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Article

Prediction of Longline Fishing Activity from V-Pass Data Using Hidden Markov Model

Dae-Woon Shin [1)] · Chan-Su Yang [2)3)4)†] · Ahmed Harun-Al-Rashid [5)6)]

Abstract: Marine fisheries resources face major anthropogenic threat from unregulated fishing activities; thus require precise detection for protection through marine surveillance. Korea developed an efficient land-based small fishing vessel monitoring system using real-time V-Pass data. However, those data directly do not provide information on fishing activities, thus further efforts are necessary to differentiate their activity status. In Korea, especially in Busan, longlining is practiced by many small fishing vessels to catch several types of fishes that need to be identified for proper monitoring. Therefore, in this study we have improved the existing fishing status classification method by applying Hidden Markov Model (HMM) on V-Pass data in order to further classify their fishing status into three groups, *viz*. non-fishing, longlining and other types of fishing. Data from 206 fishing vessels at Busan on 05 February, 2021 were used for this purpose. Two tiered HMM was applied that first differentiates non-fishing status from the fishing status, and finally classifies that fishing status into longlining and other types of fishing. Data from 193 and 13 ships were used as training and test datasets, respectively. Using this model 90.45% accuracy in classifying into fishing and non-fishing status and 88.23% overall accuracy in classifying all into three types of fishing statuses were achieved. Thus, this method is recommended for monitoring the activities of small fishing vessels equipped with V-Pass, especially for detecting longlining.

Key Words: Longlining, Fishing Activity, Hidden Markov Model, V-Pass

1. Introduction

Seas are the great source of human food. Every year million tons of fishes of various species are caught by fishing vessels. These loss of the fishes in the stocks by fishing mortality are usually replenished by the natural

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1) Ph.D. Candidate, Department of Convergence Study on the Ocean Science and Technology, Ocean Science and Technology School, Korea Maritime and Ocean University
2) Principal Research Scientist, Marine Security and Safety Research Center, Korea Institute of Ocean Science & Technology
3) Professor, Applied Ocean Sciences, University of Science & Technology
4) Adjunct Professor, Department of Convergence Study on the Ocean Science and Technology, Ocean Science and Technology School, Korea Maritime and Ocean University
5) Postdoctoral Researcher, Marine Security and Safety Research Center, Korea Institute of Ocean Science & Technology
6) Professor, Department of Aquatic Resource Management, Sylhet Agricultural University

† Corresponding Author: Chan-Su Yang (yangcs@kiost.ac.kr)

breeding and growth of fishes. It is necessary to keep the fishing pressure on fishing stocks within allowable range in order to remain those stocks sustainable. However, nowadays overfishing has become a common issue in various seas of the world which causes great loss to fish stocks; thus become the major threat to their sustainability. The overfishing is mainly done as Illegal, Unreported and Unregulated (IUU) fishing activities. Illegal fishing takes approximately 20% of the global fishing amount (Angnew *et al*., 2009); thus damages 26 to 50 billion USD on the global fishing economy (Sumaila *et al*., 2020). Therefore, to protect the marine resources it is necessary to continuously surveillance the sea with special consideration on managing IUU fishing activities (Angnew *et al*., 2009; Pelich *et al*., 2019; Sumaila *et al*., 2020).

To prevent IUU, countries usually operate vessel monitoring system (VMS) to conduct marine surveillance activities (Angnew *et al*., 2009; Pelich *et al*., 2019; Sumaila *et al*., 2020). Particularly, in Korea Automatic Identification System (AIS), V-Pass, and VHF-DSC installed on ships are used to monitor offshore ship activities (Hong and Yang, 2014; Kim *et al*., 2016; Hong *et al*., 2018; Jeon and Jung, 2018; Jeon and Yang, 2021; Cho and Choi, 2018; Han *et al*., 2021; Lee *et al*., 2021).

