Maritime Traffic Data Visualization: A Brief Review

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***Abstract*—The sustainability development of ocean engineering has witnessed the vigorous maritime activities in different waters. The rapidly increased maritime traffic contributes to the high-level accidental risk of maritime transportation. To better monitor the maritime traffic, it is necessary to deeply understand the massive vessel traffic data from different perspectives in practical applications. The advanced data visualization techniques can help us to gain deep insights into maritime traffic behavior from massive vessel traffic data. Data visualization performs well in generating visual presentation of information, which has become a powerful and widely-used tool for the analysis and interpretation of large amounts of complex big data. The primary objective of this paper is to provide a brief review for interested researchers to better understand the maritime traffic data visualization techniques. Within this brief review, data visualization techniques in the fields of spatio-temporal vessel trajectories and vessel traffic density have been comprehensively surveyed. Owing to the significant advantages of visualization techniques, there is a huge potential to utilize these techniques to assist in enhancing vessel traffic safety and service reliability in maritime activities.**

***Index Terms*—Automatic identification system, trajectory data, big data, data visualization, maritime traffic**

I. Introduction

With the rapid increase on international trade, we have witnessed the enormous prosperity of shipping industry. Benefitting from the large-carrying capacity and low cost, water transport has become the most dominating mode of transport. According to the correlative statistics from International Maritime Organization (IMO), almost 90% of world trade is carried by sea and the demand for water transport is still on the increase on account of economy globalization [1].

To meet the urgent demand for sea transport, an increasing number of vessels have been come into service, as a result, the safety and security of marine transportation have been drawn much attention. Radar, sonar, electronic chart display and information system (ECDIS) and the occasional closed-circuit television (CCTV) are conventional aid-navigation equipments, which have been equipped in vessels to assist the deck officers to make rational judgements to enhance the safety and security of navigation [2]. However, these equipments have their own disadvantages, which are not always reliable for guaranteeing maritime navigation safety. For example, the radar echo can be easily interfered by the external factors such as sea conditions and weather conditions, thus producing clutters affecting deck officers' making appropriate judgments.

From 2002, Automatic Identification System (AIS) has been made a compulsory equipment for ships over 300 gross tonnages on international voyages, cargo ships over 500 gross tonnages in all waters and all passenger ships by IMO [3]. The AIS broadcasts and receives mainly three dominating types of information (including the static, kinematic, and voyage-related information) to/from neighbouring ships every 2 to 10 seconds depending on the host ship's speed, and every 3 minutes while the ship is at anchor [4]. The static information includes ship name, ship maritime mobile service identity (MMSI), ship size, ship type, etc. While the ship speed, ship position, rate of turn and heading belong to the kinematic information. The voyage-related information is composed of departure place, destination, draught and estimated time of arrival (ETA) of the definite route. For the vessels sailing in the deep oceans, the AIS information can also be transferred in remote distances to mainland maritime authorities by means of terrestrial and/or satellite base stations for remote monitoring [2]. Combining AIS with other aid-navigation equipments to complement the disadvantages of individual equipment is the current trend, which generates satisfactory performance in practical applications [5], [6].

Owing to the large amount of advanced equipments adopted to maritime transportation, an increasing number of high-dimensional data have been generated, boosting the comprehensive researches of marine transportation. However, it poses significant challenges for navigators and supervisors to have a deep qualitative understanding of the large amount of vessel traffic data with real-time constraints in practical applications. The introduce of data visualization techniques is capable of coping with those challenges efficiently and effectively. Data visualization is essentially a graphical presentation of information, whose goal is to facilitate the users to gain a qualitative understanding of the massive high-dimensional data information. The excellent visualization system can reveal the structure within massive data, the hidden relationship among massive data succinctly, and thus can help the users to better identify patterns and detect outliers [7]. Ware [8] classified data visualization into three main categories: scientific visualization, information visualization and visual analytics. Scientific visualization demonstrates the structures and evolutions of physical or chemical properties in the spatial domains, which can be subdivided further into scalar visualization, vector visualization and tensor visualization in terms of data

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category [9]. Information visualization focuses on abstract and unconstructed data, such as textual data, software, complicated systems, etc. Graphics, data mining, and human-computer interaction constitute the visual analytics [10].

