Research Article

Marine Environment Monitoring Based on Virtual Reality and Fuzzy C-Means Clustering Algorithm

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Received 14 July 2021; Revised 14 August 2021; Accepted 31 August 2021; Published 17 September 2021

Academic Editor: Sang-Bing Tsai

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In modern society, with the rapid increase of population and the serious shortage of resources, the marine environment has been destroyed; there are also many people who go out to sea without permission, regardless of the legal constraints, fishing. This kind of behavior leads the marine environment to get worse and worse, so the real-time monitoring of the marine environment is very necessary. The main article marine environment monitoring, virtual reality technology, and fuzzy C-means clustering algorithm combine to improve the efficiency of monitoring and processing power of the data information. Through the application of virtual reality technology in the marine environment monitoring base and real-time simulation of the dynamics of the ocean, the monitoring personnel can understand the emergencies on the sea in time; the fuzzy C-means clustering algorithm is applied to the server receiving the data to classify the data. It is found in the experiment that when virtual reality technology and fuzzy C-means clustering algorithm are not used, the data of marine environment monitoring takes more than 1.3 s to return to the server, but, after applying two advanced technologies, the return efficiency is greatly improved, and the time consumed is less than 0.82 s. The results show that virtual reality technology and fuzzy C-means clustering algorithm can improve the efficiency of environmental monitoring, and through virtual reality technology, real-time monitoring of the marine environment can be achieved; in the absence of people out to sea, the actual situation on the sea can be clearly understood; and fuzzy C-means clustering algorithm can improve the speed of data processing, so that the monitoring personnel can solve the problem faster.

1. Introduction

With the development of the national economy and the increasing frequency of man-made marine activities, our coastal areas are facing major problems such as water quality degradation, environmental degradation, reduced sustainable use capacity, serious pollution, and eutrophication. Overexploitation of the marine environment will extinct certain rare species, seriously threatening the lives of local fishermen and seriously affecting the development of marine fisheries. Information explosion has become the computer industry's most intuitive performance. Smart business, social networking, and mobile devices greatly expand the range of information.

This article mainly studies the impact of virtual reality and fuzzy C-means clustering algorithm on marine environment monitoring. The purpose is to use modern

advanced virtual reality technology and fuzzy C-means clustering algorithm to provide a more convenient way for marine environment monitoring and improve the efficiency and accuracy of monitoring, thereby reducing the damage to the marine environment.

In modern society, there are many people who have shallow awareness of caring for the environment; in particular the damage to the marine environment is very serious, so the monitoring of the marine environment is extremely important for the protection of aquatic plants and animals. Gambardella believes that the ocean is vital to the health of the planet and humanity. The marine ecosystem should be protected from pollution factors through continuous monitoring; this monitoring method should be as green as possible, that is, based on sensors made from biocompatible and easily handled raw materials. He laid the foundation for the future

