Decision Support for Marine Traffic Control based on Route Clustering

V. Grinyak
Vladivostok State University of Economics and Service, VSUES
Vladivostok, Russia
victor.grinyak@gmail.com

Yu. Ivanenko
Vladivostok State University of Economics and Service, VSUES
Vladivostok, Russia
yurown92@yahoo.com

***Abstract*— Current paper is about navigation safety of marine traffic at sea areas. In addition to traditional approach of danger situation detection based on vessels approaching, the current paper introduces another metrics de-rived from kinematic parameters of the vessel itself, to identify whether it follows patterns (rules) of the traffic at a certain sea area. Authors focused their efforts on analyzing existing traffic schemas in order to identify its danger level in general rather than scrutinizing on individual cases. Along with the traditional approach of sea traffic schema identifications, proposed original method of automated identification of sea traffic schemes based on clustering of movement parameters using historical AIS data. The kinematic model with additional clustering of the objects at sea area is used. Clustering is built up on identification of "typical" objects with splitting maritime area into subsets of arias with similar movement patterns. For the clustering decomposition Mountain clustering and Subtraction clustering algorithms were considered. The model under research is built depending on the heading parameter and is applicable for both unidirectional and bidirectional traffic. The historical AIS data of sea traffic at Tsugaru strait is used for identifying traffic schema with the model designed under presented research. The proposed model shows correct identification of the traffic schema, accurately identifies straight-line traffic clustering areas crossing likes traffic clustering areas and active maneuvering areas. Based on model output results, the algorithm is proposed to help with navigation decision making for safe ship traffic in certain sea areas. The calculation of deviation between identified clusters and real ship traffic shows that about 15% of the vessels are not following sea area specific traffic schema. As a part of the work there are analyses of relevant research with emphasizes on superior differences such as automated identification of vessel movement types and quantitative measure of overall danger for the traffic scheme based on clustering analyses. Study of proposed approach for safety measures on real navigation area proves its potential for future implementation in real applications to provide navigation schema for vessel navigators.**

Keywords*— navigation safety, route planning, ship track system, clustering, AIS.

I. Introduction

Ensuring navigation safety of movement is the main problem to be solved during the operation of marine vessels. Classical industry concepts of safe traffic include three tasks that are solved by skippers and coastal service operators: risk assessment of a dangerous approach, prevention of a dangerous approach and planning a safe traffic path [1]. The first task is to detect in advance the possibility of a dangerous approach and warn the skipper that there is a risk of collision with an obstacle or of approaching it at an unacceptably small distance [2], [3]. The second task is maneuvering for the ship to move away from dangerous proximity and developing an algorithm for the actions of the skipper to avoid dangerous proximity with other objects [4] - [6]. The third task is aimed at predicting the navigation situation based on the current situation and calculating the planned trajectory of the vessel in such a way as to ensure its movement at a safe distance from other objects [7] - [9].

A constant increase in traffic intensity in the water areas of seaports and on approaches to them has been observed in recent years. In the waters adjacent to major ports of Asia, up to 3.5 thousand vessels can simultaneously be located. There, the movement of ships is a multidirectional intense traffic [10]. The systematic presence of unconventional vehicles in the water area requires special attention: drilling platforms towed to their destination; military and special vessels; and in the long term - high-speed and highly maneuverable vessels such as ekranoplans and unmanned sea vehicles with their special legal and navigation specifics [11] - [13]. In such conditions, traditional approaches become insufficient for the effective management of the collective movement of ships. This requires the development of new methods and model representations of decision support to ensure the operation of airborne and coastal traffic control systems.

The system of establishing ship traffic routes is one of the elements of the organization of collective traffic at sea [14], [15]. It is a set of restrictions imposed by a specific scheme of ship traffic ("traffic rules") adopted in a water area. The task of developing such traffic patterns was finally formed in the mid-1950s [16] - [18], when radar equipment was massively introduced in the civilian fleet, making it possible to accurately determine the location of the vessel. The purpose of the system for establishing ship traffic routes is to eliminate uncertainties or the possibility of mistaken decisions by boatmasters. Assessment of compliance with the requirements of the system of establishing paths ("traffic rules") can complement traditional safety tools in conditions of heavy traffic. Vessels that violate traffic rules in the waters, from the point of view of classical ideas, may not be dangerous at the moment. However, ships can

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lead to an intractable dangerous navigation situation after some time.

