Classification Of Coral Reefs in Marine Environments Using Deep Encoder-Decoder Mechanism

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Abstract
The aim of this paper is to investigate the efficiency of the various techniques that have been proposed to be followed when processing underwater optical image datasets. The study makes use of a variety of different texture datasets to assess the efficacy of the techniques that are proposed. The results of the study show that the speed of the technique that was recommended is noticeably higher than that of other methods. In addition, the evidence that will be presented in this paper will show that this technique can accomplish a higher rate of accurate classification than any of the other methods that were used in the past. The findings of this study will be the subject of proposals for future work: using key points instead of all points for feature extraction, using feature selection techniques for removing redundant features, proposing some structural descriptors that can be combined with statistical descriptores for better description of the textures of coral reefs, and finally applying some new preprocessing operations to extract more discriminative features.

1. Introduction

Applications of the Internet of Things (IoT), such as marine surveillance systems, which are able to identify and report on suspicious activity in real time, are an important component of smart ocean infrastructure [1]–[3]. The installation of cameras and other imaging sensors in certain types of intelligent maritime surveillance systems may be done specifically for the purpose of locating and identifying potential ships through the application of automated object identification strategies. Utilizing various methods will be able to bring about the desired results. This is because the individual devices that comprise the IoT have extraordinarily powerful computing capabilities.

Methods that are conventionally founded on the concept of machine learning have had some success in the detection of certain objects. However, because they are on average much smaller than other aspects of the image scene, maritime characteristics only constitute a very minor portion of the whole thing. It is very uncommon to accomplish such a precise detection of them.

Techniques that can recognize even relatively small objects have become an important component of marine surveillance as a direct consequence of this fact. In addition, ship detection is a common topic of conversation in academic communities all over the globe. This is because it has the potential to be applied to a wide variety of IoT-related fields and industries, such as intelligent marine surveillance systems, maritime enforcement, and even emergency assistance. The reason for this is that it has the potential to be applied to a wide variety of IoT-related fields and industries.

The overwhelming majority of early techniques for locating objects relied on simple, man-made characteristics [4, 5]. When we look at a small object, the surrounding pixels will always end up blurring the features of the object, even if the object itself is not particularly small. Recently, deep convolutional neural networks, also known as CNNs, have been utilized in detection tasks for objects with great success [6–8].

CNNs can effectively characterize a considerable number of features. However, due to the expansive receptive field and the profound structures, the particulars of the less significant things are frequently disregarded. This is because of the profound structures. In addition, for CNN-based detection methods to function correctly, a considerable amount of training data is required. In practice, there is almost never an adequate quantity of maritime training material that is uniformly dispersed across the complete industry. The capture of trespassers is merely a byproduct of the use of these methods; these methods are not capable of providing uninterrupted surveillance of the nature reserve. It is extremely challenging to collect data on the number of people who have entered protected areas, to receive instantaneous notifications if ecological damage or alteration has occurred, and to determine who is to blame for the ecological damage or alteration that has occurred. Despite the availability of these instruments and resources, illegal activities such as anchoring and harvesting are still taking place.

This investigation evaluates the efficacy of the various techniques that have been proposed to be followed in the processing of underwater optical image datasets. The study makes use of a variety of different texture datasets to assess the efficiency of the techniques that are proposed. The technique that we recommended can extract more images than the CS-LBP does because it takes into consideration the gray value of the central pixel and it relies on a new strategy for comparing the gray values of neighboring pixels. The histograms of the proposed LBP for each of the two images are compared.

2. Related works

The method of recognition and detection known as deep convolutional neural networks provides a possible answer to the issues of feature extraction and time consumption that were discussed earlier in this article. (CNN). CNNs have also shown extraordinary success in the difficult task of identifying underwater targets, presumably because of their robust automatic learning abilities on large-scale training datasets [9]-[10].

This success has been attributed to the fact that CNNs are able to learn from examples on a much larger scale. CNNs can acquire features automatically from large datasets, which has contributed to their success to date. Despite this, there is a dearth of research into the identification of crabs found in the deep sea as well as the population dynamics of these crabs [11].