development of marine environmental biosensors based on sea urchin cells cultured on nanoporous alumina. He believes that these batteries are promising because they have shown a high response to stress in previous work, and the proposed substrate is inexpensive because it is made of consumer-quality aluminum foil through an inexpensive anodizing process. Endothelial cells of Mediterranean Sea urchin, *Paracentrotus lividus*, were cultured in vitro on nanoporous alumina for up to 5 days. Then, biochemical characterization was performed to examine the cholinergic system pathways by exposure to aldehyde-induced serotonin autofluorescence and the expression and function of neuroactive molecules such as acetylcholinesterase and muscarinic acetylcholine receptors. After cultivation, the quality of living cells and system biochemistry were not affected, and electrical regulation and non-self-reactivity were maintained [1]. Although his research is feasible in theory, the actual operation is more difficult. Bian believes that, due to the impact of seawater on human life and natural ecosystems, its quality needs to be continuously monitored. However, the balance of the scope, spatial pattern, and maintenance cost of marine environment monitoring is still a challenging issue and is of vital importance to decision-makers. The main contribution of his research is to use two minimization criteria (TMC: at a given confidence level, integrating Kriging variance minimization and relative error minimization) to improve the design and optimization of the marine environment monitoring network. In order to achieve this goal, he used the spatial simulated annealing (SSA) method to determine the optimal location of the monitoring network optimization. Taking the northern coastal waters of Zhejiang Province as an example, he used phosphate (PO₄) as an indicator of seawater quality. 122 existing sites have redundancy (about 78 sites). Given the relative error (less than 10%) and confidence (95%), this redundancy can be effectively identified and deleted to reduce costs. On the basis of quantitative analysis, some new monitoring points can be added and adjusted to improve the quality of coastal zone environmental monitoring [2]. Although his research object is relatively comprehensive, the scope of application is not very wide. Przeslawski believes that marine seismic exploration is a basic tool for geological research, including the exploration of marine oil and gas resources, but the sound produced during these explorations is a source of noise pollution in the marine environment. He applied case studies on the impact of marine earthquakes to key assessments of the strengths and challenges of field-based methods in the context of future research and management priorities. He found that using an interdisciplinary approach, using both traditional (such as dredging) and innovative (such as autonomous imaging) experimental components, helped to provide a more powerful explanation and provide fault protection when appropriate data was limited. He believes that field observation research provides an unparalleled ability to conduct ecological reality research, although the actual challenges must be considered in the research planning process. He also noted the need for appropriate environmental baselines and available time series data to illustrate the spatiotemporal variability of environmental and biological parameters that may obscure the impact, as well as the need

for standardized techniques in sound monitoring and equipment calibration to ensure the accuracy of the study's sex and comparability [3]. Although his research can get a lot of useful information, it is very difficult to carry out in practice, and the data obtained may not be accurate enough.

The innovation of this paper is to combine the fastest-growing virtual reality technology with the widely used fuzzy c-means clustering algorithm in the computer field, so as to provide a good management plan for marine environment inspectors and a solid technical support for the country in marine management. In turn, it also expands the application scope of these two technologies. The solid technical backing, in turn, has expanded the application of these two technologies.

2. Virtual Reality Technology

2.1. Concept and Characteristics. Virtual reality environment is to generate three-dimensional visual and sound effects using the computer user interface. The interaction between human and computer is harmonious and friendly. Virtual reality technology (English name: Virtual Reality, abbreviated as VR) is a brand-new practical technology developed in the 20th century. Virtual reality technology includes computers, electronic information, and simulation technology, and its basic realization is that a computer simulates a virtual environment to give people a sense of environmental immersion. Through the interaction between the participants and the simulated environment, with their own help, the perception ability and cognitive ability can stimulate the thinking of the participants and help to obtain various spatial and logical information contained in the virtual environment through various methods [4–6]. Users use various interactive devices such as head-mounted displays (HMD) and data gloves to interact with entities in the virtual environment, giving an immersive feeling. The operator can actually enter this three-dimensional virtual environment to communicate. The basic characteristics of virtual reality technology are immersion, interaction, and sharing. It is difficult for the user to distinguish between the true and false environment, and the user can focus on the three-dimensional environment created by the computer. Not only can the actual environment be reproduced, but also the environment without objective existence can be freely imagined [7]. Immersion is the most important feature of virtual reality technology. It allows users to become and feel that they are part of the environment created by computer systems. The immersion of virtual reality technology depends on the user's perception system. When the user perceives the virtual world when stimulated, including touch, taste, smell, and movement perception, it will resonate thinking, causing psychological immersion, and it feels like entering the real world.

2.2. Virtual Reality Modeling.

(1) Features

- (1) There may be a very wide range of objects in virtual reality. In many cases, it is necessary to construct completely different types of objects [8].

- (2) Certain objects in virtual reality require independent actions. Other graphical modeling systems often build static objects. Even if there is motion, it is often a relatively simple form such as translation and rotation [9].
- (3) Objects in virtual reality must be able to react to the observer. When the observer interacts with the object, the object must react in an appropriate manner, and the observer's actions cannot be ignored [10].

