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Research Article

Emotional Feeling Evaluation Model in Underwater Environment Based on Wearable Sensor

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Underwater sensor network technologies, as well as devices, are developing rapidly, and underwater IoT devices have been widely used in energy surveys, environmental indicator detection, military surveillance, and disaster event monitoring. The transmission of massive amounts of underwater data to the cloud for processing and analysis has become the dominant processing paradigm, and cloud computing has become a dominant computing paradigm. The preparation strategy of elastomer-coated hydrogel optical fibers for stable optical sensing proposed in this work opens up a new method and approach for developing low-cost and highly sensitive water flow sensors while analyzing the design of wearable smart devices to assess underwater environmental emotion perception evaluation schemes. In this paper, we propose a sensory data acquisition technique for event coverage detection of underwater environmental emotions, observing that an event may correspond to deviations from the normal sensory range of sensory data from multiple adjacent sensor nodes. Distributed edge computing is introduced to assume part of the cloud computing pressure, and an edge prediction-based data acquisition and sensing scheme for underwater sensor networks is proposed to realize the conversion of the acoustic communication transmission part of underwater data into data prediction transmission, thus reducing the energy consumption caused by acoustic communication. The model established in this paper effectively reduces sensor energy consumption while ensuring accurate data transmission and can respond to the underlying demand promptly, which is significantly better than the already existing schemes.

1. Introduction

Nowadays, IoT devices are widely introduced in the marine environment and are mainly applied to explore the development of monitoring and surveying in the ocean, mainly around the sensing layer, which has played an unparalleled role in promoting the development of underwater sensor networks in the ocean. With the cellular increase of IoT devices, underwater sensor networks are becoming more and more complex and varied, and the ocean has entered the era of big data with large volume, fast flow, diversity, and high value. The data collected in underwater sensor networks are often probing values, such as acidity, carbon content, and silicon content, which often reflect the condition of the seafloor, such as whether there is an oil leak or whether unusual elements are present [1]. At the same time, the mobile devices are mobile, portable, and instantaneously reachable, so that they can always be around the user, actively acquire and analyze user contextual data within a certain authority to sense contextual changes, analyze the needs of each user, predict the user's behavioral goals, and provide targeted information services, so that the context is fully integrated with the user's task goals to achieve natural interaction. Current research on mobile context awareness focuses on basic theoretical construction, technical support, and application exploration, with fewer mature, systematic products and services or solutions for common users, and the application areas of mobile context awareness need to continue to expand [2]. The gradual development of intelligent systems such as mobile context awareness has also put forward new requirements for human-computer interaction design, from microscopic to macroscopic, from interaction mechanisms to practical scenarios, from psychological to sociological levels, and from human-computer interaction to human-computer coexistence. Researchers have explored various ways to identify emotional states in interactions, mainly focusing on facial expression understanding, speech acoustic feature understanding, body movement understanding, physiological signal understanding, and textual emotion understanding [3]. From the mathematical point of view, low-frequency sensor data is a series of nonstationary, time-varying processes of time-series waveform data. The feature extraction method of low-frequency data has many similarities with the feature extraction of audio signal. They first calculated time-frequency-domain eigenvalues and then calculated the mathematical-statistical feature of these eigenvalues. Emotional signals are mainly induced based on materials such as videos, pictures, and texts, and the data they acquire mainly include videos, speech, and pictures, which are limited to the existing technical conditions; there are still a huge amount of shortcomings in acquiring the emotions of the underwater environment.

This paper presents a sensory data collection technique for event coverage detection of underwater environmental emotions, observing that an event may correspond to deviations from the normal sensory range of sensory data of multiple neighboring sensor nodes. In this study, we will start from the actual scene where the user wears the wearable device and study the user's emotional state during the underwater process in the case of the wearable device, which is closer to the actual underwater state. The physiological signal systems used in these studies are limited by the functional configuration of the devices themselves and do not allow for effective expansion, such as the creation of physiological signal databases and the design of underwater activity content regulation systems.

2. Related Studies

Although continuous research over the years has improved the performance and robustness of underwater communication transmission systems, the harsh environment underwater makes no exact communication scheme be optimally implemented, so how to deliver data to the cloud promptly while minimizing network energy consumption during underwater data collection is a critical issue for underwater data transmission.

