognition. Figure 3 shows the framework of maritime collision avoidance. For example, Ding et al. make use of YOLOv5 with SE Attention Enhancement for ship identification and Deep SORT for target tracking, and this method can significantly improve the ability of small-size, long-range, and multi-target ship detection [78]. In terms of dynamic feature extraction, the actual distance of the ship is projected using the mirroring principle and the speed of the ship is projected using the video frame rate and the distance of the ship. Abnormal data rejection and median filtering mechanisms are introduced to improve the robustness of detection for abnormal values. Finally, we use the index model to integrate the classical shipping indicators: DCPAV (distance to nearest point of contact) and TCPAV (time to nearest point of contact) to achieve high stability and timeliness of ship warning, and to make up for the loss of early warning capability in the absence of the AIS. Bi et al. identify ship light signals as targets for collision risk assessments, which helps address the deficiencies in capturing micro-features by the AIS and radar [79] in micro-feature capture. For extraction, a macro–micro composite imaging platform using a wide-angle lens (OFFIS) combined with a zoom lens (OZISS) is used to extract the direction of the recognized target and obtain high-resolution images. After obtaining the results, an Adaboost classifier for recognizing the ship/light type is applied. The dynamic feature extraction adopts the principle of small hole imaging to design the relevant model to calculate the actual relative speed and the DCPA (distance to closest point of contact) and other indicators between ships.

Xu et al. have the same viewpoint as the above image, but a radar image is used [80]. The detection aspect is divided into three steps, first the background will be extracted, and the main aspect of the ship will be processed by grayscale transformation, binarization, and identification of connected regions. Lastly, the minimum outer circle center has been used as the ship position marker and ship tracking has been performed with the Kalman–Hungarian algorithm. Thesis subject speed and heading extraction first extracts the coordinates between frames to calculate the speed and heading, constructs a model logic approach to compare the degree of difference between the radar and AIS data, and gives weights to radar and the AIS, respectively, for fusion, using the Mamdani fuzzy inference mechanism and the center of the mass method of de-fuzzification to finally weight the fusion. Han et al. utilize the basic traditional algorithms using only radar data to simultaneously estimate the ship motion state (position, heading, speed) and ship geometry parameters (length) [81]. The key innovation is to utilize the shape of the radar echo region (sector) and the direction of the target's motion to derive the approximate length of the ship; the length is estimated using the nonlinear function Unscented Transform (UT) to estimate the mean and variance of the length. Finally, Global Nearest Neighbor (GNN) is used to correlate the data. In this way, the collision risk assessment and obstacle avoidance planning capabilities of unmanned vessels (USVs) in complex traffic scenarios are improved using purely traditional methods.

In contrast to the above ideas, Zhang et al. construct a "perception", "path planning", and "collision prediction" process for ships from the fusion of Lidar and visual sensing data collection [82]. After collecting data from multiple sources, we pre-processed and generated a fused three-dimensional map. Based on the SSD (Single Shot MultiBox Detector) method, the target was recognized. Immediately after that, the path planning of the hull was carried out, and the trajectory as generated and adjusted by noise reduction using improved RRT and artificial potential generation methods. Core collision prediction is achieved by using the traditional machine learning method Faster R-CNN with the assistance of K-means clustering to achieve high-precision collision prediction.

The AIS likewise has some applicability to ship collision avoidance in the absence of deficiency. Although the absence of the AIS may have an impact, multi-source data

processing is necessary. Relevant studies such as Forti et al. use OU stochastic process modeling, assuming that ship speed tends to the long-term average, and use the GLRT method of sliding window comparison thresholds to determine the anomalous data. In the real Ever Given case experiment, the method predicted AIS points outside the OU model ellipse 19 min in advance, and three anomalies were detected in advance [83].

