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FVRD: Fishing Vessels Relationships Discovery System Through Vessel Trajectory

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ABSTRACT Vessel monitoring system (VMS) is an effective tool for the quantified study of fishing. As the fishing vessels equipped with VMS clients, a large amount of trajectory data has been collected, which brings a new opportunity for fishing research. According to fishery safety production regulations, fishing vessels should perform grouping operations based on actual conditions, but the group information cannot be collected by the VMS. In this paper, we propose the Fishing Vessels Relationships Discovery system (FVRD) by calculating the interaction time among fishing vessels and then using it as a weight to generate a relationship network. The experiment of the proposed FVRD on the vessel dataset of Zhejiang Province reveals that the generated fishing community is consistent with the type of operation of the fishing vessels, which means the proposed method is effective. The experiment also indicates that the fishing vessel relationship network has the characteristics of small-world and scale-free that is similar to the human social network, Moreover, FVRD shows that 86.78% of vessels share the collaboration relationships over one week, 10.72% of vessels are in the long-term cooperation, confirming the regulation that most fishing vessels are sailing together for fishing.

INDEX TERMS VMS, FVRD, data visualization, fishing density, trajectory analysis, group.

I. INTRODUCTION

In recent years, trajectory research is a hot area that attracts lots of scholars to pay their attention to the study of trajectory processing [1], [2], trajectory prediction [3], [4], trajectory classification [5], [6], and trajectory matching [7], [8].

With the deployment of the vessel monitoring system (VMS) in recent years, a large amount of trajectory data has been collected. It records the sailing information of the vessel, including the vessel's ID number, position, heading, speed, and time [9], which brings a new opportunity for fishing researches to study the fishing activity and impact.

Previous research depicts the density distributions of the fishing by exploiting VMS data, all of which can be divided into two phases. The first one is to recognize the fishing segments from all VMS trajectories. Dozens of classification methods are exploited in this step, including thresholds on speed and heading [10], [11], statistical inference [12], [13], machine learning [14] and image processing [15]. With the development of deep learning technology, Zhang *et al.* propose Deep Multi-Scale Learning Model to classify transportation mode and speed [16]. The second one calculates fishing related metrics, covering fishing density [9], [17]–[23], and fishing efforts [15], [24]–[26].

Previous research depicts the fishing metrics, which are important to fishing management and ecology. However, these metrics do not disclose any properties of the fishing process. One important property is the group pattern among vessels. Fishing vessels should go out fishing in groups according to fishery safety production regulations in China [27], The group ensures the safety of fishing vessels for two kinds of reasons. First, once a fishing vessel is in an emergency, the other vessel in the same group can provide aids in time. Second, if the fisheries safety management

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center finds the loss of contact for a vessel on the VMS, it can contact the other vessel in the same group to check the status of the target vessel and to provide aids. Although every fishing vessel has its corresponding registered group, the grouping information cannot be queried in the VMS because it usually changes every year, the fishing groups may have some turbulence in practice as some vessels are in maintenance, on the vocation, or for other sakes, the dynamic in fishing groups put forward the importance of discovering the group pattern among fishing vessels.

In this study, we aim to study the social relationships and further reveal the group patterns among fishing vessels based on VMS datasets, which will help disclose the collaboration among fishing vessels. The critical challenges on digging fishing vessel relationship from VMS data lies in three folds:

1) The vessel social relationship is an ambiguous concept to be defined on the spatiotemporal trajectories of fishing vessels.

2) It's hard to calculate the spatial relationship among vessels when the timestamps of the VMS records are not aligned due to heterogeneity in VMS terminals.

3) It is also computation-extensive because of the large amount of VMS data.

To tackle these challenges, in this paper, we propose the fishing vessel relationships discovering system (FVRD) based on VMS trajectories. FVRD contains two blocks in its design. Its first block exploits the trajectory process model to interpolate the trajectory, align the time steps, and evaluate the spatial closeness among vessels to create companion relationships for fishing vessels. Then the model combines the period between continuous companion relationships to construct the relation models over the time window of one day, one week, two weeks, and four weeks. After creating the relation model, FVRD reveals some critical conclusions from calculating the critical metrics of the relationship model.

