

OBJECT DETECTION IN UNDERWATER IMAGES USING FASTER REGION BASED CONVOLUTIONAL NEURAL NETWORK

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Abstract - *The vision based method for detecting the objects under water is carried out using faster region based convolutional neural network. This computer based vision system is able to detect the objects automatically which is placed as an underground pipeline and this technique is also used to detect the fish under water. These detection process is carried out using the color compensation. By changing the color compensation and enhancement process, the object which is underwater can be detected with the certain accuracy. Faster Region based convolutional 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. Various geometric reasoning is used to reduce the unwanted region detection to improve the accuracy rate of the objects. These above method results on various underwater images is shown in the proposed work. The classification process is carried out using the faster region based convolutional neural network. Thus, the presence of these process under seaweed and sand, can be identified using various illumination process and water depth, various pipeline diameter and there is a small variations in the detection process where there is a changes in the camera angle. These will give the algorithm performances with the accuracy rate of 90%.*

Key Words: Vision system, enhancement technique, faster-region based convolutional neural network, classification, accuracy rate.

1. INTRODUCTION

Image processing is the major techniques in the object detection process. This object detection process is carried out using the thresholding process. Image processing consists of basics steps such as image acquisition, pre-processing, image segmentation and classification. This image acquisition technique indicates the acquiring the input image from the folder, pre-processing stages consists

of gray-scale conversion and filtering process. The gray-scale conversion consists of conversion of pixel value into 0 to 255 pixel range. This process consists of various methods and various image formats. Segmentation process

consists of segmentation of detected object. The feature extraction process is carried out from the Gray Level Co-occurrence Matrix (GLCM) technique. The classification process connected with optical information, like shading, surface marking and texture, is also useful for object attention. Nevertheless, visual-situated methods are based on noise of the underwater photo acquisition method which is characterised with the aid of a couple of mechanisms.

2. LITERATURE SURVEY

In clear water, optical sensors gift some advantages with recognize to the acoustical ones. First, they generate better data cost and with better resolution, they allow operations requiring excessive precision and real-time performances. Additionally, many expertise degradation of the video signal (see Sec. Three). A number of ways have been developed within the contemporary years to restrict issues connected with underwater imaging and perform computerized inspection of underwater environments or automated guidance of underwater automobiles. Some methods consist in making a mosaic of photograph images of the sea floor and plan the AUV trajectory in terms of a sequence of time-tagged station features. 10, thirteen, 19 This allows for the method to have a giant map of the ocean backside, learning best small components, where the picture degradation is small (as a rule close to the AUV). The important hindrance of these approaches, developed for station keeping 19 and generalized for motion, 21 is the giant quantity of data to be stored, that makes them vain for lengthy distances motion (e.g. Pipeline inspection). Additionally, as new images are added to the present mosaic when the AUV moves far away from original positions, these approaches yield gigantic overall distortions (the error tends to build up within the snapshot-mosaic as successive pix are added. Different studies on AUV steering had been focussed on the texture evaluation of underwater photographs by co-prevalence matrices [14] nonetheless, these ways require a large amount of calculation (and so, time) necessary for the decision of the co-prevalence metrics factors. Many efforts had been finished additionally to acquire a proper trajectory of the AUV from monocular [5] or stereo photo sequences. If the snapshot sequence is acquired and

sampled at a sufficient excessive frequency, small body to frame-disparities make optical flow methods to be had. Four If body-to-frame disparities are tremendous, a Kalmanfilter is most commonly used to perform temporal integration of extracted points. Nonetheless, incorrect elements can introduce excessive error rates. Lately, facile et al. Have developed an algorithm able to realize and discard routinely unreliable function suits over an extended picture sequence some of the interesting utility of vision-situated underwater methods is the inspection of underwater constructions, in distinct, pipelines, cables or offshore platforms.[5] Oil and gasoline underwater pipelines want periodic inspections to manage their stipulations and to avert damages due to fishing endeavor, turbulent currents and tidal abrasion a visible method headquartered on neural networks is applied to support an AUV to perform both visual inspection and navigation duties. In exact, the offered approach has been designed to identify a pipeline structure placed on the sea bottom, realize possible obstacles (e.g. Trestles) and, so as to assess the AUV.

3. PROPOSED WORK

The proposed system consists of following block diagram. The block diagram as explained in the Figure 1 indicates the proposed work.

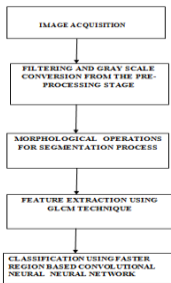


Fig -1: Block diagram

3.1 IMAGE ACQUISITION

The input underwater images are collected from the certain database. These underwater images are collected from the Aqualife database. These database images consists of various underwater images that consists of various number of objects. The selected input images are shown in the Figure 1 a.

