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Smart Water Quality Monitoring Technology for Fish Farms Using Cellphone Camera Sensor

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With the ever-changing nature of technology and the vigorous development of artificial intelligence, traditional fishery has gradually transformed into smart aquaculture. The current smart sensing instruments on the market can accurately measure water quality parameters for fish farms, but they are too expensive to be used popularly. On the basis of the mobile application developed by Taijiang Agriculture Biotechnology, a local company of Taiwan, and our empirical cumulative trend, we propose a smart technology for monitoring water quality in fish farms using a cellphone camera sensor. By the proposed method, we captured and recorded the RGB values of the water color using a cellphone camera sensor. At the same time, we measured the water quality parameters using a spectrophotometer and a Secchi disk at four fish farms. As a result of experimental design and analysis, we found an obvious correlation between water color and various water quality parameters. In the future, we expect to achieve the target that fishermen can use a cellphone to obtain real-time water quality information by utilizing the proposed low-cost and efficient aquaculture technology.

1. Introduction

The aquaculture market was valued at USD 30.1 billion in 2018 and is forecasted to reach USD 42.6 billion by 2023. This is attributed to the growing consumption of fish for its nutritional value. In addition, the increase in seafood trade and the rising trend of smart fishing are also inciting the demand for aquaculture products.(1) The Food and Agriculture Organization (FAO) of the United Nations also reported that total global seafood production is expected to increase 18% by 2030, reaching 2.01 million tons, with aquaculture providing the main output.(2–4) Taiwan is an island country and there are many coastal and offshore fisheries; therefore,

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aquaculture is an important economic industry in Taiwan. In recent years, the aquaculture output has reached more than NTD 30 billion. Furthermore, over 40% of the aquatic products have been supplied by aquaculture fishery. Nevertheless, the traditional aquaculture fishery is faced with several problems, such as an aging population, labor force shoetage, and difficulty in passing down experience. In addition, fishing villages also urgently require an accurate and efficient water quality control technology in order to reduce human error.

With the ever-changing nature of technology and the vigorous development of artificial intelligence, traditional fishery has gradually transformed into smart aquaculture. For fishery, water quality is a major factor affecting the production of aquatic products and fish health. A poor water quality may pose a health risk to people and ecosystems.(5) Therefore, for smart aquaculture, water quality monitoring is one of the most important technologies. If water quality parameters can be accurately predicted through relevant big data and intelligent algorithms, risk control can be achieved through technological means to greatly improve the production efficiency of aquaculture products.(6) In addition, if relatively accurate water quality parameters of the aquaculture environment can be obtained in real time, fishermen would be provided with an early warning of abnormal parameters, and the corresponding anomalies might even be dealt with automatically.(6) As a result, water quality monitoring attracts considerable attention and is very much in demand for realizing excellent production and environmental conditions for smart aquaculture. Over the last ten years, various kinds of sensors have been developed for detecting critical water parameters (such as dissolved oxygen, temperature, pH, and phosphate, nitrate, calcium, and magnesium concentrations).(7–14)

At present, the smart sensing instruments on the market can accurately measure water quality parameters, but they are too expensive for popular use and may be affected by algal blooms. Most fishermen in Taiwan cannot afford them. On the basis of the mobile application(15) developed by Fisherman Taijiang (a local company in Taiwan) and our empirical cumulative trend, we found that blue grayscale values of color images of the water color at fish farms have an obvious correlation with water quality parameters and could be a predictive leading indicator of environmental health for the early warning of abnormal parameters for fish farms. Through the system, fishermen can upload photos of the fish farm to the cloud and then use the analysis program to perform image interpretation and inspection and obtain data. Experienced fishermen can then convert the values gained through previous experience into data and accurately grasp the optimal breeding quality management mode and solution.

It is not difficult to set up an environmental numerical observation machine, but there is still much room for improvement to ensure that the data derived from monitoring can effectively predict the future. To achieve intelligent interpretation and expert prediction, cooperation among industry, government, academia, and research is necessary to integrate and build smart farming systems, and improve the accuracy of machine interpretation and big data analysis, in order to perfect the painstakingly developed system. As a result, in this present paper, we propose an experimental method for characterizing the water quality of fish farms using the image technique for smart aquaculture. The aim of this work is to demonstrate this method.