There are a number of research works on AIS-based differentiation of ships' fishing activities. On the contrary, there are still little works on vessels' fishing activity differentiation using the V-Pass data. However, it is necessary to monitor fishing activity status from small fishing vessels for proper monitoring, which triggers the necessity of such works by using the readily accessible V-Pass data. Park *et al*. (2021) differentiated fishing status from non-fishing status on the basis of course and speed of the small fishing vessels' V-Pass data, but didn't considered for differentiation among the types of fishing status. The analysis of fishing activities was performed according to the absolute classification of the ship's position, speed and course based on simple spatial statistics, and did not reflect the changing fishing activity of the actual vessel. They did it by applying Hidden Markov Model (HMM) on V-Pass data. HMM is a model to determine status through probability distribution for a sequence of time-series data. However, that study did not considered differentiation of fishing types from each other. For instance, in the sea around Busan and other locations of Korea, there are many small fishing vessels which use longlines for harvesting various types of fishes and squids (Kitakado *et al*., 2020; Kitakado *et al*., 2021a, 2021b; Kim *et al*., 2012; Satoh *et al*., 2020; Gil and Palmason, 2005). Therefore, in this study we have proposed an improvement to that HMM model to distinguish this longlining from other types of fishing activities. For the convenience of description any types of fishing done by small fishing vessels other than longlining henceforth will be referred to as other fishing.

2. Study area and data

V-Pass is a wireless device that automatically transmits data from ship, and according to the Fishing Vessels Act in Korea that device should be installed in small fishing vessels where AIS is not installed (Lee *et al*., 2021). V-Pass provides vessel identification number, location (coordinates), speed over ground, course over ground (COG), etc. and thus contributing a lot to monitor fishing vessels. Usually, ship navigation information is transmitted every 10 min or less in V-Pass (Lee *et al*., 2021). In this study, V-Pass data were collected for the coverage of Busan (128.5-130.0°E, 34.5-35.5°N) on 05 February, 2021 as shown in Fig. 1. The V-Pass collection system is located at Korea Institute of Ocean Science & Technology (KIOST), Busan, Korea, and also operated and maintained by KIOST. The coverage of V-Pass data collected from the fishing vessels are limited to coastal areas within 35 km

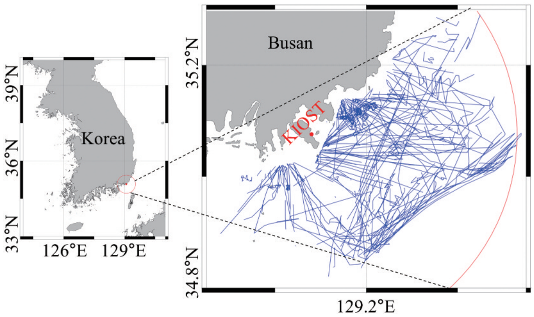

Fig. 1. Study area in Korea is shown by red circle in the left map. V-Pass based trajectories (blue lines) of 206 small fishing vessels inside the study area on 05 February, 2021 are shown in the right map. The red dot and the arc represent the location of the V-Pass receiving antenna in KIOST and V-Pass receiving antenna coverage in the sea, respectively.

radius from the receiving antenna which is placed only around 0.2 km inside from the coastline (red point in Fig. 1). The V-Pass data are received in real-time as encrypted packet information, converted to usable text information, and automatically transmitted to the data collection computer through serial port. Finally, from the data collection computer these data are stored in the PostgreSQL database through the Secure Shell (SSH) port at KIOST internal network facilities.

The collected V-Pass data consist of a sequence of time-series data comprising 9 variables, *viz*. unique identification number, time, longitude and latitude, heading, speed, license type, SOS status, etc. of fishing vessels. Among those, speed and location are the key elements to assess fishing vessel activities. The interval of V-Pass data ranged from 1 second to 2 minutes, and thus signals for 14,117 instances from 206 fishing vessels on 05 February, 2021 were used in this study.

