A Biological Sensor System Using Computer Vision for Water Quality Monitoring

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ABSTRACT Water pollution has seriously threatened our life, so an effective water quality monitoring mechanism is the most important part of water quality management. Most studies use biological monitoring methods to monitor water pollutants, such as pesticides, heavy metals, and organic pollutants. However, there are still many difficulties at present. Few methods consider the influence of illumination and complex background in the monitoring environment, and the characteristics parameters extracted in the systems are single. In addition, the results of using shallow neural networks for water quality classification are often not ideal. In order to solve the above problems, we design a water quality monitoring system combined with the computer image processing technology and use computer vision to analyze the fish behavior in real-time for monitoring the existence or not of water pollution. For the illumination problem, we use the no-reference quality assessment algorithm based on natural scene statistics for contrast distortion images to evaluate the video and configure the lighting conditions of the monitoring environment. White balance preprocessing is also performed to provide a great basis for moving target detection. Besides, we use background modeling to eliminate the influence of complex background on the moving target detection and the foreground is extracted using the saliency detection algorithm. In order to comprehensively analyze the influence of water quality on the fish behavior from the extracted foreground targets, multi-dimensional feature parameters are used to quantify the indicators, including movement velocity, rotation angle, spatial standard deviation, and body color which characterize the behavior changes of the fish. Finally, the classification model based on the long short-term memory neural network is used to classify the feature parameters data of the fish behavior in different water quality environments. In this paper, red zebra fish is used as the indicator organism and copper sulfate solution is used as the toxic pollutant to simulate the water pollution. Experiment results show that the classification accuracy rate of water quality using the proposed system can reach 100% at level 2 classification (93.33% at level 3 and 91% at level 4). Our system can achieve more accurate multi-level classification than the shallow neural network, such as RNN, and it is faster for real-time monitoring with a high reference for the water environment emergencies.

INDEX TERMS Classification model, machine vision, moving target detection, neural network, water quality monitoring.

I. INTRODUCTION

Water pollution problems seriously affect our production and life, so the effective monitoring of water quality is an important part of water management and water pollution prevention. At present, widely used water quality monitoring techniques can be divided into physical and chemical analysis methods as well as biological monitoring methods. Wang *et al.* [1] analyzed the water quality of Xi'an Chan-Ba Ecological District by monitoring the physical and chemical indexes including PH, TN and so on. Darko *et al.* [2] constructed the SCADA system for modern city water supply with continuous monitoring of the physical, chemical and biological parameters. But the physico-chemical analysis methods with higher cost require quantitative processing making it difficult to achieve online monitoring. Correspondingly, bio-monitoring which use the changes of aquatic organisms to monitor and evaluate the environmental water quality can make up for these problems. The latter with lower

cost is easy to achieve digital real-time monitoring more continuously and comprehensively. As early as the late 1940s, foreign scholars used wicker fish to test toxic substances in water quality in [5]. Williamsa *et al.* [6] used rainbow carp, marine shellfish and other animals to detect toxic substances in industrial polluted waste water. Xiao *et al.* [7] designed the data acquisition platform to present the fish tracking by occlision method.

Since fish are sensitive to the water environment, they are often used to evaluate the comprehensive toxic substances of single or multiple pollutants as important indicator organisms in water quality testing. There have been already many studies on fish behavior, however, still existing some difficulties. Koprowski *et al.* [9] estimated the fish feature by analyzing sonar images and GPS positioning with expensive cost. The Biological Early Warning System (BEWs) developed by the Center of Eco-Environmental Research of the Chinese Academy of Sciences quantifies the behavioral feature of the green carp by detecting changes of the electric field, but the inspection period is too long to meet the real-time requirements in [10].

In order to realize real-time monitoring, some studies currently use machine vision technology to record the biological behavior in different water environments via cameras. German BBE uses video analysis technology to observe the effect of continuous water flow on the activity of fish. It can comprehensively determine the toxicity of water samples by monitoring and recording the action changes of fish online. However, they does not consider the differences of light conditions and complex background which may affect the system performance. Shenzhen Water Group developed a biological water toxicity monitor (RTB) to monitor the zebra fish trajectory mutation and conduct early warning in [11] which uses a single feature, ignoring changes of other behavioral characteristics. Papadakis *et al.* [12] used computer vision systems to analyze fish behavior, but only on the characteristics of stocking density. Zheng *et al.* [13] used the SVM classifier to achieve real-time measurement of the respiratory rhythm of Japanese rhinitis. Yet the environment adaptability and detection ability can be further improved.

In view of the above problems, we design a real time water quality monitoring and early warning system based on the existence or not of pollution in the water. In order to meet the real-time requirements, machine vision and water quality monitoring are combined to achieve online analysis of fish behavior to monitor water quality changes. For the purpose of adaptively adjusting the light, the GWH-GLBH algorithm is used to evaluate the video images for configuring the lighting conditions of the monitoring environment. And then perform preprocessing techniques such as white balance to provide an excellent basis for moving target detection. Furthermore, we carry out background modeling to eliminate the influence of complex background on the extraction of moving target parameters. The saliency detection algorithm (Seg) based on the saliency metric and the conditional random field model is utilized to detect the moving target of the fish group.

Besides, in order to comprehensively analyze the influence of water quality on fish behavior, multi-dimensional characteristic parameters including activity parameters, position parameters and body color component are extracted from the foreground targets. Finally, a classification model based on LSTM neural network is realized for training, testing and classification, which can better adapt to the environment and improve the detection capability of our system. And an early warning is implemented for multiple water quality classification. Our system achieves more accurate classification results than the shallow neural network such as RNN, and it can be realized in real-time with shorter time consumption.

