DESIGN OF EUTROPHICATION MONITORING PLATFORM FOR *CHAOHU* CONNECTED RIVER CHANNEL BASED ON LoRa AND DEEP LEARNING

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Traditional methods cannot meet the requirements of real-time monitoring and scientific prevention and control of blue-green algae bloom. This paper uses multi-parameter sensors, LoRa module, 4G module, PLC and shore-based video acquisition device to build a monitoring platform to achieve real-time monitoring of multiple locations and real-time collection of video images; Aiming at the problem of image motion blur caused by shore-based video in water surface fluctuation, the Multi-scale Revolution Neural Network is used to effectively eliminate the visual artifacts of motion blur image, improve the monitoring accuracy of blue-green algae bloom, and meet the actual needs.

Keywords: cyanobacteria bloom; water quality monitoring; LoRa; MCNN

1. Introduction

Chaohu Lake has a water area of about 780km2, an east-west length of about 54.5km, a north-south length of about 21km, and an average water depth of about 3m [1]. In recent years, under the combined effect of natural factors and human factors, the water environment has undergone dramatic changes and the water quality has continued to deteriorate, making it one of the "three lakes" focused on the treatment of eutrophication in China [2]. The phenomenon of algal blooms caused by the massive propagation of algae is an important feature of lake eutrophication [3]. Because of eutrophication and the frequent occurrence of algal blooms, it has a negative impact on the lives of residents in the basin, becoming a major problem restricting the sustainable development of regional social economy.

At present, the monitoring of river and lake nutrition at home and abroad mainly includes satellite remote sensing monitoring, spectral technology research, UAV monitoring, etc. The satellite remote sensing monitoring method is mainly

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based on the difference of spectral characteristics between cyanobacteria, water bodies and aquatic plants. The disadvantage is that limited by the impact of the operation orbit and the cloud cover above the monitoring waters, the real-time monitoring function for specific waters cannot be realized, so the timeliness is not high. Spectral technology uses absorbance and fluorescence value to quickly detect algae, but requires equipment such as unmanned aerial vehicles, high monitoring cost, and high coordination of personnel [4]. UAV technology has been widely used in water monitoring, but specific water quality parameters can be monitored mainly based on models with large loads such as multi rotor equipped with hyperspectral sensors. Korean scientists have cooperated with China, and there have been successful cases of UAV remote sensing for chlorophyll ***a*** and phycocyanin con-centration in river water [5,6]. However, hyperspectral sensors and multi rotor UAVs that can carry them are currently expensive, and flight control and data processing are complex, so they cannot be directly applied to local business departments such as Chaohu Administration.

In view of the shortcomings of the existing monitoring platform[7], this paper adopts the automatic monitoring method of water land complementation, arranges water quality monitoring nodes and video acquisition devices in the water area near the Chaohu Lake connecting river, and realizes the real-time collection of monitoring data and video images from multiple locations by using the combination of multi parameter sensors, LoRa wireless modules, 4G modules, programmable logic controllers (PLC) and MCGS touch screens And compared with the established standardized database, graphical display, alarm and other functions are realized; To solve the problem of image motion blur caused by shore based video in the water surface fluctuation environment, multi-scale convolution neural network (MCNN) is used to effectively eliminate the visual artifacts of motion blurred images and improve the monitoring accuracy of cyanobacteria bloom information in video images.

1.1. Scheme design

The system consists of the on-site perception layer, transmission layer and application layer, mainly including water quality monitoring node, meteorological monitoring node, video acquisition devices and monitoring center, forming a one-stop monitoring system from the collection, transmission and storage of on-site information, remote alarm and operation instructions, as shown in Fig. 1.

