Mobility Data Mining: the Maritime Use Case

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***Abstract*—Maritime mobility monitoring can be achieved through remote sensing and self-reporting systems, which produce large datasets enabling the extraction of valuable information on global shipping trends. This extraction can be defined as a data mining task of transforming huge amounts of geospatial data, into a descriptive and compact data model, that can then be used for identifying the underlying relationships or patterns. In this work, we present a brief overview of mobility data mining as applied to the maritime use case. We highlight its unique aspects, identify six major data mining tasks, discuss indicative approaches found in literature, and address some challenges for future work.**

***Index Terms*—maritime monitoring, data mining, trajectory analytics, pattern mining, predictive analytics**

I. Introduction

During the last two decades, most industries have undergone digitalization and numerous technological advancements, such as ship tracking, have resulted in the generation and storage of large volumes of data on a daily basis [1]. The use of electronic surveillance methods, such as cameras or radar sensors, has led to the continuous generation of complex data records at a high rate [2]. Interpreting and extracting value from thousands or even millions of records is a highly complex task. While simple aggregation methods may offer basic insights into the nature and distribution of the data, more sophisticated solutions beyond traditional database queries are necessary to extract more valuable information. The process of discovering hidden information and identifying common patterns in datasets is commonly referred to as exploratory data analysis or Data Mining (DM). Different data-driven techniques have been developed to suit the purpose of each DM task.

Mobility data refers to the information that describes the behavior of moving objects. These include the trajectories of automobiles, aeroplanes and even humans. The study of mobility data from a DM perspective has lead to many dedicated works [3], that take advantage of their structure to model patterns of movement. Mobility data and their applications can be categorised according to their degree of freedom of movement [4]. The first category includes objects that move on a predefined network of roads, such as trains or automobiles. This allows their positions to be translated into sequences of road segments, providing context to their movement. For example, a car moving at high speed on a national highway may be categorized as normal, while the same movement on an urban street would be considered an anomaly and a violation of traffic customs. In the second category, when moving objects do not have to follow strict confines, their movement can be categorized as free-space. However, traffic rules and restrictions are generally present, even in scenarios where movement can be unrestricted. In such cases, the objects tend to follow certain paths and trends according to their destination and characteristics.

Maritime mobility data, and more precisely vessel trajectory data, provide an overview for global shipping activities. Due to the size and heterogeneity of such datasets [5], DM techniques can be applied to extract valuable insights and patterns in vessel movement (Figure 1). A few studies that present the state-of-the-art of data driven approaches in maritime mobility can be found in the literature, often focusing on specific goals like anomaly detection [6]–[8] or trajectory forecasting [9]. This work discusses the unique nature of maritime mobility data and presents the major tasks for vessel trajectory analytics from a DM perspective, along with some challenges that arise for future works.

II. The Maritime Use Case

In this work we focus on maritime mobility, and more specifically on surface vessels. This includes two-dimensional human activity at sea (i.e. vessel activity), excluding the underwater operations of submarines and autonomous underwater vehicles (AUVs). Vessel movement was selected for a number

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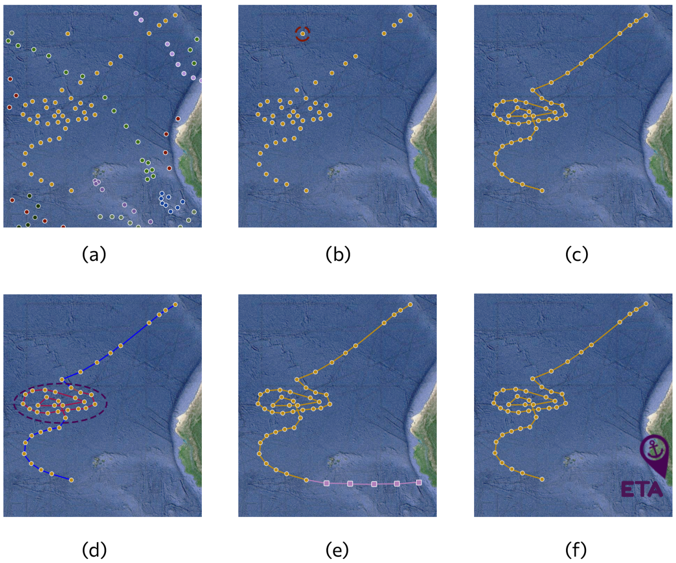

Fig. 1. An example of processing vessel trajectory data. In (a) positional messages from several vessels are depicted in different colors. Extracted patterns of movement can help identifying outlier points (b), resulting in more accurate filtered data (c). Recognition and segmentation algorithms can identify interesting activities, like trawling (d), while predictive analytics can provide a forecast on the future movement of the vessel (e) or an estimated time of arrival (ETA) at its destination port (f).