Prior to using the received V-Pass data, noise data (a few locations showing on land for only one ship) were removed by land masking. Moreover, vessels arriving on/departing from harbour were out of our interest as were not in a status of fishing operations. Thus, the vessels within 1 km distance from the port were also eliminated by adding buffer to the land mask during land masking.

3. Methodology

In this study we have predicted the fishing activity through the HMM based on the speed and behaviour of each fishing vessel. HMM assumes unknown parameters and classifies the unknown parameters from the observable parameters. The model has been applied in various fields such as bioinformatics, voice recognition, character recognition, etc. by using a number of machine learning algorithms (Franzese and Luliano, 2018). In particular, V-Pass data for Busan Port area were labelled and applied to HMM, targeting the longline fishery and other fisheries that are extensively conducted in the study area. The classification procedure is improved compared to the method presented by Park *et al*. (2021) by applying the proposed two tired HMM: the primary (non-fishing, fishing) model, and the secondary (longlining, and other fishing) model. The major steps are shown in a simplified flowchart (Fig. 2). The first step is labelling all (training and test) data into three groups of fishing activity status. Here, it can be seen that the class, longlining activity, is newly added in the current model compared to that of previous model. Then, the data is split into training and test data which are primarily divided to fishing and non-fishing status at first step of HMM, and further differentiated based on the fishing methods. Finally, the test results are compared with the truth data to estimate the level of accuracy.

In this study, at first pre-processed V-Pass information from all 206 small fishing vessels were primarily

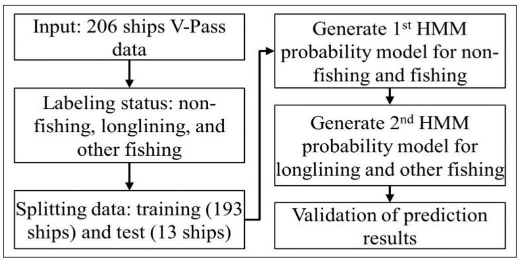

Fig. 2. Flowchart for prediction of fishing activities using HMM model.

classified and labelled into three categories namely non-fishing, longlining and other fishing (Fig. 2). From the labelled data 193 ships (4 longlining ships, 189 other fishing ships) were used for training and 13 ships (2 longlining ships, 11 other fishing ships) were used for testing the model. Based on those training data, the non-fishing and fishing status were predicted using the first-order HMM probabilistic model. The first-order results for fishing status thus produced were used in the second HMM probabilistic model to further divide it into two types of activities, longlining and other fishing.

1) Labelling

Park *et al*. (2021) classified the fishing vessels' status as non-fishing and fishing. Here, we have further classified the fishing status as longlining and other types of fishing based on speed and trajectory of fishing vessels with the opinion of some long experienced fishing vessel captains. One example of longlining from one fishing vessel is shown in Fig. 3 where red, green and blue circles indicate the longlining, other fishing and non-fishing statuses, respectively, and the lines show the trajectories. In Fig. 3(a) specific movement patterns can be observed in the form of sharp changes in shift towards almost opposite direction after a certain distance and period (here from east to west and south to north) to repeat the setting of longlines. On the contrary, different types of movements are observed in case of other fishing. Such an instance is shown in Fig. 3(b) where irregular and relatively straight patterns of shifts are observed. In contrast to these, shift of vessels with less changes in the course direction (Kim and Lee, 2020) is considered as non-fishing status (streaming or waiting for hauling).

