Detection of COTS-Starfish in Underwater Image using Convolution Neural Networks

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ABSTRACT

With the rapid escalation of digital cameras and technology, community people can acquire a huge amount of images for quantitative analysis. Manual analysis is time consuming and prone to error. This work comes under coral reef estimation domain. In this domain, the work is focussed mainly on detection and annotations of coral eating starfish. This is difficult since the image data reveals the insignificant variation depending on light scattering, image clarity and outlook. Analysis has been done on multiple papers to understand the computational model and strategies used to implement detections and annotations. The accuracy and efficiency of various papers are analysed. This gave us better understanding of the existing models and help us to design the model with better accuracy and efficiency.

KEYWORDS

Convolutional Neural networks, thematic mapping, coral eating starfish. Kernel.

1. INTRODUCTION

Australia's stunningly beautiful Great Barrier Reef is the world's largest coral reef and home to 1,500 species of fish, 400 species of corals. Unfortunately, the reef is under threat because of the overpopulation of one particular starfish – the coral-eating crown-of-thorns starfish. Existing mechanisms faces limitations, including operational scalability, data resolution, reliability, and traceability. This project will help researchers identify species that are threatening Australia's Great Barrier Reef and take well-informed action to protect the reef for future generations.

The great Barrier reef of Australia is the world's largest coral reef in the world which consists of around 2900 reefs and over 900 islands of around 2300 kilometers over an area of approximately 344,400 square kilometers. It's located in the coral sea, coast of Queensland, Australia. The coral reef is protected by the Great Barrier Reef Marine Park which will avoid human use i.e. fishing, tourism.
But still the great Barrier reef is facing so many issues like
1. Climate change
2. Pollution
3. Coral bleaching
4. Overfishing
Overfishing is a huge issue since its disrupting the food chains vital to reef life. One of the major outbreaks of overfishing is excess population of crown-of-thorns starfish which are major cause of coral loss on the Great Barrier Ref after coral bleaching, and its very important to control the population of corn-of thorns starfish.

The crown-of-thorns starfish preys on coral polyps. These when overpopulated in a particular region can cause threat to the reefs. During 2000, according to a study conducted by Reef Research Centre (RRC) an outbreak of this species caused loss of about 66% of live coral on sampled reef. These outbreaks can be caused due to poor water quality and overfishing of starfish's predators, they occur in natural cycles. The starfish shows preference between hard corals on which they feed. They don't prefer rounded corals which has less exposed surface area and always tend to feed on branching corals and table like corals. The bivalve mollusks and the worms in the surface of rounded corals might make them avoid to feed on such corals. In reef areas of low densities of hard coral, reflecting the nature of the reef community or due to feeding by high density crown-of-thorns, the starfish may be found feeding on soft corals. Their behaviour changes can be found only during two situation, mainly during breeding season and when they are at high density. They move day and night when they are at high density competing for living corals.

Hundreds of different species of corals exist around the world, in which are generally classified into hard and soft corals. Hard corals grow in colonies to build huge reef blocks. Seawater provide calcium to corals in order to build their skeletons. Soft corals construct plants or trees and do not have stony skeletons. As the number of images and databases continues to rapidly increase at many environmental research centers and aquatic-based agencies due to latest technologies in image acquisition using different autonomous underwater vehicles. Coral ecologists and environmental scientists already collected millions of coral images and thousands of hours of underwater videos, and they need massive number of hours to annotate every pixel inside each coral image or video frame such that this full manual segmentation will be time consuming and increase the ratio between labeled and unlabeled images across time. Images are manually annotated through coral experts by selecting some random pixels (10-200) in the target image, and classifying those pixels respect to predefined coral classes.A typical survey states that more than 400 hours are required to annotate 1000 images.

2. Detection of COTS-Starfish using Neural Networks

In this paper, A novel shape recognition algorithm was developed to autonomously classify the Northern Pacific Sea Star (Asterias amurenis) from benthic images that were collected by the Starbug AUV during 6km of transects in the Derwent estuary. Despite the effects of scattering, attenuation, soft focus and motion blur within the underwater images, an optimal joint classification rate of 77.5% and misclassification rate of 13.5% was achieved. The performance of algorithm was largely attributed to its ability to recognise locally deformed sea star shapes that were created during the segmentation of the distorted images. This algorithm was developed to autonomously classify the Northern Pacific Sea Star from images collected by the Starbug AUV in the Derwent estuary. The low signal to noise ratio in underwater vision, in addition to the soft focus and motion blur in images created during AUV collection, resulted in a distorted image space where classification was difficult. Despite the distorted image space, the recognition algorithm achieved an optimal joint classification rate of 77.5% and misclassification rate of 13.5%. The components of the algorithm which most contributed to the recognition performance were the salient region detection and Area Integral Invariant Matching (AIIM). Detection of salient regions with significantly reduced the area of interest for sea star identification, and hence, likelihood of misclassification. The AIIM enabled sea star to be identified despite variations in their shape class.