(2) Method classification

- (1) *Geometric Modeling*. Geometric modeling is the first model of virtual reality modeling technology. By selecting the main unit, the range of objects constructed by the modeling system can be determined. The structure is used to determine the method of combining units to form a new object.
- (2) *Physical Modeling*. Physical modeling mainly considers the physical properties of objects. The disadvantage is that too much calculation will cause real-time performance to drop. Therefore, in virtual reality, it is usually only used for static visual modeling.
- (3) *Action Modeling*. Action modeling is mainly used to create the action of the research object. If the virtual reality object has no movement or reaction, then the virtual reality is lonely, has no vitality, and is meaningless to the virtual reality. Virtual reality is essentially a simulation or refraction of the target world, and a virtual reality model is an object or object representative of the target world [11]. Regarding application system development tools, the key to virtual reality applications is to find suitable occasions and objects. Choosing appropriate application objects can greatly increase production efficiency, reduce labor intensity, and improve product quality. To achieve this goal, you need to study the development tools of virtual reality.

3. Fuzzy C-Means Clustering Algorithm and Ocean Monitoring System

3.1. Fuzzy Theory. Clustering is the process of distinguishing and classifying based on the similarity of things. Group analysis technology is a statistical analysis technology for studying (sample or index) classification problems, and it is also an important algorithm technology for data mining. In this process, since there is no special prior knowledge guidance, there is no distinction between categories. As a module in data mining, cluster analysis technology can be used as a separate tool to discover some deep information distributed in the database and generalize the characteristics of each category or focus on a specific category for further analysis.

3.1.1. Representation of Common Set Feature Function. The common set feature function represents the degree to which each element belongs to each set using an analytical method in the common set [12]. It is difficult to propose a concise classification of clustering methods, because these categories may overlap, so that a method has several types of characteristics. Nevertheless, it is still necessary to provide a relatively organized description of various clustering classification techniques. Assuming that set X is a set on domain A , the feature function of set X can be expressed as

$$\mu_x(a) = \begin{cases} 1, & a \in X, \\ 0, & a \notin X, \end{cases} \quad (1)$$

3.1.2. Representation of Membership of Fuzzy Sets. The fuzzy set is represented by a function. The function is evaluated at $[0, 1]$ in the closed interval. Assuming that set X is the set on domain A , the membership function of set X can be expressed as

$$\mu_x(a), A \longrightarrow [0, 1]. \quad (2)$$

When $\mu_x(a) \longrightarrow 0$ it indicates that element a belongs to the fuzzy set X , the degree is very low. When $\mu_x(a) \longrightarrow 1$ it indicates that element a belongs to the fuzzy set X [13].

3.2. Fuzzy Relations. Fuzzy relation is a generalization of ordinary relation. It is used to describe the degree of direct correlation between two elements. If X and Y are not two empty sets, the fuzzy subset of direct product R is called a fuzzy relationship. The fuzzy relationship is represented by the member relationship function $\mu_R: X \times Y \longrightarrow [0, 1]$ [14, 15]. Fuzzy matrix technology is used to represent a matrix of fuzzy relations. If set X has m elements and set Y has n elements, the fuzzy relationship from set X to set Y can be represented by a matrix.

Let R and S be the fuzzy relationship on the direct product of set X and set Y ; the calculation of the relationship between them is as follows:

- (1) $R \cup S: \max\{\mu_R(x, y), \mu_S(x, y)\}, \forall (x, y) \in X \times Y$
- (2) $R \cap S: \min\{\mu_R(x, y), \mu_S(x, y)\}, \forall (x, y) \in X \times Y$
- (3) $R \subseteq S: \mu_R(x, y) \leq \mu_S(x, y), \forall (x, y) \in X \times Y$
- (4) $R^c: \mu_{R^c}(x, y) = 1 - \mu_R(x, y), \forall (x, y) \in X \times Y$
- (5) $R^T: \mu_R(y, x) = \mu_R(x, y), \forall (x, y) \in X \times Y$

