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Anomaly Detection of Water Pollution Prevention Ecosystem Based on Artificial Intelligence

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Abstract: Traditional water pollution(WP) detection is mainly based on the manual use of water quality testing equipment to identify samples at fixed points, this method of detection is a huge amount of work, and to pay the high cost of testing, in addition, in some unsuitable for operators to enter the WP testing environment, the use of traditional testing equipment is difficult to complete the sampling, so that the testing work can not be carried out as scheduled, and, the current water resources collection every six months or once a quarter, in this way to collect water quality data on a long time line, can not do water quality status updated. In order to solve these problems and build a stable water environment ecosystem, this paper studies WP detection equipment, builds a WP detection system based on artificial intelligence and sensors, and integrates intelligent means to detect pollutants and prevent WP. The system can complete the abnormal detection and recording of water pollutants through different interfaces and software systems, and its advantages of miniaturization and intelligence will be applied to actual production and life.

1. Introduction

In recent years, a large number of WP incidents have occurred in China, damaging the water resource ecosystem and causing unavoidable water resource losses. How to effectively establish a water quality anomaly detection system to provide timely alerts and prevent WP has become a pressing challenge in the field of water environmental protection. Water quality data anomalies are manifested as abnormal WP environmental monitoring data. The current challenge for water resources early warning is to identify abnormal water quality conditions in the environment in a timely and accurate manner, to study the relationship between the environment and society and to formulate relevant water resources protection laws, and to provide a scientific basis for the prevention of WP [1-2].

WP detection is generally the detection of pollutant concentrations and countries have long been researching online detection systems for different purposes, but so far chemical analysis has remained the tool to achieve rapid detection of WP. In order to detect WP in a directional and intelligent manner, some scholars have studied the characteristics of light distribution, designed optical sensors by using a microwave sensor structure with strong and advanced external fibre characteristics, and conducted experimental studies on sensors, using optical sensors to detect the concentration of pollutants in water, and obtained detection results with high accuracy and sensitivity to pollutant concentration, and optical sensors have become a new means of WP detection [3]. When developing WP detection systems, some scholars have proposed two methods to compare pollutant concentrations in polluted and standard water in real time. The first method is to organise several generic sensor indicators into vectors and assess whether the distance between the current sensor data vector and the standard water quality data vector is contaminated. The second approach is to organise the sensor data into a grid and detect contamination based on the relationship between the current water quality display area and the standard water quality map. It is important to emphasise that these methods use sensor data that are standardised over time [4-5]. In summary, detection devices have been developed with the hope of combating WP and reducing stress in the water environment.

People's awareness of water resources protection has been strengthened, and various WP monitoring equipment has been applied. This paper also takes water quality detection as the research object. First, it introduces the detection principle of heavy metal elements and pollutants in water quality, and then puts forward relevant anomaly detection algorithms. Then, it builds a WP detection system based on artificial intelligence, and designs the hardware and software system of the system. Finally, it takes heavy metal detection as an example to verify the availability of this system and the accuracy of pollutant anomaly detection.

2. Basic Overview

2.1. Principle of Water Quality Anomaly Detection

Heavy metals are an important indicator for the detection of pollutants. The main methods for detecting heavy metals in water include electrochemical methods, removal of chemical voltammetry, atomic emission spectrometry, ultraviolet-visible detection, and induction plasma techniques [6]. Electrochemical sensors are used to detect more accurate data related to water contaminants. Highly sensitive electrochemical sensors are often used in output current devices because of the low relative concentrations of heavy metal ions in the water column. The environment in which the measurements are taken needs to be noise-cancelled, otherwise the accuracy of the measured data is very low. The output of an electrochemical sensor detected by Microsoft requires filtering, signal amplification, current and voltage conversion and a terminal output from the chip [7-8].

The electrochemical method heavy metal detection process starts with enrichment detection of heavy metals in water, followed by electrochemical dissolution to detect water contamination. Electrochemical measurements of size parameter values and time parameter values are used to determine the heavy metal content of the solution to be tested. The hardware and the differential input of the electrochemical sensor are designed to reduce detection interference and then the measured values are calibrated so that valid voltage parameters can be obtained [9].