FVRD solves the first and second challenges by evaluating the closeness of spatial vessel distributions within different time windows. The third challenge is conquered by applying the data processing model.

FVRD is applied to the VMS dataset logged by the Beidou-satellite system and Automatic Identification System (AIS) in the East China Sea from 2016 to 2018, all of their temporal resolutions is less than 5 minutes. FVRD shows that 86.78% of vessels share the collaboration relationships over one week, confirming the regulation that most fishing vessels are sailing together for fishing. Moreover, 10.72% of vessels are in the long-term cooperation (over four weeks), representing the core members in each group. The comparison between these two numbers shows that the collaborations among fishing vessels are only stable for nearly half core members of each group while loose for the other half.

We summarize the main contributions of this paper as follows:

1) Through the integration and processing of massive multi-source trajectory data, the distance calculation algorithms for fishing vessels with different timestamps are designed as well as the interaction time between fishing vessels is calculated, and finally, the social network of fishing vessels is generated.

2) Based on various metrics, it is found that the fishing vessel relationship network is very similar to the human social network. After analyzing and visualizing a typical community of fishing vessel, this paper employs the fishing vessel relationship network to discover the fishing vessel formation and investigate the fishing vessels out of the group, which can further be employed to explore the trend of fishing intensity changes.

3) FVRD can help to locate the dynamic group member based on the group pattern analysis when some fishing vessel loses contact in VMS, it also can disclose the safety risks for some fishing vessels which goes out fishing without a sufficient number of vessels in one group or even without a group.

4) FVRD can correct the registration error on the metadata of the fishing vessels, and point out that some transportation vessels interact with other fishing vessels.

The rest of this paper is organized as follows. In Section II, we describe the materials and methods. Section III elaborates on the principle of FVRD. Through the experiments and discussions in Section IV, we evaluate and compare the proposed variants with existing benchmarks, and present the conclusion in Section V.

II. MATERIALS AND METHODS

The vessel relation is defined as two vessels sailing along in a close distance for a certain period. Here we choose the threshold of one nautical mile for the distance, which comes from the questionnaires with the fishermen. We propose a novel algorithm for fishing vessel relationship network, and the architecture of FVRD is shown in Fig.1, which contains three steps:

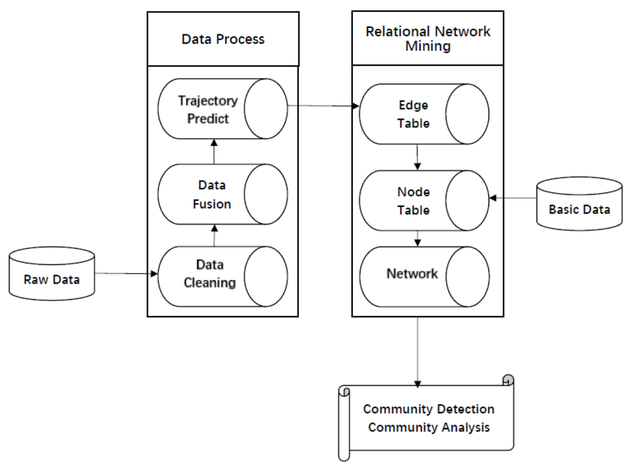

FIGURE 1. Architecture of FVRD.

Step 1: Data processing. This paper preprocesses the raw satellite trajectory data and Automatic Identification System (AIS) trajectory data, including data cleaning, data fusion, and generates predicted trajectories at a fixed time.

Step 2: Generate network. This paper uses the interaction time of each vessel as weights to generate a network of undirected graphs.

Step 3: Community division and analysis. This paper divides the community of fishing vessels and visualize the network using the Fruchterman Geingold algorithm [28].

A. DATA PROCESSING

There are several issues with raw trajectory data:

(1) A vessel usually installs several terminals, such as Beidou and AIS terminals, so the data center can receive multiple positioning data from the same vessels.

(2) Since there are interferences and noise in the transmission and decoding of data, the received data contains a certain percentage of zero values and unreasonable values.

(3) The original trajectory data fluctuates greatly. The reason for the fluctuation is that the antenna is on the top of the vessel, and the influence of waves shakes it.

To solve the above problems, we generate new data through data cleaning, data fusion, and recalculation of speed and heading.

