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Deep Learning Based Automatic Plastic Recognition Using Autonomous Underwater Vehicle

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Abstract

Plastic pollution in water bodies is one of the biggest issues in this era. It affects the marine animals in turn affecting the whole biological chain. The plastic suspended in water is consumed by many organisms which leads to their death which causes the biological imbalance. It also affects humans as drinking water can also be contaminated. So, the main motive of this project is to reduce plastic waste in water reservoirs. This paper discusses number of algorithms to detect underwater debris efficiently. Algorithms include YOLO, tiny YOLO, Faster RCNN, forward-looking imaging sonar, etc. The dataset used for training taken from JAMSTEC E-library of Deep-sea Images. This paper also discusses about the issues in underwater video processing. We have designed an underwater autonomous vehicle for detection of plastic, design of which is also discussed in this paper. Thus a complete system to detect plastic is discussed in this paper.

Keywords: *AUV, Object detection, YOLO, AdaBoost, Neural network, CNN.*

1. Introduction

Plastic pollution in water bodies is one of the biggest issues in this era. It affects the marine animals in turn affecting the whole biological chain. The plastic suspended in water is consumed by many organisms which leads to their death which causes the biological imbalance. It also affects humans as the drinking water can also be contaminated. According to 5 Gyres organization nearly 5.25 trillion pieces of plastic weighing 270,000 metric tons are on the surface of the world's oceans. Hardly there exists place on earth which is unpolluted by marine litter. Plastics also habitually exploit into the water, degrading the water quality with toxic compounds and end up harming human and animal health [10].

There are various technological achievements in many robotic field for underwater environments and it is very difficult task for autonomous robots. Localization is one of the problem in field of robotics and must tackle it. Desirable object is unambiguously determined by the shape of its edges, but the contours of physical object in a picture can be noisy, sporadic or blurry. This appears when AUV captures in muddy water, dark, with the presence of external objects, algae, marine organisms, etc. Water imparts the electrical and mechanical design of systems, intervenes with actuators and sensors by confining their capabilities, to a great extent affects information transmissions, and generally requires systems with reduced power requirements to enable sensible mission time period.

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In systems which are aimed to work underwater, primary issues are related to the ability of recovering reliable sensory activity data while also providing enough real-time data processing and cope-up with all restrictions arising in the specific situation. However, the regular image processing technique is unsuitable for the sonar image. It has low-level signal to noise ratio and ill-defined form of object due to low resolution than that of the regular(optical) image. Hence, it is hard to take out quantitative data from the sonar image.

To address such issues, neural eigenvalue analysis and neural networks are suggested. But, these techniques are not executable for the real time operation because they have complex processes. Therefore, we need to create the decent real time method that can discover objects in the underwater sonar image.

A sensor system plays a critical role in the improvement of AUV(Autonomous Underwater Vehicle) piloting systems as they supply data about the environmental situation and system state. There exist various sensors which can supply applicable and meticulous data. However, local or global position calculation of AUV is still an unsolved problem, especially when a individual sensor is used. Typically, these vehicles use many sensors for the purpose of calculating their place and deciding the position of objects in their space. Generally, pressure compasses, global positioning systems (GPS), sensors, and inertial measurement units (IMUs), are normally used. Note that, even though GPS is widely used for localization, it shows low-level execution in an marine environment. Hence, information merger is required to gain the accuracy of the position estimation.