This paper is organized as follows. We present the experiment platform and system structure in section II, and introduce the video processing methods in section III, including the illumination adaptive adjustment and the background modeling method. The feature parameters are described in section IV. Experiment is designed in V, and we give the feature analysis and detection results. We introduce the LSTM neural network and realize water quality classification in section VI. Finally, a summary is provided in VII.
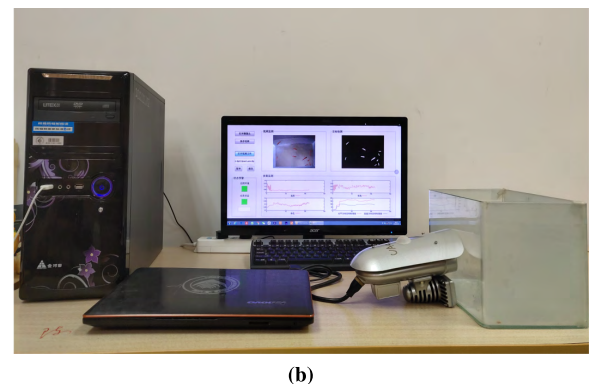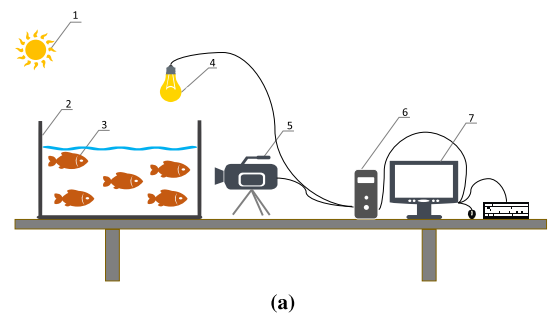

FIGURE 1. Experiment platform. (a) The design of experiment platform:1. Sunshine. 2. Fish tank. 3. Sample fish. 4. LED Source. 5. Gopro. 6. Computer processor. 7. Monitor. (b) The actual experiment platform.

II. EXPERIMENT PLATFORM AND SYSTEM STRUCTURE
A. EXPERIMENT PLATFORM AND EQUIPMENTS
The experiment platform is illustrated in Fig.1. It is primarily composed of computer, fish tank, camera, and light source. The processor used is Intel Pentium CPU G3260 @3.3GHz, 8GB RAM as well as display resolution of 1920×1080.

FIGURE 2. System structure diagram.

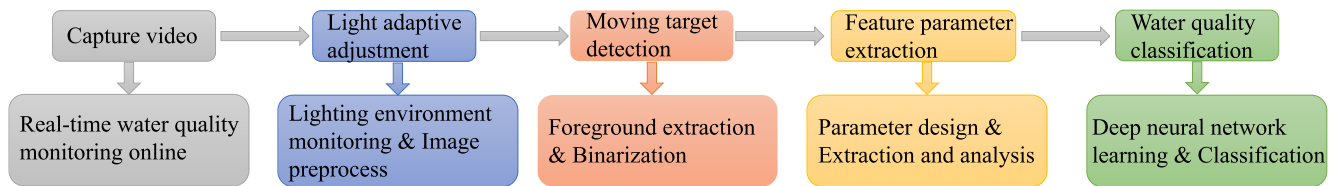The water tank is a glass tank with size of 40cm×20cm×30cm, and the back and bottom surfaces are made of frosted glass to reduce the impact of reflection. Capture the video sequence with a professional HD motion camera (GoPro HERO 5 Black) and mount the camera on the front of the aquarium. Set the camera to cover the entire aquarium. LED light is used as the experiment light source. The size of video image collected is 640 pixels×480 pixels, and the frame frequency is 30 frames per second.

B. SYSTEM STRUCTURE
In the water quality monitoring system based on fish stress behavior, the video sequence of fish behavior are computed, processed and analyzed in real-time via computer vision to extract the motion parameters of the fish for the classification and early warning of water quality status.

The system structure framework is illustrated in Fig.2. The video sequence acquired is preprocessed firstly. In order to better realize the adaptive adjustment of illumination, the GWH-GLBH algorithm is used to evaluate the video, and it is determined whether the illumination condition of the current video frame is normal. Afterwards, image processing techniques such as white balance is performed to provide an excellent basis for subsequent target detection modules. Then background modeling is used to eliminate the influence of complex background. After comparing various algorithms, the saliency detection algorithm (Seg) is selected to segment the moving target. We quantify the multidimensional feature parameters of the fish behavior from the foreground target and use statistical analysis to ensure the rationality in the next module. Finally, the feature parameters extracted are sent to the LSTM classifier to achieve water quality classification and early warning.

III. VIDEO SEQUENCE PROCESSING METHODS
A. LIGHT ADAPTIVE ADJUSTMENT MODULE
The quality of the video image is critical to the monitoring effect of systems. The lighting environment may reduce the quality of the video sequence and affect the subsequent moving target detection. In order to configure suitable lighting conditions in monitoring environment, we select Image Quality Assessment (IQA) method to detect the quality of the captured video, and then determine whether the lighting condition of the current video frame is normal. As a supplement, we also perform image processing techniques such as white balance to decrease the impact of different application environments on system detection.

Firstly, clear optical images under different natural light conditions are collected to simulate the influence of light on the image quality in the actual application environment, and the subjective quality evaluation is performed. Several objective quality evaluation algorithms are also used to calculate the quality score of the subjective quality image library. And finally, we evaluate the performance of each objective quality evaluation algorithm by calculating the PLCC, SROCC and RMSE values of the average subjective score and the objective score. In this paper, we finally select the GWH-GLBH objective evaluation algorithm to detect the quality of video frames for configuring the illumination. The algorithm used in this paper can better reflect the changes in the lighting environment and meet the real-time monitoring requirements of the system.

In addition, underwater image quality is also affected by the color shift. The color constancy of the human visual system is a necessary condition for machine vision applications such as image segmentation. To extract comprehensive information from the intrinsic color of an image, it is necessary that the image does not appear color shift. Therefore, in order to better achieve moving target detection and foreground segmentation, we perform white balance and other image processing operations to correct the color shift in the preprocessing module.

B. MOVING TARGET DETECTION MODULE
After image pre-processing in the previous section, the results of moving target detection also affect the foreground extraction. Choosing the most suitable detection algorithm is the basis for subsequent quantitative extraction of the fish behavior characteristics. In this paper, via contrast and analysis, we choose the saliency target detection algorithm (Seg) based on the saliency metric and the Conditional Random Field (CRF) model proposed by Rahtu *et al.* [14]. The algorithm is primarily divided into the following two steps.

1) SIGNIFICANT MEASUREMENT
The purpose of significant measurement is to obtain a saliency image using the statistical framework and comparing the brightness, color as well as motion information in the local features. Use a sliding window on the image to compare the distribution of certain features in the internal window with the distribution of the window edges in each window. The image F is obtained by the specific mapping function $F(x)$ for each pixel x in the original image. The feature space is

divided into mutually disjoint parts, and $Q_{F(x)}$ represents the part containing $F(x)$.

