Recognizing Fishing Activities via VMS Trace Analysis Based on Mathematical Morphology

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Abstract—**Recently, the satellite-based Vessel Monitoring Systems (VMS) have been widely deployed on fishing vessels. Recognition of fishing activity is the key task for various applications. Previous approaches are basically according to change of vessel's speed; or rely on the validated data from logbooks or documented observations. In this paper, with a rated 60-second temporal resolution VMS data for two years on 34 vessels (typed as otter trawl) in the East China Sea, we propose a Fishing Activity Recognition system (FAR). It exploits Mathematical Morphology for analyzing the VMS trace data to recognize fishing activities and obtain fishing related metrics. Different from previous approaches, FAR carries out on VMS traces only, requiring no other reference like logbooks or any documented observations.**

Keywords—VMS; Mathematical Morphology; fishing activity; fishery yield; trajectory

I. INTRODUCTION

In the last decade of years, as the Vessel Monitoring Systems (VMS) have been widely equipped on fishing vessels, vast VMS trajectory data has been generated. It contains information of vessel's ID number, time and location of that moment, instant speed and heading [1]. With this data, researches have been done on estimating fishing effort [2,3], exploring vessels' behavior and interaction [4,5], assessing changes of environment pressure, management, routine areas and fuel costs following with the alteration of fishing activity [6], studying the fishing waters history evolution [7] and even providing proof for fishing industry when maritime rights conflicts [8,9]. Although purpose varies, recognition of vessel activities, especially fishing activities, is the constant key issue.

However, presented as a series of geographic points sequentially, VMS data does not indicate vessel behavior directly. Analysis is necessary in order to distinguish different vessel behaviors and recognize fishing activity during each individual trip. To recognize fishing activity, previous researches have proposed various methods that can be mainly classified into two categories: experience-based method and statistic-based method.

The experience-based methods, referred as classic methods as well [10], are basically based on the fishing production experience that vessel speed is quite different during different activities. Usually, vessels slow down during fishing activity and, in contrast, accelerate during steaming activity as heading for fishing grounds or ports [11]. Even though simple and direct, practically, this kind of method easily misjudges speed reduction (e.g. a turning) as fishing behavior. Moreover, thresholds vary with the type of vessels [12].

Statistical methods, such as the widely used Hidden Markov Model (HMM), are based on probabilistic interpretation on VMS samples to model the vessel activity. HMM-based methods are generally robust, as they rely on learning procedures on a large data set, creating a model accommodating variations within an activity class. However, these methods require enough amount of labeled data to train the model, which should come from the other sources, like from logbooks [13] and documented at-sea-observers [14]. Then the corresponding VMS data can be characterized, divided into segments according to documented behaviors and used to train statistical models. Afterwards the test VMS data can be classified via the train model.

Therefore, to recognize fishing activity by using VMS data only, accurately and efficiently, with no other references, remains challenging. One problem is that, the individual trip needs to segment from the whole trace set for each vessel. This is challenging for no reference map to label the ports and sometimes the small ports are not even labeled on maps. The other challenging problem is how to classify the different activities from one fishing trip.

In this paper, with a rated 60-second temporal resolution (instead of a general 2-hour one) VMS data for two years on 34 vessels (typed as otter trawl) in the East China Sea, we propose a Fishing Activity Recognition system (FAR). FAR only digs into the collection of VMS data. Without map information, we locate ports of each vessel where it anchors through experience values on speed and direction information. Then we separate individual trips of all the vessels based on their own port locations. With no priori validated information to get data labeled, which means no machine learning algorithms are capable of being employed, we recognize fishing activity by applying Mathematical Morphology (MM) on each individual trip per vessel. So FAR overcomes the challenges above and realizes fishing activity recognition.

As a step forward, we explore the correlation between the changes of fishing activity and the relative yield through analyzing whole-trip and fishing duration and distance, which is 89.80% and 82.11% respectively.

