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Marine water quality detection based on neural network

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ABSTRACT

In order to evaluate the seawater quality objectively, a marine water quality evaluation model based on convolution neural network is established based on remote sensing image. The model is used to evaluate the marine water quality comprehensively. Compared with the traditional method, the convolution operation can better deal with the complex nonlinear relationship between remote sensing image and water quality parameters, effectively correct the error between remote sensing inversion parameters and measured data, and realize the classification of marine water quality more accurately.

Keywords: Marine water quality assessment; Remote sensing image; Convolution neural network

1. Introduction

The ocean is an important part of human survival and social development. With the development of science and technology, the scale of human development of marine resources is becoming larger and larger, and the degree of dependence on the ocean is becoming higher and higher. At the same time, the impact on the ocean is also increasing. In recent decades, due to the marine development and marine engineering construction, marine pollution is becoming more and more serious, and some sea areas have changed. In particular, the coastal water quality continues to deteriorate, especially in coastal waters.

There are mainly single index evaluation method and comprehensive evaluation method for sea water quality evaluation. Environmental management department applies single index evaluation method to environmental impact assessment to benefit water environment protection [1]. However, if it is applied to water environment quality assessment, the function of water area will be greatly reduced and the comprehensive effect of water environment cannot be exerted. Comprehensive water quality assessment is an important part of water environment quality assessment. It can directly show the general situation of water environment quality by quantitative characteristics, and it is an important topic in the basic theory research of modern environmental science. For example, the comprehensive index method, grey clustering method, grey pattern recognition method, fuzzy comprehensive evaluation method, and fuzzy pattern recognition method are used in the early stage. However, these methods need to assume the mode or specify some parameters subjectively in advance. Most of them need to design the subordinate function of each evaluation index to all levels of standards and the weight of each index. The evaluation results are highly subjective. Therefore, they cannot be used in practice. They can only be used as reference in environmental assessment. Single index evaluation method is still required to determine water quality categories. Therefore, it is necessary to study more objective comprehensive water quality assessment methods.

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In recent years, with the rapid development of artificial intelligence technology, deep learning is particularly prominent in the field of image understanding. Among them, convolution neural network is a kind of deep neural network with convolution structure [2]. Convolution structure can reduce the memory occupied by deep network and the number of network parameters, and alleviate the over fitting problem of model. Based on the prior knowledge neural network, a comprehensive evaluation method of marine water quality is proposed. Combined with the remote sensing image data, the multi-modal three-dimensional matrix input data is formed to train and evaluate the convolution neural network, effectively realize the classification, and recognition of marine water quality, provide accurate decision-making basis for relevant departments, protect the marine environment, and promote the healthy and harmonious development of society.

2. Overall framework of marine water quality assessment technology

The technical framework of marine water quality assessment is shown in Fig. 1. Before water quality assessment, the convolutional neural network needs to be trained. The training set consists of marine water quality assessment knowledge set, marine satellite remote sensing image data, and measured marine water quality data. In the process of marine water quality assessment, remote sensing image data, and water quality evaluation knowledge data from satellite observation are taken as input data sets, and the trained convolution neural network is used for classification and recognition [3,4]. Finally, the evaluation and classification of marine water quality are realized, marine water quality is divided into class I, II, III, and IV. For water quality inferior to class IV, it is classified as inferior class IV according to the literature. Therefore, in the process of training and identification, the above-mentioned classification standards are used as the evaluation standard indicators of marine water quality to realize the classification treatment of marine water quality.

3. Marine water quality evaluation based on convolution network 2

3.1. Ocean water quality correction

Due to the influence of the characteristics of remote sensor, atmospheric refraction, earth rotation, and imaging mode, there are some data distortion and geometric distortion in satellite remote sensing images, which will inevitably affect the image processing quality and application effect. Generally, satellite remote sensing images have been pretreated by atmospheric correction, geometric calibration, and radiometric calibration, such as geometric distortion correction, image equalization, spatial filtering, etc., but there are still problems of low accuracy, which makes it difficult to accurately reflect the state of marine water quality [5]. According to the characteristics of ocean water quality observation images and the relationship between them and the measured data, a nonlinear regression model based on remote sensing image transformation is established to determine the mapping relationship between input and output, so as to realize the correction of satellite remote sensing image.