1) Perception layer: it mainly includes water quality monitoring, meteorological monitoring, video device and on-site sensor network. By using the LoRa networking and 4G module communication mode, it executes the superior operation instructions and transmits the real-time data collected on the site upward;
2) Transmission layer: including PLC, LoRa communication module and 4G module. On the one hand, it transmits the commands issued by the application

layer, on the other hand, it gathers the monitoring data of the sensing layer to the PLC. The PLC interfaces with the on-site touch screen through the serial port, and uploads the data to the upper computer through the CP243-1 network module;

3) Application layer: The on-site MCGS touch screen can display the water quality, cyanobacteria bloom and meteorological monitoring data in a real-time graphical manner or issue some equipment control commands manually. The upper computer of the monitoring center can display the monitoring data in real time and compare with the standardized database to achieve the functions of water quality, cyanobacteria status information, alarm and emergency plan query.

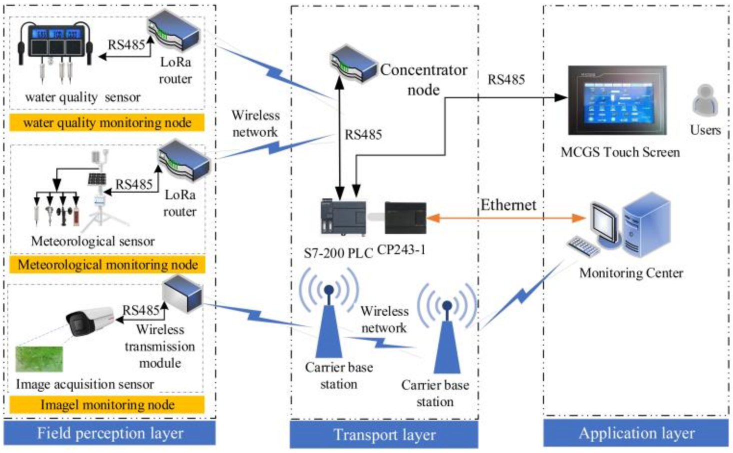


Fig. 1. Monitoring System Architecture

1.2. Establishment of standard database

The establishment of the database includes data acquisition and function realization. Based on a variety of monitoring means, multi-source monitoring data and hydrological, meteorological and other model driven data are built. By building a unified storage and integration method, data specifications and warehousing standards for different types of data, Realize the standardized processing of multi-source heterogeneous data, and finally build a standardized spatiotemporal database; The function realization includes three modules: data processing module, data analysis module and intelligent decision-making module. Among them, the data processing module preprocesses the monitoring data obtained by a variety of monitoring means to provide support for the comparative analysis of data and the intelligent decision-making of the system; The data analysis module realizes the functions of water quality, cyanobacteria bloom status information, water quality anomaly identification, etc. by analyzing the data preprocessing results and historical data; Based on the results of the data processing module and the data analysis module, the intelligent decision-making module realizes the functions of water quality exceeding the standard, alarm and emergency plan formulation, as shown in Fig. 2.