Traffic patterns can be defined in several ways. The expert method consists in considering the geography of the water area, traffic features and various practical aspects of navigation. Another method is carried out based on observations - by highlighting the established patterns of movement of a specific marine area developed by operational practice. A promising way to implement the latter approach is to analyze retrospective data on the traffic of marine areas. The model representations of this problem can be based on the idea of clustering motion parameters. The purpose of this article is to assess the feasibility of determining ship traffic patterns in this way and using them to ensure traffic safety.

II. Problem Statement and Model Representation

The movement of a real ship is a multidimensional and complex phenomenon. Traditionally resorted to simplified kinematic models in the tasks of ensuring navigational safety of ship traffic. The main parameters in these models are coordinates, course, and speed [1], [19].

The collective movement of ships is usually characterized by typical (recommended and / or marketable) heading and speed values in certain sections of the water area [20], [21]. For example, vessels proceed at strictly defined courses and observe speed limits in the fairway sections that are characteristic of straits or shallow water. The values of the courses in the areas of anchorage are diverse and a large proportion of vessels at rest. In fishing areas, ship traffic is irregular, chaotic, etc. Thus, there is a correlation of the coordinates of the vessel with the course and speed. It is convenient to use model representations of clustering from the point of view of the problem of describing the pattern of movement in the water area to specify the dependence of velocities, courses, and coordinates [22].

The idea of clustering is based on the selection of subsets of objects (clusters) that are close to each other in their characteristics. There are two types of clusters: clusters – areas of connectivity and clusters – "clots". In the first case, subsets of objects that are "similar" to each other and significantly different from other objects of the set are distinguished. In the second case, objects with the "most typical" characteristics that are taken as the centers of clusters are distinguished. The remaining objects are assigned to the corresponding subsets if they are "similar" to the selected centers. The clustering problem in both cases is solved on a certain metric - a function that defines the degree of proximity ("distance") between objects [23] - [25].

The well-known work [10] describes the problem of clustering trajectories of the first type. The signs of objects during clustering were the coordinates of the vessels. When finding the areas of connectivity, the main trajectories of the movement of vessels in the area of heavy shipping were identified. This made it possible to identify abnormally moving vessels, whose path was not typical for this area. This was of interest, for example, for law enforcement agencies). It seems advisable to cluster the trajectories of the second type from the point of view of navigation safety problems. It makes it possible to determine the characteristic values of heading and speed in a section of the water area and to evaluate the proximity of the ship's motion parameters to recommended ones.

The central element of the clustering problem is the determination of the distance metric between objects. Let each vessel be characterized by the values *LON, LAT, SPEED, COURSE* - longitude, latitude, speed, and course, respectively. We introduce the metric D_{12} of the distance between objects 1 and 2 as follows:

$$D_{12}^2 = w_{lon}(LON_1 - LON_2)^2 + w_{lat}(LAT_1 - LAT_2)^2 + \\ + w_{speed}(SPEED_1 - SPEED_2)^2 \\ + w_{course}(COURSE_1 - COURSE_2)^2.$$

The selection of weighting factors w_{lon}, w_{lat}, w_{speed}, w_{course} is carried out on the basis of ideas about the characteristic sizes of clusters for each of the measurements. For example, at the rate, characteristic sizes can be 5-10 degrees, at a speed of 2-3 meters per second. The course difference function $COURSE_1 - COURSE_2$ is redefined based on the periodicity of the angle data. Determining characteristic dimensions by coordinates is a non-trivial task. In the water area, sections of long, uniform movement of ships of several tens of kilometers and sections of maneuvering movement (turning) of several hundred meters may be found. Therefore, it is advisable for some applications to resort to decomposition of the original problem. It is required to divide the water area into small (for example, square) areas ranging in size from hundreds of meters to several kilometers. Next, it is necessary to carry out clustering for each of the sections separately, assuming that the signs of objects are only speeds and courses - individually (one-dimensional clustering) or simultaneously (two-dimensional clustering). Such a model representation is related to the practical industry specifics of the problem.