Literature [4] is a collaborative data acquisition approach for AUVs, and an AUV-assisted efficient data acquisition routing protocol (AEDG) is designed. The member nodes associate the gateway nodes with the shortest path and deliver the packets to the AUVs through the gateway nodes. This method can effectively reduce the energy consumption of the nodes on the one hand and is prone to hot zone problems on the other hand. Cengiz and Demir [5] improved the AEDG and proposed a scalable and efficient data collection routing protocol (SEDG). In SEDG, AUV dynamically allocates the sojourn time of GNs based on the number of received packets and the number of associated member nodes. Compared to AEDG, SEDG has higher energy efficiency and scalability. A hybrid data collection approach emphasizing data importance is proposed in literature [6]. The nodes forward important data to the appropriate layer through multiple hops to reduce latency, and commonly, the data are collected by an underwater vehicle AUV in a spiral trajectory from the bottom to the top. This scheme balances the energy consumption of the entire network nodes, improves networking survival, and ultimately reduces the latency of important data. However, it does little to reduce the energy consumption and latency of the entire network because of the small percentage of important data. In literature [7], the DBP sensing data prediction technique is proposed with the main purpose focused on the processing of new data. The core idea of DBP is to use a simple model to capture the data trends and a resilient rule to calculate and deal with the presence of disturbances at the same time. It is required that the user can change the parameters to control the model, such as choosing to use short-term or long-term historical data for training, provided that they have the historical data collected by the sensor nodes as samples. Ding et al. [8] investigated the application of skin conductance, skin temperature, and respiration rate in driver's emotion recognition and designed experiments to find the relationship between skin conductance and so on and two emotions: fear and fun. The experimental results demonstrate the feasibility of monitoring drivers' emotions using the selected physiological parameters. Literature [9] used a network of body sensors to acquire physiological signals from participants while the network was wirelessly connected to a PDA-like device and implemented an online emotion detection algorithm on the device. The key to literature [10], which inferred human emotions based on RF signals reflected from participants' bodies, was an algorithm designed to extract the heartbeat from the wireless signals with an accuracy comparable to that of ECG devices. The obtained heartbeat is then used as a feature for inferring emotions.

Literature [11] investigated users' acceptance of two interaction modes, active control and passive acceptance, in context-aware systems. It was found that users usually need a strong sense of control, and personalized features and services can enhance the user's sense of control; however, users are also willing to give up part of the sense of control in some cases, such as better privacy and security of the system and higher usability. Sherman et al. [12] proposed fuzzy tuning complementary filtering algorithm, which uses a fuzzy inference table to adjust the filter parameters in real-time. Occhiuzzi et al. [13] proposed a nonlinear complementary filter based on SO(3) and verified the feasibility of the algorithm for low-power embedded platform applications. The complementary filtering algorithm is simple in structure, small in computation, and suitable for low-power embedded platforms, but the accuracy is not as good as Kalman filtering. The correlation of six different emotions defined in literature [14] extracts 12 correlation features of accelerometer, gyroscope, and touch screen and concludes that simple touch behavior on a smartphone has the potential to identify the emotional state of the user. Han et al. [15] found that an application implemented on the camera of a smartphone based on photoelectric volume tracing technology could accurately measure a person's heart rate, and the study replicated classical psychological experiments where heart rate measurement using a smartphone application was effective in identifying two emotions, anger and happiness.

3. A Model for Evaluating Data on Emotional Feelings in the Underwater Environment

3.1. Low-Frequency Data Processing Methods. In the underwater environment, according to the digital sampling frequency of the sensors, the behavioral data with a sampling frequency of 100 Hz and the environmental and physical sensor data with a sampling frequency of 0.1 Hz are uniformly classified as low-frequency data in this paper. The behavioral data are mainly the three-axis gyroscope and three-axis accelerometer three-dimensional spatial data generated by the wrist motion, and the synthetic acceleration and synthetic gyroscope scheme are used in this paper for the sake of feature extraction simplicity. The environmental sensor data mainly contain ambient air pressure, ambient temperature, and light intensity, which do not change abruptly, so the sampling frequency is set relatively low. Somatic data mainly include the temperature and humidity of the skin surface, and these sensor data can directly measure the physiological indicators of the wearer [16]. From a mathematical point of view, low-frequency sensor data are a series of time-series waveform data of nonstationary, time-varying processes, and the low-frequency data feature extraction method has much in common with audio signal feature extraction, both calculating time-frequency-domain eigenvalues first and performing mathematical-statistical feature calculations on these eigenvalues.