Divide the rectangular window W into two disjoint parts: the inner window K and the boundary B of the rectangle. Assume that the point in K is significant, and the point in B is part of the background. Z is a random variable describing the distribution of pixels in W, the value of which is in the range of W. Under the above assumption, the significant measurement of the point $x \in K$ is defined as the Bayesian conditional probability as shown in the following equation.

$$S_0(x) = \frac{P(F(x)|H_0)P(H_0)}{P(F(x)|H_0)P(H_0) + P(F(x)|H_1)P(H_1)}. \quad (1)$$

Where H_0, H_1 and $F(x)$ represent events $Z \in K$, $Z \in B$ and $F(Z) \in Q_{F(x)}$ respectively. The magnitude of the significant value of pixel x is between 0 and 1. If the feature of the pixel x is similar to the feature of the point in the inner window, the pixel x belongs to the significant target portion. In other words, $S_0(x)$ is close to 1.

2) SIGNIFICANT TARGET SEGMENTATION

The saliency image obtained previously is segmented by using the CRF model based on energy minimization with the goal of restoring significant targets. And the CRF segmentation model for video combines the significant value with the target motion information. Besides, the energy function is indicated in the following equation.

$$E_V(\sigma^t, \sigma^{t-1}, \sigma^{t-2}, c^t, c^{t-1}, s)$$
$$= E_I(\sigma^t, c^t, s) + \sum_{n=1}^{N} U^T(\sigma^t, \sigma^{t-1}, \sigma^{t-2}, c^t, c^{t-1}). \quad (2)$$

Where σ^t is the segmentation block of the current frame. σ^{t-1} and σ^{t-2} are the segmentation blocks of the first two frames respectively. c^t is the current frame. c^{t-1} is the previous frame image and U^T is the term used to improve the time consistency. The formula is as follows.

$$U^T(\sigma_n^t, \sigma_n^{t-1}, \sigma_n^{t-2}, c_n^t, c_n^{t-1})$$
$$= \mu \delta_{\sigma_n^t, \sigma_n^{t-1}} e^{-\|c_n^t - c_n^{t-1}\|_\Gamma^2} - \nu \log p_T(\sigma_n^t|\sigma_n^{t-1}, \sigma_n^{t-2}). \quad (3)$$

Where μ and ν are scalar parameters. $\|\cdot\|_\Gamma$ is the Mahalanobis distance of the diagonal matrix. p_T is the prior probability density function of σ_n^t based on σ_n^{t-1} and σ_n^{t-2}. Since $p_T(\sigma_n^t = 0|\sigma_n^{t-1}, \sigma_n^{t-2}) = 1 - p_T(\sigma_n^t = 1|\sigma_n^{t-1}, \sigma_n^{t-2})$, the value of p_T is determined by the four events $(\sigma_n^{t-1}, \sigma_n^{t-2}) = \{(0, 0), (0, 1), (1, 0), (1, 1)\}$. The first item in the equation is the extra data dependency cost of the pixel label changed from the $(t - 1)$ frame to the t frame, and the extra cost of the pixel with larger inter-frame color variation is smaller. For a given video sequence, the segmentation block σ^t of the frame of $t > 2$ is calculated by the graphic cutting minimization energy function.

IV. QUANTIFICATION OF CHARACTERISTIC PARAMETERS

After extracting the foreground targets, it is necessary to further analyze the relationship between the fish behavior and

different water environments. Therefore, we extract multi-dimensional characteristic parameters from the abstract fish behavior for the purpose of water quality classification.

A. ACTIVITY PARAMETERS

The activity of the fish is the most intuitive indicator of the behavior characteristics. Under normal circumstances, the fish is in a state of smooth swimming. When the water environment is abnormal, the fish will produce stressful behavior, such as a sudden change in swimming velocity, sharp swing and so on. Therefore, we select the movement velocity and rotation angle to characterize the activity level of the fish group. At the same time, we will study the relationship between the parameters and the water quality environment.

In this paper, we use the optical flow method to extract the motion change vector of the foreground target from the two-dimensional video sequence. In particular, two adjacent frames in the video are arbitrarily selected for Lucas-Kanade optical flow calculation to obtain the optical flow field between the moving targets in these two frames. Results are presented in Fig.3.
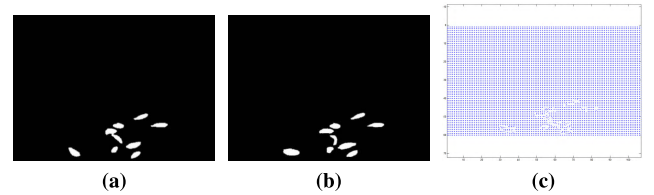

FIGURE 3. The simulation results of Optical flow method. (a) The previous frame. (b) The next frame. (c) The light flow vector.

The extracted characteristic vectors of fish behavior include the amplitude and direction information, which characterize the movement velocity and rotation angle of the fish group. Abnormal fish movements are mainly characterized by sudden changes in the velocity and rotation direction.

1) MOVEMENT VELOCITY

We obtain the motion change vector of the foreground targets via the optical flow calculation method as $\vec{u} = \begin{bmatrix} u(x, y) \\ v(x, y) \end{bmatrix}$. Where $u(x, y)$ and $v(x, y)$ are the velocity components of the pixel (x, y) in the horizontal and vertical directions respectively. The velocity of the current moment in the moving target region can be calculated by the motion vector, and the current velocity of the point (x, y) is as shown in (4).

$$V(x, y) = \sqrt{u^2(x, y) + v^2(x, y)}. \quad (4)$$

2) ROTATION ANGLE

The rotation angle of the current point (x, y) can be obtained by the motion vector $\vec{u} = \begin{bmatrix} u(x, y) \\ v(x, y) \end{bmatrix}$ of the moving target.

$$angle(x, y) = \arctan \frac{u(x, y)}{v(x, y)}. \quad (5)$$

B. POSITION PARAMETERS

Under normal conditions, the fish is randomly distributed in all directions in the water tank, and the position is evenly without drastic changes. When the water environment becomes abnormal, fish will appear stressful behaviors resulting in the change of position coordinates. Therefore, we choose the position parameters of the fish group to analyze their behavior. The foreground targets are divided into independent connected areas for representing individual fish. Calculate the centroid coordinates (X_c, Y_c) of each foreground area.

