Asia-pacific Journal of Convergent Research Interchange
Vol.6, No.3, March 31 (2020), pp.47-55
http://dx.doi.org/10.21742/apjcri.2020.03.05

Development of Fast-RCNN based Dynamic Object Detection Using an Object Motion Tracking Device in Marine Environments

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Abstract

In this paper, we propose an obstacle identification system and a corresponding algorithm for object motion tracking. The object motion tracking device detects only ships rather than all objects so it can be applied to unmanned surface vehicles' operation in marine environments. When an obstacle is detected, the object motion tracking device identifies and tracks it in real-time according to its movement. Objects are recognized using the Fast-RCNN algorithm, and their positions are measured through the transformation of an image coordinate system. A gimbal control method for a camera using only the image center and distance information of objects without using the camera's focus and zoom function was proposed. The control of the gimbal were made using serial communication based on the video system control architecture protocol, and object tracking was performed by placing the detected object toward the center of the image frame. The object tracking performance of the proposed object identification system has been verified using images in a limited environment.

Keywords : Fast-RCNN, Motion Tracking, Obstacle Detection, PTZ Camera, USV

1. Introduction

With the development of autonomous technology, a variety of research activities related to unmanned vehicles, aircraft and marine robots have increased. Among them, unmanned surface vehicles (USV) are being developed for a variety of purposes, including coast guard activities, maritime reconnaissance missions, and military purposes[1-3]. A substantial amount of research on object detection and recognition for USV in marine environments is currently underway[4].

To implement the USV's remote control and autonomous navigation functions, environment

Received(October 14, 2019), Review Result(1st: November 01, 2019, 2nd: December 12, 2019), Accepted(February 20, 2020)

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ISSN: 2508-9080 APJCRI

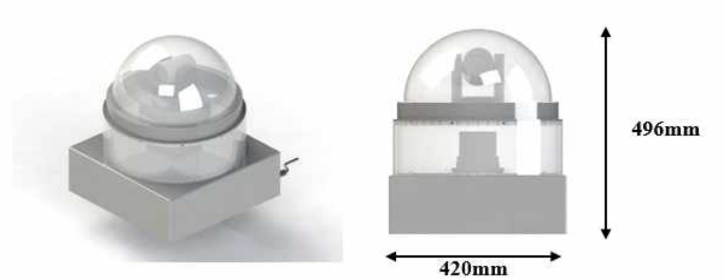
recognition sensor information is required to identify and detect maritime objects during USV operation. The movement of boats sailing on the water's surface has rapid nonlinear dynamic characteristics of various vibration modes. This makes it difficult to achieve stable environment recognition for path planning and autonomous navigation. In order to construct an autonomous navigation algorithm that avoids obstacles through object recognition, stable sensor information for environment recognition is needed[5-8].

We proposed a design and algorithm for object motion tracking device that is able to recognize objects and track their movements for USV. The object motion tracking device was not designed to recognize all objects because it is for an USV operating at sea. The device is therefore designed to detect vessels in a limited number of situations. When an object is detected, the device recognizes and tracks it in real-time as the object moves. The proposed object motion tracking device uses the Fast-RCNN[9-10] technique for image recognition to track objects in limited environments.

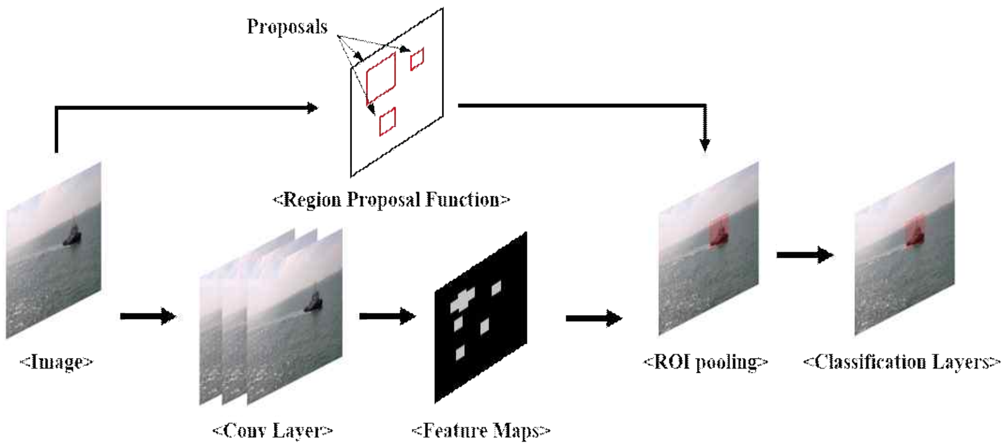
2. Design and Tracking Algorithm for the Object Motion Tracking Device

