International Journal of Research in Engineering, Science and Management
Volume 4, Issue 7, July 2021
https://www.ijresm.com | ISSN (Online): 2581-5792

Underwater Object Detection Using Image Processing

P. Srinivas Babu[1], B. Prateek[2*], P. Punith[3], B. Pramod[4], M. Nitin Patel[5]

[1]*Professor, Department of Electronics and Communication Engineering, East West Institute of Technology, Bangalore, India*

[2,3,4,5]*Student, Department of Electronics and Communication Engineering, East West Institute of Technology, Bangalore, India*

***Abstract*: This project describes the architecture and design of an improved configurable underwater object detection using image processing. The vision based method for detecting the objects under water is carried out using Yolo based convolutional neural network (CNN). YOLO (You Only Look Once) is a real time object detection algorithm. This algorithm applies a single deep neural network to the full image, and then divides the image into regions and predicts bounding boxes and probabilities for each region. These bounding boxes are weighted by the predicted probabilities. The main contribution of this project is to detect the objects and send the captured image and its real time coordinates to the specified mail address.**

***Keywords*: YOLO, CNN, Image processing.**

1. Introduction

The underwater environment is one of the most challenging conditions for object detection. The increasing demand for vision-based applications enhances the importance of camera-based object detection methods in underwater scenarios. The modern world is enclosed with gigantic masses of digital visual applications. To analyze and understand this huge sea of visual information, there exist many image analysis techniques like image processing and deep learning. Deep learning is a method that automatically detects the object needed to be detected or classified using the provided raw data.

2. Problem Description

In general, sonar and cameras are two typical sensors widely used for underwater object detection. Sonar sensors are sensitive to geometrical structure information and can provide information of underwater scenes even in low- and zero-visibility environments. However, the data acquired by sonar can only present the difference of the distance over the scanning points. Other factors such as visual features are missed by this type of sensor. As a result, sonar-based systems are feasible for top-down tasks, such as hydrographic surveying and charting, shipwreck, and marine geological surveys. In contrast to sonar, cameras can provide more types of visual information at high spatial and temporal resolutions.

Hence, in addition to these top-down tasks, underwater vision systems(cameras) possess a better ability to handle down-top tasks where we have little prior knowledge of the current underwater scenes, such as marine ecology monitoring and underwater entertainment.

3. Project Hardware Setup

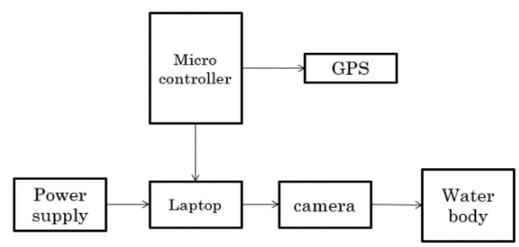

Fig. 1. Hardware setup of the proposed system

Figure 1 The above mentioned proposed system consists of a NodeMCU ESP8266 which has 128 KB RAM and 4MB of flash memory and operates at 3.3V. The SUP500F is a compact all in one GPS receiver module is connected to the microcontroller. Objects in the water are captured by using an inspection tube 3.5m camera which is submersible under the water upto 35m of depth. The camera is USB enabled which is connected to the processor (laptop). Open CV (open source computer vision) libraries are used for capturing the images for object detection. A miniature artificial water body is created with pure and impure water for experimental analysis in different scenarios.

Captured images of the object are classified using the CNN algorithm. After detection the image will be sent to a specified mail address. The GPS is used to provide the location of the detected object which in turn connected to the micro controller.

The BLYNK app is connected to the microcontroller wirelessly, that means the hotspot of the mobile is connected with the microcontroller.

*Corresponding author: prateekbb.1999@gmail.com

4. Literature Review

The literature review attempts to discuss the work carried out in the areas of object detection in underwater scenarios.

Girish Gaude and Samarth Borkar, “Comprehensive Survey on Underwater Object Detection and Tracking”, International Journal of Computer Sciences and Engineering, Vol. 6, Issue 11, Nov. 2018.