The fuzzy relationship has the following properties:

- (1) *Reflexivity*. In the case of fuzzy relations, if both parties exist, it is a recursive relation. If it is a reflexive relationship, it is said that R is nonreflective [16].
- (2) *Symmetry*. For a fuzzy relationship R , if $\forall (x, y) \in X \times X$ holds for $\mu_R(x, y) = \mu_R(y, x)$, it is said that R has symmetry.
- (3) *Transmissibility*. For a fuzzy relation R , if there is $R \circ R \subseteq R$, it is said that R is transitive.

3.3. Fuzzy Division. The fuzzy division is the inherent vector of the observation sample $x_k = (x_{k1}, x_{k2}, \dots, x_{ks})^T \in R^s$ corresponding to the point in the characteristic space, and x_{kj} is the distribution of the dimensional features. The intrinsic vectors x_k and x_{kj} generate a set of partitions in the cluster analysis of a specific group of target data objects X [17].

$$\left. \begin{aligned} X_1 \cup X_2 \cup \dots \cup X_c &= X \\ X_i \cap X_k &= \emptyset, \quad 1 \leq i \neq k \leq c, \\ X_i &\neq \emptyset, \quad X_i \neq X, \quad 1 \leq i \leq c. \end{aligned} \right\} \quad (3)$$

If the target data object set X is divided into c subsets $X_1, X_2, \dots, X_c$, this division is called the hard c division of set X [18].

$$M_{hc} = \left\{ U \in R^{cn} \mid \mu_{ik} \in \{0, 1\}, \forall i, k; \sum_{i=1}^c \mu_{ik} = 1, \forall k; 0 < \sum_{k=1}^n \mu_{ik} < n, \forall i \right\}. \quad (4)$$

Fuzzy segmentation is based on the uncertain expression of all categories, so it is possible to obtain the degree of uncertainty of the sample data belonging to each category, which can more accurately reflect the nature of the actual data [20].

3.4. Clustering Objective Function. The objective functions of hard cluster analysis are as follows:

$$\left\{ \begin{aligned} J_1(U, P) &= \sum_{k=1}^n \sum_{i=1}^c u_{ik} (d_{ik})^2, \\ \text{s.t.} \quad &U \in M_{hc}, \end{aligned} \right. \quad (5)$$

where d_{ik} represents the distortion between samples x_k of the i type and the general samples of the i type. In most cases, the distance is measured based on the distance between the two vectors [21]. $J_1(U, P)$ represents the sum of squares of the samples of each category and their typical sample errors.

The general formula for measuring the distance between sample x_k and prototype p_i of the first-class cluster is defined as follows:

$$(d_{ik})^2 = \|x_k - p_i\|_A^2 = (x_k - p_i)^T A (x_k - p_i), \quad (6)$$

where A is a symmetric positive definite matrix of order $s \times s$.

The criterion of clustering is to take the minimum value of $J_m(U, P)$:

$$\min\{J_m(U, P)\}. \quad (7)$$

The constraint on the above extreme value is the equation

If the membership relationship between sample x_k and subset X_i ($1 \leq i \leq c$) is represented by the relationship function $\mu_{ik} = \mu_{X_i}(x_k)$, then the intrinsic function of partition μ_{ik} is a subset of X_i . In this way, the algorithm of the $\mu_{ik} \in \{0, 1\}$ set can also be represented by the member function X , that is, a matrix composed of the intrinsic functions of subset c . Among them, the first row of matrix U is the intrinsic function of the first subset, and the k column of the matrix is the member function of the sample relative to subset c [19]. Finally, the hard partition space of the data object set X is as follows:

$$\sum_{i=1}^c u_{ik} = 1. \quad (8)$$

Use the Lagrange multiplier method to solve u_{ik} and p_i .

