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EXPLORING AND IMPLEMENTING HARRIS CORNER OBJECT DETECTION ALGORITHM FOR UNDERWATER ACOUSTICS NETWORK

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ABSTRACT
Due to the importance of underwater exploration in the creation and utilisation of underwater resources, underwater autonomous operation is more essential for avoiding the dangerous high-pressure underwater environment and for furthering the research of marine life. The most crucial technology for autonomous operation underwater is extensive computer vision. Underwater vision requires poor lighting and poor picture augmentation as a preprocessing method in an underwater setting.. In this paper, edge detection and grey-scale imaging are combined to improve underwater vision and detect underwater images. The research paper focuses on the working principle of the Harris Corner Object Detection algorithm.The algorithms have been analyzed and elaborated via appropriate flowcharts, algorithms, and implementations. The reading has been obtained for different performance evaluation metrics. Average R Score and Threshold values have been computed for different instances made to run on the Harris Corner Object Detection .
Keywords – grey-scale, edge detection, Harris Corner Object Detection

I. INTRODUCTION
Using various techniques, image processing is utilised to perform a function on digital images. The image is represented as a two-dimensional matrix in image processing, and the optimal outcomes are achieved by running particular operations or algorithms on this matrix. These methods include feature recognition, dithering and half toning, contrast enhancement, and others. Object detection is one of the primary applications of image processing. This technique can recognise any object, fixed or moving, in any real-time situation, whether it be an image or a video..Machine learning is crucial for the training of the data sets. Within the topic of artificial intelligence known as machine learning, a machine educates itself while adjusting to its changing surroundings. These are the trained datasets. Images are utilised to instruct in 80 percent of cases, and test in 20 percent. As the machine learning technique for this project, we chose Tensorflow, an Object Detection API that makes use of Faster R-CNN. In Tensorflow, image pixels are represented as matrices, and operations are carried out on them to get the desired outcomes. For object detection, there are many pre-trained models available, including R-CNN, Mask R-CNN, YOLO (You Only Live Once), etc. Although these pre-trained models have their own specified data sets, we must first improve the pre-trained model and then provide the proper environment in

order to employ our self-trained data. Many applications of Tensorflow are focused on deep learning and training. Python programming is used by Tensorflow, hence the appropriate Python version is used.

With the advancement of computer vision and image processing technology, the phases of image processing approaches to improve underwater image quality to meet the needs of the human visual system and machine recognition have continuously grown into a major problem. The methods for improving and restoring underwater images can now be classified into two categories: nonphysical model image improvement and physical ground image restoration.
Color correction techniques that are often used to improve underwater photos include the white balance, grey world, and grey edge hypotheses, as well as the histogram equalisation and restricted contrast histogram equalisation contrast enhancement algorithms. Sharpening algorithms are a part of conventional image processing techniques. When compared to the highest quality results obtained by traditional image processing, the results produced by these technologies are insufficient for underwater vision. The main problem is that the ocean environment is difficult and that many harmful factors, such as light scattering and absorption by water and suspended particles under the sea, substantially degrade image quality.

II. Related Work

Textural images of the seafloor, sediments, and objects are created by side scan sonar (both living and non living). On finding and categorising objects that are buried under the seabed, many researchers are concentrating. For the purpose of segmenting the auditory pictures and locating the objects, numerous research approaches have been used. We've studied some strategies whose work is similar to the research we've recommended.For the purpose of conducting picture segmentation, it was suggested to combine texture and spectral analysis [1].

Directional Filter Bank (DFB) was utilised to analyse spectral features, while Grey Level Co-occurrences Matrices (GLCM) was employed to derive texture features. The textural elements in the acoustic pictures encompass diverse regions. The original image is subsequently subjected to an active contour model.
By altering the feature selection stage, the segmentation technique utilised by [4] readjusts the weights associated with each feature. One of the method's shortcomings is its sensitivity. A new method for segmenting the aspect scan sonar images was previously presented by [6]. Using the unsupervised learning algorithm K-means clustering, the image is divided into discrete regions.. For object detection, region-based segmentation algorithms are widely used.

Object detection was done in three steps by the authors [7]. The positioning of the items is done initially using an object detection technique, and the location of the backdrop is done next using a background prior. The region merging segmentation approach is employed after these steps.

This method appears to offer an automatic way to detect things in photos taken underwater. Given that they are both textured and grayscale, medical images are compared to underwater acoustic images. For the purpose of identifying human organs in scientific photographs, a new edge identification technique based on Tsallis and Shannon entropy has been given. Because of the noise and geometrical elements [8] of the photos, the aspect detection methods cannot be employed to determine the right edges.