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II. DATA

Our data is recorded by Zhejiang Province Ocean and Fisheries Bureau, which contains records of 974 vessels (typed as otter trawl) equipped with VMS. We sift 34 otter trawl vessels as samples since each of them has more than 10,000 records. The duration of data lasts from 1st April, 2014 to 30th June, 2016, containing 2,140,288 records as 271.81 MB in total. Specifically, each vessel has 62,949.65 on average with a maximum of 144,413 records and a minimum of 15,799. Size of each vessel file is 8.24 MB on average with a maximum of 17.47 MB and a minimum of 1.91 MB.

Traditionally, VMS data contains information of vessel's ID number, time and location of that moment, instant speed and heading with a 2-hour temporal resolution. By employing the BeiDou Navigation Satellite System (BDS) as the position information resource, the VMS data in this work has a rated 60-second temporal resolution. This interval is far shorter than that used in previous research. However, due to transmission anomaly, equipment abnormal shutdown and other factors, our data are still with a small amount of outliers and missing records.

In terms of outliers, similar to [15,16], we detect the outliers based on the time interval and distance between every pair of records. Hence, we calculate the actual velocity of every two records as the VMS data only provides the instant speed of each individual record. And cut off the records with a velocity larger than the threshold, set as 30 knot since fishing vessels of the East China Sea are not capable of this velocity. The proportion of outliers exist in the whole data set is 0.24% (5224 records in total).

Although the temporal resolution is set to be 60 seconds, it varies in practice. As most of the intervals are less than 30 minutes (excluding records while anchoring), we regard intervals longer than 30 minutes as abnormal ones that indicates missing records. The proportion of these missing records is 7.8%. Considering the possibility to imitate all the zigzag and meandering vessel traces and the proportion above has limited impact to following analysis, interpolation is unnecessary in this work.

III. METHOD

Recognition of fishing activity by Mathematical Morphology (MM) can be considered as recognition of the area where the trace is presented as a zigzag and meandering pattern. However, provided with two-year overlapping VMS data traces, it is impossible to employ MM directly. As summarized in Fig.1, with no map information, our first task is to locate ports and then separate each individual trip. Afterwards, we apply MM on individual trips to recognize fishing activity and label fishing areas. At last, we explore the correlation between the changes of fishing activity and the relative yield.

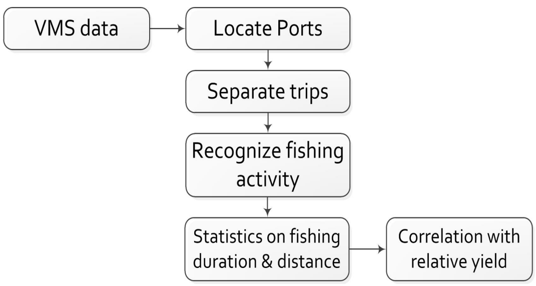

Fig. 1. Work flow of system FAR.

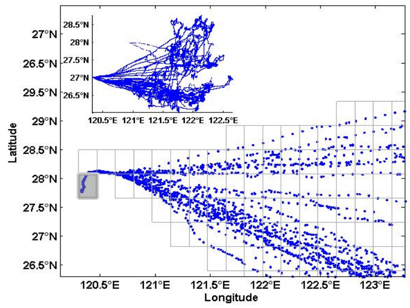

Fig. 2. The shaded grid (120.63°E, 27.48°N, 120.65°E, 27.50°N) indicates the located port (Vessel's Terminal ID: 255368).

A. *Locate the Ports and Separate Trips*

As shown in Fig.2, all the fishing trips of the same vessel in the two-year period overlap. For fishing activity analysis, it is the first task for us to separate each individual trip based on the VMS data only. Our intuition is to locate the ports from some port surveys or map information in order to separate trips. In reality, however, the tiny ports scatter in villages or on islands along the coast, which have not been recorded before. Moreover, anchoring duration of different vessels varies from several hours to dozens of days either in the ports or at the sea during a trip in practice. Besides, influenced by waves and winds, the recording equipment still reflects changes of speed and heading while anchoring. So it is unreliable to judge a vessel whether anchors in ports simply base on the duration of an immobile location.