The recent developments in underwater video monitoring system makes automatic object detection and object tracking a significant and challenging task. In such processing, the method involves preprocessing, feature extraction, object classification, object detection and tracking. Detecting moving objects from the underwater video has many potential applications for Remotely Operated Vehicles (ROVs) or Autonomous Underwater Vehicles (AUVs), such as tracking fish, recognizing underwater objects etc. Underwater object recognition is a cumbersome due to the change in water structure, seasonal, climatic changes, temperature variation and further degraded by a poor non- uniform source of artificial light. Diverse approaches using image processing and pattern recognition have been proposed by numerous scientists and marine engineers to tackle these problems using methods such as neural network, contour matching, and statistical analysis. In this article, we provide a comprehensive overview of different methods and techniques of object detection and object tracking in general and underwater scenario in particular. We have been successful in highlighting the several key features and aspects of underwater object detection and tracking which will take the work in this domain further.

G. L. Foresti and S. Gentili, “A Vision Based System for Object Detection in Under Water Images”, International Journel of Pattern Recognition and Artificial Intelligence, Vol. 3, March 2017.

In this paper, a vision-based system for underwater object detection is presented. The system is able to detect automatically a pipeline placed on the sea bottom, and some objects, e.g. trestles and anodes, placed in its neighborhoods. A color compensation procedure has been introduced in order to reduce problems connected with the light attenuation in the water. Artificial neural networks are then applied in order to classify in real-time the pixels of the input image into different classes, corresponding e.g. to different objects present in the observed scene. Geometric reasoning is applied to reduce the detection of false objects and to improve the accuracy of true detected objects. The results on real underwater images representing a pipeline structure in different scenarios are shown.

Zhen Chen, Zhen Zhnag, Fengzhaodhai,Yang buand Huribin wang, Monocular, “Vision based Underwater Object Detection”, International Journal of Computer Sciences and Engineering, Vol. 7, 2017.

In this paper, we propose an underwater object detection method using monocular vision sensors. In addition to commonly used visual features such as color and intensity, we investigate the potential of underwater object detection using light transmission information. The global contrast of various features is used to initially identify the region of interest (ROI), which is then filtered by the image segmentation method, producing the final underwater object detection results. We test the performance of our method with diverse underwater datasets. Samples of the datasets are acquired by a monocular camera with different qualities (such as resolution and focal length) and setups (viewing distance, viewing angle, and optical environment). It is demonstrated that our ROI detection method is necessary and can largely remove the background noise and significantly increase the accuracy of our underwater object detection method.

Magnuson-Stevens Fishery Conservation and Management Act. Public Law, United States, 1996.

As populations of many fish species worldwide have declined, the price of fuel has increased, and coastal development has mushroomed, fishing communities have suffered economic and social vulnerability. Since its 1996 re-authorization, the Magnuson-Stevens Fishery Conservation and Management Act (which governs U.S. marine fisheries) has included a definition of "fishing community" as "substantially dependent on or substantially engaged in the harvest or processing of fishery resources to meet social and economic needs" and a requirement (National Standard 8) to minimize economic impacts and sustain participation in fisheries in these communities. These initiatives are being implemented in conjunction with a worldwide move towards ecosystem-based management. These legal and policy requirements add a new layer to theoretical discussions of "community" and "vulnerability." We review key themes and issues from the literature on ecological anthropology, vulnerability, disasters, ecosystem-based management and fishing communities in the context of applied anthropological work in the U.S. Critical factors for understanding vulnerability in fishing communities are discussed and put in the context of more inclusive and holistic forms of management

Tiedong Zhang, Shuwei Liu, Xiao He, Hai Huang and Kangda Hao, “Underwater Target Tracking Using Forward-looking Sonar for Autonomous Underwater vehicle (AUV)”, Natural Key Laboratory of Science and Technology, Vol. 1, pp. 1-28, December 2019.

Proposed that the scenario where autonomous underwater vehicles (AUVs) carry out tasks, it is necessary to reliably estimate underwater-moving-target positioning. While cameras often give low- precision visibility in a limited field of view, the forward-looking sonar is still an attractive method for underwater sensing.