There are many ways to enhance the photos prior to object detection. The object detection procedure includes a preprocessing phase called "dynamic brightness assignment" [9].In order to compare edge detection methods, the author [10] employed a noisy image with a morphological filter.[11] has combined morphological mathematical operators including erosion, dilation, opening, and closing in research on edge detection.

III. RESEARCH METHODOLOGY

This section discusses the working of the Harris Corner Object detection algorithm. The algorithms have been elaborated and discussed via appropriate flowcharts and algorithms.

Harris Corner Object Detection Algorithm

Harris Corner detection algorithm is intended to identify an object via detecting corners of the object. The corners of the object are one such thing that witness variations in the large intensity of the gradient in every feasible direction and dimension. The algorithm is smart enough to detect the object and obtain accurate information. The algorithm extracts the corners from the input image and extracts the featured from the input image. Harris Corner algorithm is primarily as feature point detection and applies the concept of the gray difference between adjacent pixels to determine the segment of the object as edge, corner, or smooth area. Instead of depleting shifting patches for every 45-degree angle, the Harris Corner object detection algorithm takes the differential of the corner score into account with orientation to direction unwaveringly. This results in a higher accuracy for object detection.

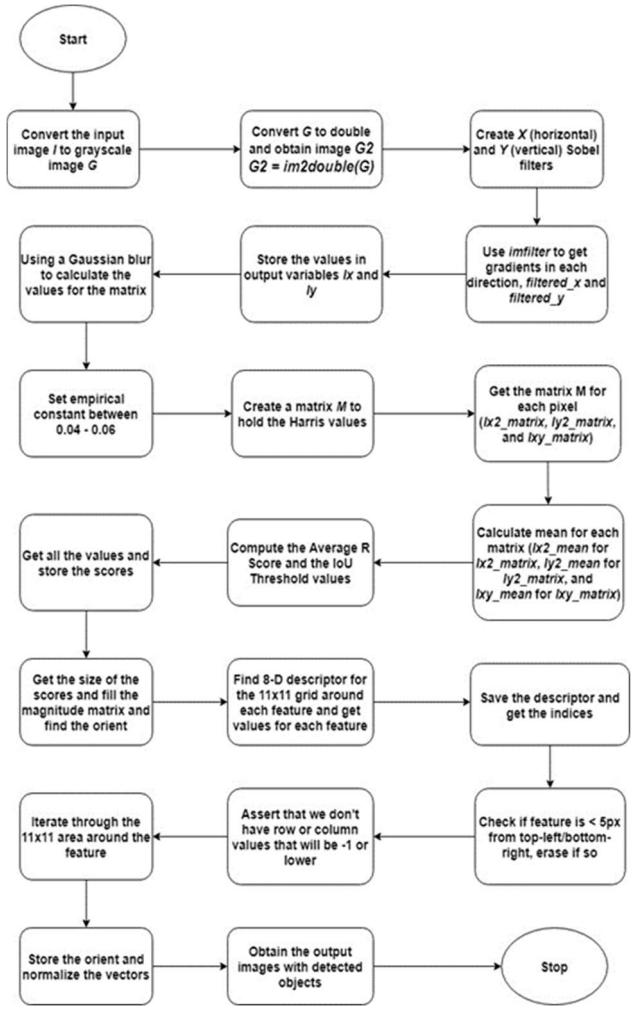


Fig. 1 Figure depicts the flowchart for Harris Corner Object Detection Algorithm

Algorithm

- Read the input image *I* and convert the input image *I* to grayscale image *G*.
- Convert *G* to double and obtain image *G2 (G2 = im2double(G))*.
- Generate *X* (horizontal) and *Y* (vertical) Sobel filters and get gradients in each direction using *imfliter* as *filtered_x* and *filtered_y*.
- Store the values of *filtered_x* and *filtered_y* in output variables *Ix* and *Iy*respectively.
- Create a matrix *M* to hold the Harris values. Get the matrix M for each pixel (*Ix2_matrix, Iy2_matrix*, and *Ixy_matrix*).
- Calculate mean for each matrix (*Ix2_mean* for *Ix2_matrix*, *Iy2_mean* for *Iy2_matrix*, and *Ixy_mean* for *Ixy_matrix*).
- Compute the Average R Score and the Intersection over Union Threshold values.
- Get the size of the scores and fill the magnitude matrix and find the orient.
- Find 8-D descriptor for the 11x11 grid around each feature and get values for each feature.
- Get the indices after saving the descriptor. Check if feature is less than 5px from top-left/bottom-right, erase if so.
- Iterate through the 11x11 area around the feature. Store the orient and normalize the vectors.
- Obtain the output images with detected objects.
- End.

IV. IMPLEMENTATION AND RESULTS

This section implements the Harris Object Detection algorithm as per algorithm.