In the original remote sensing image S, any point P is expressed as $(S_x(P),S_y(P))$, and the corresponding pixel value is $P_{\text{pixel}} = R(S(P),S_y(P))$, and R is the value calculation function of a pixel in the image. In the correction process, the corrected remote sensing image t is formed after the function of mapping function F. any point m can be expressed as $(T_x(P),T_y(P))$, and the corresponding pixel value is $P'_{\text{pixel}} = R(T_x(P),T_y(P))$, then:

$$P'_{\text{pixel}} = f \times P_{\text{pixel}} \tag{1}$$

For any point (x,y) in the corrected image, there is a mapping point (x',y').

3.2. Convolution neural network

Convolution neural network is a variant model of multilayer perceptron, which is generally composed of convolution layer, pooling layer, full connection layer, and output layer. It simulates feature differentiation by convolution, and reduces the order of magnitude of neural network parameters through convolution weight sharing and pooling operation [6]. Finally, the traditional neural network is used to complete recognition and classification.

3.2.1. Convolution layer

In the convolution layer, different convolution kernels are convoluted with all the characteristic graphs of the previous layer, and then the output neurons of the current layer are formed by modifying the activation function of linear units:

$$y_j = f\left(\sum_i x_i * k_{ij} + b_j\right) \tag{2}$$

where x_i is the input of layer i; y_j is the output of layer j; * is convolution operation; k_{ij} is layer i and j. The results show that the convolution kernel matrix between layers; b_j is the offset of the j-th layer; $f(\cdot)$ is the excitation function. The nonlinear excitation function relu is selected, and the expression is $y = \max(0,x)$.

3.2.2. Pool formation

The main functions of the pooling layer are: (1) reducing the dimension of the output feature map; (2) maintaining the invariance of the output features of the convolution layer to a certain extent (including rotation, translation, scaling, etc.).

$$y_j = f\left(\beta_j \text{ down}\left(x_j\right) + b_j\right) \tag{3}$$

In this paper, the maximum pooling method is used, that is, the maximum of the feature points in the neighborhood, which can reduce the offset error of the estimated mean value caused by the parameter error of the convolution layer, and retain more feature texture information.

3.2.3. Full layer connection

The last hidden layer of the model is the fully connected layer, which transforms the pooled feature map into one-dimensional feature, and its output formula is:

$$y_j = f\left(\sum_i x_i \cdot \omega_{i,j} + b_j\right) \quad (4)$$

Among them, x_i is the value of the pooled neurons; $w_{i,j}$ are the weight coefficients; $J \cdot b_j$ is the bias; $f(\cdot)$ is the excitation function.

3.2.4. Output layer

The output layer is soft max, which is a multi-type classifier, which is used to predict the output probability of various types:

$$P_i = \frac{\exp(y_i)}{\sum_{j=1}^{n}\exp(y_i)} \quad (5)$$

Among them, y_i and y_j are the output of the *i*th and *j* neurons, respectively, and *n* is the total number of neurons.

3.3. Structure design and training process of convolutional neural network

In order to accurately realize the evaluation and classification of marine water quality, this paper designs a convolutional neural network for marine water quality assessment, which is composed of nine layers. The input layer is the three-dimensional matrix data composed of d0, D1, TM1, TM2, and TM3 (refer to section 3.2 (convolution neural network) for details); C1, C3, and C5 are convolution layers; S2, S4, and S6 are the maximum pooling layers corresponding to each layer; F7 is the full connection layer of the neural network, and the soft Max layer is used to output the probability of various water quality grades corresponding to remote sensing images [7].

The convolution neural network model needs to be trained before the marine water quality evaluation of satellite remote sensing image. Convolutional neural network belongs to supervised learning mode, and samples need to be marked before training. The corresponding remote sensing image is marked by the measured sample results, and all weights are initialized randomly, and then forward propagation is carried out. That is, one sample is taken from the sample set (X,Y_p), input X into the convolutional neural network, and calculate the corresponding actual output $O_p = F_n(...(F_2(F_1(XW_1)W_2)...)W_n)$. Then calculate the difference between the actual output O_p and the corresponding actual sample label Y_p, and adjust the weight matrix according to the method of minimizing the error [8].

