Sensors and Materials, Vol. 35, No. 5 (2023) 1533–1537
MYU Tokyo

S & M 3266

Performance Boosting of Fishing Vessel Identification Model by Employing Heading Direction Unification Technique

Ching-Hai Lin,[1,2] Chun-Cheng Lin,[3] Ren-Hao Chen,[3]
Cheng-Yu Yeh,[3*] and Shaw-Hwa Hwang[4]

[1]National Museum of Marine Science & Technology, Keelung City 202010, Taiwan
[2]Department of Electrical Engineering, Lee Ming Institute of Technology, New Taipei City 243083, Taiwan
[3]Department of Electrical Engineering, National Chin-Yi University of Technology,
57, Sec. 2, Zhongshan Rd., Taiping Dist., Taichung 41170, Taiwan
[4]Department of Electronics and Electrical Engineering, National Yang Ming Chiao Tung University,
Hsinchu 300093, Taiwan

(Received July 19, 2022; accepted March 23, 2023)

Keywords: fishing vessel identification, heading direction recognition, image recognition, convolutional neural network (CNN)

In this paper, we report a continuation of our research based on our previous works, in which a fishing vessel recognition technique was addressed for the first time in the literature. We also propose a heading direction unification technique that boosts the performance of the fishing vessel identification model. This proposed technique is based on the finding that the recognition rate was improved when the recognition model in the originally proposed method was trained using an image database of fishing vessels with a unified heading direction. Accordingly, a model was developed to recognize the heading directions of fishing vessels as a pretreatment for the originally proposed method. Once a fishing vessel image was recognized as heading against the unified direction, it was flipped horizontally to improve the recognition rate. The model was experimentally validated to have an accuracy of up to 98.82%, and it required only 3.2 MB of memory.

1. Introduction

This paper is an extension of our recently published originally proposed method(1) by which the fishing vessel recognition rate can be markedly improved, which was developed for the following reason. The crew of a fishing vessel is requested to fill out a form that indicates the expected time of arrival in a port, the number of crew, and the quantities and items of the shipment. Next, the vessel anchors for the subsequent quarantine and inspection. Once permission is granted, the vessel is scheduled to arrive at the port. Therefore, it takes a long time to complete the whole procedure. In light of this, an improved model was developed to better recognize vessels so as to further speed up the process.

*Corresponding author: e-mail: cy.yeh@ncut.edu.tw
https://doi.org/10.18494/SAM4033

ISSN 0914-4935 © MYU K.K.
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The originally proposed method was inspired by FaceNet,(2) which is a deep-learning-based technology.(3–7) As its name indicates, FaceNet was developed exclusively for face recognition and validated to give a high recognition rate. It adopted a triplet loss function to train the model. However, there is a clear difference between fishing vessel and face images. Normally, the left half of a face image is nearly symmetrical with the right half, whereas this is not the case for a fishing vessel image except for the front view. Conceptually, the technique is very likely to give a lower recognition rate for fishing vessel recognition than for face recognition.

This work was divided into two phases. In Phase 1, the aim was to validate the postulate that the fishing vessel recognition model achieved a higher recognition rate when it was trained using a fishing vessel image database with a unified heading direction. In Phase 2, a model was developed, as reported in this paper, to recognize the heading direction of a fishing vessel image. Once the image was recognized as heading against the unified direction, it was flipped horizontally to improve the recognition rate.

2. Validation of Postulate in This Work

In this study, we employed exactly the same recognition model, the same parameter settings, and the same training image data as those in the originally proposed method,(1) except that all the fishing vessels in the image database were oriented toward the right. As listed in Table 1, the image database was composed of 7037 images, which contained 156 fishing vessels. A total of 3560 images were employed as the training data, while the remaining 3477 images were employed as the testing data. An RMSProp optimizer was used to train the recognition model with a batch size of 30 and an epoch of 1000. The weightings giving the highest recognition rate were also found.