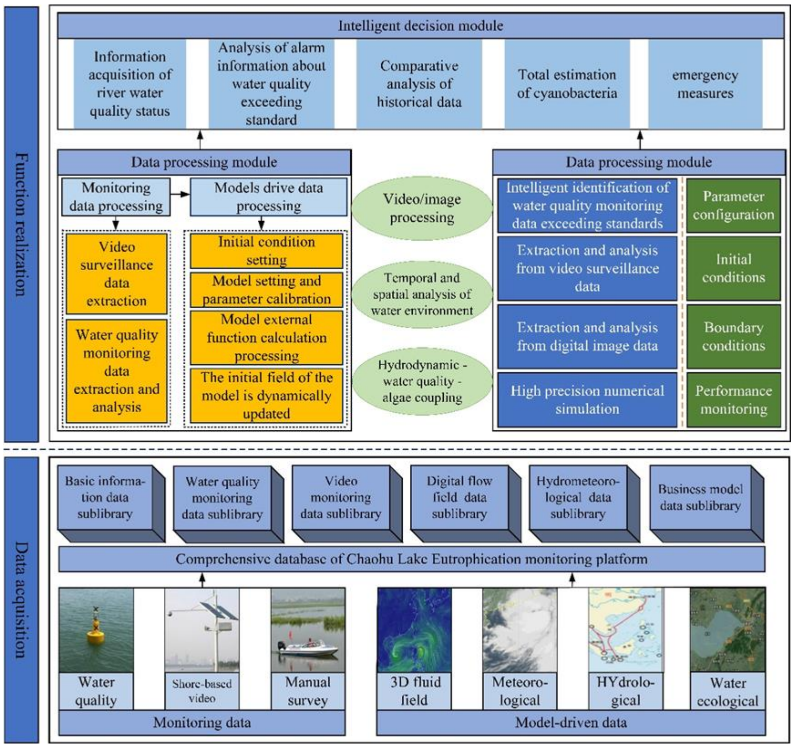


Fig. 2. Standardized database structure.

2. Overall system design

2.1. Hardware equipment selection

In order to improve the compatibility between the system and the actual application, and comprehensively consider the functional requirements of the system, the performance parameters of hardware equipment and economic costs, the statistics of hardware equipment required by the system are shown in Table 1.

2.2 Water quality monitoring nodes

The nutrient concentration in the water body is maintained at a high level for a long time. When the temperature, light and other natural factors meet certain conditions, large-scale cyanobacteria may erupt [8]. For example, the optimal temperature for the growth of cyanobacteria bloom is 25~35℃ [9]; The pH value of the water body where the cyanobacteria bloom occurs is between 7.5 and 8.5[10]. Therefore, the system chooses to monitor the pH value, ammonia nitrogen amount, temperature, dissolved oxygen and algal density. The first four parameters are measured by KM-MU multi parameter water quality monitor. Two lines (corresponding to A and B) from the two RS485 (RS485+, RS485-) interfaces at the signal output end are connected to the 485A and 485B interfaces of the LoRa module for communication. The TY-BA300 blue-green algae online monitor of Shaanxi Tianyun Company is selected for algae density. Because the LoRa module interface is limited, a multi-channel RS485 hub is added to collect signals from multiple sensors first, and then connect with the LoRa module at the node for signal transmission.

Table 1

Hardware Equipment

Equipment	Type	Number	Main parameters and functions	Communication
Multi-parameter water quality monitor	KM-MU	5	pH value:0~14	RS-485 (Modbus-RTU)
Algal density sensor	TY-BA300	1	Range:200~300000 cells/mL Resolution:20 cells/mL	RS-485 (Modbus-RTU)
Meteorological station	RS-QXZ	1	Humidity:0~100% RH	RS-485 (Modbus-RTU)
Relay	RXM4LB2P7	6	AC220V,3 A	Cable
LoRa module	LORA-13S	5	Max distance:3000 m Packet loss rate<1‰	RS-485/LoRa
PLC controller	Siemens CPU226CN	1	Data acquisition and equipment control	RS-485
Ethernet module	Siemens CP243-1	1	Connection between PLC and host computer	TCP/IP
Touch screen	MCGS Tpc1062Ti	1	Field human-machine inter face	RS485/232 TCP/IP

2.3 Meteorological monitoring nodes

Because different growth stages of blue-green algae will be affected by meteorological factors, so the system uses RS-QXZ meteorological station equipment of Shandong Jianda Renke Company. At the meteorological monitoring node, the supporting meteorological monitoring host is used to allocate data channels of meteorological elements and display real-time monitoring data on its dash-board. During work, first connect the Modbus RTU master station interface on the host with the signal output terminals of slave station transmitters such as shutter box and wind speed, collect the monitoring data of each transmitter and store it in the assigned register unit in the host; Then connect the Modbus RTU slave data output ports 485A and 485B with the LoRa interface, and upload the monitoring data collected in the host to the PLC at the sink node through the LoRa module.

