

Improving Accuracy in Detecting Unknown Objects and Enhancing Low Visibility Conditions Caused by Sea Fog in Coastal Areas

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해안지역의 해무현상으로 인한 저시정 현상 개선 및 미확인 물체 탐지 방안에 대한 정확성 개선 방안

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Abstract

South Korea's geographical position, flanked by the sea on three sides, coupled with the ongoing standoff between the North and the South, makes coastal security a critical component of national defense. However, challenges in coastal operations arise due to aging military equipment and a decrease in military personnel due to low birth rates. In this context, this paper presents automated technology based on deep learning as an alternative to manpower. In coastal areas, low visibility conditions frequently occur due to sea fog, a climatic characteristic of these regions. To address this issue, the Dehazy algorithm, a technique for fog removal, has been implemented. Additionally, an algorithm that separates the background by distinguishing between the sea and sky at the horizon has been combined to selectively identify objects over the sea. For object detection, the YOLO algorithm was employed, and this paper highlights the differences in object recognition rates and real-time processing speeds between identifying unknown objects in original images versus those detected using the proposed technology.

I. Introduction

Considering the geographical features of South Korea, surrounded by the sea on three sides, coastal border security is of utmost national importance. However, incidents such as the North Korean wooden boat docking in Samcheok and the illegal entry of a small Chinese boat in Taean, Chungnam, highlight the ever-present possibility of human error in manpower-dependent operations, posing serious threats to national security[1]. Additionally, the aging military equipment, population decline due to low birth rates, and the reduction in military service duration are expected to complicate future coastal border operations due to a shortage of border troops. In this challenging scenario, the introduction of artificial intelligence and big data technology in the military can offer efficient solutions to these issues. This study focuses on the automatic identification of unknown objects along the coast. Unlike previous research that developed dehazing and object detection models independently, this study integrates these models to perform object detection based on clear, noise-reduced images. By doing so, it aims to achieve more effective and accurate identification of unknown objects compared to earlier research. This integrated approach also proposes solutions to address human error, the reduction in military personnel, and the aging of military

equipment.

II. Related Research

Three key technologies necessary for the automation of coastal border operations can be identified: automatic object detection algorithms, background segmentation algorithms, and fog removal algorithms. Among the technologies to be discussed as automatic object detection algorithms are Faster R-CNN[2], YOLO[3], and SSD[4]. These methods serve as significant examples in this domain.

2.1 Object Detection

Faster R-CNN is an improved model based on the earlier Fast R-CNN[5], utilizing a 2-stage approach for inference. This method involves proposing object candidate regions and bounding boxes independently, which results in relatively slower inference speeds but higher accuracy. In contrast, the YOLO model employs a 1-stage approach, predicting both the type and location of objects simultaneously, which allows for faster inference speeds. Additionally, the YOLO model has been continuously updated.

2.2 Background Subtractor

To efficiently conduct coastal border operations, it is necessary to distinguish and separate the background elements of sky, sea, and land. Without this segmentation, objects in the land and sky could be indiscriminately recognized, making background segmentation a crucial strategy. For this purpose, the "BackgroundSubtraction" method[6] used in OpenCV and "Semantic Segmentation" are examples of background separation techniques. A recent advancement in background segmentation uses the WaSR[7] model, which incorporates a ResNet-101 backbone network, resulting in high accuracy for background segmentation.

2.3 Fog Removal

Fog at sea refers to the mist that occurs near the surface of the ocean. Minimizing sea fog is essential for coastal border operations due to the low visibility conditions it creates, impacting the visibility distance. Algorithms necessary for fog removal include the Dark Channel Prior (DCP)[8] and the EDN-GTM algorithm[9]. The DCP method involves identifying the RGB values of low-resolution pixels, defining these areas as the Dark Channel, and applying this channel's image values across the entire image. This process generates an image composed of the darkest brightness channel, where the darkness level of specific pixels is extracted to define the target luminance and estimate the threshold. A binary mask is created for pixels below this luminance threshold, marking dark areas with 1 and the rest with 0. After marking, the target luminance is re-estimated, and the input image is restored. The EDN-GTM model uses a U-net[10] backbone and adopts the same principle of using low RGB values as the Dark Channel. This model has demonstrated superior performance in fog removal compared to traditional methods, with an increase in the mAP measurement by up to 4.73%. Additionally, its compatibility with the YOLO model allows for its application in real-time image processing.

III. Main

The technologies previously described will be integrated to create a system capable of identifying undetected objects along the coast. The algorithmic model will consist of the Dehaze model for noise (fog) removal, followed by the Background Subtraction model for background segmentation, and the Object Detection model for automatically detecting objects.

3.1 Dehaze Model

The EDN-GTM model was used as the Dehaze model for fog removal. This model, when used as a pretrained model, demonstrated the best performance and has been successfully integrated with real-time inference models such as YOLO. Therefore, it was deemed the most efficient option for this experiment as the Dehaze model. In scientific border operations involving coastal environments, when CCTV systems process images through this model, it identifies areas

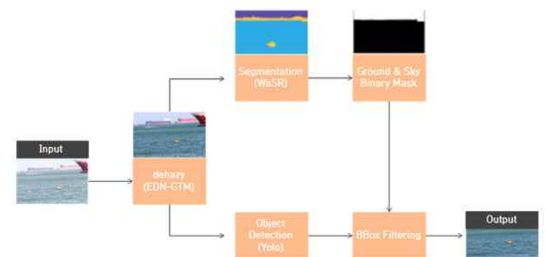
with fog and minimizes this noise, producing clearer images. These enhanced images are then fed into the next task, the object detection algorithm.