Subsequently, a threshold must be specified in advance of the vessel identification task. The optimal threshold was determined by following the steps described for the Labeled Faces in the Wild (LFW) database,(8) which were conducted on the training set in Table 1. The 3560 images in the training set were used to determine the optimal threshold. A positive pair refers to a pair of images containing the same vessel in the testing data, accounting for 113892 positive pairs in total. In contrast, a negative pair refers to a pair of images containing distinct vessels, and the same number of negative pairs as positive pairs was randomly selected. Therefore, a total of 227784 pairs of images were used for testing purposes.

Table 2 gives a performance comparison between the newly and originally proposed methods tested on the training set. As can be found therein, the proposed recognition model outperformed the original counterpart in terms of the true positive rate (TPR), false positive rate (FPR), precision, and accuracy. In particular, FPR was significantly reduced by 65% from 1.87 to 0.65%. In addition, this work and the original proposal obtained accuracies of 99.31 and 99.02% for the above-mentioned testing set of 3477 images, respectively, thus demonstrating the effect of the heading direction of vessels on the performance of the recognition model.

Accordingly, our team developed a model by which the heading direction of the vessel in an image can be automatically recognized. If the heading direction is recognized as to the left, the image is flipped horizontally to boost the performance in the vessel identification task. Figure 1

Table 1
Numbers of fishing vessels and images in the training and testing sets.

Database	Training set	Testing set
7037 images (156 fishing vessels)	3560	3477

Table 2
Performance comparison between newly and originally proposed methods tested on the training set.

Performance metrics	Originally proposed (%)[1]	Newly proposed (%)
TPR	91.93	98.44
FPR	1.87	0.65
Precision	98.01	99.34
Accuracy	95.03	98.89

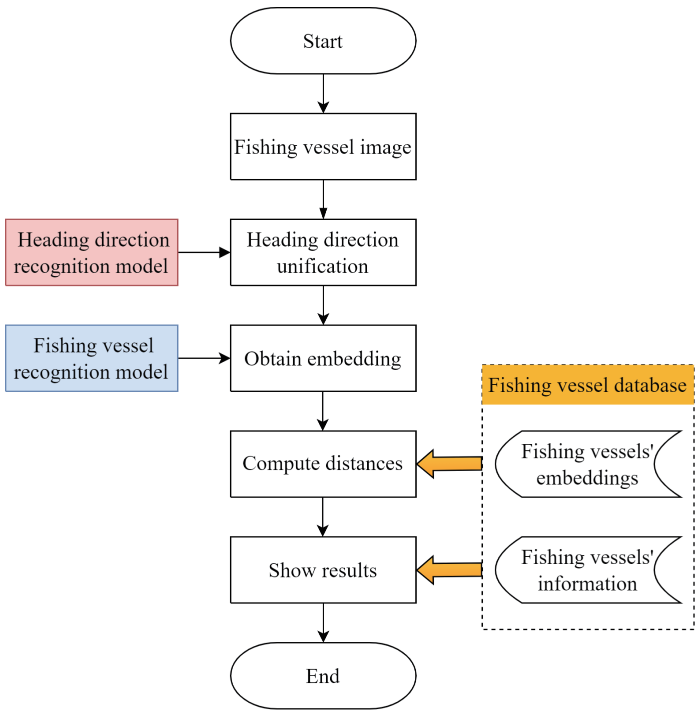

Fig. 1. (Color online) Overall flow of the fishing vessel identification task in this work.

shows the upgraded version of the overall flowchart for the fishing vessel identification task, which is based on that for the original proposal. Here, the heading direction recognition model and the process of heading direction unification are added to the flowchart of the original proposal.