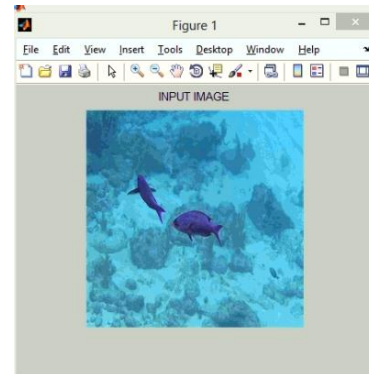


Fig -1.a: Input image

3.2 PRE-PROCESSING

Pre-processing stage consists of three stages Gray scale conversion, filtering process and histogram equalization.

3.2.1 GRAY-SCALE CONVERSION

The input RGB image is converted into gray scale image .These gray scale ranges from 0 to 255 pixel value. Thus, the gray scale conversion results is shown in the Figure 1.b.

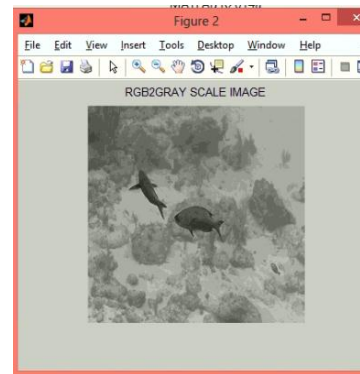


Fig -1.b: Gray Scale Image

3.2.2 FILTERED IMAGE

The converted gray scale image is processed to filtering process. Thus, the filtering process is carried out as shown in the figure 1.c.

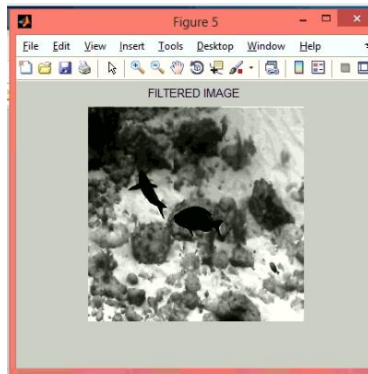


Fig -1.c: Filtered Image

3.2.3 HISTOGRAM EQUALIZATION

Histogram equalization is used to enhance contrast. It's not quintessential that contrast will invariably be developed on this. There are also some circumstances where histogram equalization can also be worse. In those cases, the contrast is reduced. Thus, the equalized histogram is shown in Figure 1.d, and the equalized value of the histogram is shown in Figure 1.e.

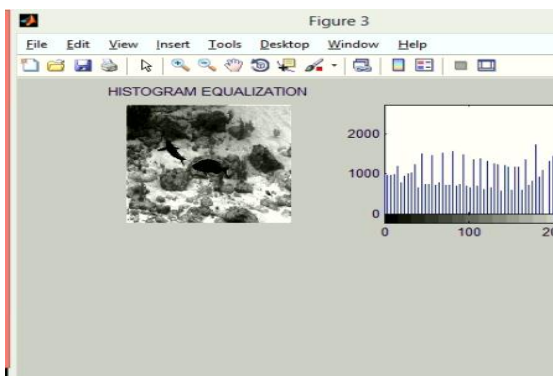


Fig -1.d: Histogram equalization

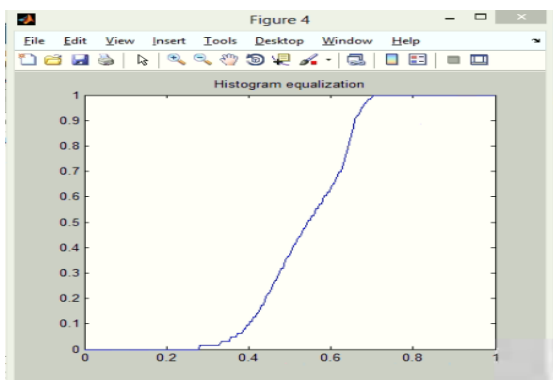


Fig -1.e: Histogram value

3.3 MORPHOLOGICAL OPERATIONS

3.3.1 OTSU THRESHOLDING

Otsu's thresholding method involves iterating through all possible threshold values and calculating a measure of spread for the pixel levels on every side of the threshold, i.e., the pixels that either fall in the foreground or the background. Thus, the Otsu thresholding of the converted image is shown in Figure 1.f.

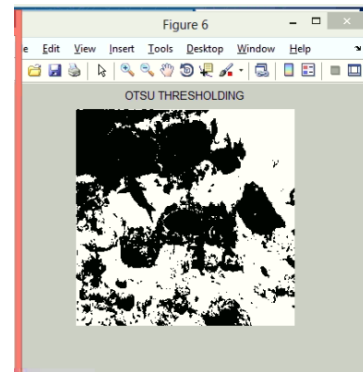


Fig -1.f: otsu thresholding

3.3.2 EROSION

The erosion of a binary image f with the aid of a structuring element s (denoted $f \ominus s$) produces a brand new binary image $g = f \ominus s$ with ones in all places (x,y) of a structuring element's origin at which that structuring element matches the input image f , i.e., $G(x,y) = 1$ if s fits f and zero in any other case, repeating for all pixel coordinates (x,y) . Thus, the erosion of the image is shown in Figure 1.g.