1) DATA CLEANING

In order to improve the availability of the data, we clean trajectory data.

Firstly, we clean missing value in the trajectory, nearly 5% of data which is rare and incomplete is deleted from the dataset.

Secondly, we define the reasonable range of data: longitude range [0,180 °], latitude range [-90 °, 90 °], and speed range [0,40 knots], about 1.5% of data which out of the scope are deleted.

2) DATA FUSION

The description of the multi-source positioning data fusion algorithm used in this paper is as algorithm 1:

The idea of Algorithm NewTrack is as follows:

After the data verification, the data update and data fusion are performed according to the timestamp, and multiple terminals of a vessel (AIS data and satellite data are merged) are updated to the fusion data table.

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After the data verification, the data update and data fusion are performed according to the timestamp, and multiple terminals of a vessel (AIS data and satellite data are merged) are updated to the fusion data table.

Through observing the vessel trajectory data, it is found that the heading and speed fluctuate greatly for there are all instantaneous values. Additionally, there are great differences between the instantaneous value and the actual value, because of the impact of vessel shaking and waves. In order to solve the above two problems, According to the Aviation Formulary [29], this paper calculates the distance and heading of the two points.

Algorithm 1 NewTrack

```
1: INPUT: AISDYNAMICLOG, TRACKS, MMSI
     //AISDYNAMICLOG: AIS Position; TRACKS:
     Satellite Position; MMSI: Maritime Mobile Service
     Identify
2: OUTPUT: NewTrack //New Position of Vessels
3: for AISDYNAMICLOG.MMSI=MMSI and
LASTTRACK.MMSI=MMSI
4:  if AISDYNAMICLOG is VALID // Data Verification
5:    update AISDYNAMIC // Update AIS Position
6:  if TRACKS is VALID //Data Verification
7:    update LASTTRACK // Update Position of Satellite
8:  if AISDYNAMIC. DRRCVTIME>=LASTTRACK.
    RECEIVE_TIME
9:    Newtrack= AISDYNAMIC
10:  else
11:    Newtrack=LASTTRACK // Use Last Position
12:  end if
13: end for
```

Because the time interval between two adjacent points on the trajectory is very short, which ranges from 300 to 600 seconds, the speed change of the fishing vessel is very small. Here, the sailing of fishing vessels is considered at a uniform speed within this interval. Therefore, we calculate the speed of the two points in the following way: $v = S / t$, where S is the distance between the two points and t is the time difference between the two points.

3) TRAJECTORY PREDICTION ALGORITHM

Since the sampled timestamps of each two vessels are asynchronous, so it is necessary to conduct interpolate operation on the sampled dataset, and finally achieve the aim of data synchronization.

Because the trajectory data is massive and the calculation cost is expensive, this paper uses Easy Dead Reckoning (EDR), which refers to the idea of the DR algorithm [30]. EDR algorithm to predict the trajectory and reduce the cost of calculation when predicting a large number of trajectories in batches, while the L-VTP [31] method is employed to predict a small number of trajectories.

The principle of EDR algorithm is similar to the Dead Reckoning Algorithm [30], assuming that the line between two adjacent points is a straight line and the speed is constant, the position of the next trajectory point can be predicted based on the heading and speed. Because the time interval of two trajectory points ranges from 5 to 10 minutes, the speed of fishing vessel always slower than 10 knots, under these conditions, there is little change in the heading and speed, so we can use the formula plane geometry to calculate it.

B. RELATIONAL NETWORK MINING

The Relational Network Mining Algorithm includes five steps:

Algorithm 2 EDR

1: INPUT: A($lon1, lat1, t1$) , B($lon2, lat2, t2$)
   // longitude, latitude, and timestamp of A and B
2:OUTPUT: C($lon3, lat3, t3$) // C is the prediction point
3:if $t2 <> t1$ then // Different timestamp between A and B
4: $lat3 = ((lat2 - lat1) / (t2 - t1) * t3 + lat1 - (lat2 - lat1) / (t2 - t1) * t1)$
5: $lon3 = ((lon2 - lon1) / (t2 - t1) * t3 + lon1 - (lon2 - lon1) / (t2 - t1) * t1)$
6: end if

Step 1: Use the EDR algorithm to predict a new trajectory from massive fishing vessel trajectory data. The trajectory starts from 00:00 every day and finally generates 144 track points one day for each vessel by predicting the trajectory every 10 minutes, such as 8:00, 8:10, 8:20, etc. As shown in Fig.2, the generated trajectory is the same as the original trajectory.