of reasons, regarding the ships' transportation modes and the availability of data. More precisely:

1) The large variety of ship types allows for different scenarios to be studied. Larger vessels that carry heavy loads only travel between ports and anchorages, mainly for safety reasons, and move with limited maneuverability. Contrarily, smaller boats often follow more complex patterns and may make a round trips to the origin point of departure. Such activities may include commercial or recreational fishing, sailing or yacht voyages. Moreover, other ship types (pilot and tug boats) are designed to operate alongside other vessels, either to guide them in challenging waters due to their lack of mobility. Other types of ships, namely search-and-rescue (SAR) boats and coast guard patrol vessels, operate solely to ensure safety at sea and are often associated with critical events. The activities of military vessels can be treated as a separate category. Since vessel mobility can be linked to commercial shipping, energy, transportation, and even sport, the applications of relative analytics are equally vast.
2) Apart from their "type", other physical characteristics of the vessels can also affect their movement patterns. Smaller vessels typically travel close to the coast and avoid areas with severe weather, while larger vessels can navigate in open waters and generally prefer to operate far from land. Besides their dimensions, their design also plays a crucial part, as vessels like tankers, with their hulls mostly underwater, are significantly affected by the underwater currents. Wind is more important for container vessels, where a larger portion of the ship is above the waterline.
3) Today, over 200 thousand ships from around the globe are constantly monitored from a data perspective, leading to the generation of large volumes of new data on a daily basis. We can distinguish two types of vessel monitoring. The first includes all means to observe a ship's movement without its active participation or consent. This can be achieved through satellite imagery, coastal or port surveillance solutions (e.g. radar and cameras), or drone technology. The second category consists of self-reporting methods of collecting positional records from vessels. More precisely, on-board transmitters send the vessel's position and attributes so that nearby receivers, including other vessels, are able to track its movement. For example, the Long-range identification and tracking (LRIT) protocol was established by the International Maritime Organization (IMO) in 2006, forcing ships to transmit their position and flag a few times a day. The most widely used protocol used around the world is the IMO-reinforced Automatic Identification System (AIS), mandated in 2004. Since protocols such as the LRIT and AIS have been operating for more than 15 years, large historical datasets can be exploited using big data mining methods to accurately model vessel behaviour [1], [10].

III. Maritime Mobility Data Mining

A lot of the published works for maritime trajectory processing fall in more than one type of DM tasks. For instance, a method that identifies common mobility patterns in a specific area can often be applied to predict a vessel's future behavior or detect anomalies. For this study we consider each work's scope in determining its category. Since we only focus on vessel self reporting data, we do not include vessel detection methods from remote sensing images or coastal cameras. Starting from unsupervised knowledge extraction (route extraction and anomaly detection) we move on predictive analytics (path prediction and arrival estimation) and provide a description of activity recognition, like fishing and search-and-rescue operations (Figure 2).

A. Route extraction

Maritime traffic can be modelled using various representations. Extracting common routes provides a street-like view of maritime traffic that is easily interpreted and can be useful for different types of applications, like anomaly detection and path forecasting [11], [12]. [13] identifies points with significant direction change on historical AIS trajectories using the Douglas-Peucker simplification algorithm and then incorporates a merging mechanism to generate a maritime traffic network. Clustering techniques are widely used to identify vessel routes. For example, [14] considers both direction and speed variations to group nearby vessel points and thus detect main traffic routes, while [15] uses an agglomerative algorithm