Inspired by the approach of partition a geographical space into grids in order to retrieve trajectories of vehicles passing a given rectangular region [15,17], we divide the whole sailing area into grids and locate the ports through analyzing the density of stopping records.

Based on the survey experience that these scattering ports usually cover an area less than 1 square mile, we set the grid as 1′ latitude × 1′ longitude since it roughly equals to 1 square mile. Considering that VMS data reflects slight movements influenced by waves etc. instead of stopping in tight, we carry out the statistics on the recorded positions of the fishing vessels when its speed and heading are in [0,1.5] knot and $[\frac{-\pi}{3}, \frac{\pi}{3}]$ [13]. After statistics, the geographical grid with the maximum record number is selected as the port. Hence, anchoring in port and anchoring at sea can be distinguished via density. The sample of port selection is also shown in Fig. 2 labeled as the shaded grid.

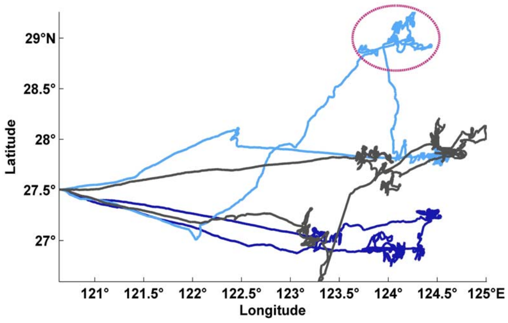

Fig. 3. Three separated trip samples of the same vessel (Terminal ID: 255368).

Consequently, according to the located ports of each vessel, we can separate each individual trip from the whole overlapping traces as vessels depart and enter the ports. For visual clarity, three trajectories of individual trips (Vessel's Terminal ID: 255368) are shown in Fig. 3.

B. Recognize Fishing Activity

A trip can be divided into three types of movements: stopping, steaming and fishing [14]. According to the productive mode of trawlers and this 60-second temporal resolution, unlike steaming which usually presented as nearly straight lines with a few turnings occasionally, the fishing movements can be targeted where tracks reflect a wandering-around pattern obviously. Fig.3 labels a circle to indicate where the vessel carries out fishing for one time. It is this distinction that makes image process recognition possible.

The approach of Mathematical Morphology provides an advantage of simplifying the trajectories. Our goal is to preserve the fishing trajectories and eliminate other parts of trajectories through a series of dilation and erosion operations of MM. So the fishing area can be labeled afterwards.

1) Image tiling: Detecting the boundaries on four directions (north, south, west and east) of every individual trip trajectory of each vessel, we get basic images of all the trip trajectories. As to reserve room for the following dilation and erosion operations, the basic image sheet needs to be expanded 0.16° both longitudinally and latitudinally. For these latter images, we divide each of them into 0.1′ longitude × 0.1′ latitude sized pixels. For example, if the boundaries of a basic image of one trip are 34°N, 24°S, 118°W and 128°E, then they will be expanded to 34.08°N, 23.92°S, 117.92°W and 128.08°E so that the image size is 6096 × 6096 pixels.

2) Mathematical Morphology (MM) operations: The key of this approach is to make the fishing traces stand out of the whole trajectories. As we can see from Fig.4(a), presented by the primary recorded points, although the fishing activity shows a zigzag tendency, those scattering points are still not distinct enough from the steaming points. By operating erosion, all the points become more evident and start to get connected with each other. In Fig.4(b), from on e trip of Vessel 255368 after erosion for 15 units per pixel, we can see that the fishing points tend to be dense areas where are far more distinct form the steaming points. Then, we operate dilation in order to eliminate the steaming poings and reserve the fishing points. Fig.4(c) indicates that with no steaming points the core regions and outlines are roughly reserved after dilation 30 units per pixel. However, comparing with Fig.4(a), we can see that the reserved components in Fig.4(c) are incapable of indicating the complete fishing areas. Consequently, for this rough result another round of erosion is necessary as to expand the detected fishing components large enough to illustrate the actual fishing activity (Fig.4(d)). Through projecting this ultimate result on the trip trajectoty, now we realize recognizing fishing activity and label the relative fishing areas (the shaded areas in Fig.4(e)).

