

RESEARCH ON HIGH ACCURACY DETECTION OF RED TIDE HYPERSPECTRAL BASED ON DEEP LEARNING CNN

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ABSTRACT:

Increasing frequency in red tide outbreaks has been reported around the world. It is of great concern due to not only their adverse effects on human health and marine organisms, but also their impacts on the economy of the affected areas. This paper put forward a high accuracy detection method based on a fully-connected deep CNN detection model with 8-layers to monitor red tide in hyperspectral remote sensing images, then make a discussion of the glint suppression method for improving the accuracy of red tide detection. The results show that the proposed CNN hyperspectral detection model can detect red tide accurately and effectively. The red tide detection accuracy of the proposed CNN model based on original image and filter-image is 95.58% and 97.45%, respectively, and compared with the SVM method, the CNN detection accuracy is increased by 7.52% and 2.25%. Compared with SVM method based on original image, the red tide CNN detection accuracy based on filter-image increased by 8.62% and 6.37%. It also indicates that the image glint affects the accuracy of red tide detection seriously.

1. INTRODUCE

Red tide is a kind of oceanic disasters caused by the explosive propagation or aggregation of plankton in sea water under certain conditions, which can cause the discoloration of the seawater. Seawater presents different colors due to different types of red tides during the red tide outbreak, but some red tide creatures do not cause a color anomaly phenomenon in the seawater. Therefore, it is difficult to accurately conclude that there is an occurrence of red tide based on the color of seawater change only. Red tide has become one of the global marine disasters, it not only affects the ecological environment of water, but also brings significant economic losses of fishery resources and production. Additionally, red tide outbreaks could force the shutdown of desalination plants, which pose a major threat to the potable water supply (Berkta, A, 2011a). In recent years, the degree of eutrophication of certain

coastal water in China has become serious, which lead to occurrence of red tide with large scale frequently. Red tide causes huge losses of the coastal economy and endangers the human living environment. Therefore, the rapid and accurate detection of red tide is basic for the prevention and control of red tide disasters. Due to the species in the sea is diverse, the color of red tide water is different. It is different to determine whether the red tide is emerging according to the color change of seawater.

Red tide, also known as harmful algal bloom, is caused by proliferation of a toxic or nuisance algae species and has been a preeminent topic of world-wide research communities for several decades (Cullen et al., 1997, Kahru et al., 2000, Ahn et al., 2006, Gower et al., 2008, Wang et al., 2011a, Hu and Feng, 2017). Red tide monitoring is realized in two ways: in-situ measurement and

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remote sensing monitoring (MA et al., 2002, Xu et al., 2014, Zhao et al., 2014b). it is very essential to detect and forecast their movement using currently available remote sensing technology because traditional ship-based field sampling and analysis are very limited in both space and temporal frequency. Remote sensing has the advantages of wide spatial coverage and short repetition period, which can monitor large area of red tide effectively (MA et al., 2002, Ahn et al., 2006). Remote sensing includes satellite remote sensing and aerial remote sensing, of which the former has shortcomings including longer observation period, lower spatial resolution, and fewer wave bands of the sensor than those of the latter. Hyperspectral remote sensing technology is the frontier of aerial remote sensing development. The spectral range of hyperspectral images is covering visible and near infrared band, which spectral resolution reaches up to nanometer level, so it is suitable to identify red tide (MA et al., 2006, ZHAO et al., 2008). The deep learning methods presents high robustness and efficiency in image processing (Hinton et al. 2014). Convolution Neural Network (CNN) (Hinton et al. 2006), a deep learning method, has the characteristics of image displacement and rotation invariance, which has been applied in image processing successfully (Cao et al. 2016). However, it is weak in the red detection. Simultaneously, it is noted that sea surface glint in hyperspectral images interferes the spectral information of the target seawater, which will affect the effective detection of red tide. The influence of sea surface glint on red tide detection is also the research direction.

Therefore, this paper put forward a high accuracy detection method based on deep learning algorithm to monitor red tide in hyperspectral remote sensing images, then make a discussion of the glint suppression method for improving the accuracy of red tide detection.

2. DATAS AND METHODS

2.1 Hyperspectral Image

The red tide hyperspectral image used in this paper is acquired from China Marine Surveillance aircraft carrying PHI (PushBroom Hyperspectral Imager) on August 12, 2001. The PHI hyperspectral image covers the Bayuquan area of Liaodong Bay in Bohai Sea. There are 124 bands in the PHI image cubic with wavelength ranging from 383.3nm to 881.4nm, the size is 652*1000, and the spectral resolution is better than 5nm, which has the ability to distinguish red tide from normal seawater. We extracted the red tide interpretation map by using human-computer interaction method to validate detection accuracy. PHI hyperspectral image and red tide verification map are shown in Figure 1.