2. Materials and Methods

We captured and recorded the RGB grayscale values of the water color at six fish farms (A, B, C, D, E, and F) using a mobile application[15] of a cellphone camera sensor. These fish farms are located in Annan District, a coastal district west of Tainan, Taiwan,[16] as shown in Fig. 1. Milkfish and white shrimp are the main products of these fish farms.

Two sets of experiments were conducted. In experiment I, the RGB values of the water color at two fish farms (A and B) were recorded for one month from 14 May 2021, and the behaviors of egrets were observed. In experiment II, the RGB values of the water color at another fish farm (C) were recorded for one month from 30 June 2021. At the same time, we measured the water quality parameters of water samples from the other four fish farms (C, D, E, and F) using a spectrophotometer [LaMotte WaterLink® Spin Touch® FX[17]], a Secchi disk, and a dissolved oxygen meter [LaMotte Dissolved Oxygen TRACER Kit, Code 1761[18]]. In experiment II, an offline digital image processing technique was used to analyze the captured image of the water color at fish farms, and the image segmentation method was applied to classify the objects in the image and extract the part to be tested.[19,20] Then, we could determine the RGB grayscale values in order to avoid errors due to human operation and the environment.[21] Here, MATLAB image processing functions were used. The proposed image processing procedure comprises three steps: (1) selecting the most suitable block, (2) cropping the photograph to proper proportions, and (3) executing the program to obtain the RGB average grayscale values. The purpose of step 1 is to select a region that accurately represents the true color of the water, by filtering out external factors that may interfere with the reading. In other words, if this step is not performed, the color reading may include the colors of foam, water plants, sunlight reflection regions, and other such factors that are unrelated to the actual water quality. Step 2 is used to make the input figure compatible with the MATLAB program. Step 3 shows the running result of the MATLAB program.

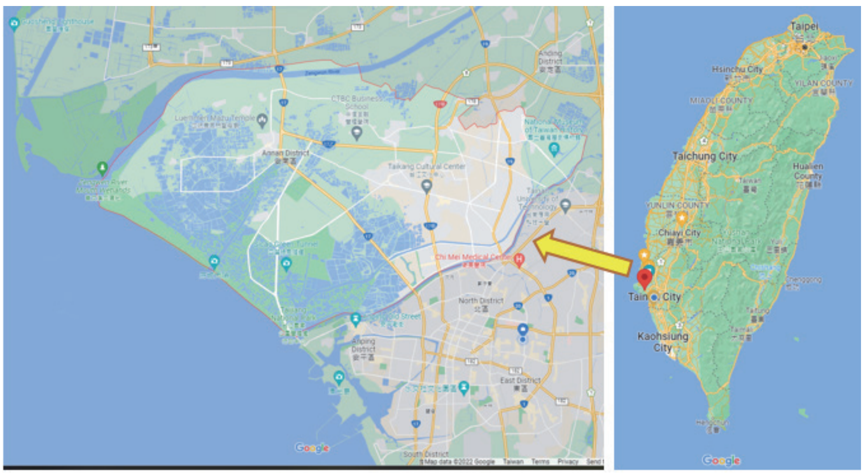


Fig. 1. (Color online) Geographical location of experimental fish farms.

3. Results

Figures 2 and 3 show the experimentally measured RGB values of the water color and behaviors of egrets for fish farms A and B, respectively, in experiment I. Figure 4 shows the proposed image processing results.

Figures 5–8 show the experimentally measured RGB values of the water color along with the measured water quality parameters for fish farms C, D, E, and F, respectively, in experiment II. Figures 9(a) and 9(b) show the photographs of the water sampling process with a Secchi disk and the water samples for the experiments, respectively. Figures 10(a) and 10(b) show the spectrophotometer and the Secchi disk, respectively.

In Figs. 5–8, the water quality parameters are as follows: transparency (TRN), pH, and the phosphate and magnesium concentrations (PHOS and Mg, respectively).