3) Statistics on fishing duration and distance: Referring back to the vessel trace on speed and heading according to the recognized fishing activity, we locate the positions of records where the fishing activity starts and ends. For example, in Fig.4(e), point A and point B label the starting and ending points respectively for one fishing activity. Then the important metrics of fishing duration and distance can be obtained by integrating the VMS records between point A and B. For the trip in Fig.4(e), we obtain the duartion and distance of all the fihsing activities are 7.96 days and 748.37 km, while the whole trip duartion and distance are 20.69 days and 2311.50 km.

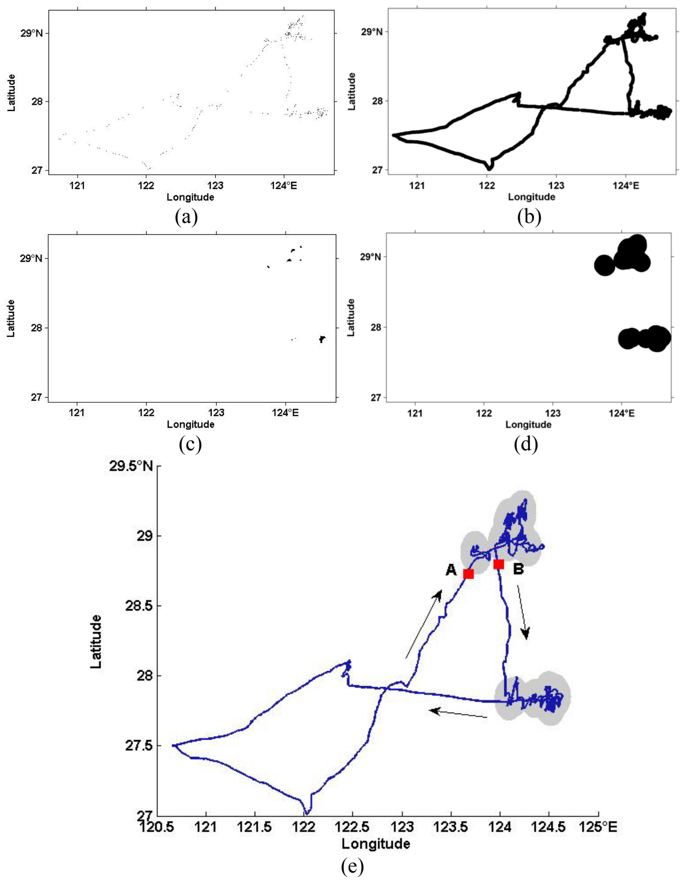

Fig. 4. Illustration of Mathematical Morphology operations (Vessel's Terminal ID:255368):(a) primary recorded points; (b) erosion to make fishing points distinc; (c) dilation to extract fishing points; (d) erosion to expand fishing area; (e) recognized fishing areas

IV. RESULT

We employ the proposed system FAR on all the 34 vessels, and the performance is illustrated as followed.

A. Port Location

As the foundation of all the operations in FAR, the accuracy of port locations is crucial to the final result. We validate all the detected ports of 34 vessels on the Google Earth. As we can see from Fig.5, all the located ports are along the coast and actually some of them indicate inshore islands precisely.

B. Recognition of Fishing Activity

We realize recognition of fishing activity only based on VMS data through MM. Taking port locations into consideration, we actually divided one whole trip into the three type of movements: stopping, steaming and fishing. We abstract VMS data and find that each average velocity is 1 knot, 6 knot and 4 knot respectively, which shows mutual corroboration with [13]. As shown in Fig.6, (a) validates the default heading of 0 while anchoring and situations of initially set a sail and ultimately enter the port; (b) confirms the fact of vessel commuting between ports and fishing grounds according to the position of coastline; (c) indicates that vessels turn by a large margin while fishing which matches the productive experience.

