TRANSNAV
http://www.transnav.eu
the International Journal on Marine Navigation and Safety of Sea Transportation
Volume 19
Number 3
September 2025
DOI: 10.12716/1001.19.03.23

Multi-ship Encounter Identification Using Community Detection of Complex Network

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ABSTRACT: With the increasing maritime traffic, the effective identification of multi-ship encounter scenarios has become an urgent demand for maritime management. Traditional clustering-based methods tend to generate identification errors in complex environments. This paper proposes a community detection-based approach for recognizing multi-ship encounter scenarios. Community detection is a technique that discovers collective behavior patterns through network topology analysis. In this study, we first construct a ship encounter network model incorporating dynamic ship features such as positions and headings to characterize encounter relationships among ships. Subsequently, we employ the Louvain community detection algorithm to identify communities within the network, where each community represents a multi-ship encounter scenario. Finally, a case study using real AIS data from the Yangtze River Estuary demonstrates that the proposed method can effectively identify multi-ship encounter scenarios.

1 INTRODUCTION

With the rapid growth of global maritime trade, multi-ship encounter scenarios in complex navigational waters are becoming increasingly frequent, placing higher demands on the timeliness and accuracy of maritime supervision systems. These scenarios involve not only direct navigational conflicts among ships but also mutually constrained dynamic decision- making processes. Their high complexity and uncertainty make traditional two-ship encounter analysis methods inadequate. Although the International Regulations for Preventing Collisions at Sea (COLREGs) clearly define two-ship encounter types such as head-on, crossing, and overtaking situations, the dynamic interaction characteristics of multi-ship encounters have yet to be unified under a comprehensive theoretical framework. Existing approaches still face significant limitations in terms of scenario representation and relationship modeling [1,2].

At present, research on ship encounter scenario identification primarily focuses on two- ship encounters. The main approaches can be categorized into indicator-based methods and machine learning-based methods. Indicator-based methods determine the presence of an encounter relationship based on the spatiotemporal interactions between two ships. Commonly used indicators include ship domain [3], velocity obstacles [4], relative distance, and relative speed [5]. While these indicators can effectively identify potential encounter relationships in simple scenarios, they often involve high computational complexity and are prone to misidentification in special or complex situations [6]. On the other hand, machine learning-based methods leverage large volumes of historical ship movement data to uncover potential encounter patterns, offering stronger generalization and adaptability [7]. However, these approaches typically rely heavily on labeled data, suffer from limited interpretability, and may lack stability when dealing with highly dynamic and uncertain environments.

Compared to two-ship encounter scenarios, multi-ship encounters involve not only direct navigational conflicts between ships but also mutual constraints in navigational decision- making, characterized by high complexity and uncertainty. In recent years, spatial clustering methods have been widely applied to identify multi-ship encounter scenarios. These methods analyze the spatial distribution patterns of ships to detect locally dense areas and identify potential encounter groups. Common clustering algorithms, such as DBSCAN [8,9] and K- means, have demonstrated good performance in processing static or near-static ship distribution data. However, these approaches primarily rely on the geometric positions of ships and fail to fully consider their motion characteristics and dynamic interactions, making it difficult to reveal the underlying structural relationships and potential cooperative behaviors among ships. Moreover, clustering-based methods typically decompose multi-ship encounters into a set of pairwise relationships for analysis, which, while simplifying the complexity of scenario identification, often overlook the intrinsic interactions among multiple ships [10].

To more effectively characterize the complex interactions among ships in multi-ship encounter scenarios, this paper proposes a community detection-based method for multi-ship encounter identification. Unlike traditional clustering methods, community detection originates from complex network analysis and emphasizes the density and connectivity of relationships within a network structure. In this approach, a ship interaction network is constructed by treating each ship as a node and defining the edge weights based on dynamic parameters such as relative position, speed, and heading. This results in a weighted graph model that captures the dynamic interaction patterns among multiple ships. On this basis, community detection algorithms are applied to identify high-density substructures within the network, enabling the effective discovery of ship groups that are in potential encounter states. The arrangement of the article is as follows: Section 2 illustrates the methodology of this paper, a case study is performed in section 3 to show the results of the algorithm and the comparison. and Section 4 discusses the proposed method. Section 5 makes a conclusion.