The group center coordinates are obtained by weighting average of the area size of the centroid for all foreground target areas. The group center coordinates on the coordinate axes of X and Y are represented by CX and CY respectively, which reflect the center position of the group distribution.

$$CX = \frac{\sum_{k=1}^{N} A_k X_k}{\sum_{k=1}^{N} A_k}, \quad CY = \frac{\sum_{k=1}^{N} A_k Y_k}{\sum_{k=1}^{N} A_k}. \quad (6)$$

Where (X_k, Y_k) is the centroid coordinate of the kth foreground target area, A_k is the projection area of the kth region and N is the total number of target areas.

In addition, the spatial standard deviation of the fish group characterizes the density of the group along the X and Y axes and the standard deviation of the projection surface are defined as SDX and SDY respectively.

$$SDX = \sqrt{\frac{\sum_{k=1}^{N} A_k (X_k - CX)^2}{\sum_{k=1}^{N} A_k}},$$

$$SDY = \sqrt{\frac{\sum_{k=1}^{N} A_k (Y_k - CY)^2}{\sum_{k=1}^{N} A_k}}. \quad (7)$$

C. BODY COLOR COMPONENT

We select red zebra fish as the test organism considering that the body color is bright red in the case of normal physiological functions. When the water environment is contaminated by heavy metals or other toxic substances, the body color will gradually change with the decrease of physiological functions. Therefore, we quantitatively analyze the relationship between the body color of zebra fish and the water quality environment. In this paper, we use the saturation S component of the Hue-Saturation-Intensity (HSI) model to characterize body color of fish. The conversion formula by the RGB model is as follows.

$$S = 1 - \frac{3}{R + G + B} [\min(R, G, B)]. \quad (8)$$

V. EXPERIMENT DESIGN AND ANALYSIS OF CHARACTERISTIC PARAMETER RESULTS

A. FISH TOXICITY EXPERIMENT DESIGN

1) EXPERIMENT MATERIALS

Most studies use zebra fish for water quality monitoring of pesticides, heavy metals, organic pollutants and other pollutants. The results show that zebra fish have high sensitivity,

so that they are suitable for biological water quality monitoring. Therefore, we select zebra fish as the test organism in our experiment.

Zebra fish have a strong stress response to heavy metal ion pollutants such as Hg^{2+}, Cu^{2+} and Zn^{2+}, which are also the common heavy metal ion in the domestic water pollution. Therefore, copper sulfate pentahydrate $(CuSO_2 \cdot 5H_2O)$ is selected as the toxic pollutant in our experiment. Assuredly, it does not pollute the environment.

2) EXPERIMENT PREPARATION

Before the formal experiment, the zebra fish are domesticated for more than two weeks in the formal experiment environment. The water used for domestication and experiment is aerated for more than 48 hours. The pH of the water maintains at 7.0 ± 0.5 and the water temperature is $20-24$°C. Give plenty light every day to ensure that the natural mortality of fish during domestication is $< 1\%$.

The experiment is carried out according to the method of acute toxicity test of fish in the Chemical Testing Method issued by the Ministry of Environmental Protection. 24-hour semi-lethal concentration $(24h-LC_{50})$ is used as the reference concentration to evaluate the toxic effects, which means that at the concentration the test organisms reach half the number of individual death within 24 hours in the toxicity test. The 24-hour semi-lethal concentration $(24h-LC_{50})$ of Cu^{2+} ions for zebra fish is 1.472 mg/L. According to the 24-hour semi-lethal concentration and the volume of the experiment fish tank, the toxic reagent solution for the experiment is configured in advance.

3) EXPERIMENT PROCEDURE

Ten zebra fish are used in each experiment and stop feeding 24 hours before and during the experiment. The process is divided into two steps: normal conditions and abnormal conditions. The experiment flow chart is shown in Fig.4.
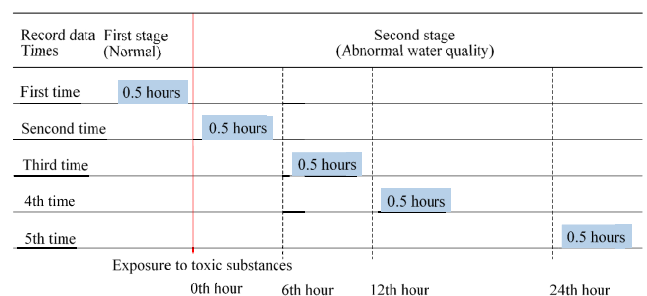
FIGURE 4. The flow chart of fish toxicity experiment.

In the normal stage, monitor the behavior of the fish group for approximately 30 minutes. And in the next toxicity experiment stage, slowly add the previously prepared toxic reagent solution to the aquarium and start recording the characteristic parameter data of zebra fish. The observation period of the whole toxicity test is 24 hours, and the zebra fish are observed to collect video and record data at 0th hour,

6th hour, 12th hour, as well as 24th hour after the toxic substance exposure. Considering that the short observation time will lead to insufficient response of toxic substances, and the long time will lose the timeliness of water quality warning, we design the duration of each video is 30 minutes.

B. ANALYSIS OF FOREGROUND EXTRACTION RESULTS

We select several widely used methods to evaluate the target detection algorithms: Precision-Recall curve (PR), Receiver Operating Characteristics curve (ROC), F-measure parameter, Area Under ROC Curve (AUC index), and directly calculate the Mean Absolute Error score (MAE) between the artificially estimated results (Groundtruth) and the target detection results by algorithms.