For the convenience of observation, each water quality parameter has been normalized as follows:

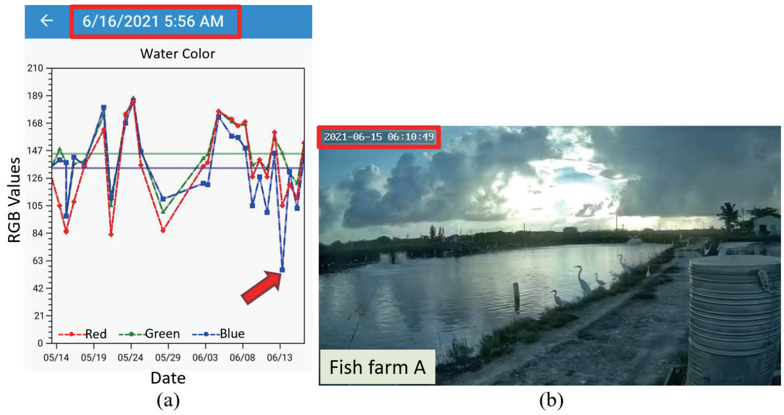


Fig. 2. (Color online) (a) Measured RGB values of water color and (b) photograph of fish farm A.

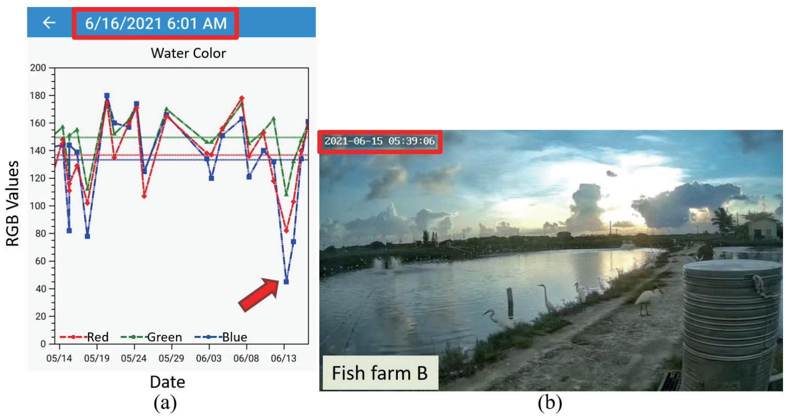


Fig. 3. (Color online) (a) Measured RGB values of water color and (b) photograph of fish farm B.