2 METHODOLOGY

In this study, the objective is to identify multi-ship encounter scenarios within a given maritime region. The study is divided into three main parts: (1) AIS data preprocessing, (2) construction of the ship encounters complex network, and (3) identification of ship encounter scenarios by community detection. The overview of the methodology is shown in Figure 1

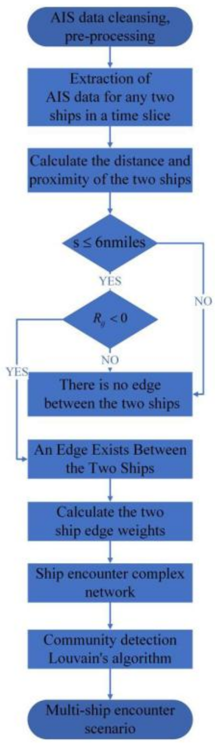

Figure 1.The overview of the methodology

2.1 *AIS processing*

AIS data preprocessing primarily consists of three key steps: decoding, anomaly detection, and interpolation. First, the raw AIS data in NMEA format is decoded to extract essential navigational information, including MMSI, latitude, longitude, speed over ground, course over ground, and timestamps. Next, a combination of rule-based screening and statistical analysis is applied to identify abnormal data, such as invalid coordinates, sudden speed changes, abrupt course shifts, and discontinuities in timestamps. Data points with significant errors are either removed or flagged. To enhance the completeness and temporal consistency of ship trajectories, kinematic interpolation[11] is used to fill short-term gaps, and the data is resampled to a uniform time interval. This results in continuous, smoothed, and high-quality trajectory data suitable for multi-ship interaction analysis. The equations of kinematic interpolation are as follow:

$$a(t) = b + m(t - t_i) \tag{1.1}$$

In this equation, b is a vector representing the initial acceleration of the moving object at the starting time t_i, while m is a vector denoting the change in acceleration over time. By integrating the acceleration function, the velocity and position functions can be obtained as follows:

$$\begin{aligned} v(t) &= v_i + b(t - t_i) + \frac{m}{2}(t - t_i)^2 \\ x(t) &= x_i + v_i(t - t_i) + \frac{b}{2}(t - t_i)^2 + \frac{m}{6}(t - t_i)^3 \end{aligned} \tag{1.2}$$

Here, v_i and x_i are vectors representing the initial speed and position. When the two endpoints p_i and p_j of the trajectory segment to be interpolated are known, their attribute values can be substituted to solve for b and m.

2.2 *Ship encounters complex network*

To effectively characterize the dynamic interactions between ships, this study constructs a ship encounter network based on AIS trajectory data. The network is modeled as a weighted undirected graph, where each node represents a ship. The existence of edges is determined by the proximity relationship between ships, while the edge weights reflect the intensity of potential encounter influence between ship pairs. The construction process consists of two main steps: edge existence determination and edge weight calculation.

Firstly, the distance between each pair of ships is calculated. If the distance is less than 6 nautical miles, the ships are considered to have a potential encounter relationship; otherwise, no encounter is assumed between them. The equation for calculating the distance between two ships is as follows:

$$\Delta x = x_i - x_j \qquad \Delta y = y_i - y_j$$
$$M_i = 7915.7\lg\left(\tan\left(\frac{\pi}{4}+\frac{y_i}{2}\left(\frac{1-e\sin y_i}{1+e\sin y_i}\right)^{\frac{e}{2}}\right)\right) \tag{1.3}$$
$$\delta = \arctan\left(\frac{\Delta x}{M_j - M_i}\right)$$
$$s = \frac{\Delta y}{\cos\delta}$$

Where, x_i; x_j and y_i; y_j are the latitude and longitude coordinates of ship i and ship j, Δx and Δy are the differences in longitude and latitude between the two ships, M_i is the meridian arc length at the location of ship i; δ is the relative bearing between the two ships; e is the eccentricity of the Earth's ellipsoid; and s is the distance between the two ships.

If the distance between two ships is less than 6 nautical miles, their relative approach rate is further calculated. If the approach rate is less than zero, the two ships are considered to be approaching each other, indicating a potential encounter relationship; otherwise, no encounter is assumed. The equation for calculating the approach rate is as follows:

$$R_{ij} = \frac{\overrightarrow{D_{ij}}\cdot\overrightarrow{V_{ij}}}{\left\|\overrightarrow{D_{ij}}\right\|} = \left\|\overrightarrow{V_{ij}}\right\|\cdot\cos\left(\overrightarrow{D_{ij}},\overrightarrow{V_{ij}}\right) \tag{1.4}$$

where $\overrightarrow{D_{ij}}$ and $\overrightarrow{V_{ij}}$ are the relative distance and speed of ship i and ship j, respectively. R_{ij} represents the proximity rate between two ships.