4. Conclusions

This paper focuses on multi-source data and reviews recent research on maritime data traffic from three dimensions: the data layer, application layer, and system layer. It first examines the current composition and primary use scenarios of multi-source data and then analyzes the mainstream datasets and their main applications. This paper also analyses multi-source data in track extraction, target identification, behavior detection, path planning and other typical application scenarios in the advantages and preface method, analyses its performance in different use of scenarios and adaptive strategies. Through the combination of theory and engineering practice, this paper also looks forward to the future direction of the development of ship intelligence, water transportation systems, and for the construction of intelligent navigation systems, provides atheoretical basis and technical support. In this study, a GAN-LSTM model is proposed for ship speed prediction. First, the algorithm takes an LSTM network as the generating network and utilizes LSTM to capture spatiotemporal dependencies between nodes. Secondly, the complementary characteristics between the generative network and the discriminant network are used to eliminate the cumulative error of a single neural network over the long-term prediction process, improving accuracy of the network for ship speed. Ultimately, the Generator-LSTM model is utilized for predicting ship speed and is compared with other models under the same AIS ship speed information in the same scene. Results show that the model achieves high accuracy in typical error metrics, which means that the model can more accurately predict ship speed. In addition, the Generator-LSTM model shows the superiority of this method in the task of speed prediction. The main reason can be attributed to the Generator-LSTM model to realize the task of speed prediction by using the spatiotemporal correlation of velocity related data. In addition, the Generator-LSTM model has a high prediction accuracy, indicating that good temporal and spatial correlation is a crucial component of the model for accurate ship speed prediction.

By analyzing recent studies and theories, this paper makes relevant inferences about the future development trend of navigation data. The development of lightweight for each data processing aspect of multi-source data. Lightweight refers to the condition of limited embedded computing resources. In future research, it is important to further investigate the performance of this model in long-term speed prediction tasks, and the research on the expression of water traffic situation knowledge based on AIS data is also worthy of further study.

Current research still faces several limitations. For instance, trajectory extraction suffers from insufficient transferability, making it difficult to deploy data prediction methods with stable performance at a global scale. In the field of target recognition, the main challenges lie in the high computational cost, long pre-training time, and the lack of lightweight and real-time recognition approaches. Developing easy-to-deploy models with low computational cost and fast response is a key future direction, especially for shipborne embedded platforms with limited resources. This includes optimizing deep visual learning models, for example, through weakly supervised or unsupervised approaches, to make them more suitable for “edge-side” devices that must meet strict real-time requirements [84]. At the same time, practical implementation must also consider challenges such as regulatory compliance and safety certification in maritime operations. Another important direction

is the joint analysis of data collected from multiple heterogeneous sensors (e.g., infrared, weather, and radar data) to achieve a more comprehensive perception of the maritime environment and ship status. From the data-level perspective, improving the processing speed and accuracy of individual multi-source data while promoting cooperative use across different data types will drive the development of multi-faceted and robust maritime data research, ultimately supporting intelligent and safe ship operations.

Maritime ship transportation is not only the core of the infrastructure of the global logistics system, but also closely related to national security and sustainable development. However, the human factor is still the main source of risk, leading to maritime accidents during current ship navigation. In recent years, multi-source data has been recognized as an important means to improve the efficiency of ship operation and navigation safety. In this paper, the major research methods and technical paths of maritime multi-source data in recent years have been systematically sorted out, and a complete technical framework from data acquisition, pre-processing to practical application has been constructed. Focusing on the three dimensions of data layer, application layer, and system layer, this paper comprehensively analyzes the key technologies of maritime navigation based on multi-source data, covering the fusion processing and intelligent application of the AIS, image, radar, and other information sources. At the same time, this paper also focuses on the advantages and cutting-edge methods of multi-source data in typical application scenarios, such as track extraction, target recognition, behavior detection, path planning, and collision avoidance, and analyzes its performance and adaptation strategies in different usage scenarios. Through the combination of theory and engineering practice, this paper looks forward to the future developmental direction of ship intelligence and water transportation systems, and provides a theoretical basis and technical support for the construction of intelligent shipping systems.

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