The authors in [12] approaches make it possible to perform effective detection of marine organisms as well as excellent observation of fixed-point targets. Both elements are extremely important to take into consideration given the limited scope of activities that marine organisms participate in.

On the other hand, the identification range of pond crab is not the same as that of sea cucumbers or saltwater fish. This is because the crabs have odd shapes, and the water in the pond is murky, which makes it difficult to differentiate individual characteristics from the images. Additionally, there are a lot of crabs in the pond. The precision of the detection will suffer substantially if the target crab is consistently moved either further away from or closer to the camera. The reason for this is that it is customary to maintain a stationary position while monitoring marine fish [13].

If one wants to guarantee that the crab recognition algorithm can fulfill the real-time application requirements of low-performance mobile devices, it is important to find a happy medium between the operational costs of the feeding boat and its productivity. On the other hand, ocean robots are not cheap, but they have sufficient computational power to function even when they are submerged in water [14]. The methods that are presently being utilized are not adequate to build an efficient solution for constructing a density distribution map of pond crabs and for the real-time accurate detection of underwater live crabs.

3. Proposed Method

When tested on local images, the preliminary LBP descriptor has been demonstrated to have a high level of effectiveness. This is accomplished by applying a threshold to the region surrounding each pixel and comparing the outcome to the value that is located at the center of the pixel. A binary identifier for the pixel is what you get because of this process. Encoding of local primitives like corners, points, and surfaces, among other things, falls under the purview of the LBP.

The current model image and the background model image are both recorded within the framework of BS to generate a representation of the environment that is based on the textures it contains. This representation is then used. Permit a pixel that is situated at some location, denoted by the coordinates $c = (x_c, y_c)$, to act as the focal point for a group of P neighboring pixels that are equally spaced around a circle that has a radius of R. This can be accomplished by allowing the pixel to act as the focal point for the group. The expression for the LBP operator is written as LBP_P,

$$LBP_{P,R}(c) = \sum_{i=0}^{P-1} s\left(g_i - g_c\right)^{2^i} \quad (1)$$

where

g_c - gray value of c

c - center pixel and

g_i - gray value of pixel, and

s – threshold:

$$s(x) = \begin{cases} 1 & if\ x \geq 0 \\ 0 & otherwise \end{cases} \quad (2)$$

The LBP operator is used to create (2) Drawing the conclusion that the length of the resulting histogram is 2P is a simple affair to do when you start with the premise that (1). This is because the number of binary terms that need to be added up is $\sum_{i=0}^{P-1} 2^i = 2^P - 1$, and this is an easy conclusion to draw. In proposed LBP, the gray levels of pairs of pixels in centered symmetric configurations are compared to one another rather than the central pixel being compared to the pixels that surround it. The central pixel is compared to the pixels that surround it. The CS-LBP operator can be represented by the following equation:

$$LBP_{P,R}(c) = \sum_{i=0}^{0.5P-1} s\left(g_i - g_{i+0.5P}\right)^{2^i} \quad (3)$$

where

g_i+(0.5P) - gray levels of symmetric pixels at the centre and hence,

$$s(x) = \begin{cases} 1 & if\ x \geq T \\ 0 & otherwise \end{cases} \quad (4)$$

where

T - user-defined threshold.

Making a low selection given that the values of the grayscale are normalized to the range [0, 1]. The research uses a value of 0.1 as our standard to gauge whether or not the experiments were successful. According to the requirements outlined in the specification, the CS-LBP description generates a histogram that has the length 1+ P/2 and the values $\sum_{i=0}^{0.5P-1} 2^i = 2^{0.5P}$.

The two images that are going to be evaluated side-by-side have both been encoded using CS-LBP as texture-based images with a lower quantization, which marginally supports robustness and is advantageous for BS. As a result of this, we suggest enhancing the CS-LBP operator by comparing the gray values of pairs of center-symmetric pixels to make improvements. This will ensure that the resulting histogram is not only compressed but also takes into consideration the pixel that is in the center of the image.

