AN ANALYISS THE SONAR CONTACT IMAGES BY USING THE LONAR ANALYSIS WITH DEEP CONVOLUTIONAL NEURAL NETWORK

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ABSTRACT

An Important oceanographic environment, the seabed images can be implemented mostly in the field of sound navigation and ranging (SONAR) procedures for submarine communication. The significance of underwater study in the improvement and use of deep-sea resources, underwater independent operation is very important to avoid the difficulties, heavy-pressure deep-sea environment. In an underwater environment weak illumination and low-quality image enhancement as a preprocessing procedure is necessary for underwater vision. In this paper, A systematic procedure was employed in transfer learning a pre-trained deep and convolution neural network in order to learn the pixel-intensity based features of seafloor anomalies in sonar images. The Automated Target Recognition (ATR) is used for the signal processing and helps to development the sonar image contact. The low-frequency analysis recording (LOFAR) analysis is visually identified the frequency information of target sonar images mines and detecting the incorporated degree of the seabed images. After the image preprocessing, a DCNN method is proposed to perform the underwater detection and classification a combination of max-RGB method and shades of gray method is applied to achieve the enhancement of underwater vision Most of the existing classification methods cannot be widely used in underwater sonar image classification.

Keywords: *SONAR IMAGE, LOFAR, The Automated Target Recognition (ATR), Deep convolutional neural network*

I. INTRODUCTION

An underwater environment, the image classification was assist to the method of the sonar contact and had a better resolution. The sonar is collecting the data is numerous devices that can be use sound wave as the information carrier. It is the technique to permit the warship and other ship is use to discover and finding the substances in the water through the rhythm of sound and echo’s.

The sonar contact is can detect, location, identification ad targeting the object in the marine environment and perform the communication, navigation, measurement and other function. The sonar image has the characteristics of low contrast, edge blur and high noise, which will seriously influence the underwater object classification. However, underwater object classification can help to find mines, submarines, and shoals and to detect the integrated degree of the dam bottom. Therefore, it has important practical significance both in military and civil fields. The Deep and convolution neural network (DCNN) is train the large number of labeled images to archive satisfactory performance.

DCNN aided by fast and powerful GPUs, are increasingly being used with significant success in a range of applications, including computer vision, speech recognition, audio recognition and bioinformatics. They have been particularly successful in applications involving recognition and classification of features in optical images, including faces and everyday objects [1]. The DCNN ha test the high pixel images from underwater images. The Automated Target Recognition is a process of scanning the large amount of sonar data target. It involves detection the region of area in image classification and identification of target object. This technique is particularly interest for navigation and retrieving the most important regions at minimum cost and risk of the sailors. There are the two main aspect of the paper describes a) Different underwater images have different color alteration and optical transmission b) improve the classification and accuracy of the seabed images.

The research paper is organized as follows: Related work about the classification and difficulties model in the section II. The method of DCNN is the framework is shown in section III. The experiment result and features extraction are in shown in section IV. The paper is concluding of the section V.

II RELATED WORK

The model named AlexNet[2] which achieved the 2012 ImageNet competition champion, had 8 layers and the top 5 error was 16.4%. In the 2014 ImageNet competition, the model named VGG won, which had 19 layers and achieved the 7.3% top 5 error. Later the 22 layers model named GoogLenet[3] achieved the top 5 error 6.7%. In the 2015, ResNet[4], 152 layers, the 3.57% top 5 error. Recently the densenet[5], 3.46% test top 1 error in Cifar10 database.

Starting with LeNet [6], convolutional neural network had become a standard structure in deep learning frameworks. Variants of this basic structure are prevalent in the image classification literature and have achieved the better results on the stand database such as MNIST, CIFAR and Imagenet. Increasing the number of layers and layer size has become the trend. In addition, Dropout is used to address the problem of over fitting.

The research of image classification about undersea image was relatively less than that of optic image spread through the air. Automatic plankton image recognition [7] combines traditional invariant moment features and Fourier boundary descriptors with gray-scale morphological granulometries to form a feature vector capturing both shape and texture information of plankton images, achieved 90% classification accuracy on six plankton taxa taken from nearly 2,000 images.