First, the character of acoustic-vision images is considered, and methods of median filtering and region growing segmentation were modified to improve image-processing results. Second, a generalized regression neural network was adopted to evaluate multiple features of target regions, and a representation of feature subsets was created to improve tracking performance. Thus, an adaptive fusion strategy is introduced to integrate feature cues into the observation model, and the complete procedure of underwater target tracking based on GPF is displayed. Results obtained on a real acoustic-vision AUV platform during sea trials are shown and discussed. These showed that the proposed method is feasible and effective in tracking targets in complex underwater environments.

5. Schematic Diagram

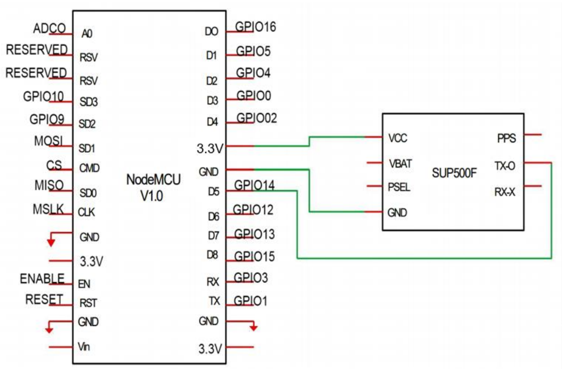

Fig. 2. Schematic diagram of the proposed system

CONTROL PINS=EN, RST The pin and the button resets the microcontroller

Analog Pin =A0 Used to measure analog voltage in the range of 0-3.3V.

GPIO Pins = GPIO1 to GPIO16 NodeMCU has 16 general purpose input-output pins on its board

SPI PINS= SD1, CMD, SD0, CLK NodeMCU has four pins available for SPI communication.

UART PINS = TXD0, RXD0, TXD2, RXD2, NodeMCU has two UART interfaces, UART0 (RXD0 & TXD0) and UART1 (RXD1 & TXD1). UART1 is used to upload the firmware/program.

I2C PIN = NodeMCU has I2C functionality support but due to the internal functionality of these pins, you have to find which pin is I2C.

SUP500F:

The SUP500F is a compact all-in-one GPS receiver module solution intended for a broad range of products.

The SUP500F GPS receiver's -161dBm tracking sensitivity allows continuous position coverage in nearly all application environments. Its high performance search engine is capable of testing 8,000,000 time-frequency hypotheses per second, offering industry-leading signal acquisition and TTFF speed.

6. Methodology

This is the detailed workflow of our project, we start off by collecting the data or capturing the image then necessary libraries such as tinker, numpy etc. are imported, the trained YOLO model is loaded, then the features of the image are classified and if the confidence value of the detected image is more than the confidence value specified then bounding boxes are drawn on the detected object. The position of the detected object is appended to the text to speech module which reads out the position and class of the object through the speakers.

7. Implementation

We have used inspection tube (3.5m) camera as our input device to capture the objects from our underwater environment setup. The captured data is sent to the laptop which will be analysed further. We are going to use two different ways for analysing the image and another way by training the model to detect a custom dataset.

1) Real time video stream

In this method the object will be detected in real time through live stream.

2) Using Graphical user interface (GUI) application

This method involves two options

a) Select photo: The image is selected from the collected data set.

b) Capture: The image is captured in real time from the input camera.