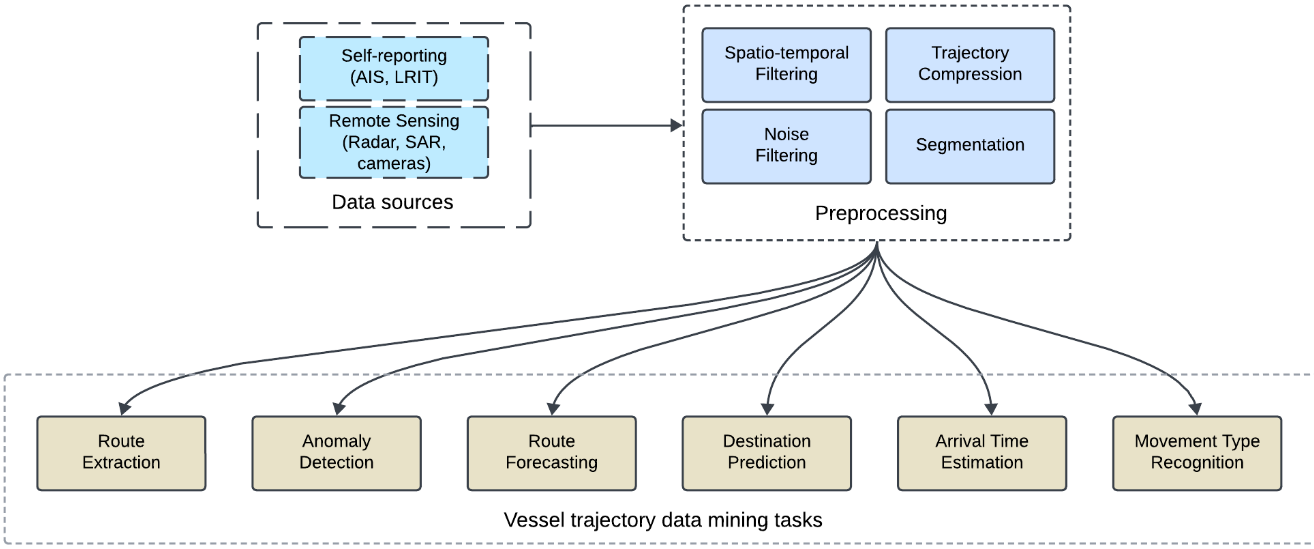

Fig. 2. Trajectory data mining tasks for vessel movement.

to create a hierarchical tree of the clusters. Murray et al. [16] proposed a framework with a two-step clustering, with the purpose of providing estimations on the vessel future paths. More precisely, the AIS points are first clustered to group vessels positions and then a Gaussian mixture model is employed to cluster the near-future trajectories of the grouped points and model possible behaviours. [17] uses a genetic algorithm to extract route waypoints, in order to address the varying traffic density of the data, and turns them into a mobility graph. On the other hand, [18] passes the raw AIS data into a grid structure and extract the routes using a selection of the grid cells.

B. *Anomaly detection*

The main reason behind the maritime surveillance and monitoring protocols is the assurance of safety at sea and accurate risk assessment. Abnormal and dangerous behaviour can be related to the vessel's position, its direction and speed of movement or its relative motion to other ships [6]. Detecting simple events like illegal passage over a restricted area or high velocities does not require DM. More complex behaviours though can be detected by first modelling normal movement in an area and then by labelling remarkable deviations as anomalies [7]. For this purpose, methods like the Gaussian Mixture Models or Kernel Density Estimation model the multivariate inputs (trajectory points) by extracting a distribution and a probability density function respectively [19]. A new input that does not conform to this modelling, i.e. has a lower likelihood than the training data, is labelled as an anomaly. Another approach is based on mobility route extraction, as instances where vessels either follow paths outside the extracted routes or move in the opposite direction are flagged [20].

Two other types of anomalies can be found explicitly in self-reporting protocol data [8]. First, the intentional disruption of the transmission of positional AIS messages occurs so that the presence of a vessel is hidden to nearby observers. The purpose for this AIS switch-off event can either be to hide improper activities, to keep areas of interest secret (e.g. fishing spots) or to avoid detection by pirate vessels [21]. An approach for such anomalies is based on the signal processing parameters by using the AIS message strength to extract a threshold for each base receiver and estimate the lack of transmissions accordingly [22]. Moreover, vessel signals in open waters are often sparse due to lack of good-enough coverage. Bernabé et al. address this issue by determining the possibility of receiving a message in an area using deep learning and flagging inconsistencies with the real data [23]. The other type of anomaly, known as spoofing, refers to the use of another vessel's identification or the transmission of false trajectories, to hide the real paths followed [24], [25]. The direction of arrival of the messages, cryptographic authentication on the transmission device and the calculated speed of the trajectories can be exploited for spoofing detection [26]. d'Afflisio et al. presented a series of works focused on this problem, based on multiple hypothesis testing, using statistical models to estimate the likelihood of such behaviour [27], [28].

C. *Route Forecasting*

One of the most significant challenges in maritime mobility analytics is obtaining accurate forecasts of vessel paths. Traditional vessel movement predictions primarily rely on kinematic equations, while data-driven approaches rely on AIS data to extract historical routes and knowledge [9]. Grid-based approaches leverage historical data to extract mobility graphs for their forecasts. For example, [29] employs an multivariate K-order Markov chain method to extract a possible future path as a series of grid cells. Extracted routes from historical data can also be utilized. More precisely, classification techniques, like support vector machines [30], are used to assign a vessel a most probable route, based on its current trajectory. A plethora of methods based on neural networks (NNs) have been developed in recent years, since the trajectories can be considered as time-series. The memory capabilities of recurrent neural networks (RNNs) are exploited to incorporate the last recorded locations of the vessels, with examples including [31] where the Long-short Term Memory architecture is used to provide forecasts for 60 minutes into the future, and [32] where the encoder-decoder architecture uses advanced RNNs and Bayesian deep learning to consider the prediction uncertainty in their results.