This paper presents a novel vision-based underwater robotic system for the identification and control of Crown Of-Thorns starfish (COTS) in coral reef environments. COTS have been identified as one of the most significant threats to Australia's Great Barrier Reef. These starfish literally eat coral, impacting large areas of reef and the marine ecosystem that depends on it. Evidence has suggested that land-based nutrient runoff has accelerated recent outbreaks of COTS requiring extensive use of divers to manually inject biological agents into the starfish in an attempt to control population numbers. Facilitating this control program using robotics is the goal of our research. In this paper we introduce a vision-based COTS detection and tracking system based on a Random Forest Classifier (RFC) trained on images from underwater footage. To track COTS with a movingcamera, we embed the RFC in a particle filter detector and tracker where the predicted class probability of the RFC is used as an observation probability to weight the particles, and we usea sparse optical flow estimation for the prediction step of the filter. The system is experimentally evaluated in a realistic laboratory setup using a robotic arm that moves a camera at different speeds and heights over a range of real-size images of COTS in a reef environment. Crown-Of-Thorns Starfish (COTS) are severely impacting Australia's Great Barrier Reef and the marine ecosystem that it supports. The results demonstrate the robustness of the algorithms in visual detection of the COTS.

Hailing Zhou et al., proposed a hybrid detection method which uses Gaussian Mixture Model for background modelling and object recognition using blob features. This method was developed to overcome problem faced by both traditional methods and advanced detection and recognition approach using image processing and deep learning to study diversity and abundance of marine animals. the traditional method such as towed nets and human observation had a threat on the animal's habitat, and the advanced technique had their own drawbacks. The statistic learning based required high amount of data to classify since they train with large number of object instances. And the learning-based model faces overfitting problem due to illumination variation in the image data set. This hybrid model first applies statistic learning on background for image segmentation and then extract the features for foreground image detection. The traditional GMM, a single GMM is created and to detect objects in different images but in this model, they automatically create a separate GMM for each image for background modelling. The clusters are then formed using Bouman algorithm. And then they are grouped into foreground and background using Otsu algorithm and then the blob analysis is done on the foreground images. In the blob analysis is done by extraction features from each blob, features such as bounding box, convex hull. Compactness etc. different blob features are used for detection of different objects based on the features of the object. The results obtained using this model performed well even with varying illumination and reflection. Observed about 90% of accuracy in the model with some small errors where it recognised other objects as the goal object.

M. *Dale Stokes et al.,* proposed a method to automate the process of classification of coral reef benthic organisms by photographic quadrant survey. The image data collected made into blocks is compared to library of manually classifies identified species block. Here the probability of identification is based primarily on the texture and color space. Previously there were attempts to automate using intensity variation and binary shape recognition for the pacific starfish. But there were drawbacks like the model could only discriminate general groups and due to variation in illumination at different level under water and the difference in level of absorption between different source of water i.e., clear and turbid. Firstly, they tried to automate the classification using Mahalanobis distance classification but it failed to discriminate the reef benthos. The main reason behind the failure was that no organism looks particularly like the average organism which was shown by classification error matrix. The procedure followed was, the image data was collected by standard digital camera with flash units on either side attached to a rigid frame. Histogram of color intensity was used to normalize illumination of image data before manual processing. In the manual image processing random subset were taken to compare with the automatic processing technique. They used software to identify and calculate the surface area coverage of reef framework corals. Then the library of images of group of species were done by selecting points of known classification on the quadrant images and the descriptive metrics were calculated and appended. This descriptive Metrix included both texture and block color, in the automated processing the metrics for each block was calculated and used as a point in hypervolume. The classification scheme calculated the probability density between sample block and that to the species library. This generates spatial maps of identifies types which helps reduce spatial noise in classification. Finally, the selection is based on the similarities found between the sample block and that within species library. Then they are formed into binary may and filtered to remove misidentified blocks. Further development must be carried to bring changes in texture discrimination metrics and segmentation of image data into different regions before performing the library classification.