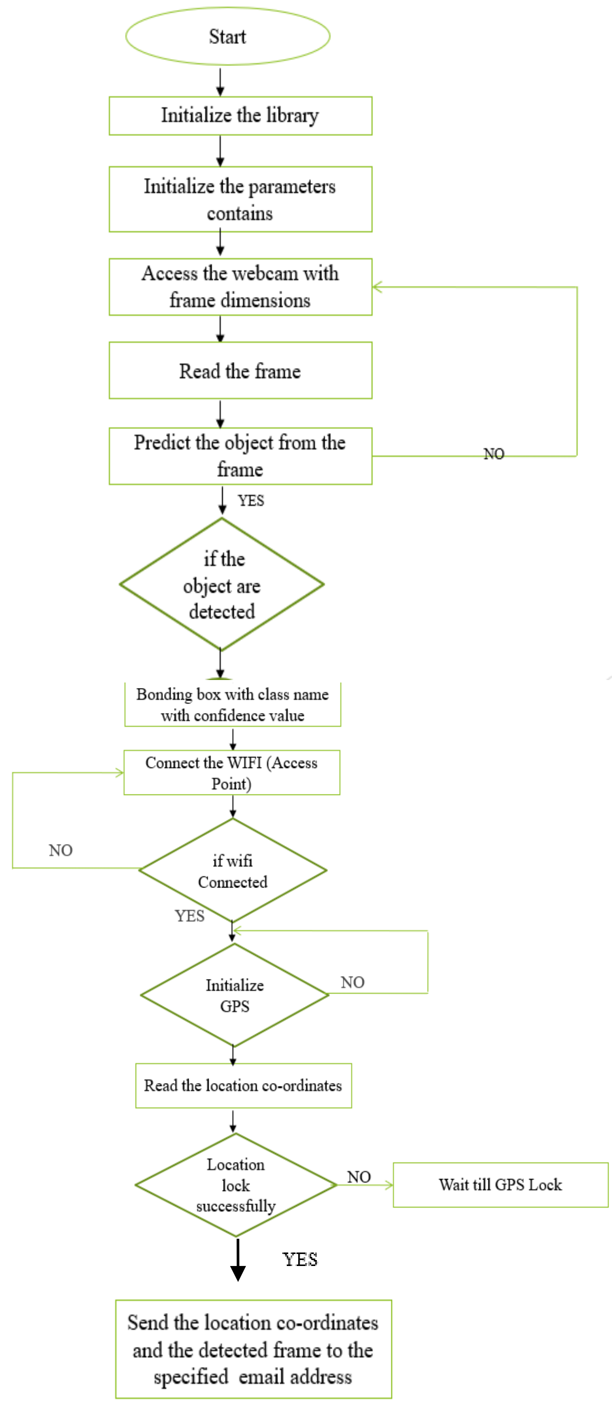

Fig. 3. Project work flow

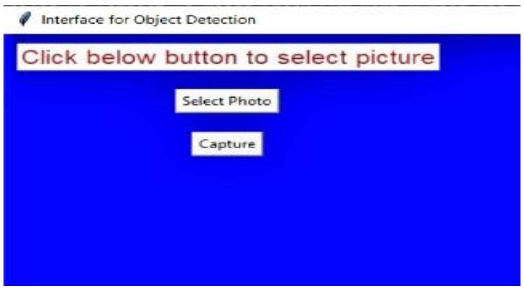

Fig. 4. GUI (graphical user interface)

3) Training our model with a custom dataset

- A custom dataset of 200 images is collected and it is annotated.
- The annotated data is then used to train the model and the weights file is obtained after 1000 iterations.
- YOLOv3 is the algorithm and Darknet is the framework that has been used to train this object detection model.

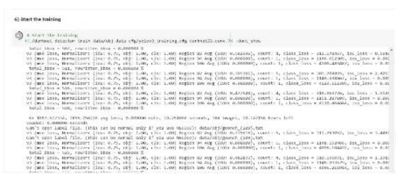

Fig. 5. Training the object detection model

8. Results

Fig. 5. The objects are detected as scissors and metal object with confidence value of 0.834 (83.4%) and 0.7940 (79.40%) respectively, Here the real time code is executed

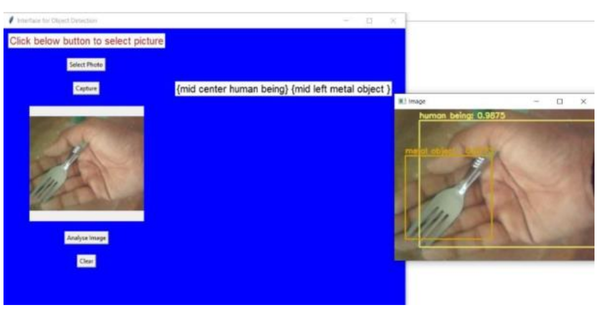

Fig. 6. The objects are detected as human being and metal object with confidence value of 0.9875 (98.75%) and 0.9773 (97.73%) respectively, Here the input is taken from the camera feed and GUI is used for further operation