Fig. 4 shows the velocity distribution graphs of ships which were also considered for classifying the ships into three categories of fishing status for labelling purpose. Though the velocity data are in integer form, in order to produce a smooth histogram kernel density estimation (Wand and Jones, 1995) is applied to

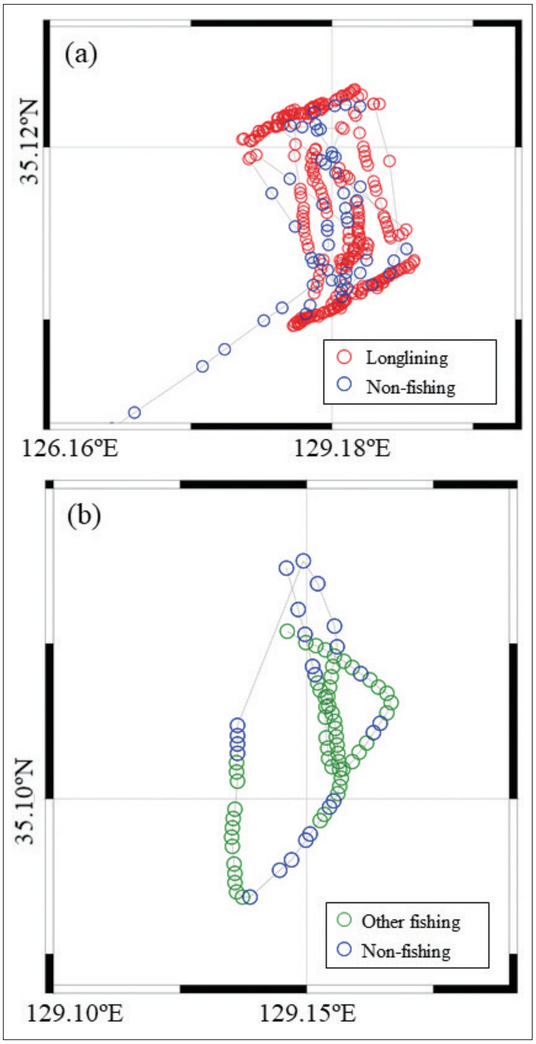

Fig. 3. Example of movement patterns of fishing vessels for labelling purpose: (a) longlining *vs.* non-fishing, and (b) other fishing *vs.* non-fishing.

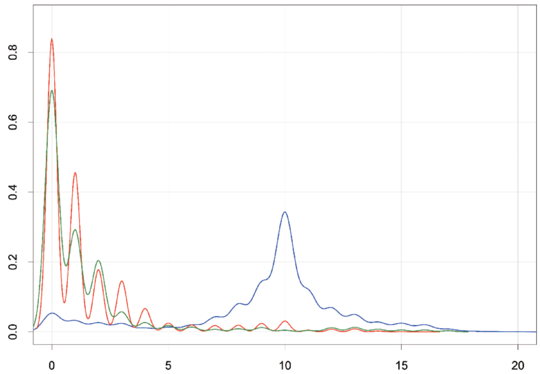

Fig. 4. Speed distribution of all fishing vessels according to their labelled fishing status.

the data values. The bandwidth according to each classification was applied by finding the optimal bandwidth size according to the number of data in the Gaussian kernel function. First, the speed distribution of non-fishing activity found to be highest at 10 knots (highest peak of the blue line-graph) whereas discriminated from fishing activities at about 5 knots (indicated by blue arrow). Although the speed distribution of longlining and other fishing show some similarities in skewness and modes for peaks and troughs at 5 distinct peaks among 0 to 4 knots, the longlining showed much high peaks and steep troughs compared to those of other fishing due to sudden change in speed caused by abrupt changes in the direction of vessels. These were considered during setting the classification number and range for speed distribution in HMM probability model structure.

2) HMM

In HMM the probability of specific states (called hidden states) is calculated by using the emission and transition probability from the time-series and states-labelled data (Franzese and Luliano, 2018; Park *et al*., 2021). The concept of this model is to assuming that the current observation (O_t) is the result of the current hidden state (H_t), and H_t is independent of the previous state (H_{t-1}) (Park *et al*., 2021; Souza *et al*., 2016). Equation 1 shows the formula for calculating the HMM probabilistic model. The probabilities of emission and transition are defined as $P(O_t|H_t)$ and $P(H_t|H_{t-1})$, respectively (Park *et al*., 2021).