In order to compare the performance of Seg used in this paper with other methods, four algorithms are used to extract foreground of the same video sequence (900 frames): visual background extractor (ViBe) algorithm, Saliency Filters (SF) based on saliency estimation algorithm, Structured Matrix Decomposition (SMD) and Seg algorithm. The target foreground extraction results are compared with the artificially estimated results (Groundtruth) as shown in Fig.5.
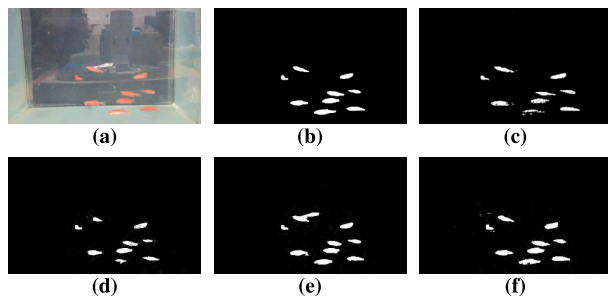

FIGURE 5. The comparison of moving target detection results. (a) The original image. (b) Groundtruth. (c) ViBe. (d) SF. (e) SMD. (f) Seg.
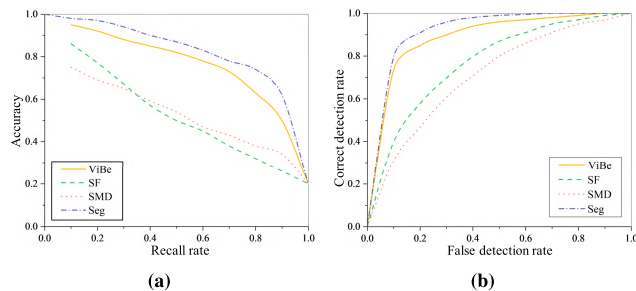

FIGURE 6. The algorithm evaluation results. (a) PR (Accuracy rate - recall rate). (b) ROC (Correct - false detection rate).

Fig.6 shows PR curve and ROC curve. According to the results, the accuracy and positive detection rate of the Seg algorithm are both higher than others.

In order to describe the performance of detection algorithms more intuitively, each algorithm is evaluated by three indicators: F-measure, AUC and MAE. The comprehensive evaluation results are shown in Table 1.

TABLE 1. The performance evaluation of algorithm simulation results.

Algorithm	F-measure	AUC	MAE	Time(second/frame)
ViBe	0.84023	0.82236	0.00875	0.0038
SF	0.82182	0.81889	0.00848	1.1482
SMD	0.84546	0.93438	0.00624	5.0974
Seg	0.93532	0.95815	0.00335	0.6117

The closer the value of the F-measure parameter is to 1, the better the performance of the algorithm is. Similarly, the closer the AUC index is to 1, the closer the result of the foreground extraction is to the artificially labeling. And the closer the value of the MAE is to 0, the smaller the algorithm error is. It can be seen that the ViBe algorithm runs much faster than other algorithms, and the Seg algorithm takes the second place. However, the Seg algorithm evaluates the best performance. Therefore, we select the Seg algorithm to extract the moving target foreground.

C. ANALYSIS OF CHARACTERISTIC PARAMETER RESULTS

The characteristic parameters of fish behavior are quantitatively analyzed from the extracted foreground targets. We collect data results of 1000 frames by observing the normal state of water quality and exposing toxic substances in water for 0 hours, 6 hours and 24 hours for data analysis.

1) RESULTS OF ACTIVITY PARAMETERS

In the above four water quality status, the velocity average distribution of fish group is shown in Fig.7 and Fig.8.

It can be seen that under normal conditions, the velocity of the fish group is mainly concentrated between 0 and 5 unit vectors and in a state of steady low-speed motion. When toxic substances such as heavy metals are added in the water to cause abnormal water environment, the fish will produce stressful behavior and the velocity is mostly distributed between 5 and 20. After the fish is exposed to toxic substances for 6 hours, the mean is still higher than the normal water quality. When the fish is exposed to toxic substances for 24 hours, the movement velocity decreases significantly. Since the movement velocity is obviously different under these four conditions, we choose it as one of the parameters to measure water quality.

The rotation angle of zebra fish is defined as no steering ($-10°$ to $10°$), general steering ($\pm10°$ to $\pm90°$) and stimulating steering ($\pm90°$ to $\pm180°$). In the above four conditions, the rotation angle of the fish group is shown in Fig.9 and Fig.10.

Under normal circumstances, the rotation angle of fish is mainly concentrated in the interval of $\pm10°$ to $\pm90°$, and the movement is relatively stable. When the water environment is abnormal due to the addition of toxic substances, the stress behavior of fish is severely deflected. The distribution of the rotation angle is mainly concentrated in the range of $\pm10°$ to $\pm90°$ and $\pm90°$ to $\pm180°$. When the fish lived for 6 hours with toxic substances, the frequency of the rotation angle is reduced. When toxic substances are exposed for 24 hours,
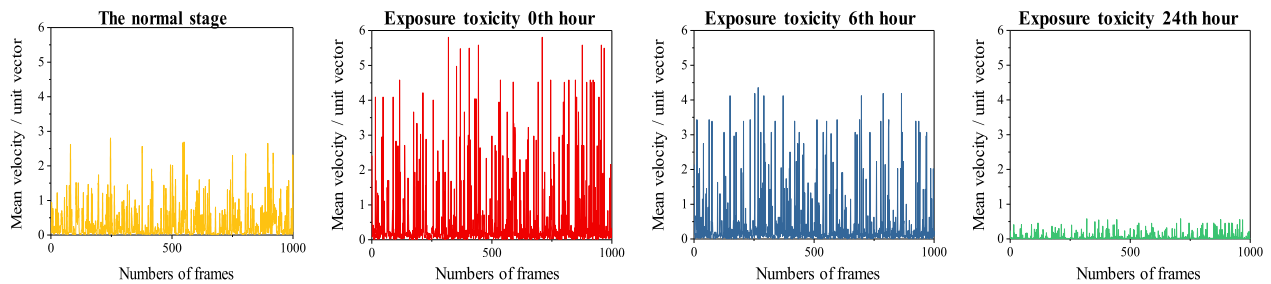
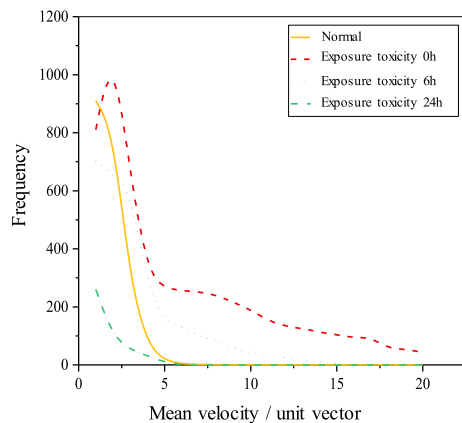**FIGURE 7.** The distribution of mean velocity at different stages.

FIGURE 8. The histogram statistics of mean velocity.

the angle is mainly distributed in the range of 0° to ±10°, and the amplitude as well as frequency of the rotation are significantly reduced. Since the rotation angle of the fish group has obvious differences, we select it as one of the parameters for water quality measurement.