Algorithms of mountain and subtractive clustering are well suited for solving the second type of clustering problem, since they did not require setting the number of clusters. The essence of the first algorithm is as follows. Let there be a set of *M* objects and a distance matrix D_{ij} defining the degree of proximity between objects with indices *i* and *j*. It should be noted that the possible centers of the clusters are the objects themselves. For each of them, a potential value is calculated that shows the possibility of cluster formation in its vicinity:

$$P_i = \sum_{j=1}^{M} \exp(-\alpha D_{ij})$$

where α is the number characterizing the scale of distances D_{ij}, exp () is the exponent operator. At the first step of the algorithm, the potential P_i of each object is calculated and the object with the greatest potential is selected. This object (let its index be equal $\max_1$) is considered the center of the first cluster. At the second step, the potential values of all objects are recounted in such a way as to exclude the influence of the

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potential of the already found cluster - from the current values of the potential P_i, the contribution of the center of the found cluster is subtracted by the formula:

$$P_i^{(2)} = P_i - P_{\max_1} \exp(-\beta D_{i\max_1})$$

where β is the number characterizing the size of the clusters. The center of the second cluster is a point with an index $\max_2$ with the maximum potential value $P_i^{(2)}$. The centers of all the following clusters are similar. The iterative procedure for recalculation of potentials and selection of cluster centers continues until the maximum potential exceeds a certain threshold. The affiliation of a point to a cluster is determined by the distance to the center of this cluster.

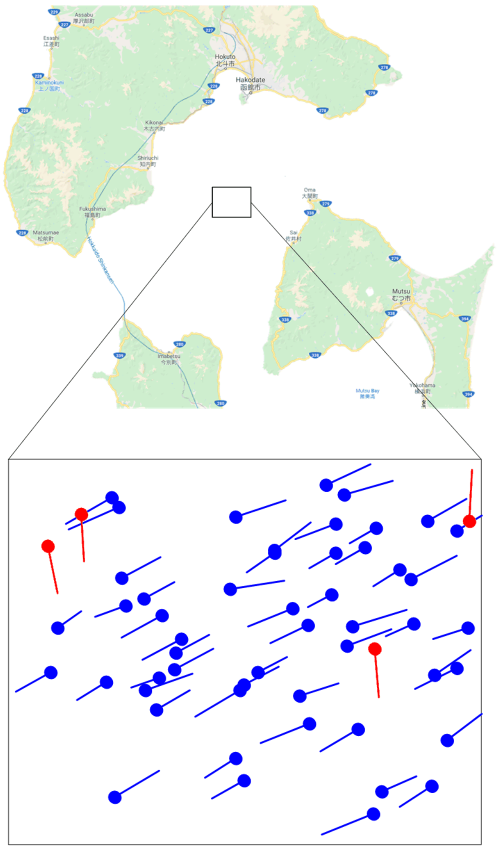

Fig. 1. Coordinates, speeds, and courses of ships in the Tsugaru Strait

The subtractive clustering method is a modification of the mining algorithm. After finding the center of the first cluster, objects belonging to the first cluster are excluded from the set of objects. The following procedure is iteratively repeated until the maximum potential value exceeds a predetermined threshold.

There is a specific feature of the data on the heading of the vessel in the problem under consideration. It is possible to set the course both on the set [0, 360 °), and on the set [0, 180 °). In the first case, ships sailing along the channel both “forward” and “backward” are distinguished. This method is suitable for modeling "two-way" movement. In the second case, vessels moving in opposite directions are not distinguishable. Such a representation is appropriate when it is important to describe the zones of intersection of ship flows.