As shown in Figure 1, the processing flow of low-frequency sensor data such as behavioral, environmental, and physical signs can be divided into a total of four steps. To offset the influence of the stationary state in long time experiments, this paper proposes the preprocessing method of debase; that is, first collect a set of sensor data under a completely stationary and quiet environment, calculate the baseline value of various features, and use a long time experimental data to subtract this baseline value first and then do the feature extraction in the later order. First, the analog data collected from the behavioral, environmental, and physical sensors are discretized at different frequencies to convert the low-frequency sensor data into discrete digital signals, then white noise and interference in the stationary environment are removed by preprocessing with debase and sliding window, then eight time-domain features and nine frequency-domain features are calculated offline on the computer, and finally, the extracted and calculated time- and frequency features are subjected to mathematical and statistical feature. Finally, the extracted time and frequency features are subjected to mathematical-statistical features, such as maximum value, plural, and minimum value. The final mathematical secondary statistical features will be correlated with the mental health questionnaire scores, PCA feature compression analysis, logistic regression linear classification analysis, and integrated learning model decision fusion analysis based on Boosting method.

There is no absolute criterion for the selection of clinostat feature values, and the main basis for our selection is the results of preexperiments and the feature sets used by researchers with better results in sentiment computation [17]. If a large number of features are extracted, on the one hand, this will increase the difficulty of classification and bring about a "dimensional disaster," and on the other hand, an unselective increase in the number of features may lead to the inclusion of redundant and relevant features, which may lead to wrong experimental results.

The signal amplitude area refers to the sum of the area enclosed by the discrete data and the horizontal time axis, and this feature is more obvious in the stationary and motion states, as shown in the following equation, where t denotes the time corresponding to a frame of discrete low-frequency data.

$$S_{\text{sigma}} = \frac{1}{t}\int_0^T [x(t) - \gamma(t)]\mathrm{d}t + C. \tag{1}$$

According to the amplitude statistical feature, let $M(i)$ be the frequency amplitude of the ith window after the FFT transformation, and N denotes the number of windows; then several statistics of the amplitude statistical feature are calculated as follows:

$$\sigma = \mathrm{Kx}\cdot\sum_{i=1}^{N}\left[M(i) - \gamma(t_0)\right]^3. \tag{2}$$

On this basis, the discrete data FFT transformed spectral waveform area is S, which is calculated as

$$S_{\text{FFT}} = S_{\text{sigma}} + \sigma\cdot\frac{n!}{i!(n-i)!}. \tag{3}$$

When calculating the eigenvalues of behavioral sensor data, to ensure the accuracy of the features while also being able to reduce the complexity of the calculation, this paper uses synthetic acceleration and synthetic gyroscope to calculate the time- and frequency-domain eigenvalues in the following manner:

$$\omega = \sqrt{\sum_{i=1}^{N}\left(\frac{i - S_{\text{sigma}}}{\sigma}\right)^3} + \lambda_{\text{shape}}. \tag{4}$$

After extracting the time-domain and frequency-domain features of low-frequency sensing data, we can find more perceptual information of behavioral, environmental, and somatic signals [18]. To counteract the influence of the stationary state in long time experiments, this paper proposes the preprocessing method of debasing, that is, at first collecting a set of sensor data in a completely stationary and quiet environment, calculating the baseline value of various features, and using a long time experimental data to subtract this baseline value first before doing the feature extraction in the later order, and it is experimentally verified that the preprocessing method of debasing can reduce the influence of the stationary state and quiet environment.

