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Vehicle detection Using Convolutional Neural Networks in Sonar Images

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Abstract- An agent system is used to improve underwater operations. Single-point robotic arm-based positioning is often used in conventional operations. In contrast to this armless operation, agent systems use agent vehicles as end effectors. The end effector can be placed anywhere as long as the agent can be located. As a means of realizing this system, technology is provided to identify the location of the agent's vehicle. This method uses look-ahead sonar imagery of moving agents. CNN is used to find out agent within sonar image. An Agent system had the advanced algorithms for object detection. Neural- network object detection methods will meet real-time detection requirements and will give exceptional effectiveness. That is the underwater robot can perform the task by its own. In real-world this approach is effective in locating agents in next sonar photos and track the progress.

Keywords—Armless Manipulation -Agent vehicles - Convolutional neural-networks - Object identification - Forward-looking sonar - Sonar image processing.

1. INTRODUCTION

In a sea there are many unknowns, is a fascinating research field.Rapid developments in Autonomous Underwater Vehicle (Auv) and Remotely Operated Vehicle (Rov) technology over past few decades have made sea exploration conceivable... These robots can use various sensors to map the seafloor or survey specific underwater. Research on control theory, navigation-system, and sensors for underwater robots is going on. Certain physical processes make the question of underwater operation more important. Underwater robots have several methods of underwater manipulation. The most common method is using a robotic Arm.By using these arms, AUVs, ROVs can perform certain physical tasks underwater. The joint angles can be precisely controlled. However, the articulated design called One Point is sturdy and takes up a lot of weight, space. The result is a weapon-free operating technique.

An end effector robotRov is attached to Auv. LoglineRov's can perform a different taskss without the necessityof large batteries or any built-in brain power. Because Auv's are unconstrained, they have more instruments and sensors. Detail can be reached using the Rov's size. This gadget enables arm-free underwater operation and agent docking. It can be used by the manipulating hand to grab objects and carry out fine motor tasks. By using the position sensors it locates the agent and the main Auv's predictive sonar, referring to it as a agent vehicle. Precise operations can be achieved using accurate location data.

In this study, the agent's vehicle position can be determined in real time using neural network-based object recognition. [4] You Only Look Once (YOLO) object recognition technology is characterized by fast and accurate recognition. We tested this technique using data from an advanced sonar system. As a result, it turns out to be used as a feedback control input.

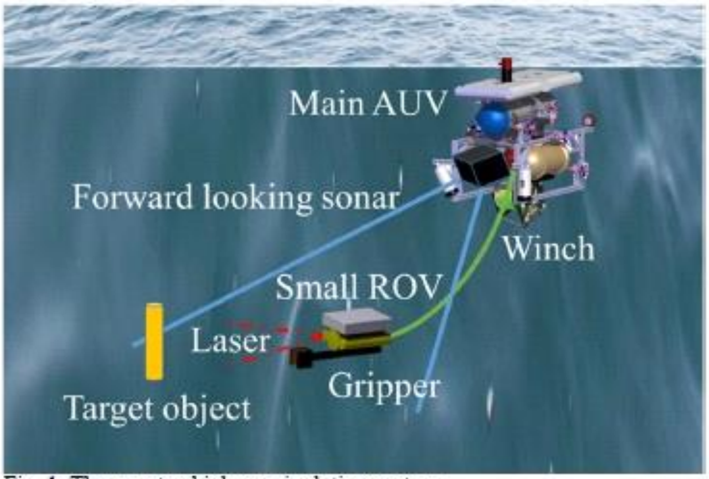

Fig. 1. The agent vehicle manipulation system.

2. RELATEDWORKS

Aural-video and images are being captured by forward-looking sonar. This method may be useful for underwater detection because it is more apparent than optical imaging. Look-ahead sonar's image quality, however, falls short of that of optical imaging. Only the human eye can tell them apart because of the poor audio-image quality Figure 2.The picture is ruined by too much noise and a lack of detail. In addition, the frame vividly illustrates the three distinct compositional components—shadows, backgrounds, and highlights. Its beautiful structure shows many shapes when viewed from various heights and perspectives. It is challenging to extract relevant information from photos because of these characteristics. As a result, sonar picture analysis using conventional image processing methods is unsuccessful. Convolutional neural networks are a supervised machine learning technique that employ neural networks [7]. Due to the growing computational capability of GPU parallel architectures, neural network modelling is currently a hot issue in image processing [8]. Rapid training and testing of large neural network models is possible [9].