Data visualization is a powerful and widely-used tool which has been applied to extensive research fields, contributing to the progress of data analysis immensely. The visual presentation of geography data facilitates the transportation as well as improves the people's life quality tremendously. Traffic congestion is virtually endemic in large cities. To deal with this conflict, an interactive system named T-Watcher developed by Pu *et al.* [11] aims to effectively monitor road traffic condition and detect abnormal traffic patterns. For the purpose of establishig a smart city and providing a better life for people, *Live Singapore* [1] is another program which generates the real-time visual representations of the city-related data concerning transportation data, weather data, etc. TripVista has been achieved successfully to investigate microscopic traffic patterns and detect abnormal behaviors from three perspectives, i.e., spatial, temporal and multi-dimensional views [12]. Text Insight via Automated, Responsive Analysis (TIARA), an interactive visual text analysis tool, has been established by Liu *et al.* [13] to help the readers to analyze large collections of text easily and efficiently. As for maritime transportation, Willems *et al.* [14] demonstrated the visual presentation of the AIS data to assist operators of coastal surveillance systems and decision-making analysts to have a comprehensive understanding of the vessel movements, thus enhancing the monitoring efficiency. Besides, medical images, weather forecast, intelligent transportation have evoluted significantly with the introduce of data visualization techniques.

The primary objective of this paper is to provide a brief review for interested researchers to better understand the maritime traffic data visualization techniques. Within this brief review, data visualization techniques in the fields of spatio-temporal vessel trajectories and vessel traffic density have been comprehensively surveyed. The remainder of this paper is organized as follows. Section II briefly views the general pipeline of maritime traffic visualization. Section III describes the visualization of spatio-temporal vessel trajectories. The current progresses on visualization of vessel traffic density are presented in Section IV and future research directions are outlined in Section V.

II. Pipeline of Maritime Traffic Data Visualization

The processing pipeline of maritime traffic data visualization is similar to other pipelines utilized in different tasks [7], [15], such as air traffic data [16], road traffic data [12], etc. The primary purpose of visualization pipeline is to simulate the main steps to transform the raw big data into interactive visualizations [15], [17]. As illustrated in Fig. 1, the general pipeline for maritime traffic data visualization mainly includes three steps. The first step *Data Transformation* transforms raw source data into the desired standard format. Raw data can be collected from different data sources including Radar, AIS and video surveillance, etc. In this work, we only take the maritime traffic data which is essentially obtained from the AIS-based vessel trajectories into consideration. It is well known that the raw maritime traffic data is often degraded with undesirable artifacts, i.e., errors, outliers, and conflicting values. Many efforts [18], [19] have been devoted to improve the quality of raw data in this step. The proposed methods first automatically detect the unwanted artifacts in raw data. The non-linear interpolation methods (e.g., curve fitting [18], multi-regime framework [19], cubic Hermite spline [20], etc.) are then introduced to replace the degraded data with clean data. Data visualization easily suffers from high computational cost due to the large volume of spatio-temporal vessel trajectories. To considerably shorten the computational time, trajectory simplification should be performed to reduce the redundant information while preserving the crucial trajectory features. Douglas-Peucker (DP) algorithm [21], [22] has been widely utilized to compress the vessel trajectories. The second step *Visual Transformation* is implemented to convert data structures into the appropriate visual structures, such as line plots, bar graphs, distribution plots, pie charts and dot charts, etc. Finally, *Visual Mapping* is performed in the third step to map visual structures into the suitable visualization scenarios, such as animation, infographics, color images, and dynamic videos, etc. In each process of data visualization, the user can interactively modulate the parameters in each step to guarantee more natural-looking visualization performance.

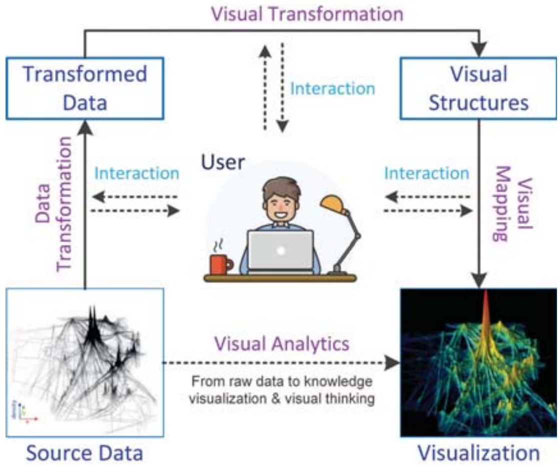

Fig. 1. The general processing pipeline for big data visualization. It has the capacity of visually displaying the essential knowledge behind the obtained raw data through three main steps, i.e., data transformation, visual transformation, visual mapping.