3. Proposed Heading Direction Recognition Model and Experimental Results

Figure 2 depicts the flow of the heading direction recognition model. Firstly, a color image with a size of 128 × 128 × 3 pixels is applied to the model. Secondly, feature maps are provided through two layers of Sub_Block_1 followed by three layers of Sub_Block_2. Thirdly, the heading direction of a vessel is recognized using Dense and Softmax. As illustrated in the right half of Fig. 2, the only difference between Sub_Block_1 and Sub_Block_2 is that thirty-two 3 × 3 filters are employed in the convolutional layer of the former, while sixty-four 5 × 5 filters are employed in the convolution layer of the latter. The model is relatively simple and takes up only 3.2 MB of memory.

Subsequently, the same image database was used to train both the heading direction recognition model and the above-mentioned model for fishing vessel identification. Table 3 gives the numbers of training and testing data for the two classes. The model was trained using a categorical cross-entropy loss function and a stochastic gradient descent (SGD) optimizer. As before, the weightings leading to the highest recognition rate were also found. The recognition model was developed using Python and the TensorFlow and Keras libraries.

The performance of the heading direction recognition model was tested using a total of 3477 images, as listed in Table 3. The confusion matrix in Fig. 3 was used to summarize the performance of the model. Accordingly, TPR, FPR, precision, and accuracy were evaluated as 98.31, 0.89, 98.39, and 98.82%, respectively. This finding validates the performance of the built model.

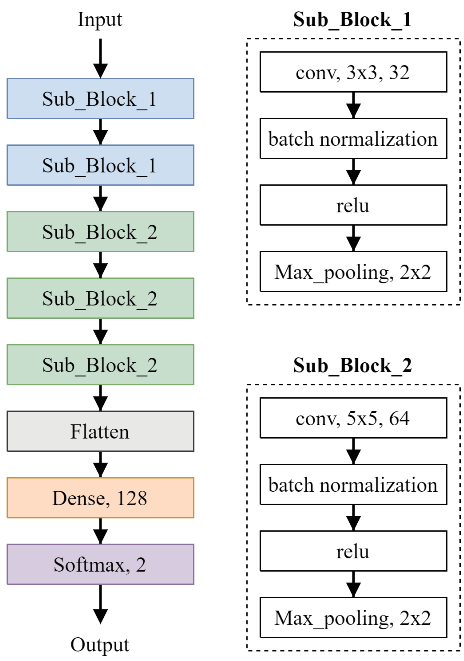

Fig. 2. (Color online) Framework design of the heading direction recognition model.

Table 3
Images collected for training and testing the model in Fig. 2.

Class number	Heading direction	Total number of training data	Total number of testing data
0	Left	2292	2235
1	Right	1268	1242

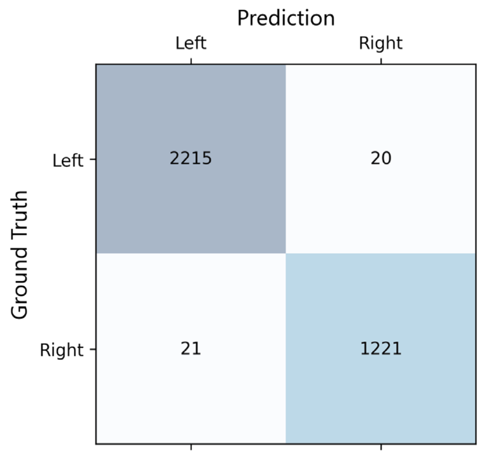

Fig. 3. (Color online) Confusion matrix used for accuracy analysis.

4. Conclusions

In this paper, we present a high-accuracy model for recognizing and then unifying the heading directions of fishing vessels. Using this model, a fishing vessel image is flipped horizontally once it is recognized as heading against the unified direction. Using this model as a pretreatment to the originally proposed method, the recognition rate of fishing vessels can be improved markedly. Experimental results show that the proposed heading direction recognition model has an accuracy of 98.82% and occupied only 3.2 MB of memory.

Acknowledgments

This research was financially supported by the Ministry of Economic Affairs of Taiwan under grant number 110-EC-17-A-02-S5-008.

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