Once the existence of an edge between two ships is confirmed, the edge weight is calculated to quantify the encounter intensity. The equation for computing the edge weight is as follow:

$$\omega_{ij} = \frac{w_1}{\left\|D_{ij}\right\|} + \frac{w_2}{\left\|V_{ij}\right\|} + \frac{w_3}{\left\|\theta_{ij}\right\|} \tag{1.5}$$

where D_{ij} and V_{ij} are the relative distance and speed of ship i and ship j, θ_{ij} is the angle of intersection of ship i and ship j.

2.3 *Identification of ship encounter scenarios by community detection*

In order to recognize the ship groups in the multi-ship encounter scenario, this paper adopts Louvain Community Detection to recognize the community structure of the network based on the constructed ship encounters complex network.

The Louvain algorithm[12] aims to maximize modularity by identifying densely connected subgroups within a network, where intra-community connections are strong and inter- community connections are sparse. The algorithm consists of two main phases. In the first phase, each node is initially assigned to its own community, and the algorithm iteratively considers moving each node to the community of one of its neighbors if such a move results in a higher modularity. Once no further improvement can be achieved locally, the second phase begins. In this phase, the identified communities are aggregated into "super-nodes" to construct a new network. The process is then repeated on the newly formed network until the overall modularity no longer increases significantly. The equation for Modularity is as follow:

$$Q = \frac{1}{2m}\sum_{i,j}\left[A_{ij} - \frac{k_i k_j}{2m}\right]\delta\left(c_i, c_j\right) \tag{1.6}$$

where A_{ij} represents the edge weights between ships i and j, k_i and k_j represent the total marginal rights of ship i and ship j . m is the sum of the weights of all edges in the network.

The Louvain algorithm identifies communities in which nodes are densely connected internally but sparsely connected to nodes in other communities. In the context of maritime traffic, this implies that ships within the same community are more likely to interact and influence each other, while ships outside the community have relatively limited impact. Each detected community can therefore be interpreted as a multi-ship encounter scenario.

3 CASE STUDY

3.1 *Data description and processing*

To validate the proposed methodology, we conducted a case study using real-world Automatic Identification System (AIS) data collected from the Yangtze River Estuary, China. The dataset spans a 24-hour period from May 27 to May 28, 2019. Figure 2 illustrates the visualization of raw AIS trajectories within the study area. The AIS data underwent rigorous preprocessing to ensure reliability. First, erroneous entries were removed. Anchored ships were filtered out by retaining only ships with speeds between 2 and 20 knots. To address irregular sampling intervals in the raw data, we implemented a kinematic interpolation method. Specifically, trajectory gaps exceeding 2 seconds were filled, ensuring temporal consistency and spatial continuity. Table 1 shows the AIS configuration information for the case study

Table 1 Configuration of the case study

Item	Configuration
Area:	Yangtze River Estuary
Latitude:	122°E to123°E
Longitude:	30.5°N to 31.3°N
Time:	2019-05-20 16:00:00 to 05-21 15:59:59
Speed:	2 knots to 40 knots

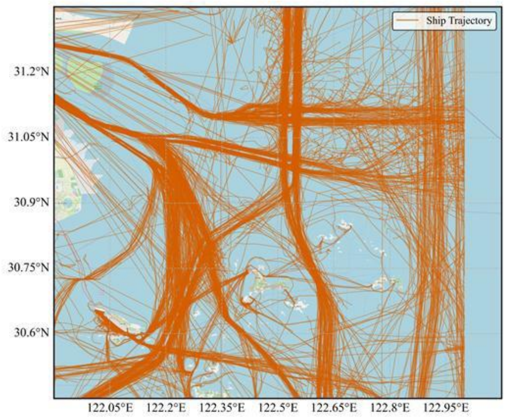

Figure 2. AIS trajectories

3.2 *The construction of ship encounters complex network.*

In this study, we constructed a complex ship encounter network to represent potential interactions among ships within a specific region. The network was then partitioned into distinct encounter communities, each representing a multi-ship encounter scenario. Throughout this paper, we refer to these scenarios as multi-ship encounter communities.