Harris Object Detection Algorithm

This section implements the Harris Corner Object Detection algorithm as per the discussed methodology in Section III. Different underwater images have been taken into consideration and the Harris Corner Object Detection algorithm has been made to run on them to calculate the Average R Score and the threshold values.

Average R Score

R is a score that is calculated for each window as defined below in equation 1.

$$R = \det M - k(\text{trace } M)^2 \quad \text{---------- (1)}$$

Where

$$\det M = \lambda 1 \,.\, \lambda 2 \text{ and } \text{trace } M = \lambda 1 + \lambda 2$$

Here λ1 andλ2 are the eigenvalues of M. It is these eigenvalues that decide whether the detected region of an object is a corner, edge, or flat based on below mentioned details.

- If λ1 andλ2 are small, the value of R will be lesser. In such cases the detected region of the object is flat.
- If λ1 > λ2 or λ1 < λ2, the value of R is less than 0. In such cases, the detected region of the object is an edge.
- If λ1 and λ2 are large and λ1 ~ λ2, the value of R is greater. In such cases, the detected region of the object is a corner.

The average value of all such windows is referred to as Average R Score.

IoU (Intersection over Union) Threshold Value

IoU is defined as the difference between the predicted bounding boxes and ground truth annotations. During object detection, for each object there exist several multiple bounding boxes and depending on the confidence scores of each bounding box, the unrequired boxes are removed based on their threshold value. IoU is computed as mentioned below in equation 2.

IoU = Area of Union / Area of Intersection ---------- (2)

The Harris Corner Object Detection algorithm has been made to run on a few of the underwater images to perform object detection. The Average R Score and IoU Threshold values have been computed in each case.

Instance 1:

Fig. 2(a) displays an underwater scenario and Fig. 2(b) detects the objects marked with red color in Fig. 2(a).

Fig. 2(a) Underwater image 1

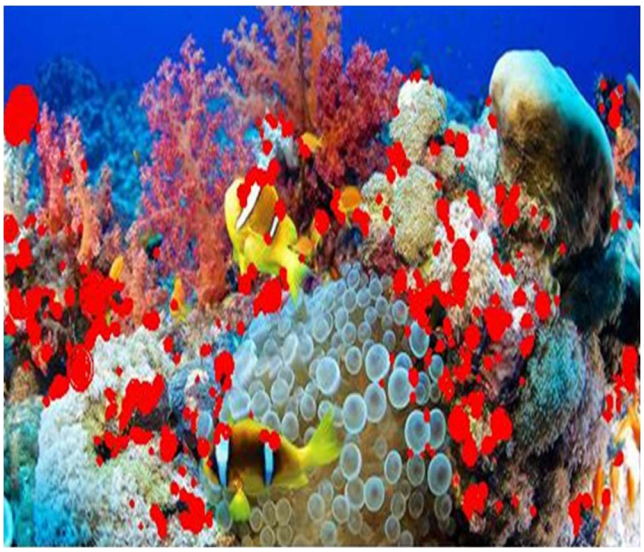
Fig. 2(b) Underwater object detection in image 1

Computed Result:
Average R Score = 0.0299
Threshold = 0.1495

Instance 2:
Fig. 3(a) displays an underwater scenario and Fig. 3(b) detects objects marked with red color in Fig. 3(a).

Fig. 3(a) Underwater image 2

Fig. 3(b) Underwater object detection in image 2



Computed Result:

Average R Score = 0.0603

Threshold = 0.3016

Instance 3:

Fig. 4(a) displays an underwater scenario and Fig. 4(b) detects objects marked with red color in Fig. 4(a).

Fig. 4(a) Underwater image 3

Fig. 4(b) Underwater object detection in image 3

Computed Result:
Average R Score = 0.0025
Threshold = 0.0124

Instance 4:
Fig. 5(a) displays an underwater scenario and Fig. 5(b) detects objects marked with red color in Fig. 5(a).

Fig. 5(a) Underwater image 4

Fig. 5(b) Underwater object detection in image 4

Computed Result:
Average R Score = 0.0357
Threshold = 0.1783

Instance 5:
Fig. 6(a) displays an underwater scenario and Fig.6(b) detects objects marked with red color in Fig. 6(a).

Fig. 6(a) Underwater image 5

Fig. 6(b) Underwater object detection in image 5

Computed Result:
Average R Score = 0.0019
Threshold = 0.0093

V. CONCLUSION

UWSN plays a significant part in marine accomplishments such as exploring underwater, collecting scientific data, and monitoring the environment. Underwater wireless communications is a stimulating task because of harsh and exceptional circumstances that exemplify underwater channels. The research paper discussed Harris Corner Object Detection flowcharts, algorithms, and implementation.Eight different instances having underwater images as input have been made to run through the Harris Corner Object Detection algorithm to detect the objects. The values for Average R Score and IoU Threshold have been calculated in each case.

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