3.5. Fuzzy C-Means Clustering Algorithm. In the total $X = \{x_1, x_2, \dots, x_m\}$ of the data in the sample, the FCM algorithm divides a group into different clusters $2 \leq n \leq m$, which are used to represent $A = \{A_1, A_2, \dots, A_n\}$ n clusters [22]. Finally, when the objective function J takes the smallest value (denoted as $J_{\min}$) or is lower than a certain set threshold, the clustering result is better. The FCM algorithm divides a group into different clusters, which are used for performance. The formula of the objective function is as follows:

$$J = \sum_{j=1}^m \sum_{k=1}^n (\mu_{jk})^c (d_{jk})^2, \quad (9)$$

and meet the following two constraints:

$$\left\{ \begin{aligned} \sum_{k=1}^n \mu_{jk} &= 1, \quad \forall j = 1, 2, \dots, m, \\ \sum_{j=1}^m \mu_{jk} &> 0, \quad \forall k = 1, 2, \dots, n. \end{aligned} \right. \quad (10)$$

where μ_{jk} indicates the degree of membership of x_j to A_k , that is, the proportion. c ($c \geq 1$) determines the ambiguity between categories. The larger the c value, the less obvious the boundary between different clusters. Many clustering algorithms work well on small data sets of less than 200 data objects; however, a large-scale database may contain millions

of objects, and clustering on such large data set samples may lead to bias of the result. We need clustering algorithms that are highly scalable.

Consider the set $\tilde{I}_j = \{(i, j) | x_j = v_i, 1 \leq i \leq c\}$; if $\tilde{I}_j = \emptyset$, there is

$$u_{ij} = \left[\sum_{i=1}^c \left(\frac{d_{ij}}{d_{rj}} \right)^{2/m-1} \right]^{-1}, \quad i = 1, 2, \dots, c; \quad (11)$$

$$j = 1, 2, \dots, n; \quad r = 1, 2, \dots, n.$$

If $I_j \neq \emptyset$, then u_{ij} is any nonnegative real number.

The flowchart of fuzzy C-means clustering algorithm to classify data is shown in Figure 1. The FCM algorithm first initializes the start center of the cluster, and the member matrix is also initialized, continuously changing the value of the cluster center until the set end conditions are met. The specific steps are as follows:

- (1) Set the center of the first cluster to c ($1 < c < n$); set the fuzzy index m ($1 \leq m < \infty$), convergence accuracy set, and initial iteration number $k = 0$
- (2) Calculate $U^{(k+1)}$
- (3) Calculate $V^{(k+1)}$ and then make $k = k + 1$

Repeat steps 2 and 3 until the termination condition is met:

$$\|V^{(k)} - V^{(k-1)}\| \leq \varepsilon, \quad k \geq 1. \quad (12)$$

The entire calculation process of the above algorithm is actually a process of repeatedly modifying the clustering center and dividing the matrix. After modifying these repetitions, the algorithm is satisfying that it can converge from any initial point along the iteration subsequence to the minimum point or saddle point of the objective function $J_m(U, P)$ [23–25].

3.6. Marine Environment Monitoring System. The business flowchart of the marine environment monitoring business is shown in Figure 2. Monitoring technology includes sampling technology, testing technology, and data processing technology. Before sailing, decide whether it is a temporary mission or a national mission based on the sailing mission. Different task categories determine different preparations. For the analysis of the components of pollutants in environmental samples and their state and structure, chemical analysis methods and instrumental analysis methods are currently mostly used. Observation and record work when going out to sea is the key to sampling and data recording and is the beginning of data processing for the entire marine environment. Software testing technology is an important part of the software development process. It is an activity process that runs through the entire software development life cycle and verifies and confirms software products (including phased products). Its purpose is to discover in software products as soon as possible. There are various problems such as inconsistency with user needs and pre-defined definitions. Not only the sampling information but also the blank sample information and parallel sample

FIGURE 1: Flowchart of data classification using fuzzy C-means clustering algorithm.

information collected on-site need to be recorded, [26, 27]. Considering the data itself, data mining usually requires 8 steps such as data cleaning, data transformation, data mining implementation process, pattern evaluation, and knowledge representation. After going to sea for data processing, the type and number of samples are required to be correct, and after the samples are fully confirmed, the calibration of the samples is completed [28]. Then, check the password of the sample. After the password is completed, it is necessary to add quality control samples to the samples whose number exceeds a certain limit [29]. Next, distribute circulation cards for analysis and testing, measure samples, and record the measured experimental results in the data record table [30].