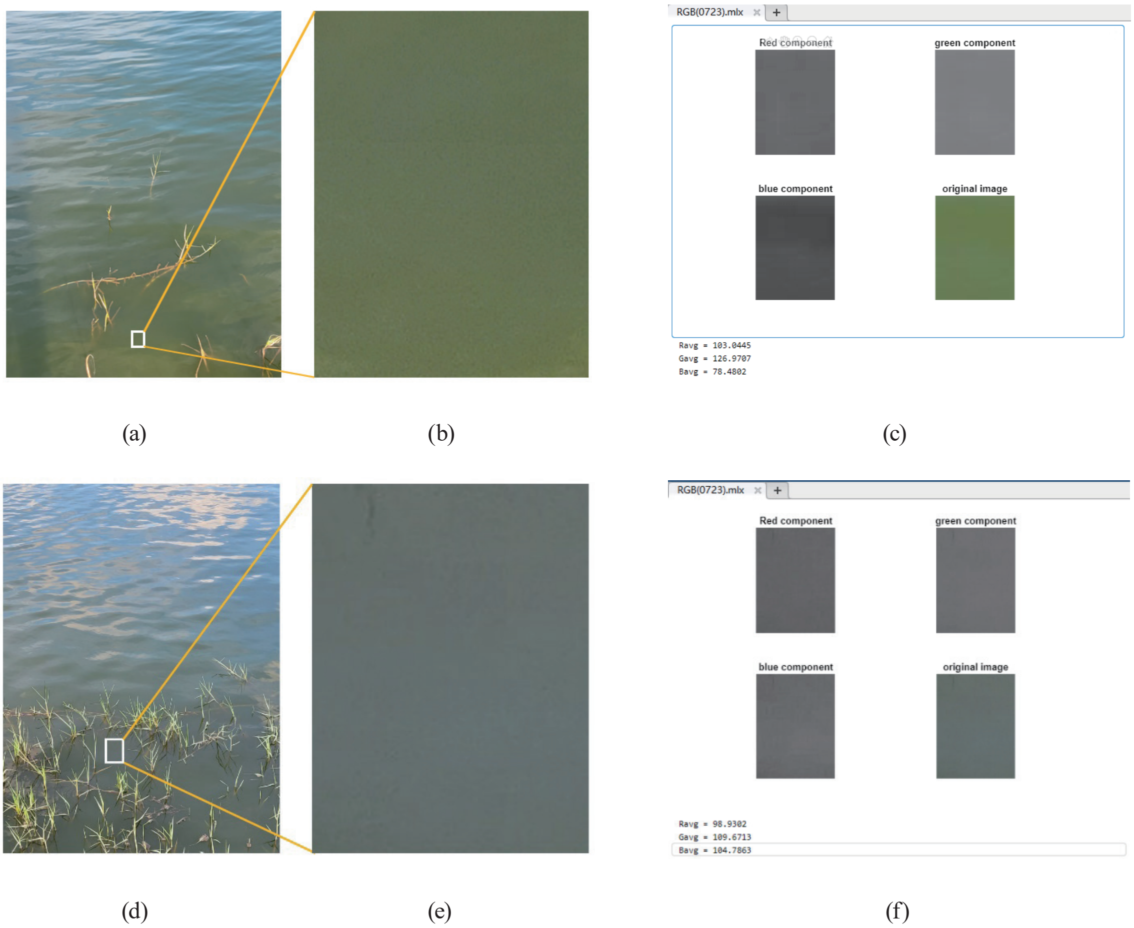


Fig. 4. (Color online) Image processing results 1 (a), (b), and (c) and 2 (d), (e), and (f). (a) (d) Selecting the most suitable block. (b), (e): Cropping the photograph with proper proportions. (c), (f) Average grayscale values obtained by MATLAB program.

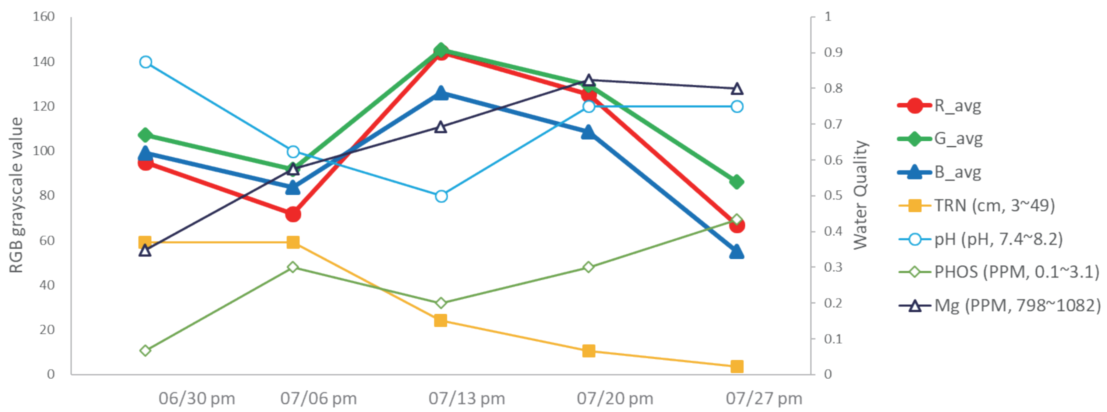


Fig. 5. (Color online) Measured RGB values of water color and measured water quality parameters of fish farm C.

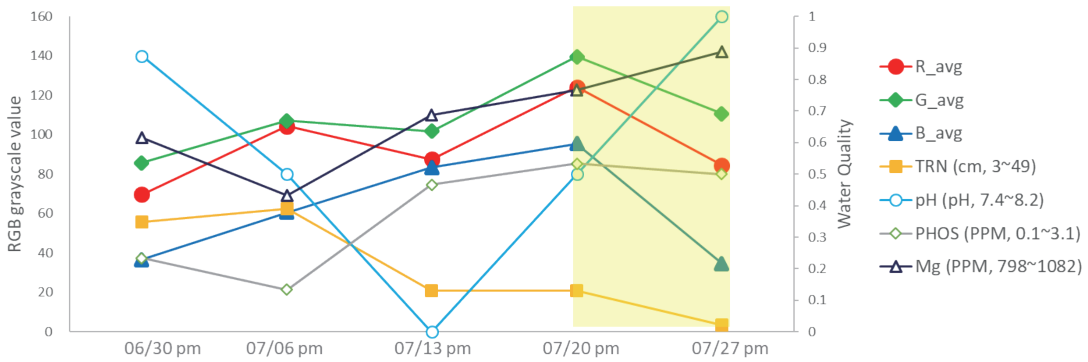


Fig. 6. (Color online) Measured RGB values of water color and measured water quality parameters of fish farm D.

