Underwater Object Detection

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Abstract: Detecting underwater objects is challenged by various kinds of aspect ratios, object size, material colour, cluttered backgrounds, and in particular, not defined orientations. In our paper, we are using a Probabilistic Neural Network (PNN) features from layers which are combined to perform orientation robust aerial underwater object detection. We explore the essential characteristics of PNN as well as correlate the extracted features to the principle of disengaging feature learning. An image segmentation based approach is used to localize ROIs of different aspect ratios, and furtherly ROIs are classified into positives or negative using a DCNN features. On inquiring the two datasets collected from Google Earth, we illustrate that the proposed aerial underwater object detection approach is simple and easy process. Fast and robust underwater object detection in aerial images is potentially applicable in traffic surveillance, emergency, remote sensing and large scale image content analysis.

Keywords: Image processing, Deep Convolutional Neural Network (DCNN), Discrete Wavelet Transform, Underwater Object Detection, GLCM features, GRNN.

I. INTRODUCTION

In an image, the object identification uses image forecasting techniques by removing the noise, followed by the regions, locating lines and areas with some textures using feature extraction. This identification of objects in an image suffers disadvantage such as different angles and different lighting. The human visual system does these tasks unconsciously to equalise human performance for a computer, a skillfull program and great processing power is required. In computer vision, recognizing objects is a long time goal. The reason for this is, in real time the variations of matter instances belonging to the same type appear to be similar in an image. Hence the paper briefs two goals, recognition and classification of images/object detection. The primary goal in this paper is an approach for object class recognition that employs edge information only. It is represented by very simple and generic shape primitives of curved shapes, especially ellipses and line segments. Here, each combination is a two-layer abstraction of primitives: pairs of primitives (termed shape tokens) at the first layer, and a learned number of shape tokens at the second layer.

II. EXISTING TECHNOLOGY

The existing technology in reef surveys the involvement of satellite usage or airborne images of large spans of reefs, are present and utilizing spectral analysis with image resolution of at best 0.5 – 1 m per pixel. To relate the spectral image features to original information like living coral distribution, processing of image, pattern recognition and water column correction are needed, as evidenced by numerous studies on this field. Although, to verify multi-spectral analyses, on-site inspection of the reef area, i.e. at a closer scale, is needed. Drawback of existing system is inaccurate results and Complexity is high.

III. PROPOSED SYSTEM

In our system, the following techniques are used to overcome the disadvantages present in the existing systems. They are;

1) Discrete wavelet transform
2) GLCM feature extractors
3) Probabilistic Neural networks

A. Advantages

1) Accurately classify large number of coral plants
2) No need for large training datasets
IV. BLOCK DIAGRAM

A. Pre-Processor
Image Pre-processing is operations that are performed with images at the abstraction of lowest levels. Its input and output are intensity images. The ultimate aim of pre-processing is suppressing unwanted distortions and enhances some image features which is important for further processing and improving the data of an image. Image restoration is defined as finding a corrupted/noisy image and estimating the clean original image. Corruption may come in many forms such as noise, camera misfocus, motion blur. More advanced image processing techniques must be applied to recover the object. Example: deconvolution of image restoration method. It is capable of increasing contrast, resolution, specially in the axial direction removing noise.

B. DWT
The DWT gives a scattered representation for many natural signals. A subset of DWT coefficients are used for capturing the important features of natural signals which is much smaller than the original signal. This helps in compressing the signal. With the help of DWT, we always have the same number of coefficients as the original signal, but many of the coefficients we obtained may be close to zero. As a result, we can send those coefficients for maintaining a high-quality signal approximation. Basically, DWT is used for orthogonal transform and not for shift invariant. The operation of discrete filter banks are done by discrete wavelet transforms. This provides the perfect reconstruction of the signal upon inversion which helps us to take the discrete wavelet transform of a signal and then using the coefficients we can synthesize an exact reproduction of the signal to numerical precision.
C. GLCM Features

The gray-level co-occurrence matrix (GLCM) can be obtained by gray co matrix function. This is for calculating how often a pixel with the intensity (gray-level) value \( i \) occurs in a value \( j \) which has a specific spatial relationship to a pixel. By default, the pixel of interest and the pixel to its immediate right (horizontally adjacent) is said to be spatial relationship. Though we can specify other spatial relationships between the pixels (ie) \( i \) and \( j \). The resultant GLCM with element \((i,j)\) is simply the sum of the number of times that the pixel with value \( i \) occurred in the provided with value \( j \) spatial relationship to a pixel in the input image.