The solution to the described clustering problem is possible using the data provided by the services of the Automatic Identification System (AIS). The data can be both relevant and retrospective, available on open Internet resources such as [26]. In figure 1 shows an example of visualization of such data. A section of the water area of the Tsugaru Strait in the zone of intersection of ship flows with the coordinates and courses of the vessels that were on it for a day is shown. The prevailing ship rates are clearly visible in the figure — movement in the north-south directions (red circles and arrows) and west-east (blue circles and arrows). This confirms the constructiveness of model representations based on the idea of clustering.

III. Numerical and Full-Scale Results

The study was carried out on real data on the movement of ships in the Tsugaru Strait, collected from the resource [26] using a specially developed software system [27]. Traffic data for one week was taken, about 1.5 million records in total. The water area shown in figure 1, was divided into square sections with a side of 1 km. Clustering was carried out for each of the sites where the number of data was more than 20. Courses were considered signs of objects.

The metric of the distance between objects with indices *i* and *j* was set as $D_{ij} = \sqrt{(COURSE_i - COURSE_j)^2}$, the course difference was additionally determined taking into account the periodicity of the angle values. Courses were given on the set [0, 180 °). The number of course values in some areas reached 200.

The subtractive clustering method was used. The values of the method parameters were selected in such a way as to correctly identify the clusters of the reference sample. As one of such samples, the data shown in figure 1. As a result, the value of the parameter α was chosen corresponding to the characteristic radius of the cluster 16 °. Objects were considered to belong to the cluster if they lay closer than 20 ° from its center (1.25α). The iterative procedure for searching for cluster centers ended if the potential of the next cluster did not exceed 10% of the potential of the first cluster. In this case, the remaining clusters were considered insignificant.

In figure 2 shows data on the number of clusters found. Blue areas of the water are shown where ship rates form one cluster, green - two, yellow - three, red - four. No sites with many clusters were found.

In figure 2, blue areas are clearly visible, in which zones of regular movement of vessels with constant courses are marked. Green areas are areas of intersection of two ship flows. Yellow and red are zones of intersection of several ship flows and zones of irregular chaotic movement (in the area adjacent to the port of Hakodate).

In figure 3 lines show courses corresponding to the first (blue lines) and second (green lines) cluster. It is seen that the found course values fully correspond to the direction of movement of real ship flows.

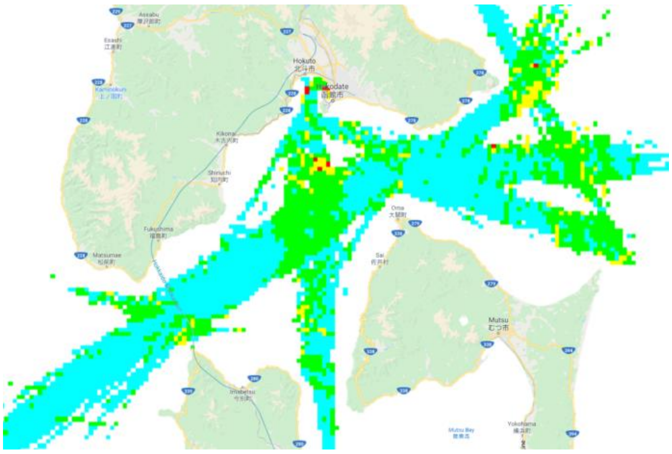

Fig. 2. The number of clusters in ship course data

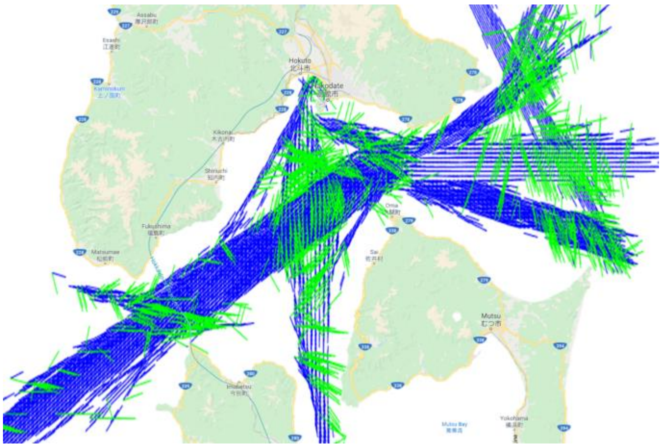

Fig. 3. Centers of the first (blue) and second (green) clusters in ship course data