2) RESULTS OF POSITION PARAMETERS
Fig.11 shows the changes of the group heart coordinates (CX, CY). There is not any significant change of the group coordinates under normal and abnormal water quality conditions. Therefore, group coordinates are not suitable as the index for determining water quality status.

Fig.12 shows the variation of the spatial standard deviation (SDX, SDY) of the fish group distribution. Under normal water quality conditions, the fish is evenly distributed in the water tank. The horizontal spatial standard deviation is mostly concentrated between 100 and 175. And the vertical direction is mainly between 75 and 100. When toxic substances are added to the water, the fish escape randomly and the spatial standard deviations in the horizontal and vertical directions are stable in the range of 200 to 275 and 150 to 200 respectively. When the fish is exposed to toxic substances for 6 hours and 24 hours, the physiology of individual with slower action is impaired and distributes more dispersedly. The horizontal spatial standard deviation is mainly between 150 and 200. However, the vertical spatial standard deviation

is mainly from 100 to 150. Therefore, considering the obvious differences, we choose it as one of the parameters for monitoring water quality.

3) RESULTS OF BODY COLOR COMPONENT
Fig.13 shows the variation of the color component of the fish group under different water quality conditions. The body color component is mainly distributed between 0.25 and 0.4 under normal water quality. When the toxic substance is added to the water, there is no significant change. When the fish is exposed to toxic substances for 6 hours, the body color component decreases in the range of 0.15 to 0.3. When the fish is exposed to toxic substances for 24 hours, the body color becomes more gray mainly between 0.05 and 0.2. Therefore, body color is a good indicator for monitoring the individual physiology of fish.

D. STATISTICAL ANALYSIS
We analyze the experiment results of the characteristic parameters visually in the previous part. A more reasonable method is to perform a statistical significance test on the data in order to determine whether the difference between the two types of data is caused by the experiment itself or the sampling error. We use the Mann-Whitney U test to perform a statistical significance test on the sample data so that the data indicators can be comprehensively evaluated.

The premise of using the Mann-Whitney U test method is that the two sets of sample data must be independent of each other, so the sample data must be carried out independence analysis before using the test method. 500 samples are extracted from the overall data as samples, and the auto-correlation function as well as the partial auto-correlation function of the sample are calculated by Time Series Analysis. Set the hysteresis number to be 50. As shown in Fig.14, the dotted line is the critical value and there is no overflow both in the autocorrelation and partial autocorrelation. Therefore, the sample data are determined to be independent and the Mann-Whitney U test method can be used in our system.

The results of the significance detection under normal and abnormal conditions are shown in Table 2, including the following parameters: the velocity V, the rotation angle A,
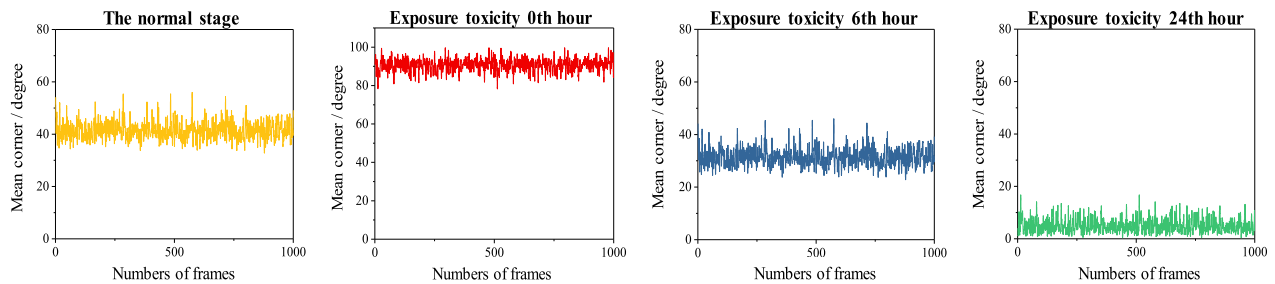
FIGURE 9. The distribution of rotation angle at different stages.

TABLE 2. The statistical characteristics of the sample under normal and abnormal conditions.

Parameter	Normal (Mean±SD)	Abnormal (Mean±SD)	Significant test (P value)
V	1.29±0.36	3.46±0.62	0.0000**
A	41.38±4.95	55.67±4.46	0.0000**
CX	8.64±2.43	7.34±2.97	0.0400**
CY	8.17±1.00	8.35±1.25	0.0910
SDX	136.29±34.56	100.28±39.84	0.0000**
SDY	85.55±23.85	58.18±17.76	0.0000**
S	0.27±0.01	0.25±0.02	0.0000**

Mean = sample mean value.
SD = sample standard deviation.
** indicates the results are significantly different.
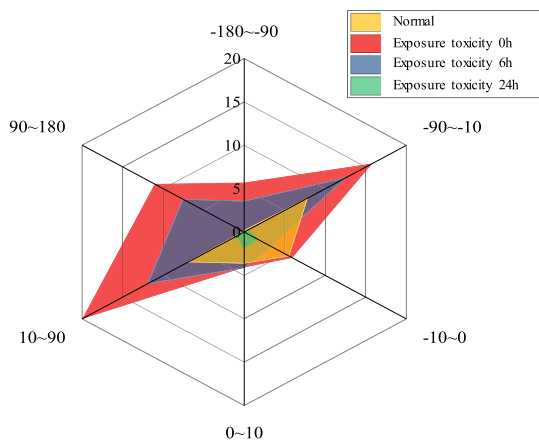

FIGURE 10. The behavior statistics of fish group rotation angle (thousand times).
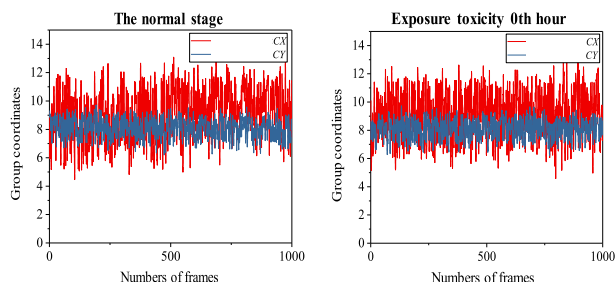
FIGURE 11. The distribution of group heart coordinates.

the group horizontal coordinate CX, the group vertical coordinate CY, the horizontal spatial standard deviation SDX, the vertical spatial standard deviation SDY and the body color

component S. Take a significant level of 0.05. Except for CY, the other six parameters selected in our system have significant differences under normal and abnormal conditions ($P < 0.05$, Mann-Whitney) which can be used to characterize the change of water quality.