4. Marine Environment Monitoring Experiment Combining Virtual Reality Technology and Fuzzy C-Means Clustering Algorithm

4.1. Experimental Environment and Data Set. The experimental test system environment is shown in Table 1. Android terminals use sample recording Qualcomm Snapdragon S4 Pro 1.5 GHZ MDM9215 quad-core processor, with Android 4.2 operating system.

The data set used in the experiment is shown in Table 2. The parameter values before measurement are $C=5$, weighted index $m=3$, maximum iteration number $t_{\max}=100$, and threshold $\varepsilon=1e-005$.

4.2. Server Configuration. The test server and client are composed of CPU P5 2.3 G, 2 GB memory, and 170 GB hard disk. In the test, the width and height of the image data were

FIGURE 2: System business flowchart.

TABLE 1: System environment.

Hardware environment	Processor	Qualcomm Snapdragon S4 Pro 1.5 GHZ MDM9215
	RAM	2 GB
	External storage	16 GB
	Screen size	10.1 inches
Software environment	Terminal	Android 4.2
	System client	Windows 7
	Server	Windows Server 2003
	Database	Microsoft SQL Server 2005

TABLE 2: Data set.

Type	Numerical value
Number of clusters	$C = 5$
Weighted index	$m = 3$
Maximum number of iterations	$t_{\max} = 100$
Threshold	$\epsilon = 1e-005$

selected as 6542 and 8842, the data format was BSQ and 6 frequency bands, and the length and width of the raster block were set to be the same.

4.3. Experimental Process.

- (1) Connect the multichannel data collector to the computer

- (2) Set the corresponding parameters in the server software so that the computer and the data acquisition circuit are in a communication state; then, the data acquisition system saves the collected network chemical electrical signals to the computer hard disk at set intervals
- (3) In order to verify whether the chemical signal measured by the system is stable, maintain the above

measurement state for at least 4 hours to facilitate the observation of data stability

- (4) Linearity detection: input high-precision current signal through the DC signal source and record the input signal value and the signal value measured by the system
- (5) CTD is connected to the data collector through the RS232 serial port, and the collected data is sent to the data collector CR1000
- (6) ADCP sends data through Bluetooth module and data collector CR1001

5. Analysis of the Impact of Virtual Technology and Fuzzy C-Means Clustering Algorithm on Marine Environment Monitoring

5.1. System Performance Test Analysis. Table 3 shows the statistics of the amount of downloaded data for different missions to the sea and the average time required for downloading. It can be seen from the table that the size of the downloaded data is about 5 MB, and the average download time does not exceed 2.5 s. There is a failure record when downloading the biological test task, which shows that the fluency and accuracy of this system are still lacking.

After the sampling and recording of the sea operations are completed, the amount of uploaded data and the average time for each sea mission are shown in Table 4. As can be seen from the table, the average data upload time is about 0.75 s. The time spent in the data upload process depends largely on the performance of the server. It can be seen that the server is very important for monitoring the marine environment.

It can be seen from Tables 3 and 4 that the average download time is 1.78 s and the average upload time is 0.75 s. The time consumed by downloading is greater than the uploading time. This is because the process of data uploading mainly depends on the running speed of the server, while downloading needs client to complete related work. For a single test project, the download time and upload time are within the acceptable range.