In this case study, we first extracted AIS data corresponding to the timestamp 2019-05- 21 09:31:58, and set the encounter threshold to 6 nautical miles. The distance between each pair of ships was calculated using Equation (3). For ship pairs within this threshold, their relative approach was determined based on Equation (4). If a ship pair was determined to be approaching each other, the encounter influence—i.e., the edge weight in the network—was computed using Equation (5). In Equation (5), the weighting coefficients, and are set to 0.3, 0.3, and 0.4, respectively. The constructed ship encounter complex network is illustrated in Figure 3.

In Figure 3, the link between the two ships only indicates the existence of a encounter influence between the two ships and does not represent the magnitude of the encounter influence

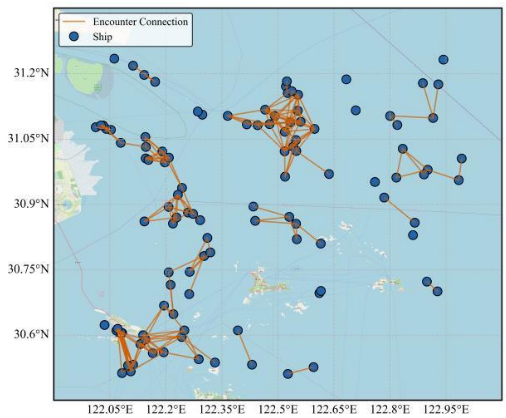

Figure 3. Ship encounters complex network

3.3 *The identification of multi-ship encounter scenario*

After constructing the ship encounter complex network, we applied the Louvain algorithm for community detection to identify multi-ship encounter scenario in the network. The modularity calculation used in the Louvain algorithm is detailed in Equation (6).

In the Louvain algorithm, the resolution parameter controls the granularity of community division, thereby revealing community structures at different scales. This parameter needs to be selected according to the actual situation; typically, the range is between 0.1 and 5.0. Smaller resolution values tend to identify larger communities, while larger resolution values tend to identify smaller communities. In this study, we set the resolution to 1, and we consider the community size obtained under this resolution to be appropriate.

Figure 4 shows the results of identifying a multi-ship encounter scenario using community detection, where each color represents one identified community, i.e., a multi-ship encounter scenario

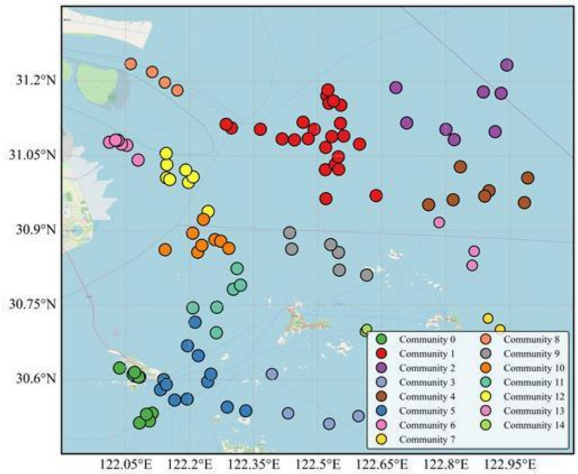

Figure 4. Identification of multi-ship encounter by community detection

Table 2 provides the MMSI information of the ships with the ships identified in the multi- ship encounter communities, based on the community detection method.

Table 2. MMSI in different multi-ship encounter communities

Community	MMSI
0	219xxx000, 412xxx860, 413xxx750, 13xxx650, 413xxx290, 413xxx820, 413xxx780, 413xxx110, 413xxx430, 413xxx000, 563xxx900,
5	354xxx000, 412xxx720, 412xxx520, 412xxx440, 413xxx000,413xxx770, 413xxx620, 413xxx650, 413xxx630, 413xxx890, 414xxx260, 414xxx230,
4	351xxx000, 354xxx000, 412xxx290, 412xxx690, 412xxx580, 413xxx370 413xxx770, 413xxx810, 413xxx490, 413xxx110, 413xxx040, 413xxx070, 413xxx000, 413xxx920, 413xxx040, 413xxx330, 414xxx000, 477xxx900, 538xxx255, 538xxx202, 538xxx464, 564xxx000, 613xxx545, 636xxx895
11	412xxx450, 412xxx710, 413xxx770, 413xxx320, 413xxx050, 413xxx030, 413xxx170, 413xxx240

4 DISCUSSION

4.1 *The validation of the methodology*

In this section, we verify the effectiveness of our proposed method by analyzing the topological connection characteristics of each identified multi-ship encounter community. First, we examined the encounter connections within and between communities, as shown in Figure 5.