4. Experiment and result analysis

4.1. Sample data acquisition

Taking Guangdong Province as the experimental analysis area, the experimental data are from the Landsat 7 ETM + satellite remote sensing image data set with 8 spectral bands in the same period as the actual observation. The remote sensing images of TM1 (blue band), TM2 (green band), and TM3 (red band) which have good response to the characteristics of marine water quality are selected to evaluate the water quality. The blue and green bands are sensitive to chlorophyll and pigment 3. The distribution of suspended sediment in the Pearl River estuary is sensitive to the water depth of the Pearl River and the lower reaches of the Pearl River.

4.2. Experimental process

The experimental process is shown in Fig. 1. Firstly, the remote sensing images of TM1, TM2, and TM3 bands are corrected by using the nonlinear regression correction model; secondly, the prior knowledge of marine water quality assessment is coded, and the training samples are formed by combining the remote sensing image and the measured target data, and the convolution neural network is trained; finally, based on the trained convolutional neural network, the training results are compared with the experimental data [9]. The remote sensing image test data and marine water quality assessment knowledge are used as test sample set to evaluate the water quality of test points.

The input data mainly includes the prior knowledge of marine water quality assessment and remote sensing image data, and the prior knowledge of marine water quality assessment includes two types of data: (1) prior knowledge of geographical distribution of marine water quality and seabed depth, and coding them (such as land mark 0, bay area mark 1, shallow water area mark 2, deep water area mark 3) to form coding template d0 (128 × 128), (2) according to the marine water quality classification data obtained by interpreting the pseudo color composite image corresponding to the remote sensing image, as shown in Fig. 2, the estimated division of Guangdong ocean water quality categories is obtained, for example, the black part represents the poor water quality area (marked as 3), the light black part represents the general water quality area (marked as 2), and the gray area represents the area with good water quality (marked as 1),The remote sensing image data mainly include blue band remote sensing data TM1, green band remote sensing data TM2 and red band remote sensing data TM3. Due to the large coverage and high resolution of the original image, it is divided into 128 × 128 image sequences, which are trained and evaluated in turn with the sampling points. The input data is a three-dimensional matrix data (128 × 128 × 11) composed of d0, D1, TM1, TM2, and TM3. It covers most of the prior data of water quality assessment and remote sensing images of key bands of water quality assessment. The feature information and differences among the modal data are extracted automatically by 3D convolution. It is helpful to improve the accuracy of marine water quality assessment. The measured target data in the training process are the processing results of ship voyage observation data in a certain year [10,11].

The experiment is based on the C toolkit secondary development library of erdas9.0, and combined with Jia Yangqing's open-source fast deep learning framework Caffe, a total of 500 groups of training samples are generated,