3.2 Object Detection Model

After undergoing the initial task of fog removal, the resultant images are processed through an object detection algorithm. The YOLO model is an ideal choice for this purpose. Considering that YOLO continues to be researched and updated, it has improved not only in real-time processing capabilities but also in accuracy, which were limitations of earlier versions. The YOLO model requires images in Tensor format, so after the fog removal task, the images must be converted into Tensor form before proceeding to the second task, which involves processing them through the YOLO model for object detection.

3.3 Background Subtraction

The next step is to enhance the detection accuracy of unidentified objects by segmenting the background based on the sea, sky, and obstacles. The WaSR model has been adopted for this background separation process. WaSR is chosen for its capability to adjust brightness preprocessing, which is crucial in various maritime conditions such as water reflections and weather conditions. Background subtraction is not a step that follows object detection; rather, it occurs simultaneously with the receipt of dehazed images, making it more accurately described as the second task. Thus, images cleared of fog undergo object detection and background subtraction concurrently, with the results combined and outputted together.



[Fig 1] Framework

3.4 Training Dataset

The dataset used for training includes MaSTr1478, a standard dataset for maritime object detection, and 24,000 images from the Alhub maritime open dataset. Of these, approximately 10,000 images will be converted into foggy images using the Haze Image Synthesis[11] algorithm. These images will be used for training with the EDM-GTM algorithm, while the remaining data will be trained using WaSR and YOLOv7.

IV. Experiments

4.1 Experimental Environment

The PC environment used for model training will operate on Red Hat Enterprise Linux Server Release 7.9. The specifications include an

Intel(R) Xeon(R) Gold 6248R CPU @ 3.00GHz, and the training was conducted using two NVIDIA A40 graphics cards.

4.1 Experimental Results

Experiments were conducted on coastal environment images. In the initial experiment, inference was carried out using pretrained models of EDN-GTM, Yolov7[12], and WaSR. The results were as follows.



[Table 1] Original image



[Table 2] Inference result

The results indicated successful detection of unidentified objects on the sea. However, the fog removal performance was unsatisfactory. It is hypothesized that this issue arose due to the use of pretrained models rather than models trained directly with specifically obtained weight files. Consequently, a re-experiment was conducted using models trained directly. For the EDN-GTM and WaSR models, directly trained versions were used, while for the object detection, the pretrained Yolo model was used. The results were as follows.



[Table 3] An example of the haze dataset used for inference



[Table 4] Validation result

Models trained with images containing fog demonstrated more flexible adaptation to foggy conditions compared to those used in the initial experiments, as evidenced by [Table 7]. The identification detection rate for unidentified objects also increased. The next experiment will compare object detection rates before and after fog removal.



[Table 5] Validation result (Before haze removal)



[Table 6] Validation result (After haze removal)

It was observed that images processed for fog removal exhibited more accurate object detection rates compared to those detected directly from pre-fog removal images, as confirmed through [Table 8] and [Table 9]. Next, the inference speed will be measured. Due to the inability to perform inference in a GPU environment, the comparison was conducted using CPUs to assess the speed.

```
1/1 [=====] - 4s 4s/step
1 512
1/1 [=====] - 4s 4s/step
1 512
1/1 [=====] - 4s 4s/step
1 512
1/1 [=====] - 4s 4s/step
1 512
```

[Fig 2] EDN-GTM + Yolov7 + WaSR (Using CPU)

When the model was used, the inference speed was recorded at 4 seconds. Common models used for marine environment detection include not only Yolov7[12] but also Scaled Yolov4[13] and Yolov5[14]. Therefore, Yolov5 will be used as the object detection model to compare speeds.

```
YOLOv5 2023-9-15 Python-3.11.4 torch-2.0.1+cpu CPU
Model Summary: 488 layers, 64363101 parameters, 64363101 gradients, 143.259238400 GFLOPS
1/1 [=====] - 10s 10s/step
1 512
1/1 [=====] - 9s 9s/step
1 512
1/1 [=====] - 9s 9s/step
```

[Fig 3] EDN-GTM + Yolov5 + WaSR (Using CPU)

When Yolov5 was used, the inference speed was between 9 and 10 seconds, which is about 5 seconds slower compared to when Yolov7 was used. This indicates that Yolov7 is more suitable for real-time detection due to its faster speed.

III. Conclusion and Future Research

5.1 Conclusion

This study utilized deep learning as a method to replace human personnel in military science-based coastal border operations. The initial task focused on removing sea fog in coastal areas, and the images obtained from this process were used for object detection. The Yolo model was employed for object detection, comparing results between Yolov5 and Yolov7. It was found that Yolov7 had a 5-second faster inference speed than Yolov5 and additional segmentation of the

sea, sky, and land enhanced object detection accuracy in maritime environments. However, one drawback observed was the misidentification of reflections on the sea surface or waves created by ships as unidentified objects. To improve accuracy and achieve more suitable real-time detection, considering the introduction of TensorRT[15] for lightweight processing of the EDN-GTM model is necessary.

5.2 Future Research

Future research aimed at overcoming these limitations will focus on improving model accuracy and real-time detection through model lightweighting. For lightweighting, the introduction of TensorRT is considered, and for accuracy improvements, the adoption of the OOD[16] approach is contemplated. OOD models, which utilize a K-means clustering unsupervised learning method and identify unidentified objects based on the distance between feature vectors, could refine detection of objects incorrectly marked as unidentified when integrated with existing models.

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