The structure of the HMM probabilistic model constructed by using the learning data is schematically shown in Fig. 5. Here, in both steps observations were grouped into 5 range categories according to the speed distribution. The probabilities of emission and transition computed from labelled data are the key characteristic for operation. Fig. 5(a) shows the structure of the non-fishing/fishing HMM prediction model using V-Pass data of 193 ships, and Fig. 5(b) shows the longlining and other fishing HMM prediction model for those data identified as fishing status in Fig. 5(a). Here, H_t were set for each fishing activity according to Fig. 5(a) and 5(b). Hidden states consist of fishing activity statuses, and observation sequences consist of 5 different ranges of speeds.

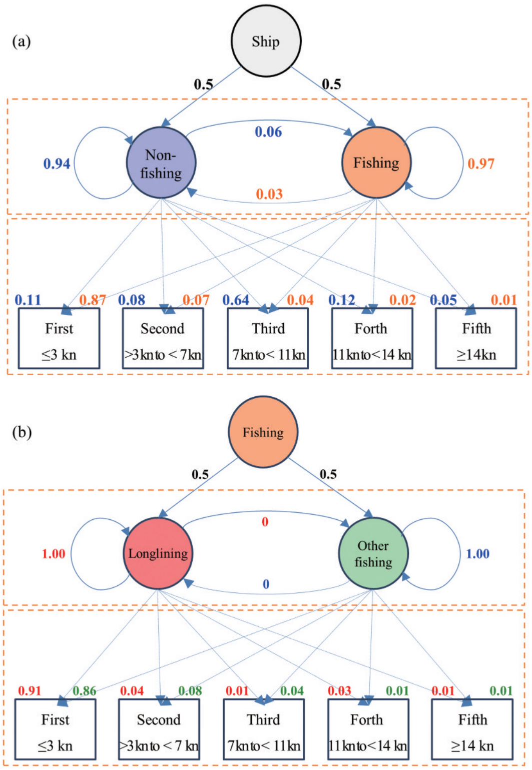

Fig. 5. HMM probability model structure with five ranges of speed as observation sequences: (a) 1st step of HMM for distinguishing fishing status from non-fishing status, (b) 2nd step of HMM for distinguishing the longlining from other fishing.

$$P(H_{1:T} \mid O_{1:T}) = P(H_1)P(O_1 \mid H_1) \prod_{t=2}^{T} P(O_t \mid H_t) \; P(P(H_t \mid H_{t-1}) \quad (1)$$

Here,

P = Probability
H = Hidden states (non-fishing, longlining, and other fishing)
O = Observation (speed)

The transition probability is defined as the probability of a hidden state in the previous step (t) become a hidden state in the current step (t+1) (Park *et al*., 2021).

Table 1. Initial setting of transition probability

Ratio (probability)			
Non-fishing	Fishing	Longlining	Other fishing
0.5 (50%)	0.5 (50%)	0.5 (50%)	0.5 (50%)

Table 2. Transition probability from training data

t \ $t+1$	Position counts (probability)		t \ $t+1$	Positon counts (probability)	
	Non-fishing	Fishing		Longlining	Other fishing
Non-fishing	3,999 (93.59%)	274 (6.41%)	Longlining	1,706 (100%)	40 (0%)
Fishing	264 (2.68%)	9,580 (97.32%)	Other types of fishing	0 (0%)	8,115 (100%)

Table 3. Emission probability from training data

Observation sequences	Position counts (probability)			
	Non-fishing	Fishing	Longlining	Other fishing
First	483 (11.48%)	8,643 (87.21%)	1,637 (91.15%)	7,006 (86.33%)
Second	319 (7.58%)	724 (7.31%)	69 (3.84%)	655 (8.07%)
Third	2,708 (64.38%)	397 (4.01%)	25 (1.39%)	372 (4.58%)
Fourth	502 (11.94%)	124 (1.25%)	43 (2.39%)	81 (1.00%)
Fifth	194 (4.61%)	23 (0.23%)	22 (1.22%)	1 (0.01%)
Sub-total	4,206	9,911	1,796	8,115

Transition probability requires an initial setting, but since there is no way to discriminate longlining and other fishing through the starting value (speed), the probability of the initial setting was set to 0.5 for both classes as shown in Table 1.