When all these elements are brought together, the description that is produced therefore is one that is more impervious to the impact that noise has on the BS application.

The proposed LBP for a neighborhood with a size of P = 8. This is done to make the comparison easier to understand and to facilitate improved comprehension of the comparison. Consider the fact that the levels of image compression generated by code lengths of 8 bits and 4 bits are distinct from one another and must be taken into consideration.

Even though the histogram that the proposed LBP generates is just as short as the one that the CS-LBP generates, the proposed LBP is still able to extract more image details than the CS-LBP does because it takes into consideration the gray value of the central pixel and it relies on a new strategy for comparing the gray values of neighboring pixels. The descriptor is more effective than LBP for modelling the background and subtracting it is more impervious to noisy images.

4. Results and Discussions

This investigation makes use of a variety of different texture datasets to assess the efficiency of the techniques that have been proposed to be followed. It is necessary to begin by adjusting the values of the grayscale images before continuing with anything else. `HICRD' (Heron Island Coral Reef Dataset) is used in the study and it involves a total of 6003 underwater images.

It is recommended that preprocessing operations be carried out before the process of feature extraction if the images contain noise; however, this was not the case with the datasets that were used in this study. to evaluate the efficacy of the various strategies that have been proposed, grayscale images of each coral reef have been utilized. That is to say that the recommended methods only rely on edges and local details, and they completely ignore any information regarding color in the process. Specifically, this means that: The study conducts a comparison of the images by looking at the corresponding histograms of the LBP for each of the two images. The chi-squared test is the method that is utilized for the purpose of determining the distance between two points. The goal of the chi-square test, which includes allocating a test sample T to a class of models, is to obtain the smallest possible value for the chi-square statistic. This can be accomplished by achieving the smallest possible value for the statistic.

$$D = \sum_{i=1}^{B} (T_i - L_i)^{2(T_i + L_i)}$$

Where

N - bins in histogram, and

Ti – sample values

Li - model image.

The inequality that was presented earlier demonstrates that the usefulness of LBP declines even further when there is no background noise present. This is the case because the inequality was presented above. It is possible to determine the degree to which two images are dissimilar to one another by using a combination of the distance and the chi-square distance when making a comparison between the images. The recall time that can be achieved by LBP with a small number for K is substantially improved when compared to that which can be achieved with a large one.