D. Destination Prediction

The destination port may be included in the AIS messages, however, as a manually inserted field, its accuracy is often lacking. The user input is often incorrectly spelled, left unchanged from a previous trip, or refer to multiple ports in passenger vessel trips. The similarity of the current vessel trajectory and past tracks, together with port traffic can be exploited to determine the destination [33]. Eljabu et al. have proposed a methodology that first transforms the input trajectory (through segmentation and interpolation), and then uses different similarity measures to return the most possible destination [34]. Gouareb et al. on the other hand, transform the moving space (trajectories and ports) into a graph and then use an ML technique to provide prediction upon these graphs [35]. The location data are transformed into an encoded sequence and a sequence-to-sequence architecture is utilised in Nguyen et al., to determine the possible future path of the vessel including the end port [36].

E. Estimated Time of Arrival

A critical part of shipping is accurate scheduling, due to the scarcity of available berths at ports. The results of path-finding algorithms may be exploited and expanded to extract an estimated time of arrival (ETA) of vessels [37]. Noting that a vessel's speed is directly affected by the current weather conditions, Ogura et al. addresses this issue by incorporating the wave height and period, the wind speed and the direction of the ship's bow to first determine a probable path and then use distribution of similar vessels to determine the average moving speed, and hence the final ETA [38]. Alternatively, the ETA without path predictions can be achieved by exploiting statistics from historical data. Kolley et al. follow this approach by translating the problem as regression and apply a series of statistical and ML models on AIS-based records [39]. Using a feature set that includes the distance to the destination port, the speed and difference between heading and course (drift), together with the vessels' dimensions, the k-nearest-neighbours algorithm and the NNs seem to outperform the other models. An indicator whether the vessel is currently in open waters or not is also considered by the network. Similarly, the positional and movement features of AIS and LRIT data are used in an experimental comparison of different NNs, including recurrent neural networks (RNNs), by el Mekkaoui et al. [40], that showcased the performance of such architectures. Several weather features, such as the wind intensity and direction and water level, are also fed into a multi-layered NN in Jahn et al [41]. Recently, Zhang et al. has included booking information of a predicted pilotage area for the vessel, to generate an ETA based on a temporal convolutional neural network [42].

F. Activity Recognition

While underway, the vessels take part in various interesting activities. Dedicated methods for detecting such events exploit the vessel mobility characteristics, its shapes of movement and the area attributes; here we present examples for detecting three types of activities. The modelling of vessel fishing patterns has been the focus on several published works [43]. Supervised learning on labeled mobility data, by domain experts, is employed in [44], where the authors use a convolutional neural network (CNN) to classify the activity from scaled and segmented trajectories. A computer vision approach is followed in [45], where different types of activities (including two types of fishing) are detected through classification. The input vessel trajectories are first translated into images and then get fed to a CNN that provides an activity estimation. Classification is also utilized in SAR operations detection. An experimental comparison of different ML techniques (like Random Forests and Gradient Boosted Trees) for classifying SAR instances from AIS trajectories [46] has showcased their accuracy. Vessel speed and the duration of the trip are identified as the most important features for these classifiers.

The case where vessels spend an unusual amount of time in a specific area without significant movement is called loitering and may indicate suspicious behavior. [47] first partitions positional data using the Leader algorithm and then soft computing relationships are explored to extract different zones of movement. A loitering instance can be identified, using statistics on the vessels stay in each zone. [48] calculates a loitering score, based on spatio-temporal characteristics like the frequency of extreme turning and difference of vessel heading and course, with an Isolation Forest algorithm employed to extract the appropriate parameters.

IV. Conclusions and Future Works

In this work we briefly discuss the major tasks for vessel trajectory data mining tasks found in the literature. Prior works leverage large vessel monitoring datasets to extract patterns of frequent movement, recognize complex activities and provide forecasts on the vessel's path.

Various challenges can be identified in the literature and should be addressed by future works. First, due to the profound nature of each data source, methods should be able to easily incorporate data from different sources. The uncertainty or incompleteness of the raw trajectory data can be addressed through fusion techniques [49], [50]. Moreover, hidden relationships between features of different sources may be uncovered to improve accuracy. Another aspect found in literature is the reliance of many of the approaches in neural network architectures. Although these techniques often display an advantage in terms of accuracy and modeling normal behavior, they are not able to effectively uncover the mobility patterns in an interpretable way in most cases. This black-box approach [51] makes it difficult for such models to be incorporated in real-world solutions, as their results cannot be trusted by the users. Explainable artificial intelligence [52] and visualization methods [53] may be utilized to provide a clear description of the resulting models. Finally, as these extracted models may be used in safety-critical applications, the performance and scalability is of high importance. The proposed solutions should be able to handle large datasets effectively, and perform in real-time (with low latency) without losing their accuracy, in order to be incorporated in the emerging intelligent transportation technologies [54], [55], like autonomous surface vehicles [56], [57].

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