Table 2 shows the calculation of the transition probability between each fishing behaviour. From the result of transition probability between non-fishing and fishing, the probability of moving to the same type of fishing activity was found to be higher than 90%. Since the two fishing types are fully different and do not interact with each other, the probability of transitioning to the same type was set to 100% and the probability of transitioning to a different types of fishing activity was set to 0%.

Emission probability means the probability of observation which was calculated from the hidden states. The emission probability was calculated for each type of fishing activities as shown in Table 3. Setting the classification number and range of status of emission probability is crucial for extracting the characteristics of each fishing activity. During determining the number of classification for emission status, using a relatively small number of divisions like 2-4 divisions in our cases are found to degrade the HMM performance in distinguishing fishing activity as because each division includes a wide range of speeds. Using a relatively large number of classifications, such as 6 classifications or more could not increase the performance as well. Thus, after several trials the best result was achieved from 5 classes. The velocity range for emission probability was divided by applying the K-mean clustering technique, which showed better performance than dividing the speed range at equal intervals. Thus, after applying several trials we determined the best suited ranges for the 5 classes as 0 to 3 knot, more than 3 knot to less than 7 knot, 7 to less than 11 knot, 11 to less than 14 knot, and 14 knot to above (Fig. 5).

4. Results and discussion

The performance of generated HMM was evaluated in terms of accuracy (%) by applying the Equation 2. The derived value of accuracy represents the degree of closeness of measurements of a quantity to that quantity's true value. Four parameters, *viz*. True Positive (TP), True Negative (TN), False Positive (FP) and False Negative (FN) were used in this equation. These parameters were calculated by comparing the labels of actual and prediction. TP was considered when both actual data and prediction results were positive, whereas TN was considered when both the actual data and prediction results were negative. FP means that actual data is negative, but the prediction result is positive, whereas FN means the opposite (Park *et al*., 2021).

$$Accuracy\ (\%) = \frac{TP+TN}{TP+TN+FP+FN} \times 100 \qquad (2)$$

Tables 4 and 5 show the confusion matrix and accuracy results, respectively for actual and prediction for the three fishing behaviours. The confusion matrix of status classification for multiple vessels explains the performance, showing that in the prediction 113 instances mismatched as non-fishing and 130 instances mismatched as longlining and other fishing. However, the performance was around 90% for the first step and 86% for the second step of HMM.

Table 4. Confusion matrix of HMM application by each fishing activity using test dataset

Test dataset		Prediction		
		Non-fishing	Other fishing	Longlining
Actual	Non-fishing	372	130	–
	Other fishing	113	1,286	288
	Longlining	–	0	485

Table 5. Accuracy calculation results for actual and prediction

Classification	Accuracy (%)
Non-fishing/fishing	90.45
Longlining/other fishing	86.01
Non-fishing/longlining/other fishing	88.23

The test data set for verification was done by random selection of 13 fishing vessels (2 longlining and 11 other fishing vessels) out of total 206 ships. The prediction result is visualized in a map (Fig. 6) for analysing comparison with actual fishing activity classification. Fishing/non-fishing prediction results shows high accuracy of 90.45%. Although ratio of correct prediction was high in the entire research area, some mispredictions (TN) were found at the entrance of Busan Port where density of fishing vessels was very high in that narrow entrance (downward facing arrow