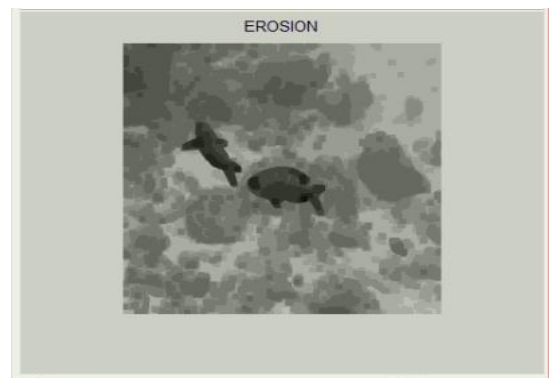


Fig -1.g: Erosion

3.3.3 DIALATION

The dilation of an snapshot f by means of a structuring element s (denoted $f \oplus s$) produces a new binary image $g = f \oplus s$ with ones in all locations (x,y) of a structuring element's origin at which that structuring element s hits the enter photograph f , i.e. $G(x,y) = 1$ if s hits f and nil otherwise, repeating for all pixel coordinates (x,y) . Dilation has the reverse outcomes to erosion -- it adds a layer of pixels to each the internal and outer boundaries of areas. Thus the dialated results is shown in the figure 1.h Dilation.

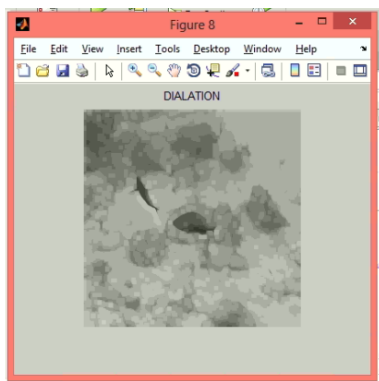


Fig -1.h: Dilation

4. CLASSIFICATION

The proposed system consists of faster region based convolutional neural network. Proposed a process where we use selective search to extract simply 2000 regions from the picture and he called them area proposals. Accordingly, now, as an alternative of making an attempt to categorise a giant quantity of regions, that you would be able to simply work with 2000 areas. The CNN acts as a function extractor and the output dense layer contains the features extracted from the photograph and the extracted facets are fed into an SVM to categorise the presence of the article within that candidate region proposal. Furthermore to predicting the presence of an object inside the neighbourhood proposals, the algorithm also predicts 4 values which might be offset values to expand the precision of the bounding box. For illustration, given a vicinity suggestion, the algorithm would have envisioned the presence of a man or woman however the face of that character within that vicinity suggestion might've been reduce.

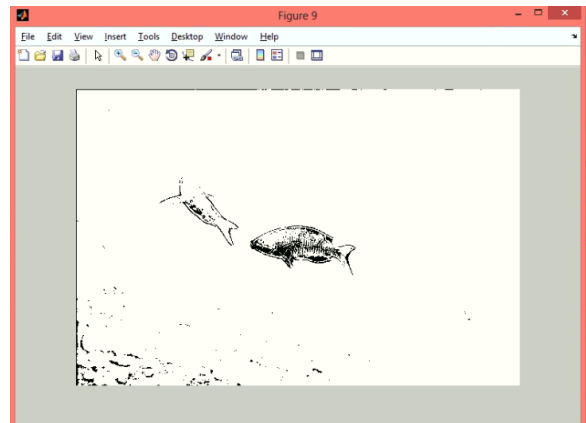


Fig -2: Classification

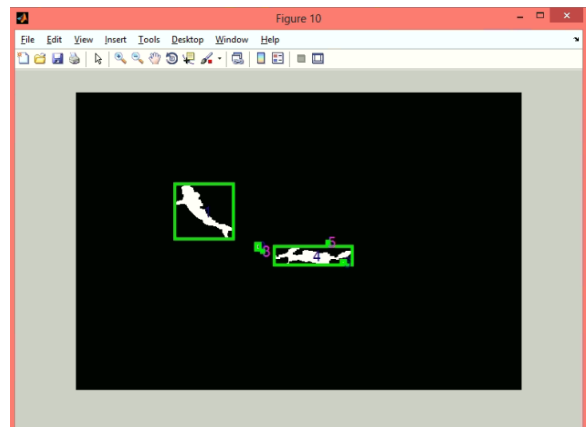


Fig -3: Detection

5. RESULTS

Thus the classification has the accuracy range of 90%.In the future work, thus the classification and detection process can be achieved with the more accuracy rate.

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Installing and compiling MatConvNet library. This may take a few minutes.
Finished install. Matconvnet is ready!
Custom parameters ready.
1 generated image(s) can be found in generated_montages.
Train dogan... Done
Mean Square Error =
    1.9256e+04

RMSE =

    138.7648

Peak Signal to Noise Ratio =
    5.2852
    
```

Fig -4: Performance metrics

6. REFERENCES

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