III. Visualization of Spatio-Temporal Vessel Trajectories

A spatio-temporal trajectory $\mathbf{d}$ is essentially a sequence of timestamped locations $\mathbf{d} = \langle d_1, d_2, \cdots, d_{l_{\mathbf{d}}} \rangle$. Each data point

[1] http://senseable.mit.edu/livesingapore/index.html

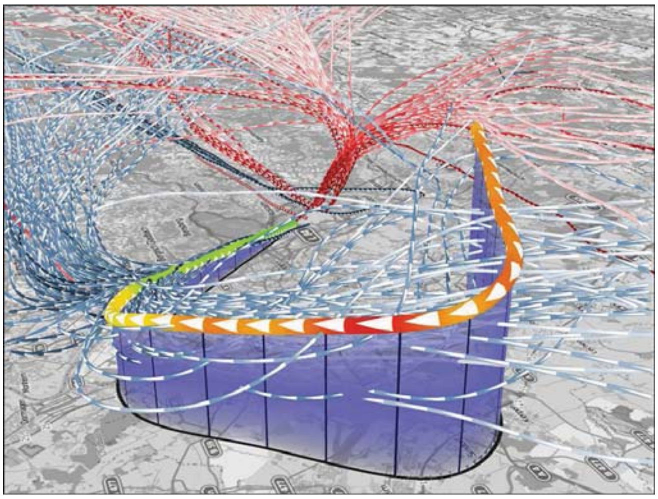

Fig. 2. Exemplary visualization of aircraft trajectories using color mapping, texturing and animation. The image shows departing (red) and arriving (blue) aircrafts. For a selected trajectory, animated arrows depict the direction, while acceleration is visualized by color mapping [23].

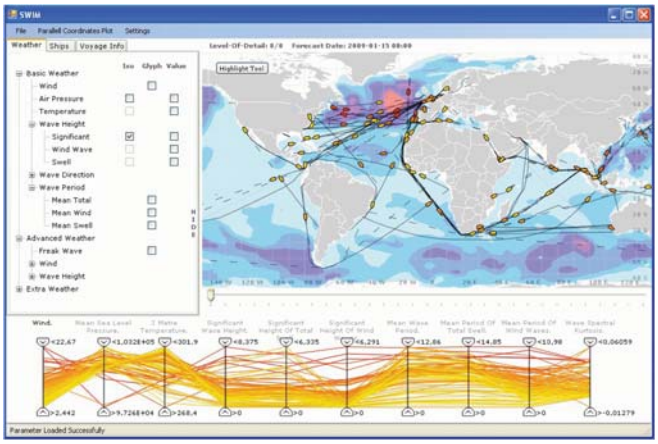

Fig. 3. The SWIM System. The weather data and the planned routes are visualized in the world map. The time slider positioned underneath the map could be used to select the interval you are interested in. The user can select which parameters to be demonstrated with the weather parameter menu on the left. The weather parameters are plotted in the form of parallel coordinates at the bottom [24].

$d_k : 1 \leq k \leq l_{\mathbf{d}}$ in this work is of the simple structured form $d_k \in \left(S^2 \times T\right)$ with S^2 being the geographical latitude and longitude, and T denoting the timestamped point. The visualization of spatio-temporal trajectory is the fundamental but significant visualization technology. The spatio-temporal visualization of human, underwater creatures, vehicle, air traffic and vessel trajectories has been comprehensively investigated in the literature [23], [24], [25], [26], [27].