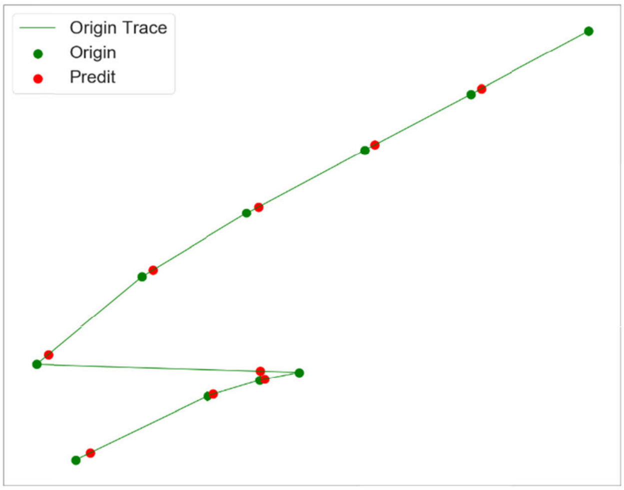

FIGURE 2. Comparison of the original trajectory and the trajectory predicted by the EDR Algorithm.

Step 2: According to the new trajectory and the port area delineated by VMS, select the trajectory outside the port.

Step 3: Generate four one nautical mile grid centered on each fishing vessel at each timestamp, and count other fishing vessels in the grid. If there are fishing vessels in the grid, regard the interaction time as 10 minutes. As shown in Fig.2, the side length of each grid is one nautical mile, and other fishing vessels in the four grids (gray) around the red vessel are recorded as interacting with the red vessel.

Step 4: Calculate the cumulative one-year interaction time for all registered fishing vessels and delete the duplicate data.

Step 5: To calculate the interaction time which is not shorter than one day of each vessel, the interaction time is used as the weight to generate the edge table, and the node table is generated from the fishing vessel basic information database, which represents the basic situation of fishing vessel nodes. Then combine the edge table and the node table to generate the relationship network data of the fishing vessels.

This paper takes the interaction time of fishing vessels as weight, and the unit is a day. Due to the volume of the data is large, we conduct the relational network algorithm to generate a total of 663,465 rows of relational network fishing vessel relational network data (edge table data from 2016 to 2018). The average time taken to create the network every year is 164 hours and 53 minutes.

C. COMMUNITY DETECTION AND ANALYSIS

We detect the fishing vessel community by referring to the Fast Unfolding Algorithm(FUA) [32]. The basic idea of the algorithm is to conduct local optimization, and combine with multi-level clustering technology:

Step1: Assume that we start with a weighted network of N nodes, and assign a unique community to each node of the network, then the number of the communities is equal to that of the nodes in this initial partition.

Step2: For each node i, we consider the neighbors j of i and we evaluate the gain ΔQ of modularity [28] that would take place by removing i from its community and by placing it in the community of j. The node i is then placed in the community for which this gain is maximum, but only if this gain is positive.

Step3: If no positive ΔQ is possible, i stays in its original community. This process is applied repeatedly and sequentially for all nodes until no further improvement can be achieved and the first phase is then complete.

The gain in modularity ΔQ obtained by moving an isolated node i into a community C can easily be computed by (1):

$$\Delta Q = \left[\frac{\sum_{in} + 2k_{i,in}}{2m} - \left(\frac{\sum_{tot} + k_i}{2m}\right)^2\right] - \left[\frac{\sum_{in}}{2m} - \left(\frac{\sum_{tot}}{2m}\right)^2 - \left(\frac{k_i}{2m}\right)^2\right] \quad (1)$$

where $\sum_{in}$ is the sum of the weights of the links inside C, $\sum_{tot}$ is the sum of the weights of the links incident to nodes in C, k_i is the sum of the weights of the links incident to node i, $k_{i,in}$ is the sum of the weights of the links from i to nodes in C and m is the sum of the weights of all the links in the network.