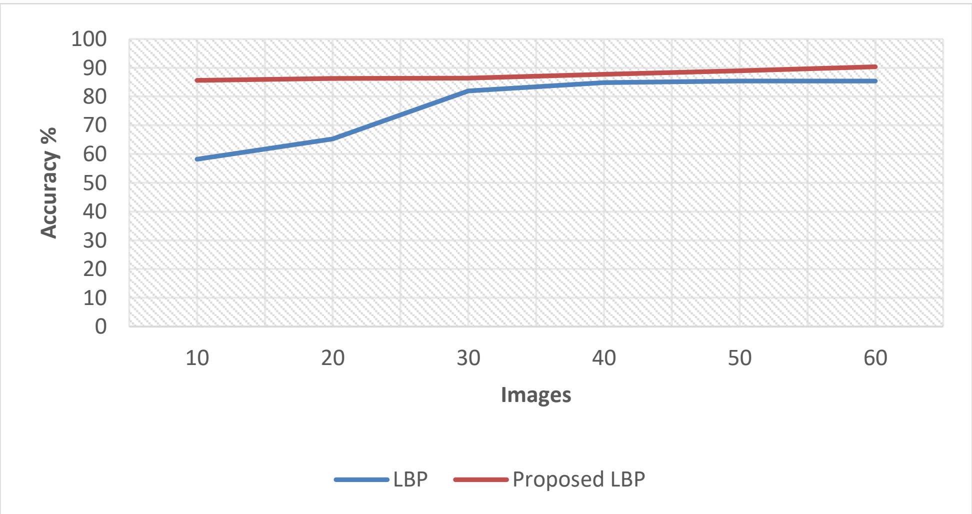

Figure 2: Accuracy

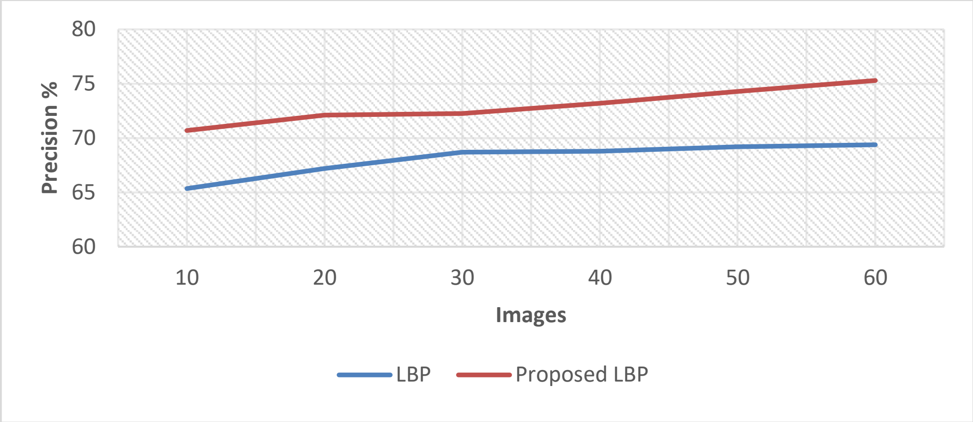

Figure 3: Precision

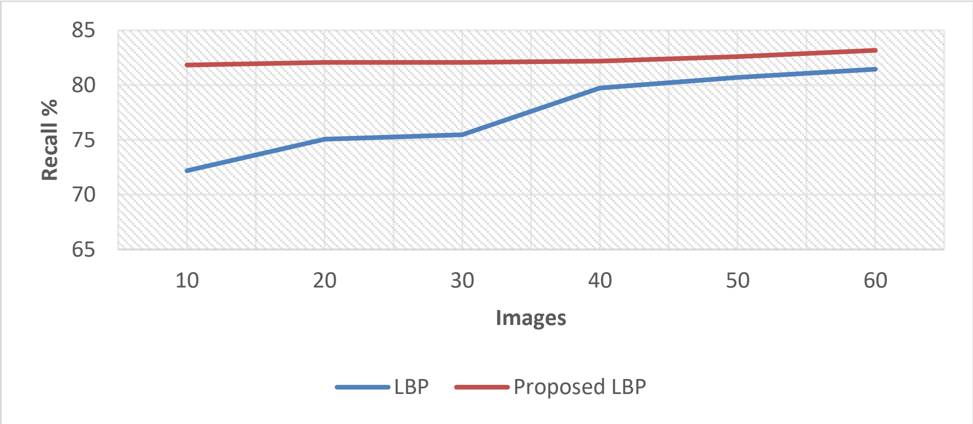

Figure 4: Recall

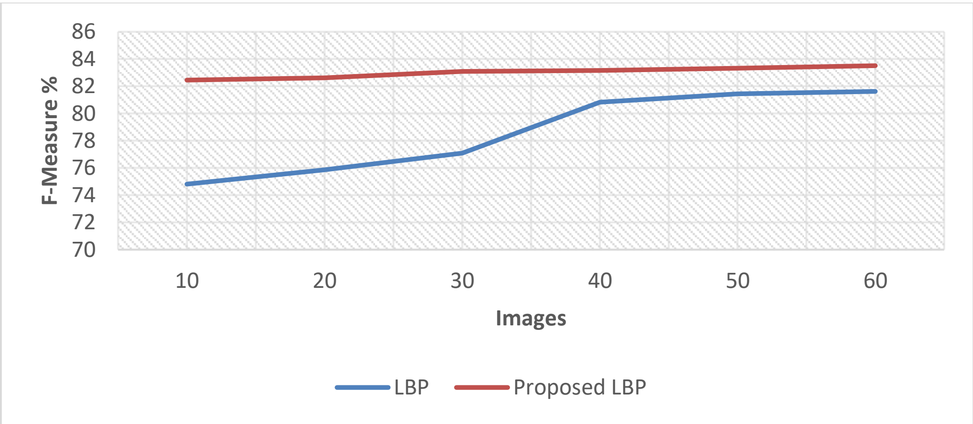

Figure 5: F-Measure

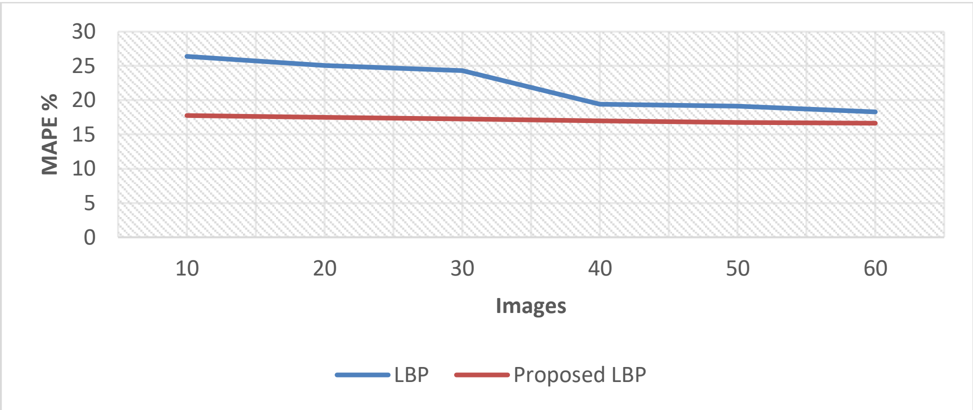

Figure 6: MAPE

When processing underwater optical image datasets, each of the processing methods that have been used in the past had a propensity to depend on a limited number of schemes that could be applied anywhere in the world. It is important to note that these methods do not constitute a comprehensive approach to the categorization of textures because they have certain limitations in terms of their applicability and there is a probability that they are not always the best answer for other kinds of problems.

When compared to the technique that we recommended, this approach results in an accuracy improvement that can range anywhere from two percentage points to twelve percentage points, depending on the dataset. On the other hand, the evidence that will be presented in the paragraph that follows will show that the speed of the technique that was recommended is noticeably higher than that of other methods.

In addition, the proposed framework can accomplish a higher rate of accurate classification than any of the other methods. They can reduce the number of features by combining two distinct approaches, the first of which involved condensing numerous features into a single collection.

However, when applied to LBP, the number of features significantly decreases, and the accuracy may also marginally decrease as a result. The mapping methods provide many features for highly accurate approaches like LBP; however, when applied to LBP, the number of features significantly decreases. This is something that emerges when looking at the image in question.