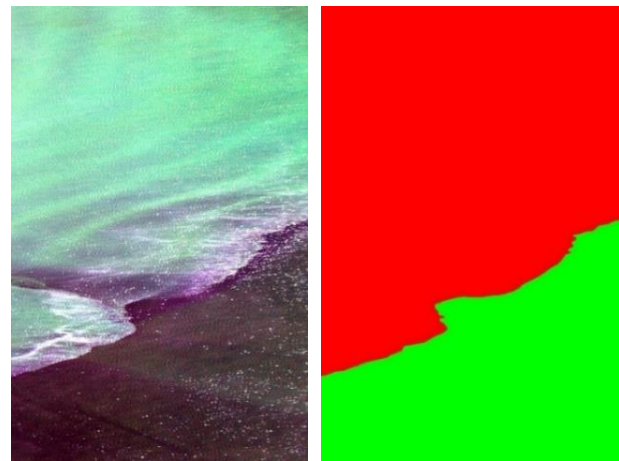


Figure 1 the map of PHI spectral remote sensing image (R:10, G:60, B:100) and the red tide validation map (red: red tide, green: seawater)

2.2 Red Tide CNN Detection Model

This paper developed a fully-connected deep CNN detection model with 8-layers to detect red tide based on PHI hyperspectral image. The model includes 1 input layer, 2 convolution layers, 2 drop samples layers, 2 fully-connected layers and 1 output layer (Figure 2).

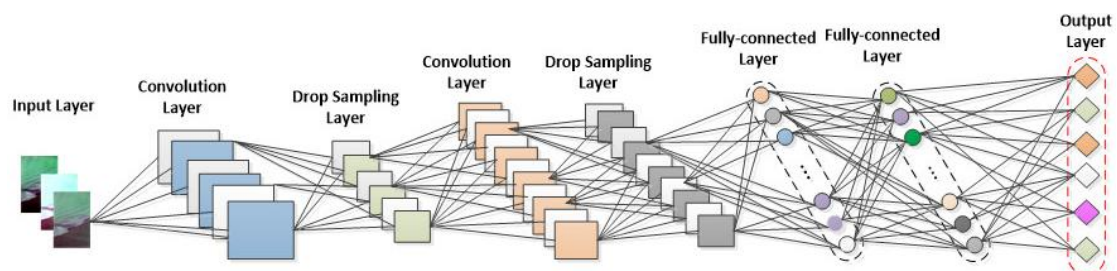


Figure 2 The structure of CNN red tide detection model

We take the spectral feature information as the input information in CNN model. The spectral feature information contains the original spectra and the first derivative spectra. The first derivative spectra of the original spectral reflectance, that is, the slope value of the spectral curve, can reflect the rate of change of the original spectral curve, where the positive value represents the band where the reflectance increases the most, and the negative value represents the band where the reflectivity deceleration is the largest. The first derivative spectra can be expressed by the formula (1).

$$\frac{dL}{d\lambda} = T \cdot E \cdot \frac{d\rho}{d\lambda} + \rho \cdot T \cdot \frac{dE}{d\lambda} + E \cdot \rho \cdot \frac{dT}{d\lambda} + \frac{dLp}{d\lambda} \quad (1)$$

Where L is the energy of imaging spectral image

ρ is the ground object reflectivity

T is the atmospheric transmittance.

E represents the solar irradiance

Lp represents the process radiation

λ is the wavelength

The paper takes the balance of the samples into account, we randomly sample a certain number of pixels from the hyperspectral image for training and use the rest to evaluate the performance of the proposed network. we select 6750 training samples and 2652 testing samples of red tide and seawater for the

CNN detection model. For each training pixel, we crop surrounding 3×3 neighboring pixels for learning convolutional filters, and the convolutional layer is activated by the sigmoid function. The down-sampling layer adopts the maximum pooling method, and the size is 2×2. The fully-connected layer is used for high level reasoning. Neurons in this layer have full connections to all activations in the batch normalization layer so as to integrate information across all locations in all the feature maps of the previous layer. The dropout used to avoid overfitting. The output layers are activated by the softmax function. The number of units in the output layer is set as the number of classes. When a pixel is fed to the network, it is classified to the neuron with maximum outputs.