2.4 LoRa wireless communication module

The LoRa well unifies low power consumption and long distance. According to the characteristics of the water area, the system communication adopts the star networking mode. The system uses CORAS Electronics LORA-

13S module. The networking architecture based on LoRa wireless communication mode includes the following four parts: terminal node, gateway (concentrator node), NS (network server), and application server. A total of 5 LoRa nodes are set up, of which one concentrator node is used as the network convergence center to organize and manage the LoRa network, and the other four are router nodes, which are respectively connected with each water quality and weather monitoring node to collect the sensor data and collect it to the concentrator node, and then transmit it to the PLC through the serial port.

3. Shore based video image deblurring algorithm

In order to monitor illegal fishing and other activities, 33 cameras are installed along the coast of Chaohu Lake, which can automatically focus and set the observation angle. Compared with satellites, continuous observation can be carried out in sunny and partly rainy days [11]. However, in windy weather, the video image will be blurred due to water surface fluctuation, and its effectiveness will be greatly reduced. Therefore, a method for obtaining cyanobacteria bloom information from fuzzy video images is designed to achieve automatic extraction of cyanobacteria information, as shown in Fig. 3.

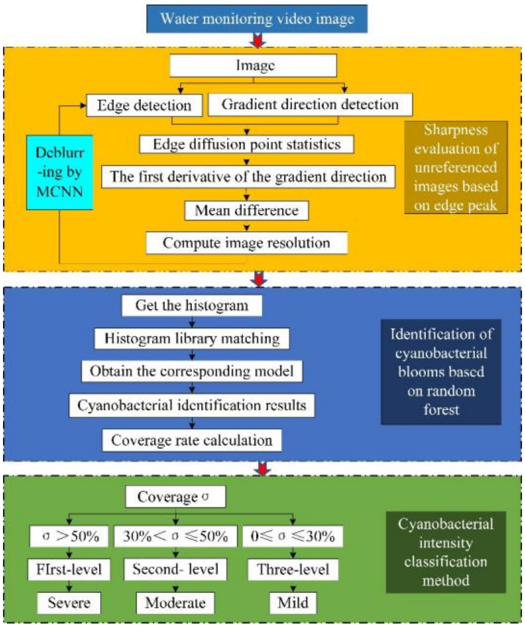


Fig. 3. Acquiring method of cyanobacteria bloom information from video blurred images.

The main solutions include: 1) The best shooting angle is specified, the water surface is continuously monitored, and images are captured regularly, and the image data is transmitted to the server through the 4G network; 2) The sharpness of the input image is judged by the non-reference image sharpness evaluation method of the edge kurtosis. For the blurred image, MCNN is used to remove the visual artifacts of the motion blurred image, and the image is restored from different scales; 3) Using the method of cyanobacteria bloom recognition based on random forest [12], the coverage of cyanobacteria bloom in image is calculated and the level of cyanobacteria bloom

3.1. MCNN network architecture

Image blur is the main factor of image degradation. In image restoration, some researchers upgrade the picture quality by combining image prior knowledge, such as, mathematically driven discriminant prior [13,14]. The dis-advantage is that the ladder may be too large to train, and complex fuzzy cores need to be estimated. The wrong core may cause visual artifacts in the image. Therefore, an image processing method using MCNN is proposed, which eliminates sense of sight and restores blurred picture in a peer-to-peer manner without appraising fuzzy cores [15]. This method sets the scale level in the descending order of resolution, that is, the finest scale is one level, and there are three levels. In the training process, the fuzzy picture is input and the clear picture is output. The resolution in the Gaussian pyramid picture is set to 256×256, 128×128, 64×64.The ratio of image sizes between scales is 1:2. To enlarge the receptive field, set the measurement of all convolution filters to 5×5. The specific network architecture is shown in Fig.4.