Space-time cube is the dominating means for visualization of spatio-temporal trajectories. The early studies on visualization of spatio-temporal trajectories in the form of space-time cube could be found in an analytical review article [28]. Stacked visualization of trajectory attribute data has been proposed in Ref. [29], which covers space, time and attribute values. The conventional space-time cube would result in clutters and overlays when analysing massive vessel trajectories, making it difficult for users to have a qualitative understanding of spatio-temporal trajectories in practical applications. To cope with this obstacle, space-time density has been developed by Urška *et al.* [30], however, the problems of clutters and overlay could not been settled down perfectly considering the visual confusion. The space-time density should be further modified to meet the requirement for visualization of massive vessel traffic trajectories, and the comprehensive and detailed density visualization will be further discussed in Section. IV.

For air traffic and submarine exploration, the height and depth are vital factors and should be considered. As a consequence, the 3D (three-dimensional) coordinate system is introduced to enhance visualization performance. For example, animated visualization of spatio-temporal trajectory data for air traffic has been generated in Fig. 2. More attributes are demonstrated by the means of varying colors and symbols [23]. For the sake of better understanding, a survey article for humpback whales has been generated in Ref. [27].There is an intuitive and deepgoing research of the life habits and underwater trajectories of humpback whales.

With the application of data visualization, meteorological routes have progressed tremendously. Ship and Weather Information Monitoring (SWIM) [24], a visual analytics system which visualizes weather data and planned ship routes, aims to provide support for decisions making. The SWIM analytics system is visually displayed in Fig. 3. By visual presentation of the related data, i.e., weather forecast data (e.g., wind velocity and direction, wave direction and strength, temperature, etc) and planned routes, it is of great convenience for shipping companies to monitor their fleet and the weather development along planned routes, thus changing the planned routes timely to guarantee the safety and security of people and property. However, many severe challenges need to be worked out due to the low accuracy of the weather forecast data.

IV. Visualization of Vessel Traffic Density

A. KDE-Based Density Visualization

At present, kernel density estimation (KDE) is the dominating means to visualize the vessel traffic density. The core of KDE is to place a symmetrical surface over each point and then calculate the distance from the point to a reference location and finally calculate the sum of all values for each surface. Let $x_1, x_2, \cdots, x_n \in \mathcal{R}^d$ denote an independent, identically distributed random sample. Mathematically, the general formulation of KDE can be expressed as follows

$$\hat{f}_h(x) = \frac{1}{nh^d} \sum_{i=1}^{n} K\left(\frac{x_i - x}{h}\right), \tag{1}$$

where $K : \mathcal{R}^d \mapsto \mathcal{R}$ represents a smooth function called the kernel function, and h is a bandwidth parameter controlling the degree of smoothing [31]. The widely-used kernel functions $K\left(x\right)$ could be found in Table I. The statistical concept of KDE has been introduced [32] to deal with streaming AIS

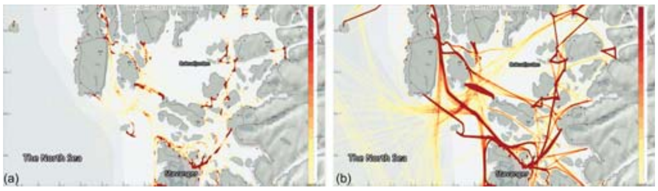

Fig. 4. Two KDE-based visualization results in western Norway. The left subfigure illustrates the position samples as point kernel, while the right one demonstrates the same data using the line kernel proposed in [32].

data. Compared with the convolution kernels along AIS ship paths proposed by Willems *et al.* [14], the introduced line kernel [32] for KDE-based visualization performs better in terms of computational time and visual performance. As shown in Fig. 4, the KDE-based visualization can be implemented on Graphics Processing Unit (GPU).

TABLE I
THE WIDELY-USED KERNEL FUNCTIONS

Kernel Function	$K(x)$
Uniform	$\frac{1}{2}I(\|x\| < 1)$
Gaussian	$\frac{1}{\sqrt{2\pi}}e^{-\frac{1}{2}x^2}$
Epanechnikov	$\frac{3}{4}(1-x^2)I(\|x\| \leq 1)$
Biweight	$\frac{15}{16}(1-x^2)^2 I(\|x\| \leq 1)$
Triweight	$\frac{35}{32}(1-x^2)^3 I(\|x\| \leq 1)$

B. Massive Vessel Density Visualization

Owing to the extensive utilization of AIS, massive vessel traffic data have been generated, facilitating the correlative maritime transportation researches significantly. However, considering the large amount of AIS spatial trajectories may lead to overlays and visual confusion in practical applications. The aggregation algorithm-based density maps are capable of coping with these obstacles commendably.