2.1 Object Motion Tracking Device Configuration

The schematic diagram of the hardware system for the object motion tracking device is shown in [Fig. 1]. The device is 496 mm high and 420 mm wide and is designed with a three-layer structure. The structure of the dome without interference from the camera's tilt movement was considered. The mechanism of the gimbal structure was applied considering the nonlinearity of the dynamic form above the surface of the sea. The gimbal structure of the camera was designed a pan rotation ±170° (Pan: 60°/sec) and tilt rotation -30° to +90° (Tilt: 30°/sec).



[Fig. 1] Object Motion Tracking Device 3D Modeling



[Fig. 2] The Architecture of Fast-RCNN

The camera was configured to have a working humidity in 20-80% considering sea conditions. The object motion tracking device was divided into detection, tracking, and control units.

2.2 Method for Detection and Control of the Object Motion Tracking Device

The method used to detect obstacles proposed in this paper is meant to detect obstacles based on the Fast-RCNN technique. Afterward, the location of objects in the images is determined through image coordinate system conversion. The object motion tracking device then performs real-time detection depending on the movement of the obstacles. The Fast-RCNN technique for obstacle detection is shown in [Fig 2]. As an obstacle detection method, the input image is divided into the Convolution Layer. Then, the Feature Maps is created through CNN (Convolutional Neural Networks). A feature is then made by pooling only the parts of the vessel corresponding to the ROI (Region of Interest). Finally, the object class and coordinates are obtained through the classification layer.

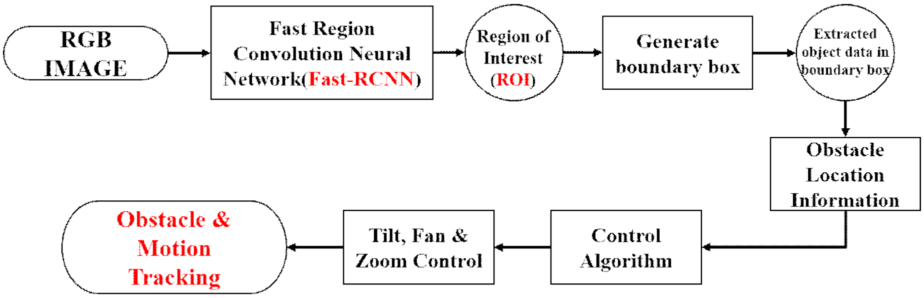
Obstacle identifiers do not use the camera's focus and zoom during the detection process. The movement of the obstacle is tracked using only the distance information between the center of the image and the center of the obstacle.

$$d_x = x_{center} - x_{obj,t} \tag{1}$$

$$d_y = y_{center} - y_{obj,t} \tag{2}$$

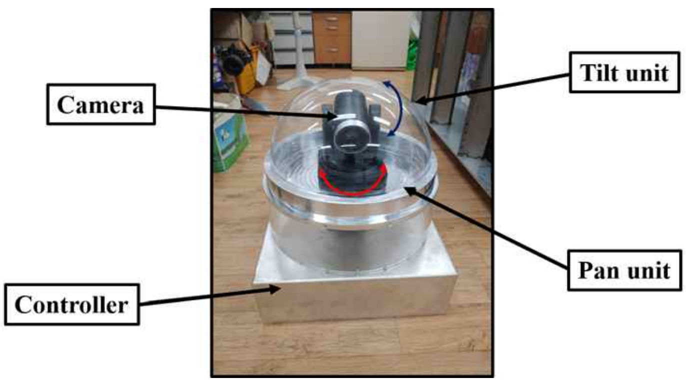
$$x_{center},\ y_{center} : Obstacle\ Motion\ Tracking\ device\ center\ point \tag{3}$$