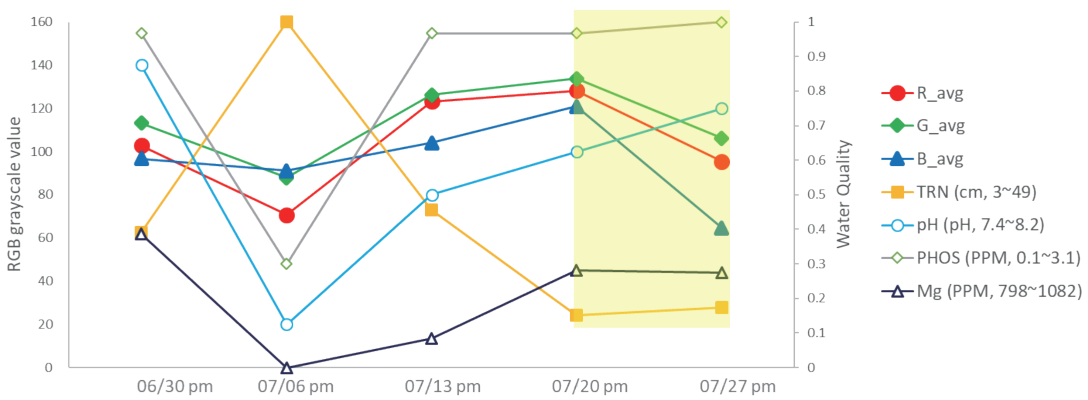


Fig. 7. (Color online) Measured RGB values of water color and measured water quality parameters of fish farm E.

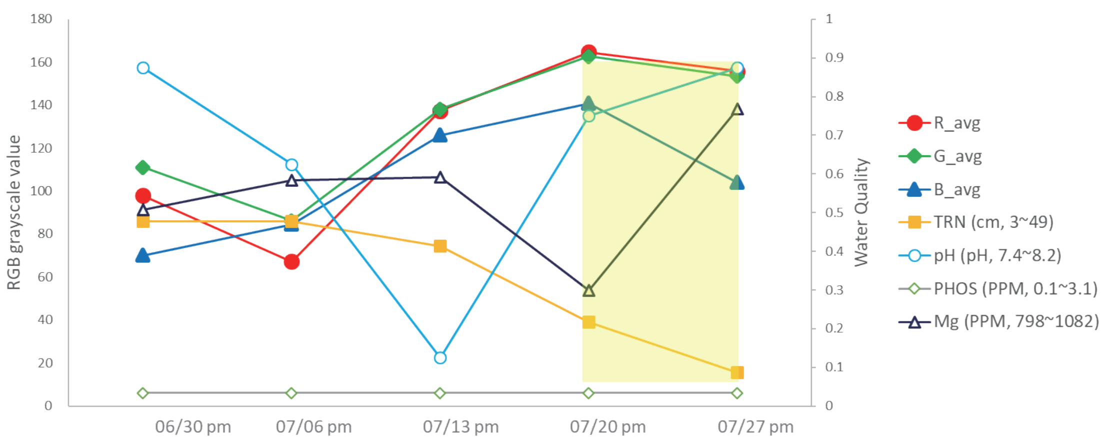


Fig. 8. (Color online) Measured RGB values of water color and measured water quality parameters of fish farm F.

(a) (b)

Fig. 9. (Color online) (a) Water sampling process with Secchi disk. (b) Water samples.

(a) (b)

Fig. 10. (Color online) (a) LaMotte WaterLink® Spin Touch® FX. (b) Secchi disk.

$$X^N(i) = \frac{X(i) - X_{\min}}{X_{\max} - X_{\min}}, \tag{1}$$

where $X(i)$ is the original value of each water quality parameter, $X_{\max}$ is the maximum value of the water quality parameter, $X_{\min}$ is the minimum value of the water quality parameter, and $X^N(i)$ is the water quality parameter after normalization, which ranges from 0 to 1. In these figures, the values in brackets correspond to the real minimum and maximum values of the water quality parameters. Table 1 shows the values of all water quality parameters without normalization.