KDE-based vessel density visualization was implemented by Li *et al.* [22] to gain a deep understanding of crucial characteristics of massive vessel trajectories. Three terms, i.e., vessel density, traffic density and AIS receiving frequency, have been defined absolutely by Wu *et al.* [33]. However, visual presentation of single attribute is of limited use in practical applications, impeding further synthetical visual analytics. To eliminate the bottleneck, many efforts [14], [34], [35] have been devoted by correlative researchers. Based on two varying kernels, the mainstream lanes and the velocity fields are presented integrately through which we can have an overview + detail visualization of vessels sailing in the monitoring waters [14]. In the following researches, Scheepens *et al.* [34] have developed modified density maps to interactively explore multiple attributes of massive trajectories. The resulted maps illustrated outstanding performances in the fields of anomaly detection, risk assessment and hot spot identification, shown in Fig. 5. A flexible architecture [35], a modified version of [34], has been proposed to generate more satisfactory density

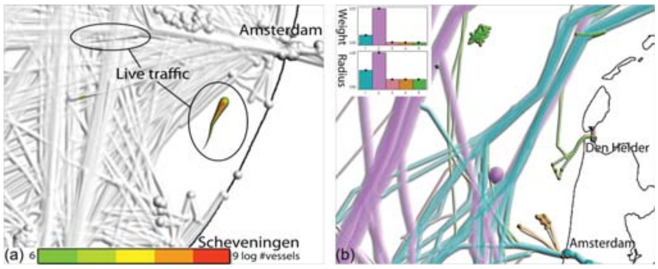

Fig. 5. (a) There are two density fields, one is composed of data of six days, the other is the data of last two hours. The potential anomalies are displayed in color from white (none) and green (low) to red (high). We can see that the left-top ellipse represents the normal behavior while the right-bottom one is detected as abnormal. (b) A risk map with various vessel types: large cargo vessels (blue), large tankers (purple), small passenger ships (pink), small high speed craft (orange), and other type of small ships (green) [34].

maps. The visualization results can enable users to have a self-defined and versatile exploration via the application of multiple density fields.

By comparing the three most dominating visualization means, i.e., density, animation and space-time cube, Willems *et al.* [36] summarized that the vessel density performs best in terms of finding stopping objects and fast moving objects, estimating the busiest routes. A novel practical application has been proposed by Chen *et al.* [37] based on density maps. It is well known that principal fairways (PFs) are the crucial components to be considered when formulating planned routes. A space-use method has been proposed to obtain PFs through massive vessel trajectories, which can decrease the possibility of collision when passing through congested waters.

C. Visualization of Fishing Activities

Fishing activity is one of the most significant exploitative activities by which human harvest natural resources from oceans to get food resources [38]. With the rapidly increased population in the world, the demand for fishery products is rising at a fast rate, thus booming the fishing activities tremendously. However, due to the scanty aid-navigation equipments fitted in the fishing vessels and fishing overexploitation, the monitoring of fishing activities and conversation of ocean natural resources face severe challenges in fishing industries.

To enhance the safety and security of fishing activities and monitor the fishing activities, great efforts have been made by concerning maritime authorities and researchers [39], [40], [41], [42], [43]. An increasing number of advanced technologies and facilities have been applied to fishing vessels. For example, European Union (EN) issued that all the fishing vessels with an overall length exceeding 15 meters must install AIS. Based on collected AIS data, Fabrizio *et al.* [40] have evaluated the equipment condition of AIS for fishing vessels and identified whether it is fishing activity or not based on specific characters of fishing vessels. Through massive data analysis, Daniel *et al.* [41] demonstrated that AIS is able to narrow the gap of national boundaries for enhancing conservation and biodiversity of marine organism.

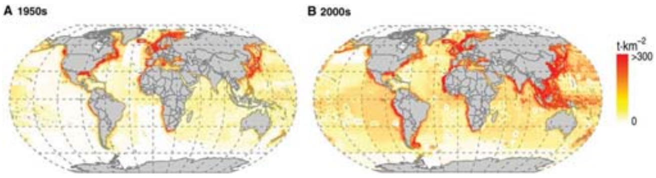

Fig. 6. Spatial distribution and intensity of industrial fishing catch from global perspective. Mean fisheries catch in metric tons per square kilometer by location in the period of (A) 1950s and (B) 2000s [44].