$$x_{obj,t},\ y_{obj,t} : Obstacle\ Center\ Coordinates \tag{4}$$



[Fig. 3] Process Chart for Object Recognition and Motion Tracking

As the control method, the center point of the moving object was created in the input image, and then the virtual center point of the object motion tracking device is created and compared. Then, the difference between the (x, y) position of the center point of the moving object and the virtual center point of the object motion tracking device is measured. The fan and tilt motor are controlled by the difference in position (x, y). The obstacle detection and tracking algorithm are shown in [Fig. 3].



[Fig. 4] Configuration of the Object Motion Tracking Device

3. Experiments and Results

3.1 Experimental Configuration

The sensors and components used in this study were constructed as shown in [Fig. 4]. The camera sensor used to detect obstacles was the FLA-HDB520U23T. This camera had a 20X optical zoom, 10X digital zoom, and 54.7° view angle. The maximum resolution of the camera sensor was 2.0 megapixels and it supported a video format up to 1920 x 1080. Images acquired from camera sensors were entered into input images of the controller through serial communication using video system control architecture protocols between controller and camera. Location was controlled using the camera's fan and tilt motor with RS232 communication.

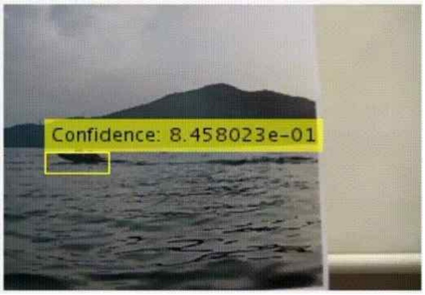
The controllers used for the learning and detection experiments used Intel (R) Core (TM) i7-7700HQ. The CPU supported 6MB of cache, four cores and six threads. The GPU for image processing used the NVIDIA GeForce GTX 1060. Matlab 2018b was used for Fast-RCNN and camera control. The learned image of the model vessel is shown in [Fig. 5]. The learning specifications of Fast-RCNN for obstacle detection are shown in [Table 1]. The convolution layer size is shown according to filter size, straight, and wero padding.

[Fig. 5] Fast-RCNN Training Data

[Table 1] Fast-RCNN Training Specifications

Batch Size	128
Convolution Layer Size	128*256*512
Training Data	1024 Image
Training Image Resolution	1280*720