LBP is an effective descriptor for extracting discriminative features from image textures; however, it is not without its flaws and limitations. The LBP approach, in addition to being a local descriptor, is a technique that is particularly sensitive to the presence of background noise.

The efforts of a great number of researchers, a multitude of noise-resistant LBP techniques have subsequently been proposed. In addition to this, when it is expanded, it does not disseminate very well, and this hinders its effectiveness. These are two substantial problems with the way that this person is portrayed in the narrative. There are some more complicated variations of LBP, such as CLBP, that have drawbacks, the most noteworthy of which is that they have many neighbor points. These disadvantages include many features as well as a time-consuming method for mapping and matching features.

5. Conclusions

This study aims to evaluate the efficacy of the various techniques that have been proposed to be followed when processing underwater optical image datasets. The study makes use of a variety of different texture datasets to assess the efficiency of the techniques that are proposed. In addition, the study conducts a comparison of the images by looking at the corresponding histograms of the LBP for each of the two images. The evidence that will be presented in this paper will show that the speed of the technique that was recommended is noticeably higher than that of other methods. On the other hand, the proposed framework can accomplish a higher rate of accurate classification than any of the other methods, which could be the subject of proposals for future work: using key points instead of all points for feature extraction, using feature selection techniques for removing redundant features, and finally applying some new preprocessing operations to extract more discriminative features.