Figure 5 presents a comparison of internal and external connections for each community. The results demonstrate that the number of internal connections within communities is significantly higher than connections between different communities, indicating that our community partitioning successfully captures dense connection patterns in the complex network of ship encounters.

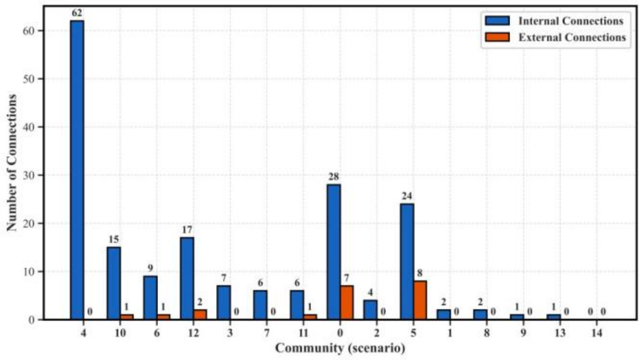

Figure 5. Comparison of encounter relations internal and external in communities(scenario)

In real maritime traffic environments, these dense connections indicate that ships within the same community face encounter conflicts with multiple ships simultaneously. These ships and their encounter relationships collectively form a multi-ship encounter scenario. This finding provides evidence that our proposed method, based on complex network community detection, effectively identifies areas with dense ship encounters—specifically, the multi-ship encounter scenarios existing in the region.

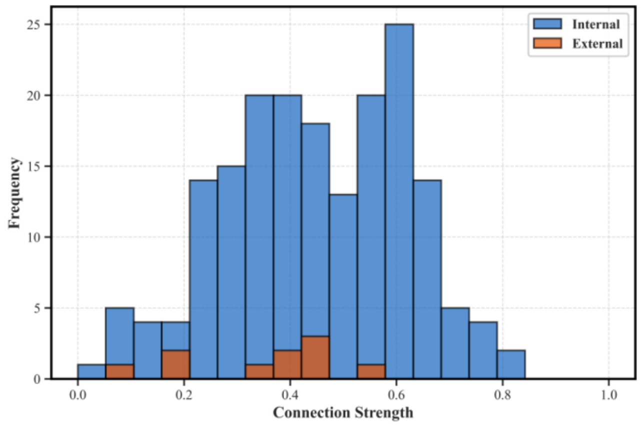

Figure 6. Distribution of connection strengths for internal and external in communities

Furthermore, we analyzed the distribution of connection strengths for each identified multi-ship encounter community, as shown in Figure 6. The average strength of internal connections was found to be substantially higher than that of external connections. This significant difference demonstrates that encounter conflicts within each multi-ship encounter community are considerably more intense than conflicts between communities. In identifying multi-ship encounter scenarios, ships belonging to the same community exhibit more frequent and stronger interactions, while interactions between ships from different communities are notably weaker. This pattern aligns closely with the characteristics of real-world multi-ship encounters. The statistical features illustrated in both figures collectively validate the high accuracy and reliability of our proposed community detection method in extracting multi-ship encounter scenarios.

4.2 *The comparision with DBSCAN*

In this section, we use the DBSCAN algorithm to recognize the multi-ship encounter scenarios in the region, and compare the results with those of the proposed method in this study, and the results are shown in Figure 7.