3. RESULTS AND ANALYSIS

In order to validate the influence of red tide detection from the glint image, we adapt the median filter algorithm, the filter size is 3×3, then carry out detecting red tide based on the denoise image. Then we used the red tide interpretation map to validate the accuracy of red tide detection. The effectiveness of the proposed method is evaluated by comparing it with the state-of-the-art classification approach SVM. The detection results are shown in Figure 3 and Table 1.

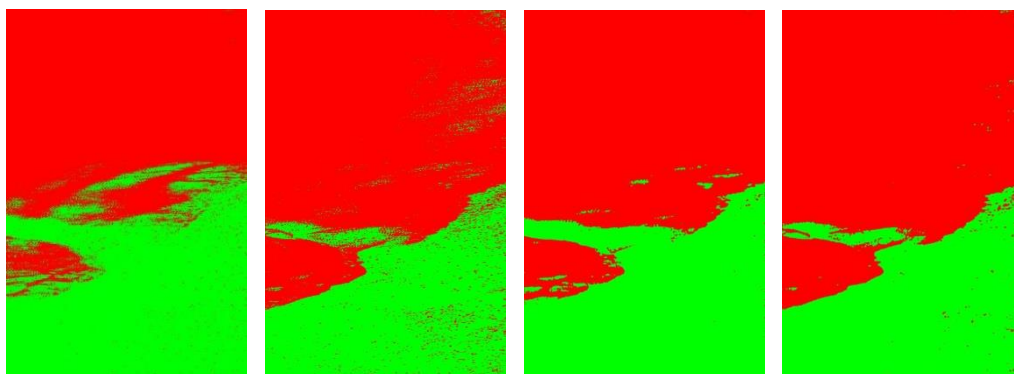


Figure 3 the red tide detection results (From left to right: SVM, CNN, Filter-SVM, Filter-CNN)

| Types | SVM | CNN | Filter-SVM | Filter-CNN |
|-----------------|-------|-------|------------|------------|
| Red tide | 83.41 | 95.71 | 92.91 | 96.80 |
| Seawater | 99.27 | 95.35 | 87.84 | 98.81 |
| OA | 88.83 | 95.58 | 95.20 | 97.45 |
| Kappa | 0.76 | 0.90 | 0.89 | 0.94 |

Table 1 The red tide detection accuracy (%)

The results show that the red tide detection accuracy of the proposed CNN model and SVM method is 95.58% and 88.83%, and the Kappa coefficient is 0.90 and 0.76, respectively, the CNN detection accuracy is increased by 7.52%. Base on the PHI hyperspectral image after median filter, the red tide detection accuracy of the proposed CNN model and SVM is 97.45% and 95.20%, respectively, and the Kappa coefficient is 0.94 and 0.89, the CNN detection accuracy is increased by 2.25%. Compared with SVM method base on original image, the red tide detection accuracy increased by 8.62% and 6.37%. The accuracy of CNN red tide detection based on original image is similar with that of SVM red tide detection based on filter-image, the reason is that the convolution process in CNN detection model has a filtering effect, so the CNN model can suppress sea surface glint in a certain extent. Compared with the red tide detection accuracy of SVM method, the accuracy of CNN model is improved by 2.25% base on filter-image. The red tide detection method based deep learning CNN shows that it is a practical approach for red tide detection in challenging conditions of sea surface glint in image. It indicates that the proposed CNN hyperspectral detection model can detect red tide accurately and effectively, and the image glint affects the accuracy of red tide detection seriously.

4. CONCLUSION AND DISCUSSION

Red tide is caused by proliferation of a toxic or nuisance algae species and has been a preeminent topic of world-wide research communities. This paper developed a red tide CNN detection model with fully-connected 8-layers based on PHI hyperspectral images, which combined original spectral feature and the first derivative spectral feature information. We compared it with the SVM classification algorithm. At the same time, we evaluated the accuracy of the hyperspectral red tide detection by the remote sensing interpretation map. The results show that the proposed CNN hyperspectral detection model can detect red tide accurately and effectively. The red tide detection accuracy of the proposed CNN model based on original image and filter-image is 95.58% and 97.45%, respectively, and compared with the SVM method, the CNN detection accuracy is increased by 7.52% and 2.25%. Compared with SVM method base on original image, the red tide CNN detection accuracy based on filter-image increased by 8.62% and 6.37%. We will explore the impact of red tide hyperspectral detection by different glint suppression methods in the future work.

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