In the next section, we analyze the communities of fishing vessels and compared them with existing benchmarks.

III. RESULTS AND DISCUSSION

A. DATA

The dataset about VMS trajectories of active fishing vessels is recorded by Zhejiang Oceanic and Fishery Bureau, China. Specifically, the trajectory data contains the time, position, speed, and heading, etc. of the fishing vessels in the East China Sea from 2016 to 2018. The dataset has a total of 2,966,826,384 records of Beidou satellite positioning data and 9,584,361,895 records of AIS data, respectively, both of their temporal resolutions is less than 5 minutes.

TABLE 1. Statistics of fishing vessel networks in Zhejiang province.

Metrics	2016	2017	2018	Mean
Node	13468	13451	13368	13429
Edge	536886	546886	526436	536736
Average Degree	79.728	77.728	76.325	77.927
Diameter[34]	15	14	14	14.333
Average Path length[34]	3.936	3.535	3.536	3.669
Modularity[32]	0.885	0.865	0.866	0.872
Connected Components[35]	128	136	116	126.667
Average Clustering Coefficien[36]	0.339	0.346	0.324	0.336

B. ANALYSIS OF FISHING VESSEL RELATIONSHIP NETWORK

1) RELATIONSHIP NETWORK

The fishing vessel relationship network is regarded as an undirected graph. The edge table and node table are imported into Gephi software [33] and combined to generate a community network.

This paper generated the fishing vessel relationship network from 2016 to 2018 according to their weight (weight>=1), and the metrics are shown in Table 1.

The network has the characteristics of small-world [37] and scale-free [38]. It can be observed from Table 1 that the average degree of nodes is reaching up to 77.927, and the actual group of fishing vessels is only 6-10. In addition, the fishing vessels group only exists in the same operation mode, so this indicator can only explain frequent interactions while cannot explain the formation of vessels. The study of the fishing vessel network in Zhejiang Province found that the diameter of the network was 14.333, and the average distance was 3.669 among all types of vessels (13,429 vessels), indicating that any two vessels can make connections bypassing less than four vessels on average. The modularity is 0.872, and the larger the modularity, the more reasonable the corresponding community division. The number of connected components reaches 126.667, indicating that there are many disconnected networks. When fishing vessels are in operating, the fishing vessels are grouped into three types of operations: Trawl, Purse Seine and Gill Net. Among all the auxiliary vessels, transportation vessels interact with other fishing vessels. We generate the four types of interaction time as shown in Table 2.

From Table 2, it can be found that the weight distribution of Trawl, Purse Seine and Gill Net is concentrated between 1-2, and the distribution of weights conforms to the power-law distribution [38]. Moreover, it also reveals that the median weight is about 2 conforms to the power-law distribution.

The interaction frequency is relatively concentrated in the weight of 1-2. It is not the actual grouping, but the fishing vessels of the same operation method have interaction in the same fishing area. Therefore, it is of practical significance to study the fishing vessel relationship network in the same area.

TABLE 2. Weighted statistical metrics (2016-2018 Zhejiang fishing vessel average).

Metrics	Operation type			
	Trawl	Purse Seine	Gill Net	Transportation Vessel
Average	2.7824	2.9022	2.5695	2.4789
Standard deviation	2.2510	2.2617	2.0963	2.0452
25%	1.3542	1.4097	1.3125	1.2569
50%	1.9583	2.0972	1.8194	1.7083
75%	3.2153	3.4444	2.8750	2.7639

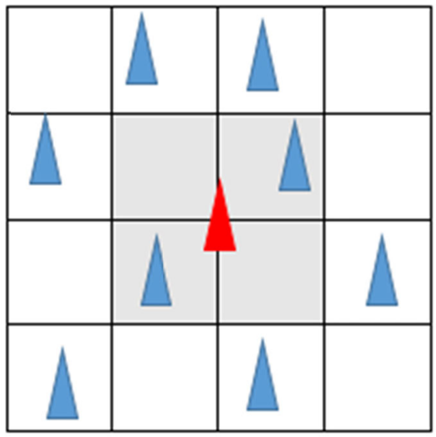

FIGURE 3. Record the interaction time, vessels in the gray grids around the red vessel are considered as interacting with the red vessel.