2. Proposed system

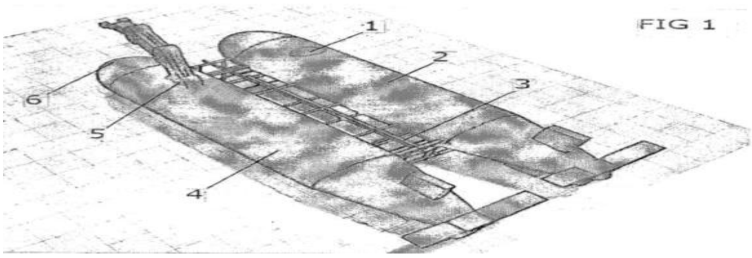

Figure 1. Proposed AUV

Sight based systems are a great choice because they cater advanced resolution images at reduced cost with higher pace of acquisition. However, in maritime environments the colour fading creates low perception when the distance is increased. In contrast, at little distances the visibility may be enough and the measurement quality improved and better than other sensing elements. Therefore, processes in which visual data is used are limited to object identification and manipulation. Optical systems can be used in AUVs, and they provide a system which gets depth estimations based on camera recorded information. The system is reliable in software components and mechanical structure . In fig. 1, notation 1 shows the hole of compartment inside which we will put plastic using robotic arm shown by notation 5. Notation 2 shows compartment having compressor. Notation 3 shows the net to store collected plastic. Notation 6 shows the water tanks for sinking and floating of AUV. Notation 4 shows the compartment containing Raspberry pi. Above system(Fig. 1) is designed and comprises of following parts :

2.1. Camera:

This unit is used to record live video of underwater. This unit gives dynamic input to proposed AUV. This live video will be further divided into frames. With the help of this frames are generated and available plastic will be detected. There are many techniques to detect underwater plastic which will be discussed in further section of this paper.

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2.2. Raspberry Pi

This is main component of proposed system. This is a component where trained model is kept. With the help of algorithms dataset is trained. This trained model is kept on Raspberry Pi. Basically it is a file onto which algorithm writes detected object depending upon category of object.

2.3. Arduino for Controlling Robotic Arm

Robotic arm being itself a new and vast project. This robotic arm mentioned has 6 degrees of freedom. Robotic arm picks the target plastic and input it to compressor unit. Arduino being sensor is used for controlling robotic arm.

2.4. Compressor

Compressor unit is designed to achieve space optimization. As plastic bottles may occupy more space. In proposed system they have proposed to use net to collect this bottles. After plastic is detected, robotic arm would put plastic into AUV from (1) of Fig.1 This compartment is compressor unit. Here collected plastic will be compressed and further put into net.

2.5. Battery

As AUV is autonomous vehicle it has to move on its own. In order to do these batteries are used. Thus serving purpose of supply.

2.6. Propellers

Propellers are wing for AUV. The navigation of AUV is done with the help of this component.

2.7. Robotic Arm

It is used to collect the detected plastic inside the water.

3. Dataset Description

All The dataset that we will be using consists of some images from JAMSTEC E-library of Deep-sea Images[] and other images are collected by us from the internet independently. It consists of around 2000 underwater images which contains the objects of the 6 classes. Detailed description is as follows :

Table 1. Dataset Details

No. Of images	2000
No. Of classes	6
Class labels	Cups, Plastic bottles, Straws, Bags, Wrapper, Paper-box

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4. Image Preprocessing

A pre-processing method is proposed for underwater image enhancement and correction. Thanks to some transmitting characteristics of light inside the water, underwater images suffer from uneven lighting, color diminished, low-level contrast, and blur. Now a days, preprocessing [1] techniques mainly concentrate on colour rectification or uneven lighting and sometimes necessitate additional cognition of the environment. The technique projected in this paper is an automated algorithm to preprocess underwater images. It makes image better. It consists of many consecutive separatist processing steps which improve uneven illumination, control noise, intensify contrast and adjust colours.

Pre processing Algorithm Description :

1. Removing presence of a wavy repetitious structure on the image. It occurs when image is converted from analog to the digital. This structure is abstracted via analysis of spectrum by detection of peaks within the Fourier transform and removing those.

2.Resize and increase the image symmetrically to induce a squared image. Symmetrical extension avoids from possible edge eff ects and resizing to square shaped image increases the speed of the future process by sanctioning to use fast wavelet transform and fast Fourier transform techniques.