4. Discussion

For experiment I, from Figs. 2(a) and 3(a), it can be seen that there was an obvious reduction in the measured blue grayscale value of the water color on 13 June 2021. On the basis of accumulated years of experience as a fisherman, this phenomenon means that water quality will deteriorate and that some milkfish and white shrimp will die. Then, we will observe a congregation of egrets next to the fish farm to feed. As shown in Figs. 2(b) and 3(b), many egrets

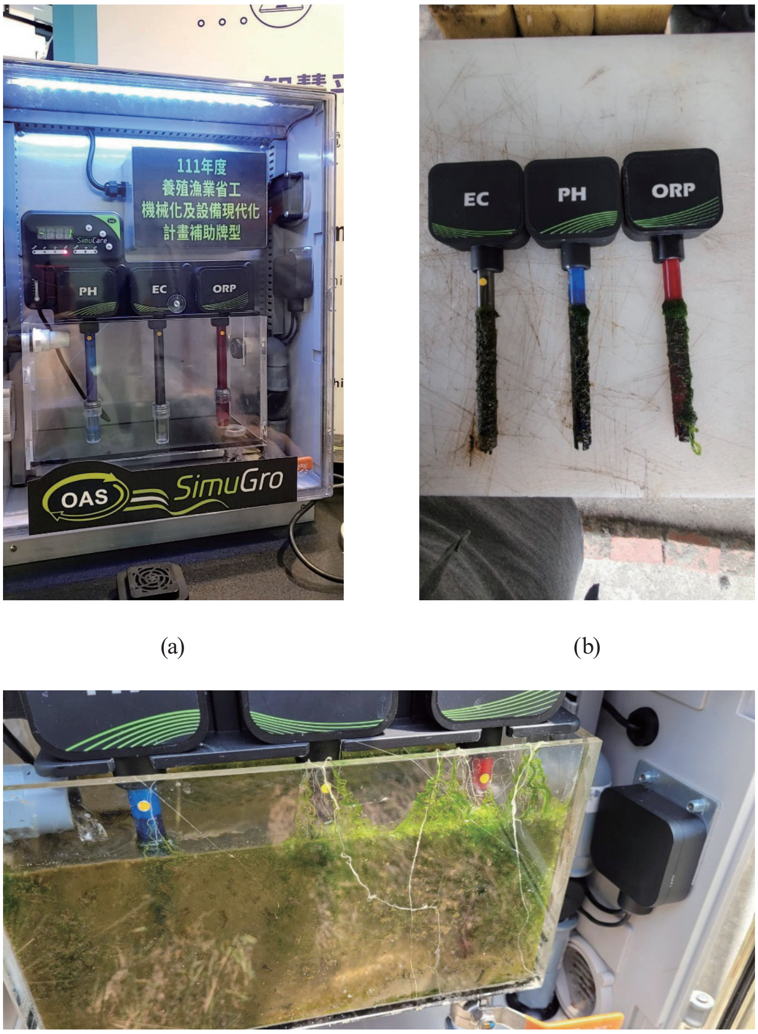
Table 1
Water quality parameters without normalization.

pool	No.	time (pm)	R_avg	G_avg	B_avg	TRN (cm)	pH	PHOS (PPM)	Mg (PPM)
	1	0630	94.94	107.23	99.08	20.00	8.10	0.30	897.00
	2	0706	71.84	91.76	83.65	20.00	7.90	1.00	961.00
C	3	0713	144.18	145.42	126.10	10.00	7.80	0.70	995.00
	4	0720	125.42	129.67	108.65	6.00	8.00	1.00	1032.00
	5	0727	67.09	86.18	54.98	4.00	8.00	1.40	1025.00
	1	0630	69.75	85.81	36.69	19.00	8.10	0.80	973.00
	2	0706	104.38	107.19	60.54	21.00	7.80	0.50	921.00
D	3	0713	87.61	101.81	83.28	9.00	7.40	1.50	993.00
	4	0720	124.20	139.64	95.52	9.00	7.80	1.70	1016.00
	5	0727	84.57	110.68	34.68	4.00	8.20	1.60	1050.00
	1	0630	102.76	113.24	96.67	21.00	8.10	3.00	908.00
	2	0706	70.73	87.87	91.13	49.00	7.50	1.00	798.00
E	3	0713	123.21	126.21	103.95	24.00	7.80	3.00	822.00
	4	0720	128.23	133.83	120.84	10.00	7.90	3.00	878.00
	5	0727	95.47	106.26	64.59	11.00	8.00	3.10	876.00
	1	0630	97.95	111.03	70.16	25.00	8.10	0.20	942.00
	2	0706	67.17	86.18	84.56	25.00	7.90	0.20	964.00
F	3	0713	137.47	138.13	126.01	22.00	7.50	0.20	966.00
	4	0720	164.73	162.64	140.87	13.00	8.00	0.20	883.00
	5	0727	155.75	153.57	104.11	7.00	8.10	0.20	1016.00

suddenly congregated next to fish farms A and B to feed on the morning of 15 June 2021. These results provide evidence that supports the idea that blue grayscale values of color images of the water color of fish farms have an obvious correlation with water quality parameters.