5.2. Analysis of the Impact of Virtual Reality Technology on Marine Environment Monitoring. Virtual reality technology enables people to monitor environmental problems on the sea in real time. You can see the situation of the marine environment within the monitoring range without personnel going to sea; when you go to sea, you can also use this technology to give feedback in real time and accurate problems to the base in real time. In order to speed up the processing of data, the complexity of the problem can be solved in a distributed scenario.

5.2.1. Data Feedback Efficiency. The comparison of data feedback efficiency between marine environment monitoring without using virtual reality technology and after use is shown in Figure 3. It can be seen from the figure that when virtual reality technology is not used, the time it takes for the

ocean environment monitoring data to return to the server is more than 1.3 s. After applying the two advanced technologies, the return efficiency is greatly improved, and the time consumed is 0.82 s. It can be seen that virtual reality technology greatly improves the information feedback speed of marine environment monitoring, which is of great significance to the management and control of the marine environment.

5.2.2. Data Accuracy. Marine environment monitoring requires high accuracy of data. If the sea-going personnel cannot return the actual situation of marine environment to the base or there is a big deviation in the information return, this will make the situation not able to be solved well. Virtual reality technology can simulate the marine environment, and people can observe the actual situation on the sea even if they do not go to sea. In addition, nowadays, environmental problems are increasingly prominent, and more and more people pay attention to them, so it is necessary to carry out real-time monitoring of the marine environment, but it is difficult to do it by manpower alone, so using virtual reality technology to simulate the marine environment can achieve real-time monitoring; once there are abnormal problems, measures should be taken immediately.

The comparison of data accuracy before and after the application of virtual reality technology is shown in Figure 4. It can be seen from the figure that, when not in use, the highest accuracy rate of the collected data is 78%, and the average accuracy rate is 71.5%, which brings about great inconvenience to the monitoring of the marine environment; and, after the application, the accuracy of the data has been significantly improved. The highest accuracy can reach 99%, which is more than 20% higher than that when it is not used. It can be seen that virtual reality technology can improve the accuracy of the collected data, thereby increasing the speed of people discovering problems and better solving problems.

5.2.3. Server Data Processing Capability. Figure 5 shows the comparison of the amount of data processed by the server after the virtual reality technology is not applied and the fuzzy C-means clustering algorithm and the application. It is not difficult to find from the figure that, when not applied, the amount of data processed by each server is between 7800 and 9200; after the application of virtual reality technology, the server's ability to process data is about 10,000; when the fuzzy C-means clustering algorithm is applied, the maximum amount of data processed by the server at one time is 13400. It can be seen that virtualization technology can improve the data processing capability of the server. For marine environment monitoring, the faster the server processes data, the faster the problem is discovered and the faster the problem is solved.

5.3. Analysis of the Impact of Fuzzy C-Means Clustering Algorithm on Marine Environment Monitoring. Fuzzy C-means clustering algorithm is an efficient way to process

TABLE 3: Data download times and average time.

Download task	Data size	Number of downloads	Number of failures	Average time
Water quality test	3.4 MB	20	0	1.33 s
Sedimentation test	4.5 MB	20	0	1.42 s
Biological test	5.1 MB	20	1	2.05 s
Organism test	2.9 MB	20	0	1.88 s
Blowdown test	3.1 MB	20	0	2.25 s

TABLE 4: Data upload times and average time.

Download task	Data size	Number of downloads	Number of failures	Average time
Water quality test	14.5 MB	20	0	0.77 s
Sedimentation test	22.8 MB	20	0	0.81 s
Biological test	10.7 MB	20	0	0.69 s
Organism test	9.2 MB	20	0	0.75 s
Blowdown test	MB	20	0	0.76 s

FIGURE 3: Comparison of information feedback efficiency before and after application.

data. Real-time monitoring of the environment will inevitably produce huge data. Relying solely on the server will make the whole process of processing data jammed and will even make the server paralyzed. Fuzzy C-means clustering algorithm can well divide the data, it uses the concept of membership degree to describe the degree of belonging of the object, and the range of membership degree value is 0-1. This method can effectively reduce the loss of data and improve the accuracy of environmental monitoring. More initial clustering centers can be set up in clustering for the problem of same object and different spectrum.