Based on massive amount of high-dimensional data generated by advanced marine facilities, a great deal of concerned researches have been carried out. A visualization framework for fishing vessels has been developed by Rakesh and Sunanda [43], which is capable of monitoring fishing vessels with high efficiency. By projecting the geographical position of fishing activities into world map, the visual analytics of fishing footprint have been investigated from global view [39], [44]. From a global perspective, the patial distribution and intensity of industrial fishing catch at different periods have been visually illustrated in 6. Furthermore, we are able to analyze fishing activities through spatial and temporal aspects. The map of bottom trawling activity has been generated by Carmen *et al.* [42]. There are still huge potentials to utilize advanced visual analytics techniques to monitor the fishing activities efficiently for establishing a sustainable development world.

D. Visualization-Guided Ship Safety Domain

Ship safety domain (SSD), an extension of simple safety distance, has attracted significant attention among the research areas of collision avoidance and maritime traffic engineering, etc. The methodologies for determining SSDs are proposed mainly from three different aspects, i.e., theoretical analysis, knowledge of experts, and empirical-driven analysis [45]. Owing to the wide utilization of radar equipment, ship navigation records could be intuitively obtained through manually collecting the radar data. In the 1970s, the concept of SSD was originally proposed [46] and further optimized [47] by utilizing the radar-based ship positions. With the support of massive AIS data, the probability distributions of ship safety distance for various ship types and sizes were determined in Singapore port waters [48]. It is well known that SSD should be modelled using a safe two-dimensional space distance between ships. The empirical SSDs have been proposed based on massive AIS data from southern Danish waters [49], Singapore Strait and Singapore Port [50], respectively. As shown in Fig. 7, the shape of SSD could be visually determined through the intensity plots which visualized the two-dimensional distances between neighboring ships. These SSDs have significant similarities compared with traditional domains [45], [46], [47] in terms of geometrical size and shape. The massive AIS data has also contributed to discussing the relationship between the size of SSD and the dynamic factors (e.g., ship speed, relative bearing and heading) [50]. To further improve the reliability

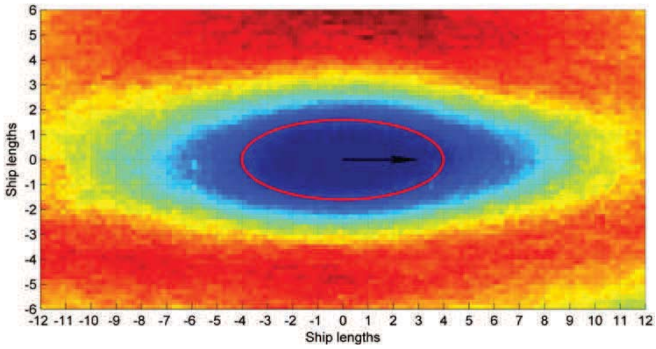

Fig. 7. Intensity plot for all AIS registrations in the Fehmarnbelt area together with a plot of the ellipse predicted by the ship safety domain [49].

of SSD modelling, as discussed in Ref. [45], both ship-related factors, situation and environment-related factors should be taken into consideration. Ship-related factors mainly include own ship's length, speed and maneuverability as well as target ship's length and speed. On the other hand, encounter type, weather conditions, traffic conditions, COLREGS[2], human judgment and perception form the primary situation and environment factors. Most of these influential factors, which assist in determining reliable SSD, could be directly (or indirectly) extracted from the massive AIS data. How to incorporate these factors into traditional data visualization framework to visually determine SSD is an interesting but difficult problem to settle in practical applications.

V. Conclusion

With the rapid development of big trajectory data analytics and computing techniques, data visualization has evolved into a compelling method to discover the power of knowledge from massive vessel trajectories. In this article, we provided a brief review of the research results in the challenging field of maritime traffic data visualization, e.g., visualization of spatio-temporal vessel trajectories and visualization of vessel traffic density. There is a huge potential to adopt these visualization techniques to better understand maritime traffic data and improve maritime transportation safety in practical applications.

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