III METHODOLOGY

A).Automatic Target Recognition (ATR)

Automatic target recognition (ATR) of underwater substance in sonar data is of substantial attention computerized procedure of scanning through large area of sonar data for objective[8]. ATR in a sonar image involves detection of regions of interest in the image, classification of the regions according as whether they include objects or not, and identification of target objects within regions. Detection, classification and identification of undersea objects in real time using AUVs are of particular interest to the Navigation as a way of separately studying the important regions at low cost and low risk to sailors. However, examining sonar images, which are typically characterized by highlights and shadows, can be challenging for detection and identification of targets [9].

B) Image Preprocessing

Image preprocessing is at the low level, the fundamental purpose is to improve image contrast, to weaken or suppress the influence of various kinds of noise as far as possible, and it is important to retain useful details in the image enhancement and image filtering process. The preprocessing technique is LOFAR[9], analysis to predicts the objective machinery's noise trembling by providing the machinery noise to the sonar operator. This analysis, based on spectral estimation, supports the detection and classification of targets. The signal to noise ratio (SNR) is low due to the discreteness of the sources. The narrowband component of signals provides an image of frequency and time, commonly known as lofargram. The function of sonar image preprocessing should be maximized to any kind of noise and reduce the impact of noise on the target area, and at the same time, enhance the actual target image in the water and parts of interest

C) Permutation Of Max-Rgb Method And Shades Of Gray Method.

The assimilation of water to light leads to the refuse the color of underwater images. As the red and orange light are absorbed at 15 meters deep in the water, the underwater images usually blue-green color. In classify to eradicate the color variation of underwater images, color correction of underwater images. The color correction of the normal image has been established. Many white balance methods, such as Gray Word method, max-RGB method[10], Shades of Gray method, and Gray Edge method, are used to correct the color deviation of the image according to the color temperature. In this paper, the original max-RGB method and shades of gray method are combined to identify the illuminant color.

$$n\ I(x) = \int_w e(\alpha)s(\alpha,x)a(\alpha)d\alpha, \qquad (1)$$

whe $I(x)$ is the input underwater image, $e(\alpha)$ is the radiance given by the light source, α is the wavelength, $s(\alpha,x)$, $a(\alpha)$denotes the sensitivity of the sensors, and w is the visible spectrum.

The illuminant e is defined as

$$e = \int w\, e(\alpha) d(\alpha) a\alpha \qquad (2)$$

The average reflectance of the scene is gray according to the Grey-World assumption

$$k = \frac{\int s(\alpha,x)dx}{\int dx} \qquad (3)$$

The illumination by explaining that the average color of the entire image raised to a power *m*

$$ke = \left[\frac{I^n dx}{\int dx}\right]^{1/2} \qquad (4)$$

According to the max-RGB method, the above equation can be modified as

$$ke = \max I(x) * \left[\frac{\int I^m dx}{\int dx}\right]^{1/n} \qquad (5)$$

D) Deep Convolutional Neural Networks for Sonar Imagery

The deep convolutional neural networks is already well-established, so more focus is dedicated here to the data preparation events and network architecture blueprint that developed in particular for classification process with sonar imagery.

The DCNN simulates the perceptual process of visual nerves in the cerebral cortex, and only a small number of neurons are active when it identifies an image. On the basis of this local receptive field, the DCNN can use the convolution operation to effectively extract the features of images. Meanwhile, due to the characteristics of the feedforward neural network and local sensing, the DCNN has good applicability in image classification, image recognition and even speech recognition[11]. Therefore, it is considered as the most popular deep learning model for underwater sonar image classification. The structure of the DCNN includes the input layer, the convolutional layer, the pooling layer, the fully connected layer and the output layer. The convolutional layer is used to train the local receptive fields of the input underwater sonar images, which can further extract the abstract features of underwater sonar images.The underwater sonar image feature matrix is obtained by the convolution operation between the filter and underwater sonar image.The specific convolutional process is as follows:

$$z_j^m = f\left(\sum_{i\in T} k_{ij}^m * z_i^{m-1} + b_j^m\right) \qquad (6)$$

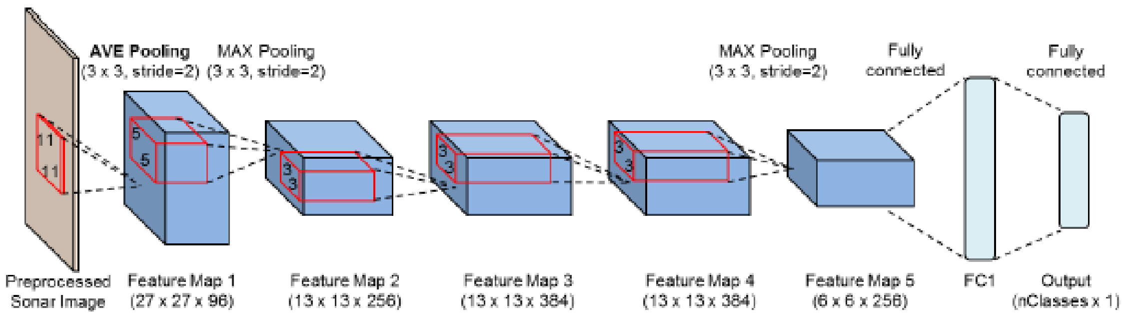

Fig 1: Architecture of Deep Covolutional neural netwok

The DCNNs designed is each consist of alternating layers of convolution and pooling layer, followed by a fully-connected layer, and a final the output layer. The inputs to a given layer are the outputs from the past layer. Each convolutional layer and fully-connected layer employs a sigmoid activation function before the result is passed to the subsequent layer. Each pooling layer, which effectively down samples, uses pure averaging rather than the commonly used max-pooling approach because the former is more robust when dealing with the speckle properties of sonar imagery. The training process of a DCNN learns the parameters of the model, which for the convolutional layers are the filters and associated bias terms.

IV.EXPERIMENTAL RESULT

A)Dataset

To evaluate the accuracy of our approach for underwater images classification by using the CNN model. The UCI machine learning database contains 497 datasets to serve the Machine Learning approach. The repository also contains ”Mines vs. Rocks” dataset.This dataset contains multivariate data types. This dataset objective to differentiate between rocks and metal structures, which can be called mines. The experimental setup consists of a cylindrical rock and a metal cylinder, each of length 7 feet, kept on the sandy ocean floor, sonar inclination, which are wide-band linear frequency modulated. The file “sonar.rocks” include of 99 patterns accomplish from rocks below identical conditions. Each record carries the letter “R” or letter “M” containing on the object and it contains: “R” for the rock and “M” for the mine. The transmitted signal is a frequency-modulated chirp signal, which rises in frequency[12]. The dataset consists of signals acquire from a variety of individual aspect location, spanning 90 and 180 degrees for the cylinder and the rock, respectively. Each pattern is a set of 60 numbers in the range 0.0 to 1.0, where each value signifies the energy within a specific frequency band, combined over a specified duration. of these factors used this dataset for analyzing the hidden units in a layered network to classify sonar targets.

B)Network Architecture

Three binary classification experiments were measured in this work, the variation between them individual which objects were treated as belonging to each class. However, the same deep network architecture was used in all experiments. Specifically, a 10-layer convolutional neural network was designed, with this consisting of alternating layers of convolution and pooling operations, remaining layer are fully-connected layer. The inputs to a given layer are the outputs from the foregoing layer, There were four sets of convolution layers and pooling layers. Each convolutional layer and fully-connected layer used a sigmoid activation function, Each pooling layer, which successfully down samples, used averaging rather than the commonly used max-pooling approach ,the averaging was performed always using patch sizes of 4x4 .Each convolutional layer is associated with a fixed number.

C)Analysis the Pattern Rock Vs Mines

The problem is to predict metal or rock objects from sonar return data. Each pattern is a set of 60 numbers in the range 0.0 to 1.0. Each number represents the energy within a particular frequency band, integrated over a certain period of time. The label associated with each record contains the letter R if the object is a rock and M if it is a mine (metal cylinder).

V.CONCLUSION

In our propsed deep convolutional neural network models to identify tonal frequencies in a lofargram. We divide a lofargram into several small patches, and a CNN model predicts the probability that the patch is from a tonal frequency. Our model shows 92.5% of precision and 99.8% of recall, and 0.150 seconds of processing time for an inference batch at a specific time frame.

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