(2) Detection of water pollutants

There are numerous pollutants in the water body, in addition to COD, heavy metal elements and PH value, there are also indicators such as temperature, suspended matter and coliform count [10]. PH value can be measured with test paper, which is both simple and fast, but in order to understand the automatic collection process of PH value and prevent water sample pollution, the system can measure the PH value in the measurement chamber by connecting chemical sensors such as ds18b20 temperature sensors to PH values with more accurate measurement results [11]. Water temperature also reflects important water characteristics such as anisotropy and other factors that may cause water temperature anomalies. Infrared temperature measurement devices can accurately measure the temperature of the water column, but for automated collection, temperature collection is often embedded in the system to facilitate a comprehensive water quality analysis [12]. The technology for temperature measurement is well established, and sensors of varying accuracy are selected to meet different needs. Other methods are often available to identify contaminants, but there is a greater probability of selecting chemical sensors for data collection so that the process of automatic collection can be understood.

2.2. Related Learning Algorithm

(1) Supervised learning algorithm

Support vector machines are modelled by treating instances as points in space and using different mapping functions to map entry points into high-dimensional functional regions in order to construct hyperconductor planes, intuitively, the larger the classification limit on the training point data, the better [13]. The explicit equation for delineating the hyperplane is:

$$w^T x + b = 0 \tag{1}$$

Where w and b represent normal vector and displacement term respectively. The distance from any point x in space to the hyperplane target is to find a target that can satisfy the hyperplane condition and make γ Maximum, i.e. Formula (2) and Formula (3).

$$\max_{w,b} \frac{2}{\|w\|} \tag{2}$$

$$s.t.\, y_i(w^T x + b) \geq 1 \tag{3}$$

(2) Unsupervised learning algorithm

The isolated forest is an efficient outlier monitoring algorithm that randomly selects a function and then randomly selects segmentation levels for the maximum and minimum values of the function. The above steps are performed recursively after the tree is formed and the distance from the root node to the number base is the number of segments [14]. To improve the robustness of the model, multiple trees are also randomly selected, eventually forming a forest.

One Class SVM is also an unsupervised learning method that belongs to the SVM family and is often applied to anomalous behaviour detection based on the uneven distribution of data samples, where the existing anomalous behaviour is based on the majority of regular samples from anomalous behaviour recognition tasks [15]. When learning a large number of regular sample data, the model saves support vectors, uses the support vectors to create domain equations, determines the distance between the registry data and the domain based on the saved domain when identifying unknown data, and identifies it as anomalous when a threshold is exceeded. Finding the support vector for the split hyperplane allows spherical boundaries to be obtained around the data in the graph space, thus minimising the impact of anomalous data [16-17].

3. Artificial Intelligence Based WP Detection System Design

3.1. Hardware Design of the System

(1) Chemical oxygen demand (COD) sensor circuit design

The continuous development of electronic technology has led to the development of WP detection systems in the direction of intelligence, networking and portability. The system will use ARM master control chip to collect the chemical oxygen demand (COD) through chemical sensors and AD conversion chips, and then analyse it through the built-in system to finally derive the value and result of COD [18]. The system will use a three-electrode chemical sensor to measure the COD of the water body, and its sampling control flow is shown in Figure 1.

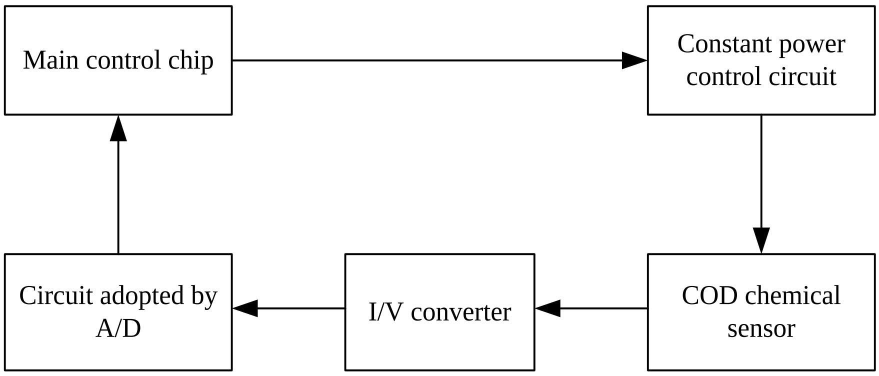

Figure 1. Block diagram of COD measurement

The chemical sensor used in this system determines COD by free radical oxidation (OH-).The relevant characteristics of the sensor should be fully considered during hardware design. Due to various sample errors, factors such as filtering and resistance should be considered and addressed when transmitting analogue levels from the sensor to avoid unreasonable detection results due to the accumulation of constant errors.

(2) Heavy metal sensor circuit design

For heavy metal element detection, the system will use the stress decomposition method. For the three electrodes of the sensor, noise flow should be added to the design of the detection circuit and physical noise also needs to be removed to detect the water sample as the power detection is generated at a stage when the actual detection process has very small metal concentrations.