VI. WATER QUALITY CLASSIFICATION MODEL
A. CLASSIFICATION MODEL BASED ON LSTM NEURAL NETWORK

Compared with the traditional classification method, the model combined with the machine learning theory can be optimized by continuous learning and has better classification effect. Therefore, we combine neural networks with traditional model to achieve multi-state classification. Since the LSTM neural network solves the gradient disappearance problem of RNN by introducing the core storage unit, we build a model based on LSTM for water quality classification. The basic architecture of LSTM is illustrated in Fig.15.

LSTM comprises of a set of connected memory blocks. Each memory block contains one or more self-connected memory cells and three multiplicative cells which are called input gates, output gates and forgetting gates respectively. Their function is to provide successive write, read and reset operations for the memory cells.

The three multiplicative units allow the storage unit to store and access information for long periods of time for the purpose of avoiding gradient disappearance issues. The working process of LSTM is shown in Fig.16.

Similarly, the shadow of nodes indicates their sensitivity to the input data at the earliest moment. The states of the
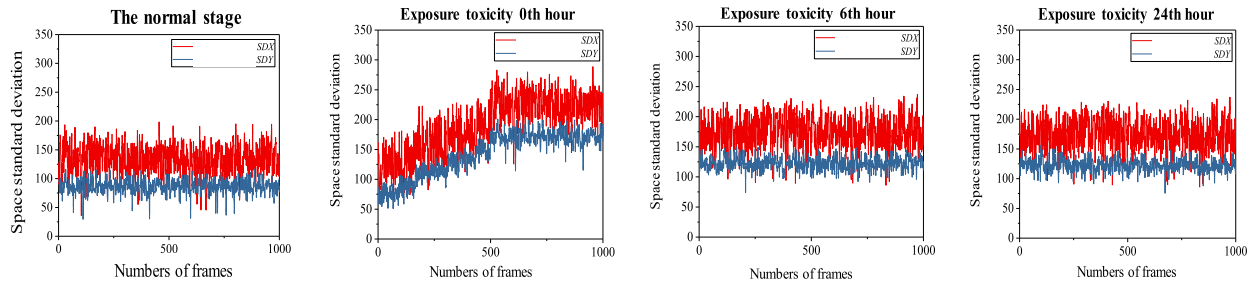
FIGURE 12. The distribution of space standard deviation.
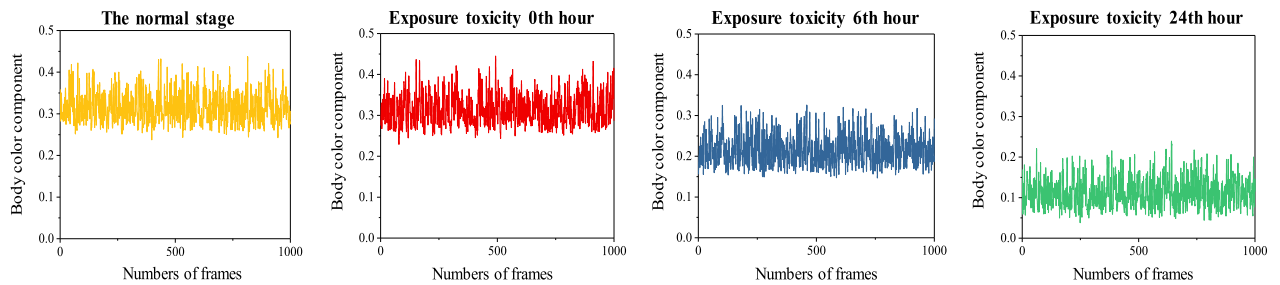
FIGURE 13. The distribution of body color component.
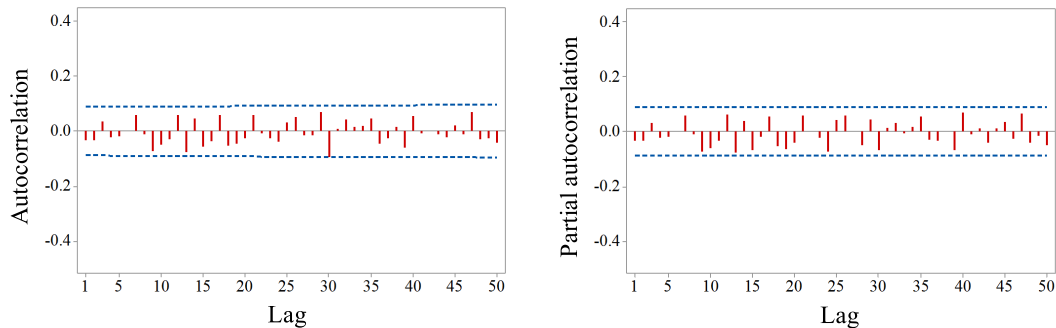
FIGURE 14. The sample independence test.

input gate, the forgetting gate and the output gate of the corresponding storage unit are respectively displayed below, on the left and above the hidden layer node. "○" indicates that the door is completely open and "−" indicates that the door is completely closed. As shown in the figure, as long as the forgetting gate is opened and the input gate is closed, the memory unit of the subsequent time node can "remember" the data input by the first time node and the sensitivity of the output layer can be independently controlled by the output gate opening or closing. In other words, it has no impact on the storage unit.

Let the number of input layers be I, the number of output layers be K and the number of hidden layers be H. In each layer, only the output of the memory unit b_c^t is connected to other memory blocks. Let h be the output of other memory block storage units in the hidden layer. Input data x of sequence length T into the network and perform forward

calculation to update the network from time 1. At time $t = 0$, all states and activation functions are set to zero.

Let ω_{ij} to be the weight value from the unit i to the unit j and the result of the network input to the *jth* unit at time t is a_j^t. After the *jth* unit, the value calculated by the nonlinear differential activation function is b_j^t. ι, ϕ and w are input gates, forgetting gates and output gates respectively. c is the storage unit. s_c^t is the state of the c storage unit at time t. f is the activation function of the gate. g and h are the input and output activation functions of the storage unit respectively.