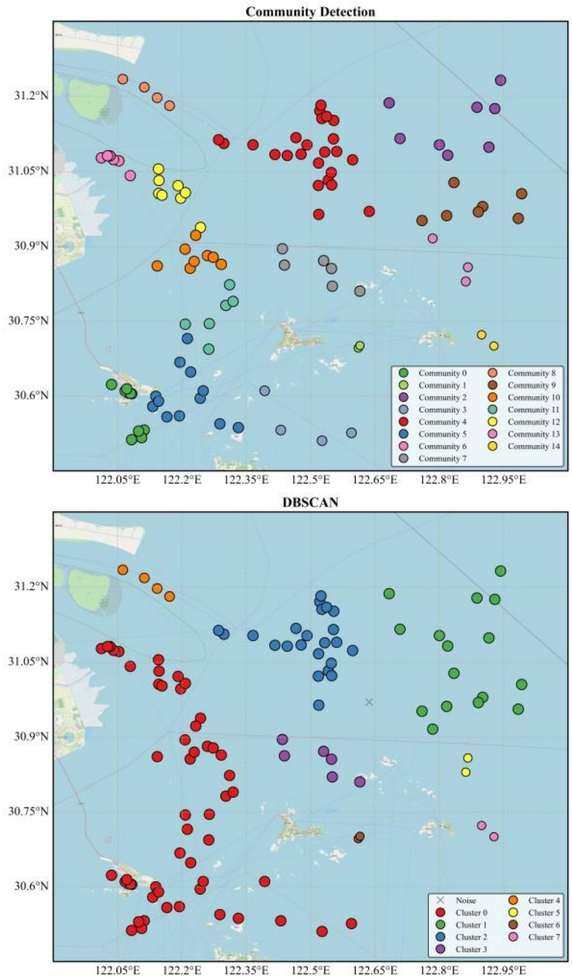

Figure 7. The comparison of community detection and DBSCAN

DBSCAN is a density-based clustering algorithm that identifies clusters by evaluating the density of data points. In Figure 6, to ensure consistency with the parameters used in the community detection method, the neighborhood radius was set to 6 nautical miles, and the minimum number of points (MinPts) was set to 2. As shown in the figure, DBSCAN is capable of effectively identifying densely grouped ships.

However, it also highlights two key limitations: first, the occurrence of density-connected clusters, where ships that are spatially close but belong to different traffic behaviors are incorrectly grouped together; and second, the identification of noise points. These noise points refer to isolated ships that do not meet the density threshold, which may lead to the exclusion of potential multi-ship encounter scenarios, resulting in recognition errors.

In contrast, community detection methods such as the Louvain algorithm do not rely on spatial density but instead partition the network based on the encounter relationships between ships. By optimizing network modularity, the algorithm effectively identifies tightly connected and frequently interacting groups of ships, making it more suitable for analyzing complex ship dynamics and potential multi-ship encounters. Moreover, community detection demonstrates stronger robustness and adaptability, allowing it to reliably uncover meaningful encounter clusters even in cases where the network structure is complex or the spatial distribution is uneven.

5 CONCLUSIONS

In this study, we proposed a community detection-based method for identifying multi- ship encounter scenarios within a specific region using complex networks. Specifically, after preprocessing the regional AIS data, we divided it into time slices and represented each ship as a node in the network. The encounter influence between ship pairs—calculated based on geographic distance, relative motion, and crossing angle—was used as the weight of the edges. In this way, a weighted complex ship encounter network was constructed. We then applied the Louvain algorithm to perform community detection, aiming to identify encounter communities within the network. Each community represents a multi-ship encounter scenario in the region. Finally, a case study using real AIS data from the Yangtze River Estuary was conducted, and the results demonstrated that the proposed method can effectively identify multi-ship encounter situations in regional maritime traffic.

Finally, we further validated the effectiveness of the proposed method by analyzing the internal and external connectivity of the identified multi-ship encounter communities. We also compared our approach with DBSCAN, highlighting the strengths of our method. While DBSCAN is capable of effectively identifying dense clusters of ships, it may misclassify noise points and suffer from the issue of density-connected clusters. In contrast, the community detection method based on the Louvain algorithm is more robust in identifying complex multi- ship encounter scenarios and provides clearer structural insights. However, despite its advantages, the proposed method also has certain limitations. The accuracy of community detection largely depends on the resolution parameter in the Louvain algorithm, which requires careful tuning to balance the granularity of the detected communities. Moreover, although the method performs robustly in detecting ship encounters under most conditions, it may struggle in cases where ships are evenly distributed, making community boundaries less distinct. Future work will focus on enhancing the adaptability of the algorithm by integrating additional factors to improve performance in such scenarios.

ACKNOWLEDGMENT

This work is supported by the National Natural Science Foundation of China under grants 52101402, 52271367, and 52271364. The historical AIS data is provided by the Wuhan University of Technology.

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