Figure 4 shows the distribution of degrees of all fishing vessel relationship networks in Zhejiang Province in 2016, and the degree of nodes is a dense area from 0 to 10, which is the same as the actual number of group members.

The degree distribution of the fishing vessel relationship network is not uniform. Only a few nodes have many connections with other nodes and become "central nodes". From the overall trend of the degree distribution in Fig.4, it can be seen that the nodes with smaller network degree values account for a large proportion, but the nodes with large degrees are very rare, so it demonstrates that the network follows the power-law distribution.

Because the generation of relational network data is generated by the trajectory of fishing vessels leaving the port, and the number of fishing vessels group ranges from 6 to 10, we get an average degree of 77.927, which indicates that the interaction between fishing vessels is frequent. The average degree shows that in addition to the grouping of fishing vessels, there are interactions with other fishing vessels.

This paper explores the social network of fishing vessels from 2016 to 2018, with an average of 13429 nodes and 536736 edges annually.

We use the FUA algorithm to detect the communities of the dataset, and compare it with several other popular algorithms, the result of which is shown in Table 3.

The modularity of the network, as we know, reflects the structural degree of the communities. It can be observed from

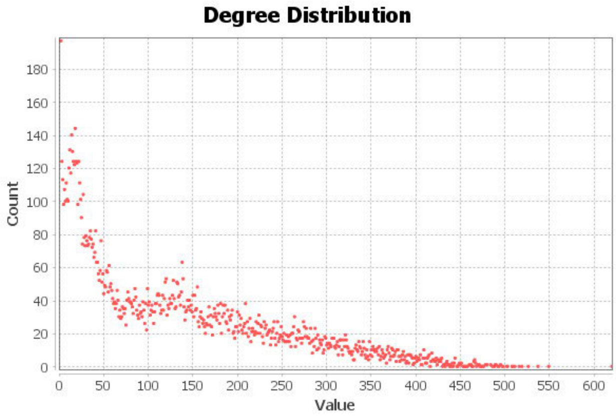

FIGURE 4. Distribution of the degree of all fishing vessel relationships in Zhejiang Province in 2016.

TABLE 3. Test results of community detection algorithm (2016-2018 Zhejiang fishing vessel average).

Algorithm	Metrics		
	Modularity	Number of Communities	Time (S)
FN	0.852	67	32.568
GN	0.861	92.333	2925.364
FUA	0.872	62.667	9.337
Walktrap	0.817	318.667	66.258
LPA	0.802	256.363	10.253

Table 3 that the communities detected by modularity based algorithms such as FUA algorithm, FN algorithm [39], and GN algorithm [40], have higher modularity, which proves the feasibility of modularity based algorithms in detecting communities.

Although the modularity and the number of communities with FUA, FN, and GN algorithms are similar, the GN, unfortunately, converges with an average of 2925.364 seconds, while that of FUA algorithm is only 9.337 seconds.

According to the fishery administration, the actual number of communities is between 60 and 90. However, the number of communities detected by Walktrap algorithm [41] and LPA algorithm [42] is much larger than the actual value. Obviously, the more communities the algorithms detected, the weaker the community structure will be.

Table 4 shows companion relationships to the relation models over the time window of one day, one week, two weeks, and four weeks. We can see that the longer the interaction time, the fewer nodes and edges, the higher the degree of modularity. It can also be seen that the longer the interaction time, the greater the number of communities. We can see that the vast majority of fishing vessels have interacted for more than one week, reaching 86.78% (11653/13429), usually from the same operation mode of fishing vessels from the same region, and communities that have interacted for more than four weeks have reached 1440, and they account for about 10.72% (1440/13429). These fishing vessels are Pair Trawls, which work together.

TABLE 4. Analysis of network metrics for various interaction times (2016-2018 Zhejiang fishing vessel average).

Interaction Time	Metrics			
	Modularity	Number of Communities	Nodes	Edges
One day	0.885	68.333	13429	536736
One week	0.958	266.333	11653	92118.667
Two weeks	0.980	815	9904	40772.333
Four weeks	0.993	1440.667	6900.333	14646

TABLE 5. Ruian's fishing vessel network from 2016 to 2018.