3.The homomorphic filtering is used to correct uneven illumination in image and to strengthen contrast. It's preferred to others techniques because it sharpens the perimeters and corrects non uniform lighting at the identical time.

4. Correcting intensity: This step includes improving contrast by correcting image intensity level. It inhibits outlier pixels to heighten contrast stretch. It then elongates contrast to use the full range of intensity spectrum and if necessary it saturates some high or low values.

5. Equalizing colour mean : In marine imaging colour channels are hardly balanced rightly. It's rather used to create a more enjoyable image than to elevate segmentation. The reason is segmentation is generally performed on gray image and color equalization does not actually change the gray image.

5. Comparative Study of Algorithms

5.1. YOLO v2

YOLO stands for You Only Look Once. Version2 is the successor of YOLO. Though YOLO is much faster than other algorithms, it has depressed recall and localization errors in comparison with other object detection algorithms. With the help of batch normalisation, a advanced resolution image as input, and a change in the manner we generally use bounding boxes and proposed to use anchor boxes, YOLOv2 has better accuracy than YOLO [7]. YOLOv2 uses a customized network called Darknet-19 instead of VGG-16. Many object detection algorithms use VGG- 16 network. For quicker processing Darknet-19 is used. It takes only around 1/6th of the floating point dealings of VGG-16 for a single running of an input image consequently helping in speeding up process and indirectly improving efficiency.

5.2. Tiny-YOLO

It was presented along with YOLO. It is founded on neural networks. It has little no. of layers and filters in the layers as compared to the network of layers used in YOLO. Tiny-YOLO shares the identical factors with YOLO for training as well as testing. So, tiny YOLO runs at better speeds than YOLO [7]. But tiny-YOLO has

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analogous mean Average Precision values as YOLO. Tiny YOLO is very helpful to apply object detection on machine which have constricted power for computation. So in robotics tiny YOLO can be used effectively.

5.3. Faster RCNN with Inception v2

It is is a successor of R-CNN. It makes use of Region Proposal Network. It is used in order to make the entire object detection network end to end trainable. The Region Proposal Network [7] utilizes the rearmost convolutional characteristic map to create region proposals. It is then handed over to the completely connected layers for the final detection of the object. VGG-16 is used in actual execution for feature extraction. Here we use the Inception v2 for feature extraction. It is done in order to produce good performance in regular datasets.

5.4. Single Shot Multi Box Detector (SSD)

Generally, object classification and localization is not achievable in single forward pass of the network. In comparison with YOLO, SSD [7] has minute architectural difference. It comes with more convolutional layers which are at the end of a base network. Thus, improves performance. MobileNet v2 is used as base network. classification is not possible in single forward pass of network.

The fig. 2 Shows the graph of the performance of above algorithms at detecting plastic and bio (marine life).[7]

