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Review

Coral reef image classification employing Improved LDP for feature extraction

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ABSTRACT

This paper presents a scheme for feature extraction that can be applied for classification of corals in submarine coral reef images. In coral reef image classification, texture features are extracted using the proposed Improved Local Derivative Pattern (ILDP). ILDP determines diagonal directional pattern features based on local derivative variations which can capture full information. For classification, three classifiers, namely Convolutional Neural Network (CNN), K-Nearest Neighbor (KNN) with four distance metrices, namely Euclidean distance, Manhattan distance, Canberra distance and Chi-Square distance, and Support Vector Machine (SVM) with three kernel functions, namely Polynomial, Radial basis function, Sigmoid kernel are used. The accuracy of the proposed method is compared with Local Binary pattern (LBP), Local Tetra Pattern (LTrP), Local Derivative Pattern (LDP) and Robust Local Ternary Pattern (RLTP) on five coral data sets and four texture data sets. Experimental results indicate that ILDP feature extraction method when tested with five coral data sets, namely EILAT, RSMAS, EILAT2, MLC2012 and SDMRI and four texture data sets, namely KTH-TIPS, UIUCTEX, CURET and LAVA achieves the highest overall classification accuracy, minimum execution time when compared to the other methods.

1. Introduction

Submarine imagery is an aspect of marine science. Object identification in uneven submarine surroundings is not an easy task for several reasons. Coral reefs are some of the most diverse and precious ecosystems on the Earth [1–5]. Coral reefs, similar to every other ecosystem, obviously change over time. Healthy coral reefs provide home to over one million diverse aquatic species. They provide revenue in the order of billions of dollars and millions of jobs in over hundred countries around the world. Submarine natural scene coral images present several challenges [6] that may vary a lot from one data set to another. The following are the common problems concerning coral images: Imbalanced information about coral reef is a general crisis as some coral species are tremendously rare. Submarine coral images have different scale, orientation and lighting. When travelling submarine, a common artifact, red channel information [7,8] loss occurs. Many of the coral classes are difficult to model. So, submarine image classification with feature extraction is not a simple task. This accentuates the necessity to classify the image with the help of its texture to reflect the actual information collected from the real world.

The rest of the paper is structured as follows: Section 1.1 discusses the contribution of the proposed work. A survey of coral image enhancement techniques, feature extraction techniques and classification techniques is given in Section 1.2. Section 1.3 discusses the overview of the proposed work. Section 2 represents the concepts of the proposed feature extraction approach Improved Local Derivative Pattern (ILDP). The experimental results are presented in Section 3. Finally, conclusion and future work are discussed in Section 4.

1.1. Contribution in this paper

The contributions of the proposed work are as follows

(i) An improvement in LDP termed as ILDP is proposed which has reduced the bin size of histogram, thereby reducing the time complexity improving the recognition rate.
(ii) For an effective classification, three classifiers namely K-Nearest Neighbor (KNN), Convolutional Neural Network (CNN) and Support Vector Machine (SVM) are used and the results are compared.
(iii) The effectiveness of ILDP is demonstrated by comparing it with existing approaches in terms of accuracy and time complexity on five coral and four texture data sets.
(iv) The suitability of the proposed work for both texture and coral

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data sets is justified with experiments and the comparative analysis made with the state-of-the-art approaches.

1.2. Related works

Coral image classification is to be addressed in three stages, and so the related researches are presented in their order of occurrence, namely Coral Image Enhancement, Feature Extraction and Classification.

1.2.1. Coral image enhancement techniques

Pre-processing is the first step of coral image enhancement. Image enhancement is needed to improve the classification accuracy. The related papers pertaining to coral image enhancement are as follows: Blanchet et al. [6] have used Histogram Equalization for enhancing the submarine images. Kevin et al. [9] have proposed a software package using Visual Basic program CPCe (Coral Point Count with Excel extensions) for the purpose of coral image using random point count methodology. These techniques are used for preliminary image analysis such as enhancement, edge detection and segmentation. Beijbom et al. [10] have used coral image with color spaces such as RGB, LAB and HSV for enhancements such as intensity stretching and color channel stretching. Eduardo et al. [11] have used normalization process to measure the range of pixel intensity values of coral image so as to increase contrast. Mohammad et al. [12] have used Normalization to remove global illumination influence in coral images. Shihavuddin et al. [13] have considered Contrast Limited Adaptive Histogram Specification (CLAHS) as an important enhancement technique which provides better results for image enhancement. Dead corals and sand have similar chromaticity and differ only in glowness. So, Shiela et al. [4] have combined Histogram Back propagation with color matching technique to improve the results. Judgment on the best enhancement method for a given coral data set is a challenging task. Most importantly, all enhancement methods could not address the red channel information loss challenge, which is however necessary for extracting useful color features.