Nodes				Operation Method
2016	2017	2018	Mean	
74	75	63	70.667	Shrimp Trawl
35	38	35	36	Otter Trawl
96	84	70	83.333	Pair Trawl
134	135	131	133.333	Gill Net
0	4	2	2	Stow Net
30	25	22	25.667	Transportation Vessel
368	361	323	350.667	Total

This further verifies that the fishing vessels are worked in groups.

2) VISUALIZE FISHING VESSEL COMMUNITIES

This paper generated a fishing vessel network map of every city in Zhejiang Province from 2016 to 2018 through a force-oriented layout algorithm-Fruchterman Geingold algorithm [28]. The connection between every two vessels indicates that the two vessels have a special relationship, which can be a grouping or commercial relationship.

The network diagrams generated are shown in Fig.5, which is the fishing vessel relationship network in Ruian City as a typical fishing vessel community for analysis. It can be seen that the visualization of the fishing vessel's network relationship reflects the operation of the fishing vessel.

It can see from Table 5 that the average number of nodes generated by the algorithm is 350.667, which is consistent with the number of fishing vessels in actual operation, and the average number of registered fishing vessels in Ruian City from 2016 to 2018 is 436.

From Fig.5, it can be seen that fishing vessels of the same operation type are clustered together, which is consistent with the actual fishing vessel operation method.

However, there are also different types of vessels mixed in the cluster of pair trawl, which may be induced by two reasons:

The first is the registration information error. As shown in Fig.6, we found that two Gill Net (blue nodes) were divided into the cluster of the Pair Trawl (green nodes). To explain this phenomenon, we replayed the trajectories and then we found that the trajectories of the two vessels were almost the same, which matched well with the trajectory characteristics of the Pair Trawl trawling together (Fig.7).

Therefore, this paper verified the information of these two Gill Net with the management department, and it turned out that the actual type is Pair Trawl which is misregistered as Gill Net. Additionally, we used the same method to find out the other three vessels with incorrect registration information.

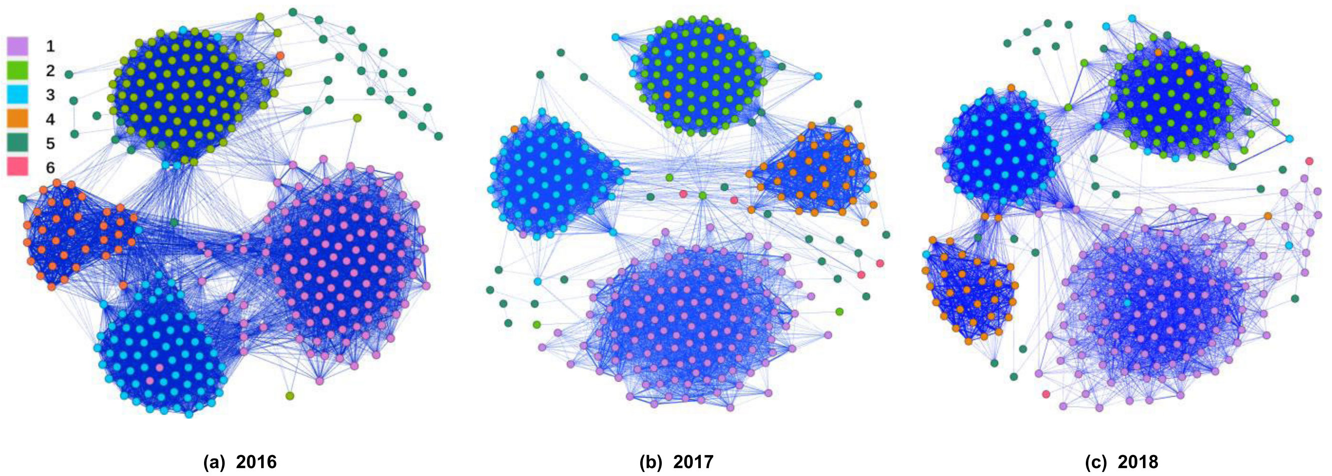

FIGURE 5. Visualize all fishing vessel relationship networks in Ruian from 2016-2018 (fishing vessel operation method:1-Gill Net; 2-Pair Trawl; 3- Shrimp Trawl; 4-Otter Trawl; 5-Transportation Vessel; 6- Stow Net).