Ellen M.Ditria et al., proposed a model of object detection using Mask R-CNN, it works by classifying and localizing region of interest. The model was developed using ResNet50 configuration and was trained on ImageNet 1K dataset on Azure VM which was equipped with NVDIA V100 GPU. The annotation part for the training data set was carried out on software developed by Griffith university. The mean average precision value mAP50 was used in this study, it determines the ability to mask around the region of interest. The F1 was also taken into consideration which calculates the maximum number of goal object in the frame. This F1 determined the success of the model since the model was built to answer the abundance of object in the specific region. The training data was divided by 80/20 i.e., 20% was used to form validation dataset. The overfitting of the model was minimized by using early stopping technique and by assessing on a set of 2500 iteration of validation set the performance was continuously monitored to determine where the model drops in performance. 3 different models were used and performance curve for each was generated and made sure that all 3 had consistence performance. The performance of the model was high both unseen and test datasets. Since the conclusion was based on F1 score, it turned out to be high F1>92%. This model was mainly proposed because the manual processing of image data to collect information on abundance, distribution of animals was very difficult and only 5% of the collected data was analysed. Since the rate at which the data set generated is high, the processing of all the information to get desired output need to be increased and deep learning can be very handy since the processing of still image data sets or the video data sets can be done using deep learning. The automatic processing can be done at the faster rate. The results of the model shows the robustness of mode even under variation in illumination and clarity of water and also the rate at which the model processes when compared to manual processing. The future work would be to test on different novel locations and compare different sites that varies in environmental condition.

Mohamed Elsayed Elawady et al., proposed a CNN architecture that provides a solution to the classification of coral into multiple classes. This architecture mainly includes input layer, hidden layers and output layer. Input layer consists of three basic channels of colour image plus extra channels for texture and shape descriptors consisting of following components like zero component analysis whitening, phase congruency, and Weber local descriptor and preprocessing step like colour correction/enhancement, smoothing filter. Hidden layers contain one or more layer(s) in which each layer consists of convolution layer followed by down-sampling layer in such a way that the network can find suitable weights of convolutional kernel and additive biases. Output layer acts as a classification layer. The logistic (sigmoid) function which is the most common activation function is used in convolution layers. The datasets are from Moorea Labelled Corals and Atlantic Deep Sea. In both of these dataset, there are 5 coral and 4 non-coral classes. Each image is of size 181*181, number of output classes = 9, number of samples per class = 300, number of input channels = 3, normalization method = min-max, learning rate = 1, number of network epochs = 10, number of hidden output maps = 6-12, and ratio of training/test sets = 2. Proposed framework provides a higher classification rate for some corals (Pavon) and misclassification for some corals (Monti) due to similarity in their shape properties or growth environment. The limitation of this framework is a lack of performance on large-sized input data and dilemma to find out best parameters for the deep convolutional neural network.

Oscar Beijbom et al., proposed a method to determine the percentage of the reef surface covered by rock, sand, algae and corals. It includes classification of corals based on size, color, shape and texture of each class. The color extension was introduced to encode important color information. The datasets are from Moorea Labelled Corals. In this dataset there are 5 coral and 4 non-coral classes. Almost 96% of annotation is done on each image covering 400,000 points. This method mainly includes four steps: Preprocessing, Texture and Colour, Descriptors and Machine Learning. In the Preprocessing step, all the images are downsized by a factor of 2. For each of the RGB channels, ColorChannelStretch method is applied to increase the intensity across each channel. In Texture and Colour, they used Maximum Response filter which encodes rotational invariance by first filtering with bar and edge filters at different orientations and then outputting the maximum over the orientations. In the Descriptors step, texton maps are created using filter responses from each of the nine classes across images and k-means clustering with 15 cluster centers are applied to each set. In the Machine learning step, they used the implementation of Support Vector Machines (SVM) with the Radial Basis Function kernel. For each experiment the RBF-SVM training step is preceded by 4-fold cross validation on the training data where parameters like C and gamma are optimized using a hyper-parameter tuning method called Grid Search. For each experiment they reported the accuracy of 74% in 2008, 67% in 2009 and 83% in 2010. This method handles ambiguous and organic object boundaries by a multiple scale approach, which is superior to using any single patch size. They showed that this method accurately estimates coral coverage across reef sites and multiple years, which offers exciting potential for large scale coral reef analysis.