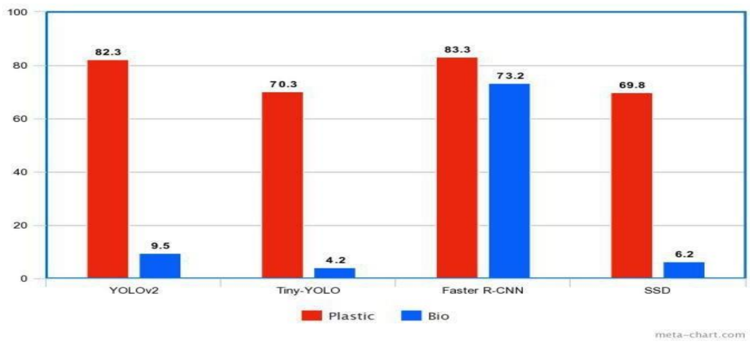

Figure 2. Comparative Study of Algorithms

6. AUV Navigation Using Adaboost Method with Cascade Structure

AUV navigation is one of the challenging tasks [8]. We can't use a GPS as EM (electromagnetic) waves can't profoundly pierce the water surface that's why we can't use a GPS. Also it is not easy to use a sight structure due to the dark and turbid underwater territory. Forward-looking imaging sonar [2] is appropriate for real time dealing of AUV as it provides the real time video at a higher frame rate. Usually, how AUV performs operation on the basis of forward-looking imaging sonar that it utilizes the geometrical information of objects captured in sonar-images. But, before using the technique, AUV must make a decision whether the object is existing or not in the clicked sonar-image. However, the regular image-processing technique is not appropriate for the sonar-image. It is hard to select computable facts from the sonar-image. To address these problems, eigenvalue analysis and neural networks are projected lately. This technique uses Haar- like features [2] for the weak-classifier. Then, the strong-classifiers are made by the adjustive-boosting (AdaBoost) technique. Additionally, using the cascade-structure of strong-classifiers, the productiveness of computation of suggested method can be improvised. The principal idea

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of sonar-imaging is to gauge the reflected beam's intensity

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which is released in direction of the object by the suggested system. It has greater reverberation than backstage. Hence, the highlighted part is nearly equal to white, and the shadowed part is nearly equal to black as there isn't any reflected beam. Feature value is the deviation among the mean intensity of the white portion and the mean intensity of the black portion. A weak-classifier h(x) [2] can be described using the feature-value function F (x). A powerful-classifier C(x) can be defined using the weak-classifier W(x). Adaboost technique[2] is kind of a learning technique that amplifies accuracy by weighting data which is misclassified. Adding some weak classifiers to make the strong-classifier, the coefficient αw [2] is calculated by the error of the weak-classifier. Also, weight of mis- classified training data by included weak-classifier is improved. This is done to permit the strong-classifier in the next loop to classify training-data that were wrongly classified in the former loop. Majority area of sonar-images are backgrounds which do not contain any object. So, it is mandatory to lessen the candidate region. For these reason, the cascade structure of strong-classifiers is suggested[2]. Structure that notably shortens candidate object region. It reduces the no. of repeat calculations. In addition to that, the chance of incorrect positive of cascade structure is considerably decreased.

7. Issues in Underwater Video Processing

Functioning in underwater environment is a very hard task [9]. Sight(vision) systems are confronted by the lack of consistency and difficulties of aquatic environments. It has issues like computational performance, heat dissipation, energy power ingestion, and network ability. Perception and localization must tackle problems which are not yet solved while working under water. Along with above mentioned challenges, underwater interventions such as object retrieval and equipment support are difficult tasks without human intervention, as they require object cognition and localization with economic accuracy. During sunny day, due to the powerful light back-scattering, feature based techniques are not useful for detection and localization of objects. Further, since color distortion go on accelerating as we go deep down the sea, object-detection based on comparing with original colour in the air may be also challenging. Hence, colour repair methods are necessary[4]. Water situation also changes from to turbid from clear, light backscatter alters significantly with daylight & level of water, colour damage is dependent on aquatic conditions, and other changeable weather conditions factor in perceptual problems. Complex methods for image restoration, de-blurring and enhancement, as well as for feature spotting and organization, can be used since they are postponed to offline processing. Feature based vision methods have also been planned in aquatic navigation. Aquatic environments, navigation is difficult due to generally miserable vehicle odometry (use of data to find out change in position with the help of motion sensors) and lack of GPS signal.

Furthermore, environment causes trouble that stops us from reusing the techniques and methods existing in other robotics fields like space, air and ground too. These hurdles actually come from response of water while signal transmission. Water opaqueness, color variations, backscattering phenomena and light reflections are major problems with underwater computer vision.

8. Conclusion

In this paper we have discussed about the detection of underwater plastic using deep learning. We have seen the design of AUV and studied various algorithms for detection of plastic. We will be using the raspberry pi in AUV for video processing. Raspberry pi has limited processing power. Hence, it is necessary to use algorithm which will use less computing power. Tiny-YOLO is one such algorithm with good accuracy. Hence, it can be used for processing on raspberry pi. We have also seen the details of AUV design and navigation.

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