Fig. 7. The captured image i.e. fig. 6. is sent to the specified mail address with its location co-ordinates, this automatically happens when the 'Analyse 'button is clicked while using the GUI

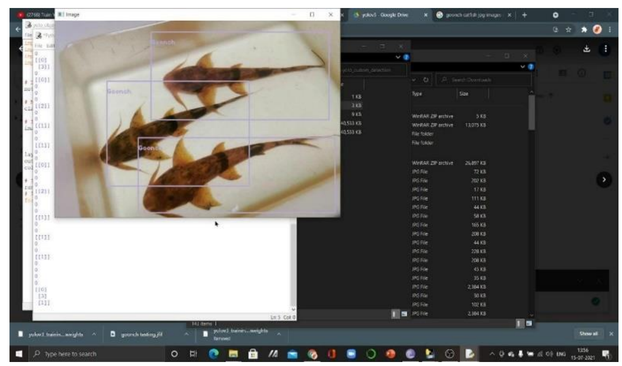

Fig. 8. The custom dataset that is "Goonch catfish" is detected by the object detection model, Here the confidence value was set to be above 0.4 i.e. above 40 % and the accuracy was found out to be 79%

9. Conclusion

Convolution Neural Network algorithms are identified as suitable deep learning algorithms. They are trained with a dataset containing objects in various underwater scenarios, aiming to detect and track these objects in an underwater environment which can then be retrieved. The results obtained are collected and analyzed using accuracy, precision, recall, training time and detection speed metrics. After analyzing the results, it is found that Convolution Neural Network showed the best results. Thus YOLO is the algorithm of choice to effectively detect and track the objects.

10. Future Scope

We can implement our model with a night vision and thermal vision enabled camera in place of normal camera for higher applications. Our current model is static to a particular location, But we can make it mobile using automation . This model can be also linked to satellite for live streaming also. Using automation and IoT we can convert this model into an underwater drone.

References

[1] Tiedong Zhang, Shuwei Liu, Xiao He, Hai Huang and Kangda Hao, "Underwater Target Tracking Using Forward-looking Sonar for Autonomous Underwater vehicle (AUV)", Natural Key Laboratory of Science and Technology, Vol. 1, pp. 1-28, 23 December 2019.

[2] Fatma Günseli Ya Şar Hüseyin Kuseto Ğullari, "Underwater Human Body Detection Computer", 26th Signal Processing and Communications Applications Conference (SIU), pp .1-20, 2018.

[3] Girish Gaude and Samart Borkar, "Comprehensive Survey on Underwater Object Detection and Tracking", International Journal of Computer Sciences and Engineering, vol. 6, pp. 304-313, November 2018.

[4] Zhen Chen, Zhenzhnag, Fengzhaodhai, Yangbu and Huribinwang, "Monocular Vision-Based Underwater Object Detection", International Journal of Computer Sciences and Engineering (JCSE), pp. 1-5, 2017.

[5] G. L. Foresti and S. Gentili, "A Vision Based System for Object Detection in Under Water Images", International Journal of Pattern Recognition and Artificial Intelligence, Vol. 2, pp. 167-188, March 2016.

[6] A Martin, K. Nelson and Smith, "Obstacle detection by a forward-looking SonarIntegrated in an AUV", Ocean 2000 MTS/IEEE Conference and exhibition, vol. 40, pp. 397-407, August 2015.

[7] Yingchun Lu and Enfang Sang, "Underwater Target's size/shape dynamic analysis for fast", International Symposium on Underwater Technology, pp. 374-377, 2015.

[8] Magnuson-Stevens Fishery Conservation and Management Act. Public Law, United States, 1996.

[9] Wang G, "AUV control system based on multi-sensors", Harbin Engineering University School of Automation, vol. 1, pp. 1-9, 2014.

[10] Dong J G, "Research on AUV underwater acoustic communication system", Harbin Engineering University College of Underwater Acoustic Engineering, vol. 2, pp. 321-325, 2013.