References

[1] Kennedy, E. V., Roelfsema, C. M., Lyons, M. B., Kovacs, E. M., Borrego-Acevedo, R., Roe, M., ... & Tudman, P. (2021). Reef Cover, a coral reef classification for global habitat mapping from remote sensing. *Scientific Data*, *8*(1), 196.

[2] Hopkinson, B. M., King, A. C., Owen, D. P., Johnson-Roberson, M., Long, M. H., & Bhandarkar, S. M. (2020). Automated classification of three-dimensional reconstructions of coral reefs using convolutional neural networks. *PloS one*, *15*(3), e0230671.

[3] Asha Paul, M., Arockia Jansi Rani, P., & Liba Manopriya, J. (2020). Gradient

based aura feature extraction for coral reef classification. *Wireless Personal Communications*, *114*, 149-166.

[4] Kennedy, E., Roelfsema, C., Lyons, M., Kovacs, E., Borrego-Acevedo, R., Roe, M., ... & Tudman, P. (2020). Reef Cover: a coral reef classification to guide global habitat mapping from remote sensing. *bioRxiv*, 2020-09.

[5] De Oliveira, L. M. C., Lim, A., Conti, L. A., & Wheeler, A. J. (2021). 3D classification of cold-water coral reefs: a comparison of classification techniques for 3D reconstructions of cold-water coral reefs and seabed. *Frontiers in Marine Science*, *8*, 640713.

[6] Sharan, S., Kininmonth, S., & Mehta, U. V. (2021). Automated cnn based coral reef classification using image augmentation and deep learning. *International Journal of Engineering Intelligent Systems*, *29*(4), 253-261.

[7] Wan, J., & Ma, Y. (2020). Multi-scale spectral-spatial remote sensing classification of coral reef habitats using CNN-SVM. *Journal of Coastal Research*, *102*(SI), 11-20.

[8] Caballero-Aragón, H., Perera-Valderrama, S., Cerdeira-Estrada, S., Martell-Dubois, R., Rosique-de la Cruz, L., Álvarez-Filip, L., ... & Ressl, R. (2020). Puerto Morelos coral reefs, their current state and classification by a scoring system. *Diversity*, *12*(7), 272.

[9] Stewart, H. A., Wright, J. L., Carrigan, M., Altieri, A. H., Kline, D. I., & Araújo, R. J. (2022). Novel coexisting mangrove-coral habitats: Extensive coral communities located deep within mangrove canopies of Panama, a global classification system and predicted distributions. *Plos one*, *17*(6), e0269181.

[10] Abouelmagd, L. M., Shams, M. Y., El-Attar, N. E., & Hassanien, A. E. (2021). Feature selection based coral reefs optimization for breast cancer classification. In *Medical Informatics and Bioimaging Using Artificial Intelligence: Challenges, Issues, Innovations and Recent Developments* (pp. 53-72). Cham: Springer International Publishing.

[11] Rashid, A. R., & Chennu, A. (2020). A trillion coral reef colors: Deeply annotated underwater hyperspectral images for automated classification and habitat mapping. *Data*, *5*(1), 19.

[12] White, E., Amani, M., & Mohseni, F. (2021). Coral reef mapping using remote sensing techniques and a supervised classification algorithm. *Advances in Environmental and Engineering Research*, *2*(4), 1-13.

[13] Xu, H., Liu, Z., Zhu, J., Lu, X., & Liu, Q. (2019). Classification of coral reef benthos around Ganquan Island using WorldView-2 satellite imagery. *Journal of Coastal Research*, *93*(SI), 466-474.

[14] Williams, I. D., Couch, C. S., Beijbom, O., Oliver, T. A., Vargas-Angel, B., Schumacher, B. D., & Brainard, R. E. (2019). Leveraging automated image analysis tools to transform our capacity to assess status and trends of coral reefs. *Frontiers in Marine Science*, *6*, 222.