(a) RC boat Image Test

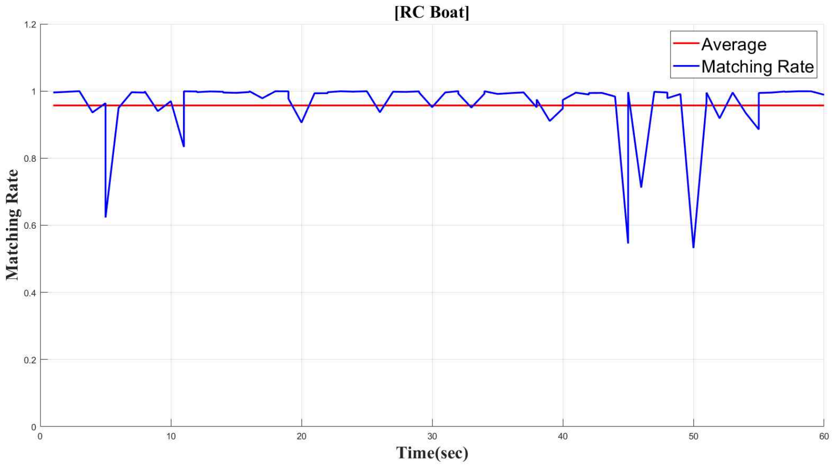


(b) RC Boat Test Result

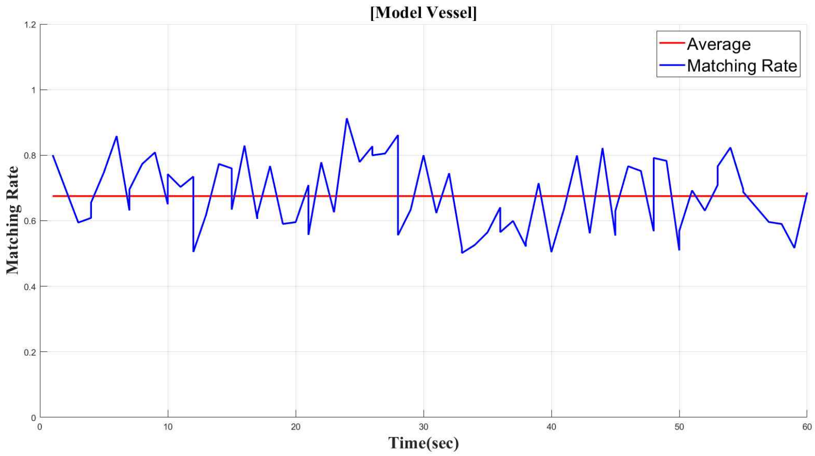
(c) Model Vessel Image Test

(d) Model Vessel Test Result

[Fig. 6] Object Motion Tracking Test



[Fig. 7] RC Boat Matching Rate And Average



[Fig. 8] Model Vessel Matching Rate And Average

[Table 2] Comparison of Object Recognition Rate in the Object Recognition Prior Study

	Fusion	Sensors	Objects
MV-RGBD-RF[11]	Yes	LIDAR+CCD	Vehicles - 57.5%
3DOP[12]	Yes	CCD+Stereo	Vehicles - 79.1%
OH[13]	Yes	LIDAR+CCD	Vehicles - 81.4%
CHAVEZ[14]	Yes	LIDAR+CCD+RADAR	Vehicles - 92.0%
KHUV[15]	Yes	LIDAR+CCD+RADAR	Vehicles - 90.0%
Ours	No	CCD	RC Boat - 95.7% Model Vessel - 67.5%

3.2 Results

The proposed object motion tracking device set up the model image on the surface of the water as an obstacle, not as a sea environment. The experiment was performed as shown in [Fig. 6] and [Fig. 7]. When the experiment was conducted with the Fast-RCNN algorithm, the RC boat average matching rate was 95.7% and model vessel average matching rate was 67.5%. For the proposed Fast-RCNN, the image processing speed was shown to be very slow at 2 FPS. The results of the experiment were compared with the results of a prior study of object recognition through sensor fusion in [Table 4].

Other research and experimental conditions are different, but the object recognition rate is high without sensor fusion.

Through FPS result, we were able to see that there was a lack of real-time functionality. Thus, when detecting obstacles in real-time, the obstacle identification system encountered problems that could not be tracked continuously.

4. Conclusion

The object motion tracking device design, obstacle detection and tracking experiments were conducted. The completion rates of the experiments carried out in this study were still low.

This is because the obstacle detection and tracking experiments must be conducted in the original sea environment and in actual vessel conditions. However, in this paper, basic obstacle detection and tracking studies were conducted.

We have decided that the primary priority is to accurately detect and evade vessels where unmanned platforms might encounter obstructions. Therefore, the Fast-RCNN, which is relatively fast in image processing and is well matched, was selected among various obstacle detection algorithms. However, as shown in [Fig. 6], the image processing speed was very slow at 2 FPS, resulting in the following problems.

If the model vessel image moves at a slow speed, the object motion tracking device can continue tracking. However, the rapid movement of the model vessel image resulted in an inability to keep tracking. Considering the dynamic nonlinearity of the sea's surface, object motion tracking devices should also be able to detect obstacles moving at high speeds. Therefore, the current algorithm is judged to lack real-time capabilities for unmanned platforms operating in sea environments.

In the future, experiments should modify and supplement algorithms to secure real-time functionality. The object motion tracking device should include the camera's focus and zoom function. In addition, LIDAR might be applied to carry out the study of object motion tracking device that can ensure continuous tracking by providing feedback on the distance and location of obstacles as well as the image information of the surrounding obstacles.

Acknowledgments

This development project was supported by the LIG Nex1 (20192610).

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