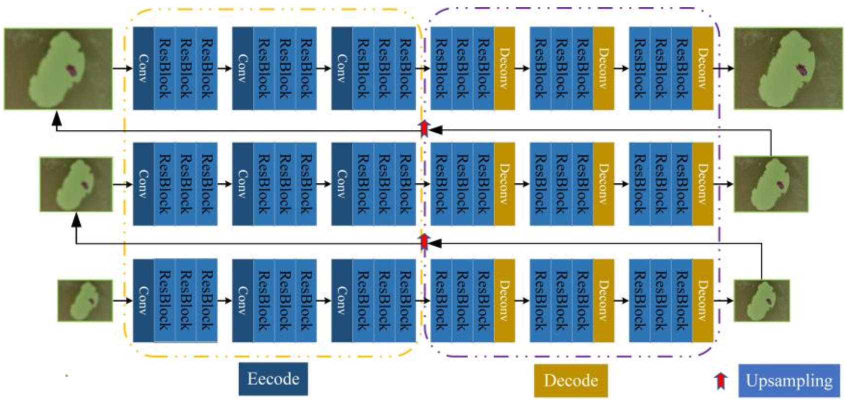


Fig.4. MCNN Network Architecture Diagram

MCNN uses a structure from coarse to fine, and gradually refines the output through a very small scale to simplify the training. In the coarsest network with M=3, the first volume of the integration layer will be 64×64 blurred images are converted into 64 characteristic images, which are then input into an encoder and decoder consisting of a convolutional layer, a deconvolution layer, and a ResBlock unit to output a potentially clear images in proportion. Then, the blurred image of size 128×128 and the output image of level M=3 are taken as the input of level M= 2. This process is up sampling. It connects the feature image with the blurry block with finer scale, eliminating the redundancy between blurring and sharp spots [16]. The network structure of each scale subnet is basically the same, and the relationship between each subnet is up sampling. The potential clear image of the original resolution is ultimately restored at the finest scale level M=1.

3.2 Network training

The network model is trained in Gopro data set and video clear fuzzy image pair, and the tested data set is the fuzzy image collected by shore based monitoring. In this paper, 400 pairs of clear fuzzy image pairs are made, including 320 pairs of fuzzy-clear image pairs and 2210 pairs of Gopro data are used as training data. The trained network is embedded in the fuzzy subsystem, and then tested. In training, all weights and deviations are initialized, and only batch data is used for each iteration, so as to find the minimum value faster. Adam uses adaptive learning rate and momentum to improve the convergence speed. The super parameter uses the default value, as shown in Table 2.

Table 2

Network hyperparameter setting

The exponential decay rate of the moment estimate β_1	The exponential decay rate of the moment estimate β_2	A constant used for numerical stability ϵ	Global learning rate η
0.9	0.999	10e-8	0.001

In order to prevent the network from overfitting, several data enhancement techniques were used in the experiment. In terms of geometric transformation, the image block is randomly flipped 90° in the horizontal direction. In terms of color, RGB channels are randomly arranged and multiplied by random numbers within [0.5, 1.5] on the basis of HSV color space saturation. The experiment uses a small batch of Adam optimization program with size 2 to train the network. The learning rate from 5×10^{-5} starts adaptive adjustment, after 3×10^{5} iterations, it was reduced to one tenth of the original. After 9×10^{5} iterations, all training is completed.

3.3 Multi scale loss

The experiment uses multi-scale content loss to optimize parameters and train the network model. In the coarse-to-fine structure, the output of each scale is the corresponding level of potentially sharp images, which are combined to form a Gaussian pyramid of potentially sharp images. MSE criterion is applicable to each layer of the pyramid, the formula of multiscale content loss function is defined as:

$$\mathcal{G}_M = \frac{1}{2M}\sum_{M=1}^{M}((\frac{1}{\lambda_M \omega_M h_M}) \| J_M - K_M \|^2) \qquad (1)$$

Where, J_M represents the estimated clear image output, and K_M is the sharp ground image of the corresponding scale, λ_M, ω_M, h_M represents the number, width and height of loss channels in the subnet.