The feature space is divided into $8 \times 8 \times 8$ grids, the fuzzy weighted index $b=2$, the threshold $\varepsilon=0.001$, and the number of clustering centers $C=8$. The same object types are combined. 100 pixels are randomly selected to evaluate the accuracy of classification results of marine utilization, and the classification error matrix is shown in Table 5. It can be seen from the data in the table that the error value of some islands in the ocean is 78 due to the relatively variable environment, while the error value of aquatic organisms in the ocean is 82, because there are many uncontrollable factors in the marine organisms, so it is easy to produce relatively large errors in monitoring. The monitoring error value of aquatic plants is 90; because plants also have certain

variability, it is difficult to count the exact data. The highest monitoring error value of water body is 96. This is because of the strong mobility of seawater and the frequent changes of water body caused by human factors. Fuzzy c-average clustering algorithm can classify data sets. Fuzzy segmentation is based on the description of uncertainty of all categories, so the degree of uncertainty of each sample data belonging to each category can be obtained, which can more accurately reflect the nature of the actual data. In the result of segmentation, fuzzy segmentation also points out several continuous discretions between each part of segmentation and the periphery of segmentation and provides a lot of valuable details. Fuzzy C-means clustering algorithm transforms clustering into constrained nonlinear planning problem, which is an optimization problem. At the same time, the nonlinear planning classical mathematical theory is used to solve the problem. Finally, the purpose of data set fuzzy clustering is achieved by optimizing the solution. This method is easy to realize by programming. Therefore, with the development and progress of computer technology, this fuzzy clustering algorithm based on objective function has become one of the most popular research topics in the field of clustering. When monitoring the marine environment, there will be a huge amount of data, which requires that the

FIGURE 4: Comparison of accuracy of collected data before and after application.

FIGURE 5: Comparison of server's ability to process data before and after application.

TABLE 5: Classification error matrix.

Marine type	Islands	Water body	Aquatic organisms	Aquatic plant	Line total
Islands	78	2	3	21	104
Water body	3	96	1	1	101
Aquatic organisms	2	1	82	8	93
Aquatic plant	4	4	2	90	100
Column total	87	103	88	120	398

data processing performance of the server be very perfect; otherwise, it is easy to cause the server to crash because of the large amount of data, so it cannot solve the problems in time and effectively.

6. Conclusion

In this paper, in view of the problems of untimely information processing and slow data analysis in the current marine environment monitoring process, the application of

virtual reality technology and fuzzy C-means clustering algorithm in it can effectively improve the speed of data analysis. At the same time, the data loss is also significantly reduced. It can be seen that the fuzzy C-means clustering algorithm plays a significant role in the clustering analysis of data.

There are many potential crises in the current network environment, so a marine environment monitoring system capable of real-time online monitoring and remote data transmission has been developed. According to the actual

needs of users of the marine environment monitoring system, combined with virtual reality technology and fuzzy C-means clustering algorithm, it can strengthen the security of the system, complete the analysis of status information resources, deploy the security system, and implement multiple status monitoring. The service realizes the sharing of state information statistical analysis products.

Based on the application characteristics of the marine field, this article incorporates virtual reality technology into monitoring the state of the marine environment, intuitively expresses marine phenomena and structural characteristics, and provides visualization of the dynamic changes, historical reviews, and future evolution of marine phenomena. So, marine workers can intuitively and accurately understand the state of the marine environment and make correct decisions. The use of fuzzy C-means clustering algorithm to achieve data clustering analysis speeds up the process of data processing, allowing marine environmental monitoring personnel to detect and resolve anomalies as soon as possible.

Data Availability

The data that support the findings of this study are available from the corresponding author upon reasonable request.

Conflicts of Interest

The authors declare no potential conflicts of interest with respect to the research, authorship, and/or publication of this article.

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