The majority of applications require traditional image processing methods like feature matching. Low-level components of the system include certain pre-set forms or post-processing methods. Contrarily, convolutional neural networks employed training-level features [10]. The challenge of properly analysing a model increases with its complexity [8] [22]. Supervised machine learning produces accurate black-box functions for classifiers. Image classifiers can only classify images by displaying potential classifications for already-classified images.For this reason, it is difficult to identify objects on the image. A good return on investment (Roi) is very important for object recognition. There are many algorithms for finding Roi instances. SIFT or HOG algorithms were used to identify low-level features [11].

However, because to their poor validation performance and neural network-based object detection algorithms have been created.

The effectiveness of the R-CNN algorithm have been detected twice and the best compared to that of the previous algorithm [12]. [10,11] Herewe are using the Spatial pyramid pooling in deep convolutional networks for visual identification (SppNet) is 24104 times faster than R-method Cnn [13]. R-Cnn and R-Cnn improve effectiveness and detection speed [14, 15]. However, integration into embedded computer systems is somewhat time consuming. Cnn has repeatedly recalculated the model. As a result, it took us a long time to determine our target Roi.

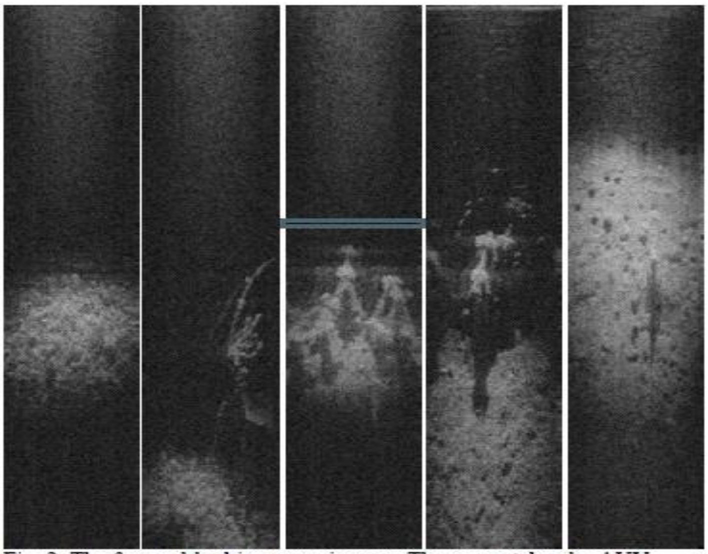

Fig. 2. The forward-looking sonar images. They were taken by AUV 'Cyclops' [17].

3. PROPOSED SYSTEM ARCHITECTURE

The underwater mini ROV is equipped with our real-time object detection technology. But before we can recognize an object, we must first recognize the object. It uses sonar imagery to indicate the probability that a target is present. A classifier model is the best to differentiateboththe positive and the negative images. For the positive pictures, we used properly cropped Rov images. For the negatives improperly cropped or used background images were used. After developing the classifier, the model was evaluated and the computational weights were calculated again. The model was assessed after classifier development, and new computational weights were determined. Training also utilised prior look-ahead sonar scans without targets. The likelihood of missing something in the background is decreased by post-processing.If your model has a high classification rate, you can use object detection techniques. For example, you can identify a region of interest (Roi). The neural network strategy and the sliding window method were both put to the test. I have to use machine learning methods, such as image training, to train a lot of photos. There is a model for a traditional convolutional neural network (Cnn) known as a darknet referenced model (Cnn). It is a small model, but powerful. It contains 6 max pooling layers and 7 convolution layers. A training data set was obtained using a real-world experiment. Forward-facing sonar photos were taken by a hovering Auvcyclops in 2016 [19]. When they launched together, the Auv picked up a little Rov. The 2000 pictures were all recoverable. We spent