4. System test

4.1. Water quality detection data accuracy test

The designed water quality monitoring system is applied to the waters near the Yuxi estuary of Chaohu Lake (117.842N, 31.590E). With five water quality monitoring collection points as the test object, the sensor is set to collect data once every 1min.Four parameters of pH value, temperature, dissolved oxygen and ammonia nitrogen of water quality is selected for error test. Before the test, the sensor needs to be calibrated to eliminate the deviation. During the actual test, the data of No. 5 water quality monitoring node was selected to compare with the U-50 series of HORIBA for 20h data collection. The collection interval was 60min. The data comparison results showed that the difference between the monitoring data of this system and the test value of HORIBA water quality analyzer was not big. The pH value error was within ±0.2, the ammonia nitrogen error was ±0.03mg/L, the temperature error was ±0.4℃, and the dissolved oxygen error was ±0.3mg/L, it can meet the application requirements for water quality monitoring of Chaohu connected rivers (Fig. 5).

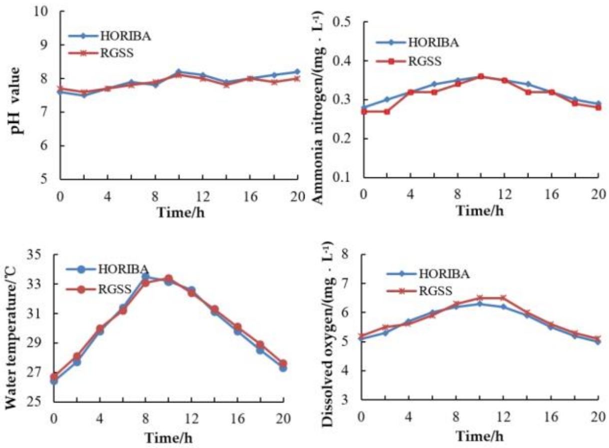
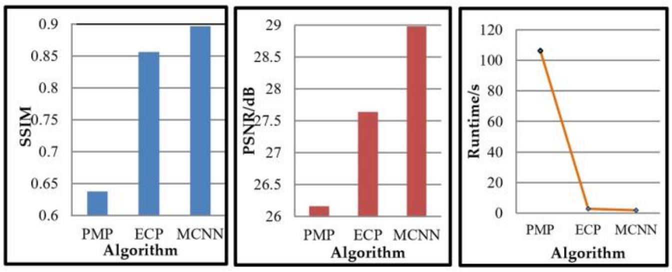


Fig. 5. Comparison test results of pH, ammonia nitrogen， water temperature and dissolved oxygen

4.3. MCNN image deblurring performance test

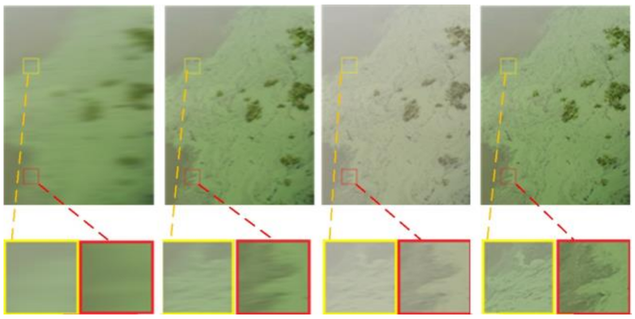
In order to verify the advantages of MCNN image deblurring algorithm in the system, it is compared with PMP [17] and ECP [14]. The source code and the training model of the deblurring method are publicly available on the author's website. In addition, in order to quantitatively and qualitatively evaluate the effect of deblurring, the structural similarity index (SSIM) and peak signal to noise ratio (PSNR) are selected as quantitative evaluation indicators. Fig. 6 shows the quantitative evaluation of water quality image deblurring effect by different methods. It can be seen from Fig.6 that the PSNR of MCNN is 1.34dB higher than

ECP and 2.82dB higher than PMP in the water surface image data set of the shooting system. At the same time, from the average image processing time of all 80 test images, due to the end-to-end characteristics, the time of ECP and MCNN is much faster than PMP, of which MCNN is the fastest. In Fig. 7, these modes can eliminate blurring, but may cause side information and visual artifacts, thus affecting the restoration effect of blurred pictures. PMP will produce artifacts when recovering images, affecting picture distortion. ECP lose chroma information in an end-to-end fashion. MCNN recovers the picture details without causing visual artifacts, preserves the details and side information, and also ensures the sharpness and naturalness of the image.