Figures 5–8 show the measured RGB values of the water color and water quality parameters of fish farms C, D, E, and F, respectively, in experiment II. As shown in the yellow squares of the figures, there is an obvious reduction in the measured blue grayscale value of the water color in these time periods (from the afternoon of 20 July 2021). From the comparison of results for the different water quality parameters in these time periods, we found regular variation trends that TRN decreases and that PHOS, pH, and Mg concentration increase. This means that water quality will deteriorate at fish farms when measured blue grayscale values of the water color exhibit an obvious reduction. Upon the deterioration of water quality, there is a proliferation of green algae, causing the measured blue grayscale values of the water color and the TRN level to decrease. We believe this to be an interesting and important preliminary finding for smart aquaculture. The results of experiment II are in good agreement with those of experiment I.

On the basis of our empirically observed cumulative trend, when measured blue grayscale values of the water color suddenly decrease, water quality will be expected to deteriorate after 48. The results of experiments I and II have proven this viewpoint. Consequently, the sudden reduction in the measured blue grayscale value of the water color is a predictive leading indicator of environmental health that can be used for the early warning of abnormal parameters of the water color at fish farms. This predictive leading indicator of environmental health obtained by applying image recognition technology to water color can surpass observation by the human eyes. The deaths of milkfish and white shrimp could be avoided and the environmental health of fish farms could be maintained if fishermen can take precautions in advance, for example, change the water, reduce feeding, turn on more oxygenation equipment, at fish farms. To the best of our knowledge, most smart sensing instruments of water quality focus on real-time data collection and interpretation.[22,23] Therefore, in this paper, we propose the powerful and efficient smart monitoring technology for water quality using image recognition technology and empirical cumulative trends. This is the main contribution of this paper. The proposed smart technology for monitoring water quality can overcome the limitations of traditional water quality sensors, which are often affected by algal blooms, as depicted in Fig. 11. However, there is still much room for improvement in the implementation of this image recognition system, since the experimental data are yet insufficient and the error in the image recognition method of water color is still very large. The method has not yet reached the standard required for practical use. In the future, to obtain more accurate results, the rules formulated by using a large amount



(a) (b)

(c)

Fig. 11. (Color online) (a) Traditional water quality sensors in a sample without algal bloom. (b) and (c) Sensors affected by algal blooms.

of data for classification and details of the correlation between water color and various water quality parameters will be established through machine learning. By applying a data analysis method, we could effectively and instantly provide a quantitative index for water quality and provide a predictive index for the early warning of abnormal parameters of the water color at fish farms. We expect to achieve the target that fishermen can use a cellphone to obtain real-time water quality information. Then, the fishery production and product quality can be improved and a low-cost and efficient new form of aquaculture management can be developed in the future.

5. Conclusions

In this paper, a smart technology for monitoring water quality in fish farms using a cellphone camera sensor was proposed. We were able to determine the state of the water quality through the image of the water color by using the proposed method. From the experimental results, we found that the blue grayscale values of color images of the water color at fish farms have an obvious correlation with water quality parameters. It was observed that when the blue grayscale value of the water color drops sharply, the TRN decreases, and the pH and Mg increase, indicating that the water quality is deteriorating, which is consistent with the experience of fishermen. Consequently, the sudden reduction in the measured blue grayscale value of the water color is a predictive leading indicator of environmental health that can provide an early warning of abnormal parameters of the water color at fish farms.

In the future, we hope to improve the image calibration technology for the water color, collect more data, find useful patterns from a large amount of big data through machine learning. Then, an intelligent water quality monitoring technology with high accuracy can be developed to monitor the water quality in real time. We can then adopt relevant measures to improve the output and product quality of aquaculture fishery, and develop low-cost and high-efficiency aquaculture management methods.

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