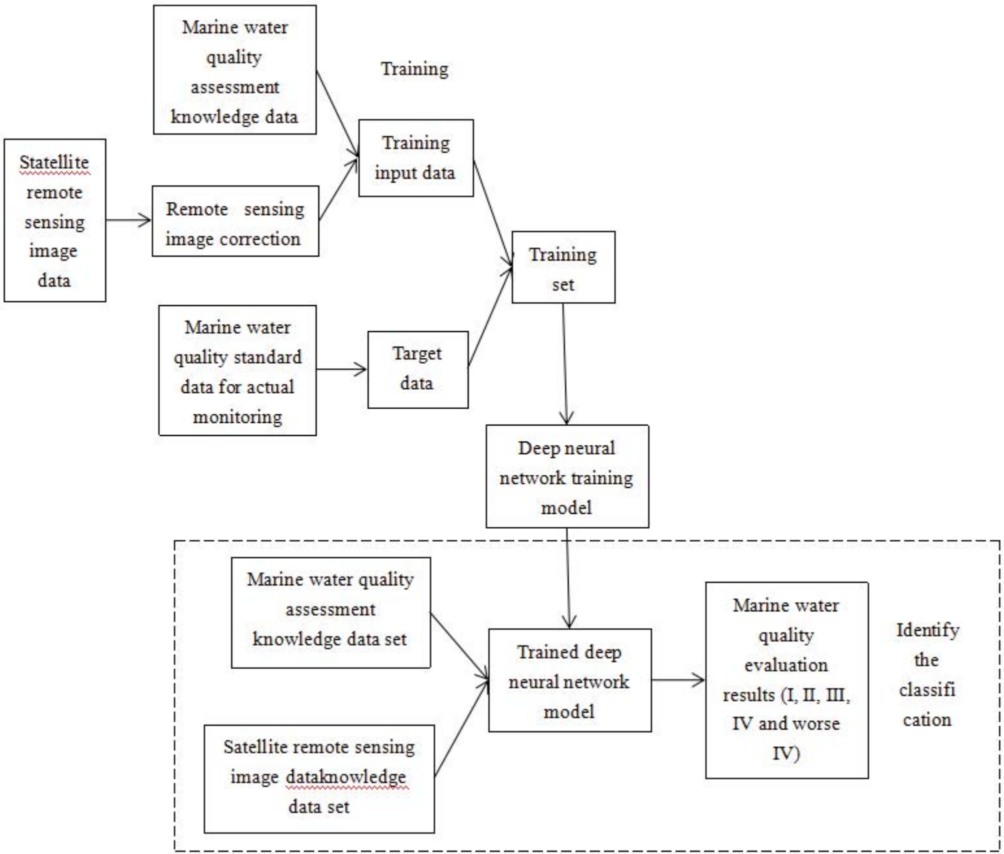

Fig. 1. Technical framework of marine water quality monitoring and evaluation.

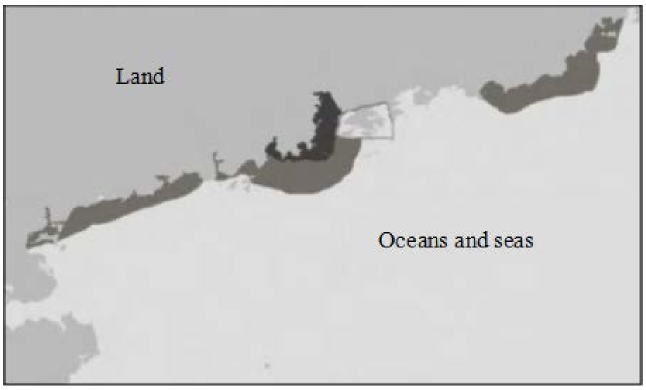

Fig. 2. Prediction and division of marine water quality grades in Guangdong Province.

including 100 groups of class I, 100 groups of class II, 100 groups of class III, 100 groups of class IV, and 100 groups of inferior class IV. Finally, 16 test sets are randomly selected for water quality evaluation.

4.3. Result analysis

According to Eq. (5), the output layer of convolution neural network outputs the probability of current test samples in various water quality grades. The maximum value corresponding to the grade is the result of marine water quality assessment. The prediction results of all test samples are shown in Table 1. Combined with Fig. 2, the measured data and prediction data show that class IV and inferior class IV water quality are mainly distributed in the Pearl River Estuary. Class III and IV water quality are mainly distributed in Shantou port and Zhanjiang port, while other sea areas are of class I and II seawater quality [12]. Based on the measured data as the evaluation standard, the accuracy of prediction results is 93.75%. Compared with the traditional method, the convolution operation is better to deal with the complex nonlinear relationship between remote sensing image and water quality parameters [12,13]. It can effectively correct the error between the remote sensing inversion parameters and the measured data [14].

5. Conclusions

In this study, Guangdong Province as the experimental analysis area, the water quality of the sea area as the evaluation factor, through the establishment of a convolution neural network method based on comprehensive evaluation of water pollution in this area.

Based on the remote sensing image, a nonlinear regression model is established. The results of the comprehensive evaluation of water quality in Guangdong Province show that the real-time processing of remote sensing image and water quality classification are applicable through

Table 1
Analysis of experimental data of marine water quality in Guangdong Province

Test area	Measured level	Predicting level	Test area	Measured level	Predicting level
1	III class	III class	9	Worse IV	Worse IV
2	I class	I class	10	Worse IV	Worse IV
3	I class	I class	11	I class	I class
4	II class	III class	12	II class	II class
5	IV class	IV class	13	III class	III class
6	Worse IV	Worse IV	14	I class	I class
7	Worse IV	Worse IV	15	I class	I class
8	Worse IV	Worse IV	16	I class	I class

multi-layer convolution and pool operation. The convolution neural network evaluation method can comprehensively consider various pollution factors and water quality standards, and has certain practical value, but there are still some shortcomings. If the dimension of input data is too large, the training process has many characteristic parameters. The input data can be optimized or the parallel network structure can be used to reduce the training complexity.

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