With a three-electrode sensor, the working and reference electrodes need to be adjusted for potential difference, as the relative tension of the different heavy metal elements is constantly changing so that their continuous tension potential can be adjusted by hardware or software. The working electrode reacts with the heavy metal ions in the water sample for measurement and ultimately for physical precipitation of the heavy metals. The detection current output from the three-electrode sensor for heavy metals will do a series of signal processing to eventually match the system to the chosen AD converter.

3.2. Software Design of the System

The contaminants in the water body are transmitted to the whole system via different sensors and the system converts the fetched analogue to A/D and writes it to a FIFO to be read or forwarded by the system. The system starts as a bi-directional FIFO when collecting data and reads the collected data during the data cycle. If there is no data it has to wait for the data to be read. When data collected by the system enters the FIFO, an interrupt is required to wake up the FIFO read function and the whole system will enter data entry operation. Figure 2 represents the flow chart of the entire system collecting data as follows.

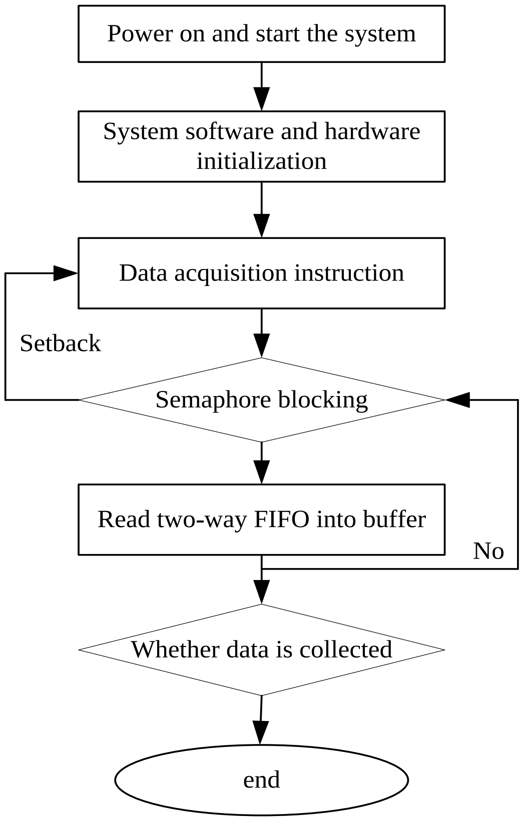

Figure 2. Flow chart of system data acquisition

For the system, after the execution of the data acquisition command, the buffer is initialised for data writing, when the FIFO storage write data is full, the system spontaneously enables interrupt service, the data reading process gets the indication signal to start reading FIFO data, into the system process then starts reading FIFO data. The software system will be configured with two external registry ports of bi-directional FIFO design, if the data triggers a read interrupt, the most in the amount of data to get 2014 * 2 word size.

4. System Validation for Heavy Metal Detection

The system validation for heavy metal detection will be done by measuring the value of the standard solution by atomic absorption spectrometry, and then comparing the two sets of data for validation after measuring the same solution by the detection system and deriving the concentration C by calculating the transmittance A of the solution.

Atomic absorption test is divided into standard curve method and addition method, such as the determination of manganese ion content in a water sample. The manganese standard solutions were taken up 5.00ml, 10.00mL, 15.00ml, 20.00mL, 25.00mL, 30.00ml and placed in six 100mL volumetric flasks for fixing, and the concentrations of 0.0698mg/L, 0.1624mg/L, 0.2281mg/L, 0.3145mg/L, 0.3792 mg/L, and 0.4533 mg/L of manganese standard solutions. The absorbance values A of each standard solution were measured under the optimized conditions obtained, and the corresponding standard curves were fitted. The absorbance values of each concentration solution are shown in Table 1 and Figure 3.