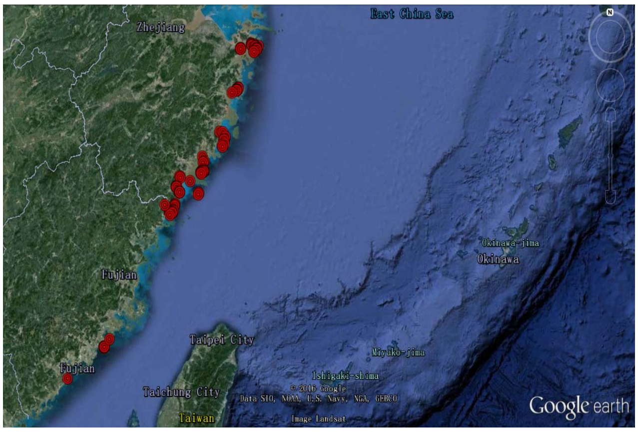

Fig. 5. Detected ports are labeled as red points on Google Earth.

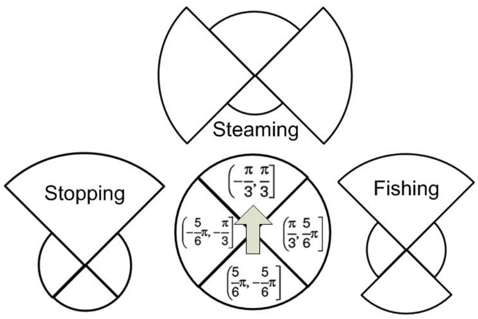

Fig. 6. Changes of headings.

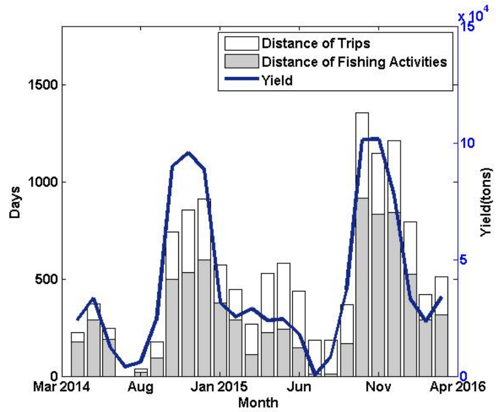

Fig. 7. Duration values and the relative yield.

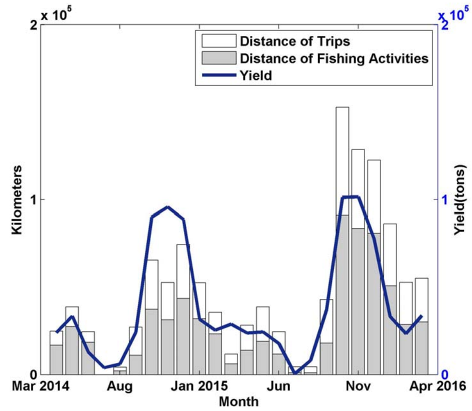

Fig. 8. Distance values and the relative yield.

A step forward, we obtain the fishing and the whole-trip duration and distance for each month among vessels. The results are depicted in Fig.7 and 8 respectively. To evaluate the accuracy of our fishing statistics, we exploit the month fishing yield survey publicized by the local ocean and fishery bureau. The total values of the yield survey are also shown in Fig.7 and 8. The correlation between our statistics on fishing durations and distances and yield survey are 89.80% and 82.11% respectively. The correlation values are reasonable in some degree, because we only choose one type of fishing vessel as our samples while the yield survey contains all fishing vessel types.

C. Changes of Fishing Areas

As we label the fishing areas of every trips, we digitalized all the fishing areas of 34 vessels per quarter in order to show the transformation of productive regions (Fig.9).