1.2.2. Feature extraction techniques

A dominant dictionary-based texture descriptor, texton, is proposed as a feature by Beijbom et al. [10]. Padmavathi et al. [14] have used Kernel Principal Component Analysis (KPCA) and PCA-SIFT (Principal Component Analysis- Scale Invariant Feature Transform) for dimension reduction and feature extraction of submarine images respectively. Shihavuddin et al. [13] have employed Completed Local Binary Pattern (CLBP), Grey Level Co-occurrence Matrix (GLCM) with twenty-two features, Gabor filter response and opponent angle and hue channel color histograms as feature descriptors. Eduardo et al. [11] have used a bank of Gabor Wavelet filters to extract texture feature descriptors with learning classifiers from OpenCV library. Shiela et al. [15] have determined the living and the nonliving count of corals by extracting texture features using LBP descriptor. Pican et al. [16] have used GLCM with six features and Kohonen Self-Organizing Map (SOM) for texture feature extraction. GLCM has twenty-four types of features for extraction, and for each image suitable features have to be chosen for extraction.

Blanchet et al. [6] have used CLBP as texture descriptor and Hue and opponent angle histograms as color descriptors for extracting submarine coral images. Oscar et al. [17] have represented texture with a bag of words using Scale Invariant Feature Transform (SIFT) which has four major stages, and each of them is a time-consuming process. Clement et al. [18] and Soriano et al. [19] have extracted texture features using LBP. According to Hedley et al. [20] ground truth comparisons have revealed high error estimates rarely surpassing with 60% accuracy results. Mohammad et al. [12] have proposed two mapping methods using CLBP. Stokes et al. [21] have considered color and texture descriptors. RGB histogram is used for color features, and Discrete Cosine Transform (DCT) is used for texture. Anand Mehta et al. [22] have employed an approach that does not require any explicit feature extraction. Support Vector classifier implicitly performs feature extraction by means of a kernel which is defined by a dot product of two non-linear mapped patterns. Though the feature representations available in literature are accepted, none has reported performance to a satisfactory level on full-scale normal coral scene image data sets. Hence there is still a need for a feature extraction technique which could better aid in the classification process.

1.2.3. Coral classification techniques

Image-based coral classification is done by extracting color and texture features and then by classifying them. Anand Mehta et al. [22] and Bewley et al. [23] have classified coral reef with its texture features using SVM. Three kernel functions, namely Polynomial, Radial basis function and Sigmoid kernel are used. Anand Mehta et al. [22] have obtained 95% accuracy while classifying three coral species, but only a small amount of samples have been used to train and test the classifiers. Dictionary-based methods are further investigated by Bewley et al. [24] using small patches characterized with Principal Component Analysis (PCA) dimensionality-reduced intensity values. Their results, however, suggest that a simple LBP representation remains competitive with such methods. Shiela et al. [4,15] have classified coral images using a feed-forward back-propagation NN with a rule-based decision tree classifier into three benthic types: living coral, dead coral and sand. Shiela et al. [15] have got an overall recognition rate between 60% and 77%. Stokes et al. [21] have used Probability Density Weighted Mean Distance (PDWMD) and Euclidean distance for classification with eighteen classes of data sets. Clement et al. [18] have applied log-likelihood measure on image blocks to find the best matched texture with an accuracy of 77%. Soriano et al. [19] have classified corals with KNN rule, and the distance metric used is log-likelihood and have reported an accuracy of 80%. Mahmood et al. [25] have used Convolutional Neural Network (CNN) with texton and color for classification.

Padmavathi et al. [14] have classified submarine images using Probabilistic Neural Network (PNN) which provides better results when compared to SIFT [26,27] algorithms with three classes of data set. Mohammad et al. [12] have classified coral and textures using KNN by considering K = 1 and have reported an accuracy of 90.35%. Shihavuddin et al. [13] have classified corals using techniques such as KNN, Neural Network (NN), SVM and Probability Density Weighted Mean Distance (PDWMD) and have reported an accuracy of 85.5%. Marine habitat is classified by Oscar et al. [17] using voting of best matches method with 95% confidence bounds. Their classification is achieved through voting for the best match. In their method, each image is classified as belonging to one class, and the sub-image level classification is not addressed. Beijbom et al. [10] have classified coral reef images using SVM with Radial Basis Function kernel. The method has reported an accuracy between 67% and 83% for a nine-class data set of natural images with over one hundred thousand labelled points. Blanchet et al. [6] have obtained an accuracy of 78.7% using three state-of-the-art feature representations, namely LBP combined with color information, textons, and a CNN-based feature. Eduardo et al. [11] have classified corals using nine machine learning algorithms such as Decision Trees, Random Forest, Extremely Randomised Trees, Boosting, Gradient Boosted Trees, Normal Bayes Classifier, Expectation Maximisation NN and SVM. On comparison of performance, Decision Trees algorithm has yielded the most accurate performance, and SVM has resulted in poor performance. Jose [28] has classified coral images using Euclidean distance and has reported an accuracy of 80.5%. The classification techniques used for coral data sets will replace many hours of labour of a marine biologist dedicated to coral reef studies. However, more work has to be done in coral reef images to improve classification accuracy.

To overcome the gaps in submarine coral image classification problems, the best enhancement technique has to be used to increase