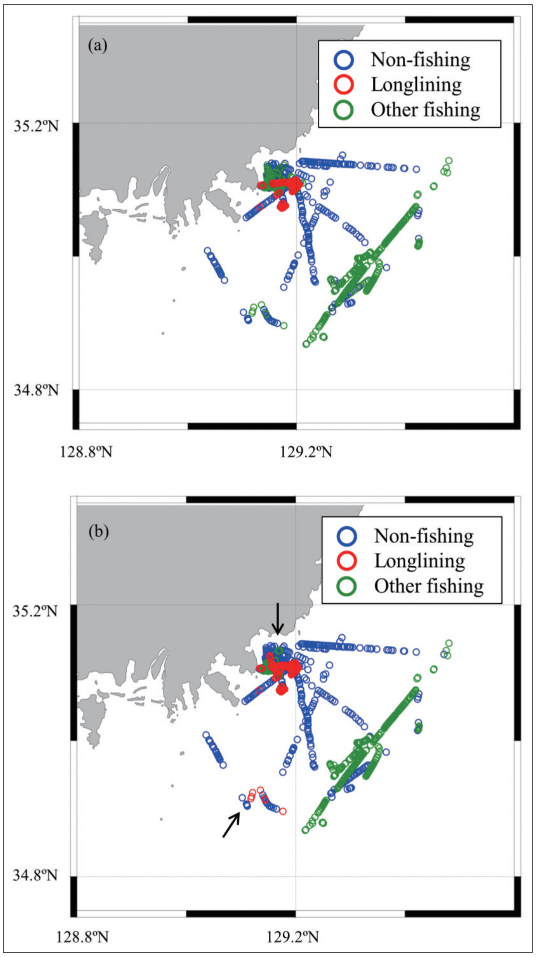

Fig. 6. Comparison of fishing activity classification between (a) labelling data, and (b) validation of prediction results for 13 fishing vessels.

in Fig. 6(b)). Another example of misprediction due to missing location and speed information during the long time interval in that ship's V-Pass data is indicated by the north-east facing arrow in Fig. 6(b). However, in this study we have ignored these few misprediction problems and considered for solving in future works through including other parameters like COG. In contrast to the result of fishing/non-fishing prediction results, it was found that the longlining has some mispredictions (FP) in the densely populated fishing area (downward facing arrow in Fig. 6(b)), and thus longlining and other fishing predictions resulted in a relatively little lower accuracy of 86.01% compared to the predications at first step of HMM. Hu *et al*. (2016) found 88.7% average accuracy in case of identifying fishing activities using AIS data. Souza *et al*. (2016) achieved average detection accuracies of 83% for trawler and longline vessels, and 97% for purse seiner by applying data mining and machine learning on satellite AIS. Park *et al*. (2021) included the same V-Pass data from Socheongcho Ocean Research Station both in training and test datasets, and thus achieved 99.43% performance accuracy. However, in this study no training and test data were overlapped, and as a whole HMM probabilistic models showed 88.23% overall accuracy for the 3 classifications of fishing activities.

5. Conclusion

In the fishing industry it is crucial step to prevent IUU fishing and overfishing. The existing VMS system allows the Vessel Traffic Service officers to observe the ship movements in real-time. The proposed fishing gear type identification method allows identification of fishing activities of small fishing vessels from their speed. There is a HMM based fishing and non-fishing determining method from V-Pass data. Therefore, we have improved that method to further differentiate the longlining activities from other types of fishing activities. We have applied that method with suitable number of training and test data. Thus, we have found that our method can differentiate longlining activities with 86% accuracy. Thus, this method of fishing activity differentiation can be used by the coast guard and researches to identify the longlining activity which will be helpful for predicting the fishing pressure to the related fishing and control overfishing as well as IUU fishing if done by fishing vessels not allowed for that type of fishing. Moreover, this method could be also applied by the researchers to estimate the correlation between depletion of fish catches and longlining by small fishing vessels. In future we would like to continue effort in this field of research to achieve higher accuracy as well as differencing other types of fishing activities by incorporating other attributes from V-Pass data.

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