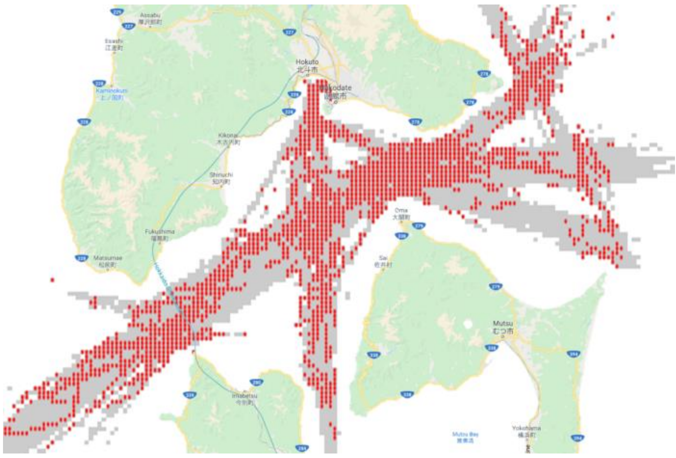

Fig. 3. The area with the established vessel rates (gray) and the points of “violation” of traffic rules (red)

Support for decision-making while ensuring the safety of ship traffic, considering the solution of the discussed problem of assessing ship traffic patterns, is as follows.

1. The assessment of the characteristic values of the courses and / or speeds of ships in certain sections of the selected water area is based on retrospective data on the movement of ships and the considered clustering algorithm.

2. The water area is divided into sections with regulated (where characteristic values of courses and / or speeds are highlighted) and unregulated movement according to the results of stage 1. An appropriate database is formed.

3. The task of risk assessment with other vessels is solved for each vessel located in the observed area. If such a dangerous rapprochement is possible, then the task of preventing a dangerous rapprochement is solved. In this case, we mean the limitations caused by the results of steps 1 and 2.

4. The task of assessing the compliance of the motion parameters with the clustering results at stage 1 is solved for each vessel located in areas with controlled movement. If the vessel moves “not according to the rules”, then the task of planning the safe movement path is solved considering the restrictions caused by the results of stages 1 and 2.

In figure 4 shows the assessment of the correspondence of the parameters of real ship traffic to the results of clustering. It is considered that the possible ship rates are set in accordance with the data in figure 3, and the deviation from the recommended rate should not exceed the accepted cluster size (20°). After it was analyzed the movement of vessels for one day following the period of the initial data on the movement. Gray indicates the area of the water area where ship rates are considered established. This is the area where the ship traffic pattern is set and controlled. Red indicates the points where the movement of vessels was recorded at rates that do not correspond to the established ones. The number of vessels that at least once “violated” the rules for movement in the water area was about 15%. This confirms the relevance of the problem under consideration.

Clustering was carried out only at courses due to the peculiarities of the available data, shown in figure 2-4 examples. Traffic in the Tsugaru Strait is characterized by the stability of ship speeds. Clustering on ship traffic data for one week is already quite representative. But in real-life systems, the sample size should be increased for a high-quality solution to the problem.

Over the past decade, researchers have clearly noted increased attention to the problems of analyzing data on movement in water areas. The work [28] deserves attention. It proposes an expert system for assessing the degree of danger of movement of vessels in limited waters, based on probabilistic model representations. The paper proposes a five-level scale for assessing the degree of danger in the ship-to-ship task and presents research data in the port of Singapore. Moreover, the types of dangerous situations are set a priori. But in the present

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work, the characteristic types of movement are identified based on retrospective data.