(a) (b) (c)

Fig. 6. Evaluation of deblurring effect of different Algorithms. (a) SSIM; (b) PSNR;(c) Runtime.

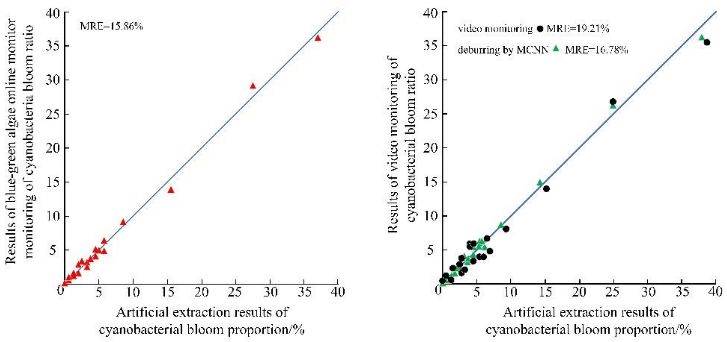


(a) (b) (c) (d)

Fig. 7. Comparison of Blur Removal Results of Blue Algae Images. (a)Blurred blue-green algae image; (b) PMP deblurring result; (c) ECP deblurring result;(d) MCNN deblurring result.

4.4 Test of cyanobacteria bloom intensity

The experiment compares the blue-green algae online monitor with manual extraction, and the shore-based video image with manual extraction data. As shown in Fig. 8a, the average relative error MRE of the blue-green algae online monitor and the artificial blue-green algae bloom extraction results in the system is 9.86%, and the accuracy is greater than 90%; It can be seen from Fig. 8b that the precision of the shore-based video image is improved by 2.43% after MCNN deblurring compared with the results of artificial cyanobacteria bloom extraction. The precision is greater than 80%; According to the Hefei Municipal Government Affairs Cloud Platform (Digital Chaohu Chaohu Blue Alga Bloom Monitoring, Early Warning and Simulation Analysis Platform) display. The results show that there was slight cyanobacteria bloom on June 20, which is consistent with the platform test results, indicating that the test platform can meet the actual needs of the current Chaohu Blue Alga Bloom Test.



(a) (b)

Fig. 8. Comparison of Test Results. (a) Functional verification of the algae density monitors for cyanobacteria bloom intensity; (b) Accuracy verification of MCNN de blurring video image monitoring function for cyanobacteria bloom intensity.

5. Conclusions

This paper aims at the monitoring demand of the "water land" mode of the Chaohu connected river channel, and uses wireless networking to build a distributed monitoring system, which realizes the all-weather monitoring function of water quality parameters (pH, temperature, dissolved oxygen, ammonia nitrogen and algal density), meteorological factors (temperature, humidity, wind direction, wind speed, air pressure and light), and the rapid acquisition of information such as the status of cyanobacteria bloom in the Chaohu connected river channel, And through the shore based video MCNN deblurring image cyanobacteria bloom information acquisition method, identify and calculate the coverage of cyanobacteria bloom, and determine the level of cyanobacteria bloom. The test results show that the realization efficiency of the core functions of the platform and the precision of the video monitoring function after MCNN deblurring are high, which can meet the actual needs of the monitoring, prevention and control of water quality and cyanobacteria bloom in the connecting river of Chaohu Lake. With the continuous development of high-performance computing, GIS spatiotemporal data analysis, hyperspectral UAV data acquisition and processing, digital twins and other technologies, it is expected to further strengthen its functions in monitoring efficiency, simulation accuracy, visualization effect and other aspects, and has broad application prospects in monitoring and early warning of cyanobacteria bloom in eutrophic lakes.

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