In the forward propagation process, the value of the input gate and the activation function are calculated in (9).

$$a_\iota^t = \sum_{i=1}^{I} \omega_{i\iota} x_i^t + \sum_{h=1}^{H} \omega_{h\iota} b_h^{t-1} + \sum_{c=1}^{C} \omega_{c\iota} s_c^{t-1}$$
$$b_\iota^t = f(a_\iota^t). \tag{9}$$

FIGURE 15. The basic architecture of LSTM.

FIGURE 16. The implementation process of LSTM.

The value of the forgetting gate and the activation function are calculated in (10).

$$a_\phi^t = \sum_{i=1}^{I} \omega_{i\phi} x_i^t + \sum_{h=1}^{H} \omega_{h\phi} b_h^{t-1} + \sum_{c=1}^{C} \omega_{c\phi} s_c^{t-1}$$
$$b_\phi^t = f(a_\phi^t). \tag{10}$$

The value of the storage unit and the activation function are calculated in (11).

$$a_c^t = \sum_{i=1}^{I} \omega_{ic} x_i^t + \sum_{h=1}^{H} \omega_{hc} b_h^{t-1}$$
$$s_c^t = b_\phi^t s_c^{t-1} + b_\iota^t g(a_c^t). \tag{11}$$

The value of the output gate and the activation function are calculated in (12).

$$a_w^t = \sum_{i=1}^{I} \omega_{iw} x_i^t + \sum_{h=1}^{H} \omega_{hw} b_h^{t-1} + \sum_{c=1}^{C} \omega_{cw} s_c^t$$
$$b_w^t = f(a_w^t). \tag{12}$$

Finally, the output of the storage unit is in (13).

$$b_c^t = b_w^t h(s_c^t). \tag{13}$$

The back propagation starts when $t = T$ and the unit derivative is recursively calculated while decreasing t. The final weight derivative value is obtained by summing the derivative values of each time node. The formula is as follows. Where O is the loss function for training.

$$\delta_j^t \overset{\text{def}}{=} \frac{\partial O}{\partial a_j^t}. \tag{14}$$

In the backward propagation process, the output value of the storage unit is in (15).

$$\varepsilon_c^t \overset{\text{def}}{=} \frac{\partial O}{\partial b_c^t} = \sum_{k=1}^{K} \omega_{ck} \delta_k^t + \sum_{h=1}^{H} \omega_{ch} \delta_h^{t+1}. \tag{15}$$

The value of the input gate is calculated in (16).

$$\delta_w^t = f'(a_w^t) \sum_{c=1}^{C} h(s_c^t) \varepsilon_c^t. \tag{16}$$

The backward propagation status value is as follows.

$$\varepsilon_s^t \overset{\text{def}}{=} \frac{\partial O}{\partial s_c^t} = b_w^t h'(s_c^t) \varepsilon_c^t + b_\phi^{t+1} \varepsilon_s^{t+1} + \omega_{c\iota} \delta_\iota^{t+1}$$
$$+ \omega_{c\phi} \delta_\phi^{t+1} + \omega_{cw} \delta_w^t. \tag{17}$$

The storage unit is as follows.

$$\delta_c^t = b_\iota^t g'(a_c^t) \varepsilon_s^t. \tag{18}$$

The value of the forgetting gate is calculated in (19).

$$\delta_\phi^t = f'(a_\phi^t) \sum_{c=1}^{C} s_c^{t-1} \varepsilon_s^t. \tag{19}$$

The value of the input gate is calculated in (20).

$$\delta_\iota^t = f'(a_\iota^t) \sum_{c=1}^{C} g(a_c^t) \varepsilon_s^t. \tag{20}$$

B. ANALYSIS OF WATER QUALITY CLASSIFICATION RESULTS

First of all, define the 0 hour, 6 hours and 24 hours of toxic pollution as initial, intermediate and final stages of water pollution respectively. The data collection and analysis of fish behavior in the normal and the above three abnormal states are carried out. Then extract and mark the feature parameters from the obtained data. 60% of the data is used as the training set and the rest is used for testing. We utilise the classification model based on RNN neural network and the model based on LSTM to classify the water quality of different pollution stages.

As shown in Table 3, the water quality classification is divided into the following three modes.

1) Class II can classify the normal and the initial stage of pollution. We mainly detect the sudden occurrence of water quality and distinguish whether the current water quality is in a normal state or an initial pollution state.

TABLE 3. The water quality classification results of LSTM and RNN.

Classification mode		RNN			LSTM		
		Accuracy	Total accuracy	Time (second)	Accuracy	Total accuracy	Time (second)
Class II	Normal	92%	94%	0.077	100%	100%	0.056
	Initial pollution	96%			100%		
Class III	Normal	96%	88%	0.082	96%	93.33%	0.060
	Initial pollution	92%			100%		
	Final pollution	76%			88%		
Class IV	Normal	88%	86%	0.792	92%	91%	0.764
	Initial pollution	96%			100%		
	Middle pollution	92%			100%		
	Final pollution	68%			72%		

2) Class III can classify the normal, the initial and the final stage of pollution. It is possible to detect the occurrence of serious fish death at the final stage of pollution.

3) Class IV can classify normal, the initial, the medium and the final stage of pollution. Comparing the three modes, we join the identification of the medium-term pollution in the last one. And we can better monitor the water pollution.

Compared with RNN, LSTM can achieve better classification results. Classification based on LSTM can be implemented faster to meet the real-time requirements. In the water quality classification of class III, the total accuracy rate decreased to 93.33% due to misclassification in the normal and the final stage of pollution. Under class IV, the normal and the final pollution are still misjudged. Experiments show that the classification accuracy of our system for the three states of normal, initial and medium water pollution has reached 100%.

VII. CONCLUSION

We improve the existing monitoring system and combine computer image processing technologies with water quality monitoring to improve the applicability, accuracy and reliability of our system. In particular, we use the adaptive optical adjustment module to effectively balance the illumination and compare various moving target detection algorithms to eliminate the influence of complex background. Finally, we achieve effective extraction of underwater video targets. At the same time, we comprehensively evaluate the fish behavior by combining multi-dimensional characteristic parameters. Last but not least, the use of LSTM neural network for water quality classification improves the detection accuracy and real-time performance of the water quality monitoring system. Our system with higher real-time performance which can be adapted to different lighting conditions and complex backgrounds achieves more accurate multi-level classification effect than RNN and other shallow networks. We will combine individual fish characteristic parameters with group parameters to make water quality monitoring results more accurate in the future work.

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