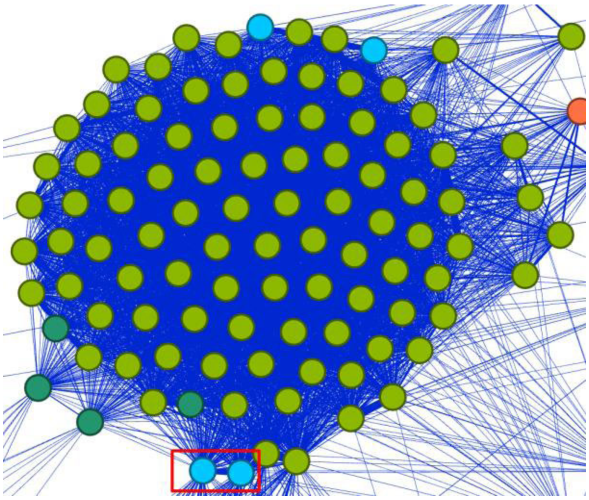

FIGURE 6. Enlarged image of Pair Trawl community in 2016.

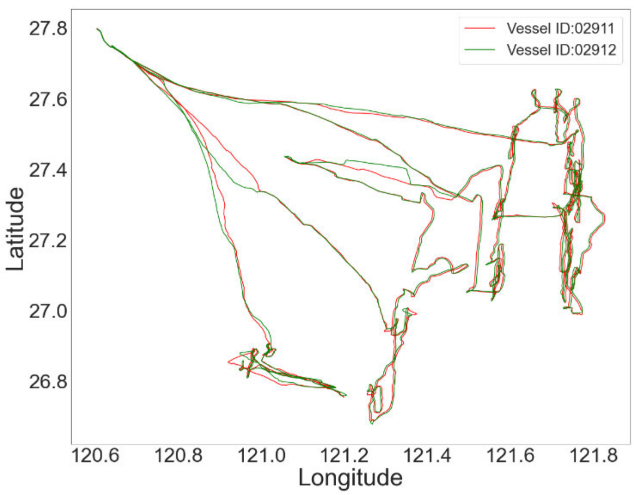

FIGURE 7. The trajectory of two pair trawls throughout 2016.

The second is because fishing vessels are not grouped out, such as Transportation Vessels, which serve fishing vessels so that they will be in the same community as a certain type of fishing vessel. There is also a strange phenomenon.

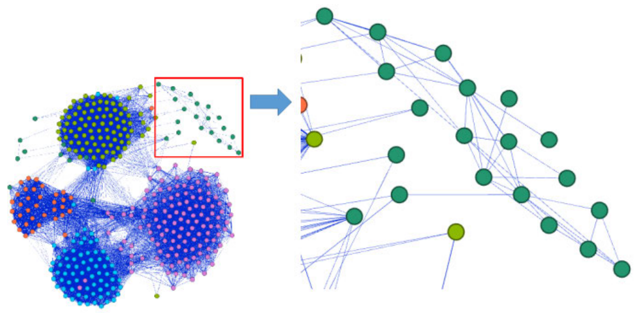

FIGURE 8. Visualize one of the Transportation Vessels community in Ruian 2016.

The Transportation Vessels in the red box in Fig.8 is a relatively independent community. In order to explain this phenomenon, we conducted an in-depth investigation and found that this part of the Transportation Vessels is not serving for fishing vessels of Ruian City. Using this method of community network visualization, this paper explains many strange phenomena of many fishing vessel communities.

IV. CONCLUSION

In this paper, we propose the fishing vessel relationships discovery system (FVRD) to discover the relationship between vessels. Firstly, a trajectory prediction and distance calculation algorithm were proposed to calculate the interaction time between fishing vessels. Secondly, the fishing vessel community was divided by the FUA algorithm for grouping fishing vessels according to operation types. Then, the proposed method was verified on the vessel dataset of Zhejiang Province. Finally, through the visualization and analysis of fishing vessel community networks, this paper explains many interesting phenomena of fishing vessel communities.

In our future work, we consider optimizing the Relational Network Mining Algorithm to improve its calculation efficiency. In particular, we will further study the evolution of the fishing vessel community.

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