V. FUTURE WORK

In this paper, our system FAR realizes recognition of fishing activity basically relies on a small temporary resolution and the productive pattern of vessels typed as otter trawl. In practice, this temporary resolution of VMS data is not common

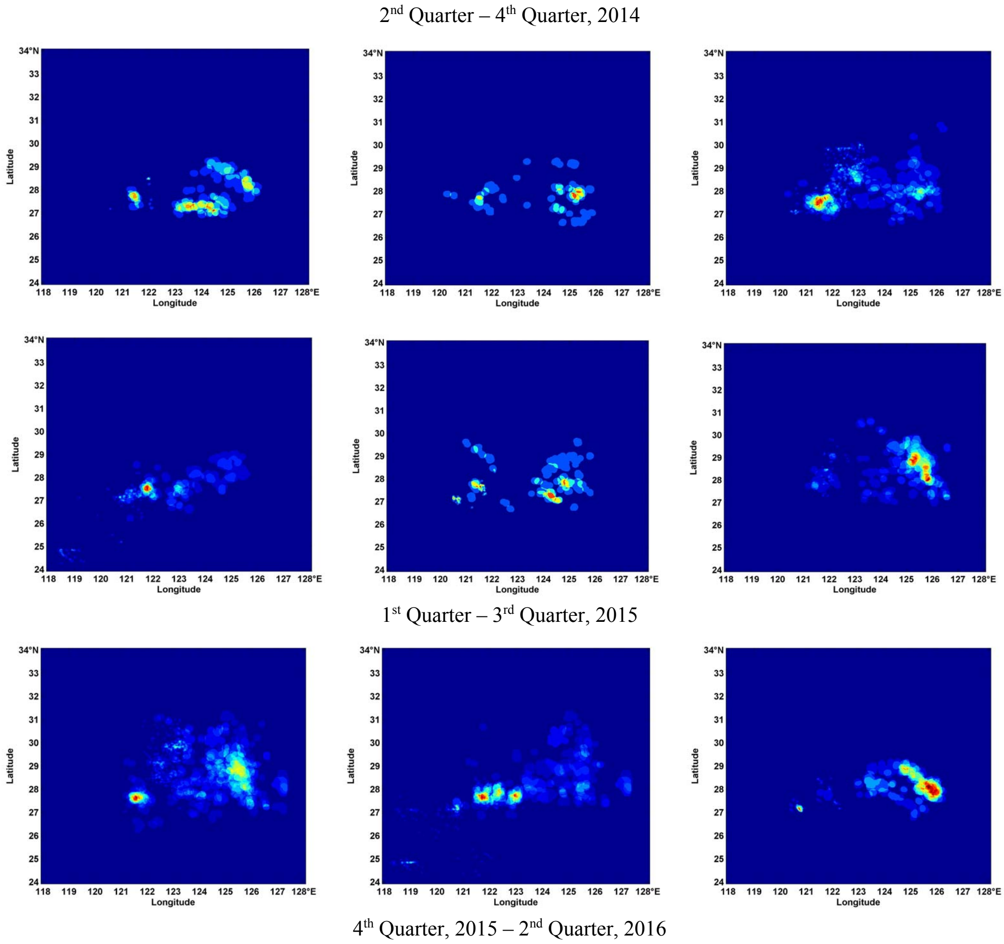

Fig. 9. Heap maps of recognized fishing areas per quarter.

as GPS is still the mainstream positioning system instead of BeiDou Navigation Satellite System (BDS) which is the data resource of this work. Besides, comparing with the other fishery productive modes, otter trawl may have a relative evident fishing pattern which makes employing MM possible. Consequently, to propose a new method which is capable of recognizing more types of fishing vessels accurately and efficiently, even based on the general 2-hour temporary resolution VMS data maybe, is a further research direction.

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REFERENCES

[1] Chang, S.K., 2011. "Application of a vessel monitoring system to advance sustainable fisheries management—benefits received in Taiwan". Mar. Policy 35, 116–121.