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the majority of our time creating the dataset. ROI and class number are included in the label data. Label data was encoded and photos were manually cropped. There are two separate ROIs for each exposure. Positive and negative are distinct from one another.Images were manually panned and randomly cropped with the mouse for precise small RovRois. This information could also create incorrect data for model revisions. Using a random sample of 1000 random sonar images, we identified two ROIs and labelled them. Additional fake background photos should be collected to improve the detection accuracy of the classifier. A 'positive' ROI on the sham background was detected by the model without modification. After retraining on fake data, no additional objects were detected from the photos. There, he discovered that the dataset could be useful in planning underwater exploration. The starting step is to take good enough pictures of the small Rov. A small Rov he has been photographed 1152 times and tagged in the photos. Then pre-scan the area surrounding the target area. There were 455 background photos in total. These can be used to train robust models. The model can then be trained using a robust computing device, like a desktop computer with a graphics processing unit (Gpu). After your workout, your strength training data is safely kept. Something that can be instantly controlled. We developed the Yolo algorithm, a novel approach to object identification [4]. Using a single Cnn model, bounding boxes and class probabilities are both predicted. The classifier model is attached to a segmented 11 x 11 region. At the conclusion of the procedure, the classifier model is fully integrated with split Rois and class probabilities (Figure 3). Their free source programme was used with our unique dataset. The dataset format includes class numbers and Rois to use.

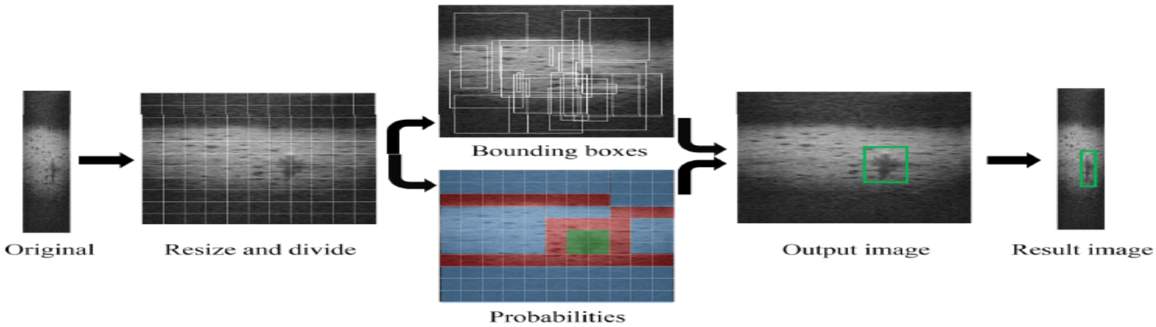

Fig. 3. The YOLO algorithm structure conducting our custom data-set [4].

4. RESULTS AND DISCUSSION

We conducted field experiments to validate the proposed strategy. As our primary AUV, we used a hovering model called cyclops [17]. An experimental station was maintained in order to keep control. Ignore positional inaccuracy which is only a few centimetres. Our Auv was equipped with a Didson system capable of taking sonar images of the agent [19]. Didson has 5 frames per one second. Sonar image resolution is 512 x 96. This means forward looking sonar can see her Rov. The Rov position was then adjusted manually. The proposed approach was used to rectify and evaluate sonar images collected during Rov operations. There are 1000 sonar images. The Yolo model was trained on 1607 images. You can monitor the training progress using the function of loss (Figure 4). Saturation of the curve trend shows that training is having a beneficial effect. Training was completedin one hour. A total of 1000 photos were able to identify each location, and Yolo's neural-network model was identified the agent’s vehicle accurately. Roi box provide the exact boundaries of each agent vehicle

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(Figure 5). Randomly selected images were inserted using an advanced sonar image database. Only negative ROIs were then found, while positive ROIs were completely absent. Also, the trajectory of each image was recorded. Track the photo's x and y axis. I removed the unknown areas and stitched images together. Route of the vehicle can be seen in diagram. The speed of the procedure is important as it should be used for real-time underwater operations. When processed offline by Gpu, Yolo object detection technique showed 107.7 Fps [20]. This method yielded 0.20 Fps (Table 1), but it was too slow. In actual life, 5 frames per second is the frame rate at which look-ahead sonar images are recorded. Therefore, it can be employed in real-time control or mission if the object detection result speed is over 5 Fps. Using forward-looking sonar data, we have created a real-time object detection technique to locate agent vehicles. Compared to others it is more reliable the more data there are. The actual tests are what comes next. When an embedded system is used instead of a robust PC, recognition performance is slowed. Use embedded systems with mobile GPUs to address this issue [21].

Neural networks can be processed on modern embedded boards with sufficient computational power and long run times.