Table 1. Data table of standard curve of manganese ion

Number	Concentration (mg/l)	Absorbance value a
1	0.0698	0.0972
2	0.1624	0.2485
3	0.2281	0.3467
4	0.3145	0.4953
5	0.3792	0.6018
6	0.4533	0.7295

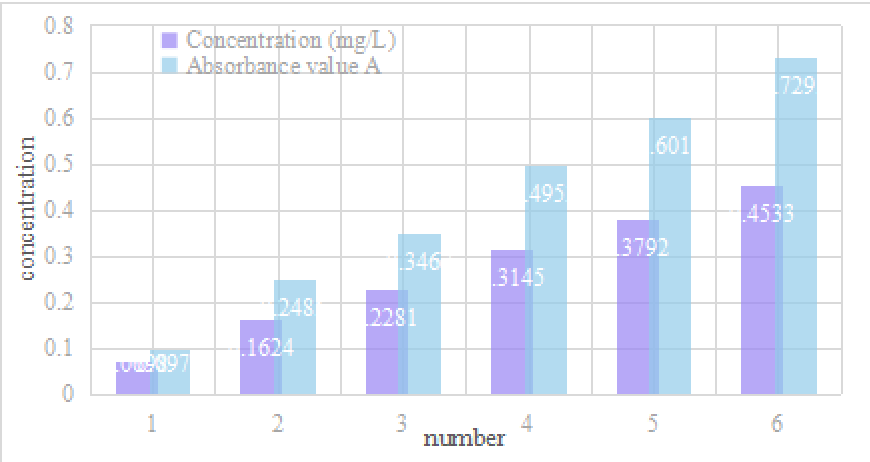

Figure 3. Manganese ion concentration data

To complete the validation of this system, the manganese ion concentration values of several groups of water samples will be actually detected, and the absorbance value A can be obtained from the linear equation fitted according to the linear relationship of absorbance values of different concentrations. to reduce the chance error of the detection system, four groups will be added to the marked six groups of solution concentration intervals to ensure the accuracy of the measurement results. Table 2 was established by measurement and calculation.

Table 2. System detection data values

Different concentrations (mg/l)	Absorbance (standard curve method a)	Absorbance (electrochemical method b)
0.0698	0.0972	0.0915
0.1157	0.1637	0.1742
0.1624	0.2485	0.2358
0.2281	0.3467	0.3296
0.2672	0.4135	0.4173
0.3145	0.4953	0.5266
0.3424	0.5489	0.5671
0.3792	0.6018	0.6294
0.4167	0.6536	0.6819
0.4533	0.7295	0.7235

From the data measured by atomic absorption light method of the standard solution of Table 1 to establish a curve, due to the high accuracy of the measurement, such as the curve A in Figure 4, can be approximately identified as a straight line. Then from the data in Table 2 to establish another curve B, the points are connected, it is concluded that A is a curve of B fit straight line, so it is concluded that the WP control ecosystem on the detection of anomalies to heavy metals accurate results.

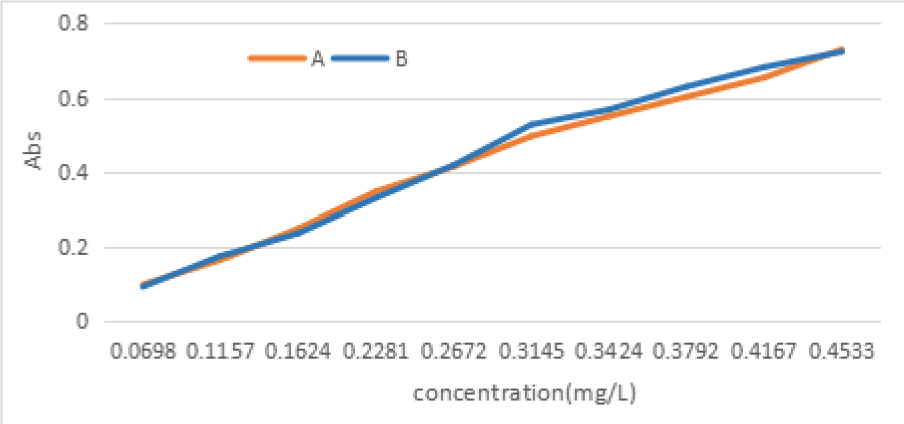

Figure 4. Heavy metal concentration versus absorbance

5. Conclusion

The discharge of domestic pollutants into clean water resources will lead to an ecological imbalance in the water resources system, which will result in the deterioration of water bodies, excessive concentrations of heavy metals, breeding bacteria, and increased dissolved oxygen levels, which, when consumed, will seriously damage human health. Therefore, timely testing of water resources conditions in the corresponding waters will avoid the aggravation of WP, while reducing the harm caused by WP to humans. And, in the face of many factories substandard sewage treatment, in addition to should increase the punishment to reduce human harm to the environment, should also establish a good water quality abnormal detection system, design a more complete WP detection system.

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Data Availability

Data sharing is not applicable to this article as no new data were created or analysed in this study.

Conflict of Interest

The author states that this article has no conflict of interest.

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