[2] Rijnsdorp, A. D., Buys, A. M., Storbeck, F., and Visser, E. G. 1998. "Micro-scale distribution of beam trawl effort in the southern North Sea between 1993 and 1996 in relation to the trawling frequency of the sea bed and the impact on benthic organisms".ICES Journal of Marine Science, 55: 403–419.

[3] Kaiser, M. J., Ramsay, K., Richardson, C. A., Spence, F. E., and Brand, A. R. 2000. "Chronic fishing disturbance has changed shelf sea benthic community structure". Journal of Animal Ecology, 69:494–503.

[4] Mackinson, S., Sumaila, U. R., and Pitcher, T. J. 1997. "Bioeconomics and catchability: fish and fishers behaviour during stock collapse". Fisheries Research, 31: 11–17.

[5] Rijnsdorp, A. D., van Maurik Broekman, P. L., and Visser, E. G. 2000. "Competitive interactions among beam trawlers exploiting local patches of flatfish in the North Sea". ICES Journal of Marine Science, 57: 894–902.

[6] Dinmore, T. A., Duplisea, D. E., Rackham, B. D., Maxwell, D. L., and Jennings, S. 2003. "Impact of a large-scale area closure on patterns of fishing disturbance and the consequences for benthic production".ICES Journal of Marine Science, 60: 371–380

[7] PulvenisJF,editor."The state of world fisheries and aquaculture", 2008.Rome: FAO; 2009.

[8] Eastwood, P. D., Mills, C. M., Aldridge, J. N., Houghton, C. A., and Rogers, S. I. 2007. "Human activities in UK offshore waters: an assessment of direct, physical pressure on the seabed". ICES Journal of Marine Science, 64: 453–463.

[9] Stelzenmu¨ller, V., Rogers, S. I., and Mills, C. M. 2008. "Spatio-temporal patterns of fishing pressure on UK marine landscapes, and their implications for spatial planning and management". ICES Journal of Marine Science, 65: 1081–1091.

[10] Janette Lee, Andy B. South and Simon Jennings, “Developing reliable, repeatable, and accessible methods to provide high-resolution estimates of fishing-effort distributions from vessel monitoring system (VMS) data,” ICES J. Mar. Sci. (2010) 67 (6): 1260-1271.

[11] Deng R,Dichmont C,Milton D,Haywood M,Vance D,Hall N,etal.”Can VMS data also be used to study trawling intensity and population depletion?The example of Australia’s northern prawn fishery” Canadian Journal of Fisheries and Aquatic Sciences 2005;62:611–22.

[12] T.Russo et al., "When Behaviour Reveals Activity: Assigning Fighing Effort to Metiers Based on VMS Data Using Artificial Neural Networks" Fisheries Research, vol.111, pp.53- 64,2011.

[13] E.Walker, "A Pioneer Validation of A State-space Model of Vessel Trajectories (VMS) with Observers’ Data" Ecological Modeling, vol.221, pp.2008- 2017,2010.

[14] Y.Vermard et al., "Identifying Fishing Trip Behavior and Estimating Fishing Effort from VMS Data Using Bayesian Hidden Markov Models" Ecological Modelling, vol.221, pp. 1757-1769, 2010.

[15] Yu Zheng, “Trajectory Data Minig: An Overview”, ACM Transactions on Interlligent Systems and Technology, Vol.6, No.3, Article 29, Publication date: May 2015

[16] J. Yuan, Y. Zheng, C. Zhang, W. Xie, X. Xie, G. Sun, and Y. Huang. 2010a. “T-Drive: Driving directions based on taxi trajectories”. In Proceedings of the 18th Annual ACM International Conference on Advances in Geographic Information Systems. ACM, 99–108.

[17] L. Wang, Y. Zheng, X. Xie, and W. Ma. 2008. “A flexible spatio-temporal indexing scheme for large-scale GPS track retrieval”. In Proceedings of the 8th IEEE International Conference on Mobile Data Management.IEEE, 1–8.