A.S.M. Shihavuddin et al., proposed a classification framework for benthic coral reef images that can be applied to both single image and composite mosaic datasets. The proposed method uses completed local binary pattern (CLBP), grey level co-occurrence matrix (GLCM), Gabor filter response, and opponent angle and hue channel color histograms as feature descriptors. For classification, either k-nearest neighbor (KNN), neural network (NN), support vector machine (SVM) or probability density weighted mean distance (PDWMD) was used. The proposed classification framework has seven steps to perform training and classification of underwater images. The choice of which to use in each step depends on the characteristics of the dataset to classify. The Image Enhancement step aims to improve image comparability and classification accuracy. It improves the visibility of image features by counteracting some of the effects of the medium such as light scattering, blurring. In Feature Extraction step they used Gabor filter response, grey level co-occurrence matrix (GLCM) and completed local binary pattern (CLBP) as texture descriptors and the opponent angle and hue color histograms (optional) as color descriptors to define the features of each image patch to be used in the classification. Kernel Mapping step is used to project the feature vectors to linearly separable feature space. They used chi-square and Hellinger kernels. Optional Dimension Reduction is performed to map the data to a lower dimensional space in such a way that the variance of the data in the low-dimensional representation is maximized. Prior Settings includes estimation of the probability that an image patch will fall into any one of the defined classes. Classification includes choosing one of the four types of classifiers depending on the characteristics of the data: support vector machine (SVM), k-nearest neighbor (KNN), multilayer perception backpropagation neural network (NN) and probability density weighted mean distance (PDWMD). Last step includes thematic mapping, applies the image classification to large area optical maps of the benthos. Since they dealt with many parameters, to select the right parameters exhaustive search was done on underwater optical image datasets. They achieved an overall accuracy of about 93% on multiple datasets. They showed that their proposed method presents a novel image classification scheme for benthic coral reef images that achieved the highest overall classification accuracy of any of the tested methods and had moderate execution times.

The targets under the sea are not convenient for the human to contact directly, so sonar is needed for detection and recognition. Traditional sonar detection mainly identifies the features or contours of marine organisms, such as the shape and texture of underwater targets. But normal sonar recognition methods are not so efficient. The convolutional neural network (CNN) model has strong characterization and modelling capabilities through supervision or non-supervision training methods. CNN can be denoted by the characteristics of the object layer, and the abstraction and description of the object hierarchism are achieved.

The most important additions and the major contributions of the paper are as follows:
• An intelligent and powerful computational model is proposed for the classification of sonar image target detection and recognition
• This work proposes an algorithm that can automatically perform target recognition, tracking, or detection works
• This work proposes a rigorous model that classifies multitype objects at the same time as the traditional approach using a feature matching technique that can detect one type of object at a time
• Finally, the proposed scheme has been extensively tested on comparative experiments and ablation studies.

A new bounding box annotated image dataset of marine animals, recorded in brackish waters, is presented in this paper. The dataset consists of 14,518 frames with 25,613 annotations of the six classes: big fish, small fish, crab, jellyfish, shrimp, and starfish. To the best of knowledge, the proposed dataset is unique, as it is the only annotated image dataset captured in temperate brackish waters.
A brief explanation of the differences between the two pre-trained object detectors are used here are:
• The YOLOv2 detector is obtained from the VIAME toolkit and is pre-trained on ImageNet and fine-tuned on fish datasets from NOAA Fisheries Strategic Initiative on Automated Image Analysis.
• The YOLOv3 detector is used in its original version pre-trained on the Open Images dataset.
Two state-of-the-art CNNs (YOLOv2 and YOLOv3) has been fine-tuned on the proposed Brackish Dataset and evaluated in order to create a baseline for future reference. The YOLOv2 object was pre-trained on Image net and fine-tuned to fish datasets and it was obtained from the VIAME toolkit. The YOLOv3 detector was the original version pretrained on the Open Images dataset. The evaluation is based on the primary metrics of the MS COCO and PASCAL VOC, which are both based on the mean Average Precision (mAP). The fine-tuned YOLOv3 network achieved the best performance with AP $\approx$ 39% and AP50 $\approx$ 84%, allowing for improvements to be made.

3. CONCLUSIONS

Coral reef image detection and annotations has been an important computer vision domain which focuses on species that are threatening Australia's Great Barrier Reef and then can take necessary actions to protect the reef for future generations. In this paper, various strategies proposed by different authors in detecting and annotating the images are discussed. Different computational model takes care of the underlined images by considering multiple parameters such as image size, number of channels, normalization method , number of network epochs, learning rate and number of hidden output maps.

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