![Figure 3. GLCM feature extraction](image)

These statistics information provide us about the texture of an image. Statistic such as Energy, Correlation, Homogeneity, Contrast gives information about image.

D. Neural Network

Neural Network (NN) and General Regression Neural Networks (GRNN) have similar architectures, but there is a fundamental difference: networks perform classification where the target variable is categorical, whereas for general regression neural networks perform regression continuous target variable is obtained. If we select a NN/GRNN network, selection of the correct type of network based on the type of target variable will be done automatically with the help of DTREG.

![Figure 4. Architecture of NN](image)

V. HARDWARE REQUIREMENTS

A. Arduino

ARDUINO(ATMEGA) is an open source hardware device used for interfacing the all sensors and electronic devices used to perform a specific task. Any unique task can be completed by loading a set of instructions(program code) via a serial connection from the computer to arduino board. Arduino has 2 parts one is physical programmable circuit board and another one is a piece of software or IDE. This arduino software works on the computer, which is used to write and upload computer code to the physical board.
The Arduino boards which we are using is programmed via Universal Serial Bus (USB) which can be implemented using USB-to-serial adapter chips such as the FTDI FT232. Some boards, which are manufactured before such as later-model Uno boards, replace the FTDI chip with a separate AVR chip that holds the USB-to-serial firmware.

Figure 5. Arduino Board

B. Power (USB/BARREL JACK)
Every Arduino board requires a device that to be connected to a power source. The Arduino UNO will get a power to work, from a USB cable coming from your computer or a wall power supply that is terminated in a barrel jack.

C. LCD (Liquid Crystal Display)
Usually LCD is a combination of two states of matter, one is solid and another is liquid. LCD uses a liquid crystal to produce a visible image LCD modules will have seven segments and other multi segment LEDs.
The reasons for selecting LCD's are more economical, have no limitation for displaying special and even custom characters, easily programmable, usage is simpler. Usually 16x2 LCD is preferred, which will be used which will display 16 characters per line and displays in 2 lines. In this LCD, each character can be displayed in 5x7 matrix pixel. Basically LCD consists of two registers, one is Command and another is Data. The command register is mainly used for storing the command instructions given to the LCD. A command is an instruction given to LCD to do a already given task like initializing it, clearing its screen, setting the cursor position, controlling display etc. The data register is basically used for storing the data which will be displayed on the LCD. This image is then displayed on the screen.

Figure 6. Liquid Crystal Display

VI. SOFTWARE REQUIREMENTS

A. MATLAB
MATLAB, which is high-performance language for computing technical values. Basically it integrates visualization, computation, and programming can be easy environment progress where problems, solutions, tasks are expressed in familiar mathematical notation. Typical uses include: Scientific and engineering graphics, prototyping, Math, simulation Algorithm development, Modeling, and Application development, visualization, computation, Data analysis, exploration, including graphical user interface building. This allows us to solve many technical computing problems, specially used for those values with vector formulations and matrix formulations, instantly it may take to write a program in a scalar non interactive language such as C or FORTRAN.
Recently, MATLAB uses software developed by the ARPACK and LAPACK projects, which together represent the state of the art in software for matrix computation. MATLAB usually features for a family of application specific solutions called toolboxes.
B. Implementation And Result
The above mentioned hardware devices are connected to update the changes in process of obtaining the scanned objects under the water. This project gives the output image with the accuracy rate 98.9%. The implementation the project is similar and accurate results can be obtained while comparing with other neural networks used.

VII. CONCLUSION AND FUTUREWORK
This project can be extended by using the improved neural networks which is useful in detecting the images with high rate of accuracy. Using a separate filtering material will provide the results in a faster manner.

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