It became possible to work with large amounts of data on real ship traffic due to the development of technologies and services of the Automatic Identification System, the concept of e-navigation [29] and cloud computing technologies by researchers. In this area, we can distinguish an article [30]. The paper describes the data available through the AIS system, examines the statistical characteristics of the trajectory data on the movement of ships off the coast of Portugal. A probabilistic model for assessing the risk of dangerous proximity of ships is proposed and an estimate of the number of dangerous situations in the region under consideration is given. Based on the analysis of traffic data arrays, characteristic ship-to-ship navigation situations are distinguished. In this part, the article intersects with the work of Russian authors [31]. This article proposes an analysis of the system of expert ideas about the collective movement of ships based on its division into basic information structures that have a common and representative characteristic. The characteristic configurations (patterns) of dangerous situations of various types (for two, three and caravans of ships) are also described. However, unlike the work [30], in the article [31] navigation situations are determined a priori, from classical geometric considerations. In [32], an analysis of data on the movement of ships in the port of Singapore was performed. The number of dangerous rapprochement of vessels of various classes in certain areas of the water area is estimated based on the classical model of the ship's domain and the assessment of the point of shortest rapprochement of vessels. And, the most difficult sections for movement are highlighted. A relative scale is used to assess hazard. It does not make it possible to assess the need and possible options for changing the existing ship traffic pattern. Only recommendations are given for avoiding marked areas by passenger ships. A similar approach is used in [33].

This article provides a method for quantitatively assessing the danger of traffic patterns in the water area by cluster analysis, in contrast to the works described above. The method reveals another side of the complex and ambiguous concept of "traffic safety". Areas with stable trajectory parameters are potentially less dangerous. The data presented in figure 2, demonstrate the option of assessing the stability of motion parameters in a section of the water area. The number of identified clusters of motion parameters, their “width”, and “spread” of values relative to the centers of the clusters are important. If 1-2 “narrow” clusters are detected at the heading, then this indicates a regular, stable traffic flow in the area. A greater number of clusters at the exchange rate indicates multidirectional intersecting traffic flows or irregular movement. For example, the data in figure 2 suggests that ship traffic is generally safe in the Tsugaru Strait. Increased attention is required only when driving in the area of intersection of ship flows in the center of the strait and at its western entrance.

IV. Conclusion

1. The paper substantiates an approach to assessing the safety of a ship’s movement that complements classical concepts. It is necessary to evaluate not only the actual risk of a dangerous approach with other vessels, but also the correspondence of the kinematic motion parameters to the acceptable values for a given point in the water area (“traffic rules”). This set of acceptable values is proposed to be determined by clustering data on the movement of ships, including the geographical coordinates, speed and course of the vessel. That is, by clustering to evaluate the parameters of the movement pattern in the water area.

2. When solving the problem, it is advisable to resort to decomposition. It is necessary to divide the water area into small sections (from hundreds of meters to several kilometers) and carry out clustering for each of the sections separately. It should be noted that the signs of objects are speeds and courses - individually (one-dimensional clustering) or simultaneously (two-dimensional clustering).

3. Algorithms focused on searching for cluster centers without first specifying their number are promising clustering methods in the problem under consideration. For example, the mountain and subtractive method.

4. The services of the Automatic Identification System can serve as a data source for evaluating the parameters of a traffic pattern in the water area. The paper shows the possibility of using not only primary AIS data, but also their options available on specialized Internet resources. Despite some "sparseness" of this version of the data, they accurately represent the summary features of the traffic.

5. Data on the movement of ships over the course of several days are necessary for clustering the parameters of the trajectories. Arrays of 1.5 million records were processed to form figures 2-4. Highly loaded water areas are characterized by data volumes of up to 50 million records per week. Solving the problem in such areas requires the development of special software systems and algorithms based on supercomputer technologies and big data.

6. Studies of the considered approach to assessing safety on real traffic data have confirmed its promise. Based on the approach, it is possible to obtain information about the formed pattern of ship traffic in the selected water area and to support decision-making while ensuring safety by airborne and coastal traffic control systems.

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