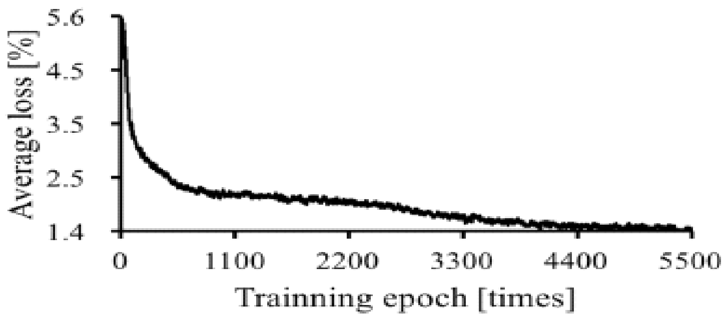

Fig. 4. The average loss function value of trainning.

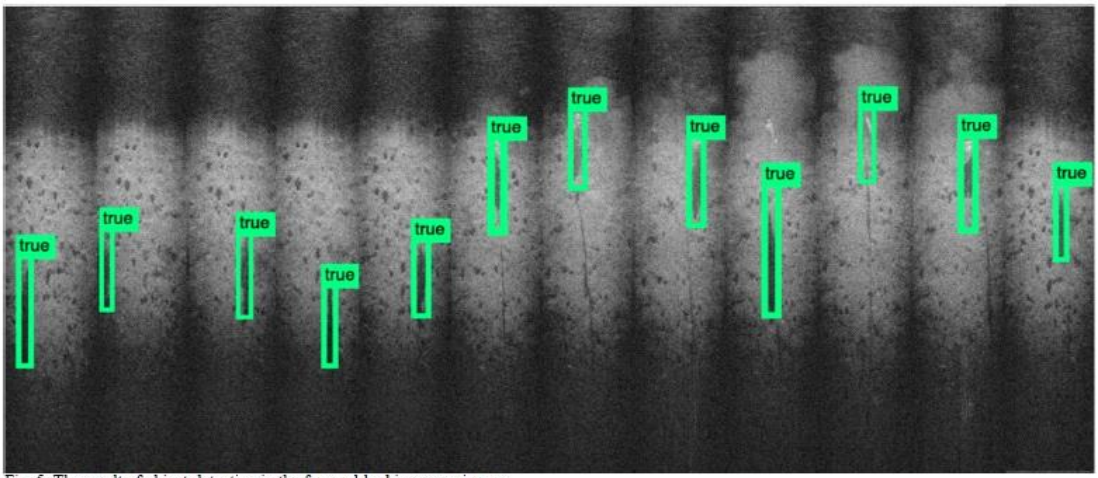

Fig. 5. The result of object-detection in the forward-looking sonar images.

TABLE I. THE COMPARISON BETWEEN TWO ALGORITHMS ABOUT FRAMES PER SECOND.

	Object-detection Algorithms	
	YOLO	Sliding Window
Frames / s	107.7	0.20

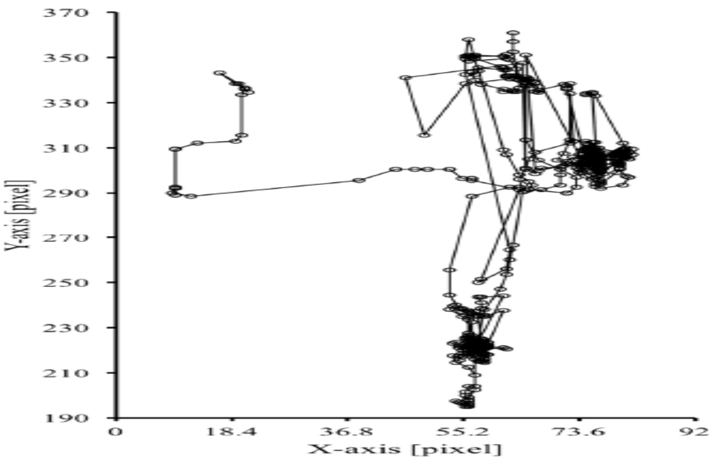

Fig. 6. The trajectories of agent vehicle on the forward-looking sonar images.

5. FUTURE SCOPE AND CONCLUSION

In this study, we usedsonar data based on Cnn and Yolo which are forward-looking to validate real-time object detection. The custom data set you produce serves as the foundation for the object detection algorithm. We then discovered that we could find a little Rov. We discovered that the Yolo method is significantly more effective at analysing look-ahead sonar images. Finally, this study demonstrates that processing sonar images using machine learning methods is substantially more efficient.

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