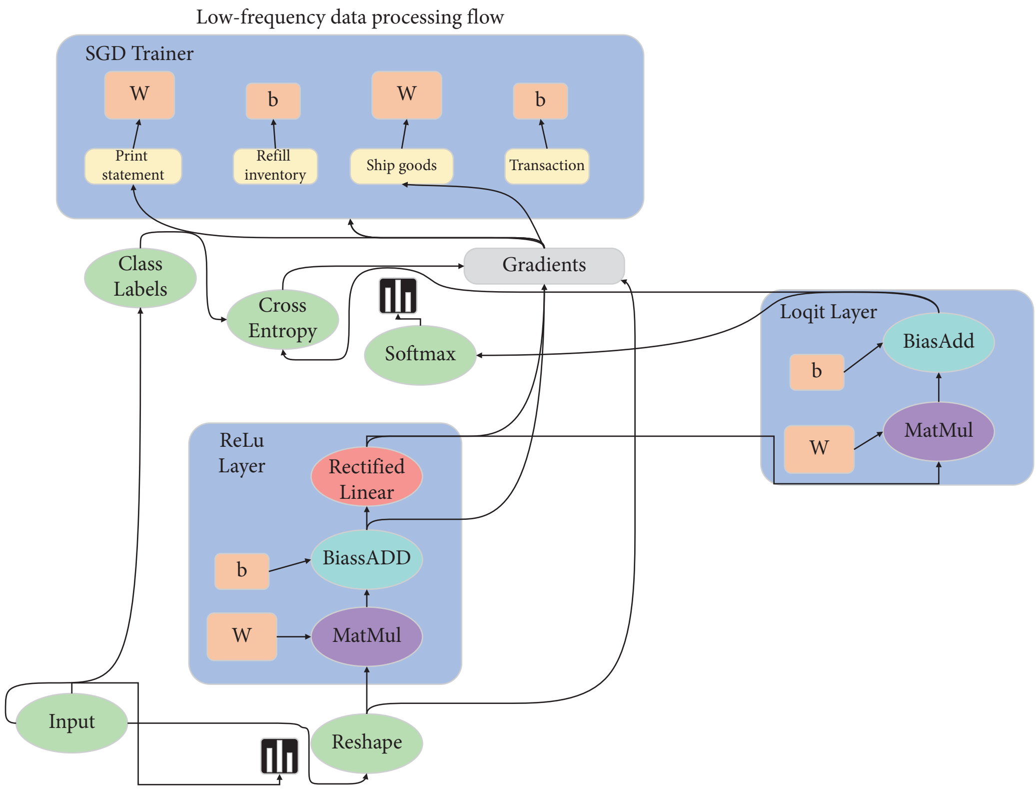

Figure 1: Low-frequency data processing flow.

3.2. A Technical Route to Edge Computing-Based Data Acquisition for Underwater Sensor Networks. The energy of the underwater nodes is mainly consumed in sending/receiving data by the UWM2000H; for example, the bottom node performs sending/receiving data with about 100 times the energy consumption of the microprocessor operation, so the key to extending the lifetime of the underwater nodes is how to reduce the amount of data sent. Thus, it is proposed that the bottom and edge layer nodes perform prediction algorithms to reduce the energy consumption of the bottom nodes during underwater data collection. At the same time, for the characteristics of cloud edge end, a suitable scheme such as the bottom layer prediction stage mainly considers the characteristics of the bottom nodes such as weak computing power and power storage or nodes are not easy; the edge layer considers the characteristics of AUVs distributed deep under the sea, which need to consume more energy to move and transmit data, and the selected model should be maximized to ensure the prediction accuracy. In response to the need for energy consumption for data transmission from underwater nodes, this thesis evolves the data transmission process into a data prediction model to minimize the energy consumption of sensor nodes. Two-level prediction is carried out, using an exponential smoothing algorithm as well as an extended Kalman filter moving the average autoregressive model to unfold separately, using the computational performance at the edge as well as the collected data to perform predictive analysis of underwater environmental mood data and analyze potential hazards promptly. The technical route of the study is shown in Figure 2.

In the traditional method, the data are obtained underwater, the bottom node transmits to the upper layer through the routing protocol, each forwarding node in the routing path acts as a relay node, then each node consumes energy to receive and send data in the forwarding process, and the node easily becomes a full shutdown node, because of the possibility of movement of underwater nodes, which increases the risk of packet loss. Moreover, when the data are transmitted to the cloud layer, there are multiple levels of multinode forwarding from the underwater device to the cloud layer with a huge delay [19]. Therefore, for the data transmission from the bottom node, an exponential smoothing calculation that can be done layer by layer is used to weaken the impact due to random factors and determine the data trend, thus getting more accurate predicted values. In the process of this interaction, a two-way mechanism is designed to ensure accuracy, with the bottom node as the transmitter and the edge mobile device as the receiver, and to ensure the accuracy of the data, the bottom node discriminates the error and feeds it back to the receiver.

Considering that the AUV is subject to its gravity and the buoyancy of the water, the direction of the AUV will deviate from the intended shortest path, and eventually, the AUV will not reach the intended target cluster head node; especially, the greater the external force is, the further the AUV will deviate from the intended target. The larger the external force is, the farther it deviates from the intended target. Therefore, it is important to keep the AUV moving on the intended path. To solve this problem, a simple and effective velocity synthesis algorithm is proposed in this paper. The edge layer can analyze

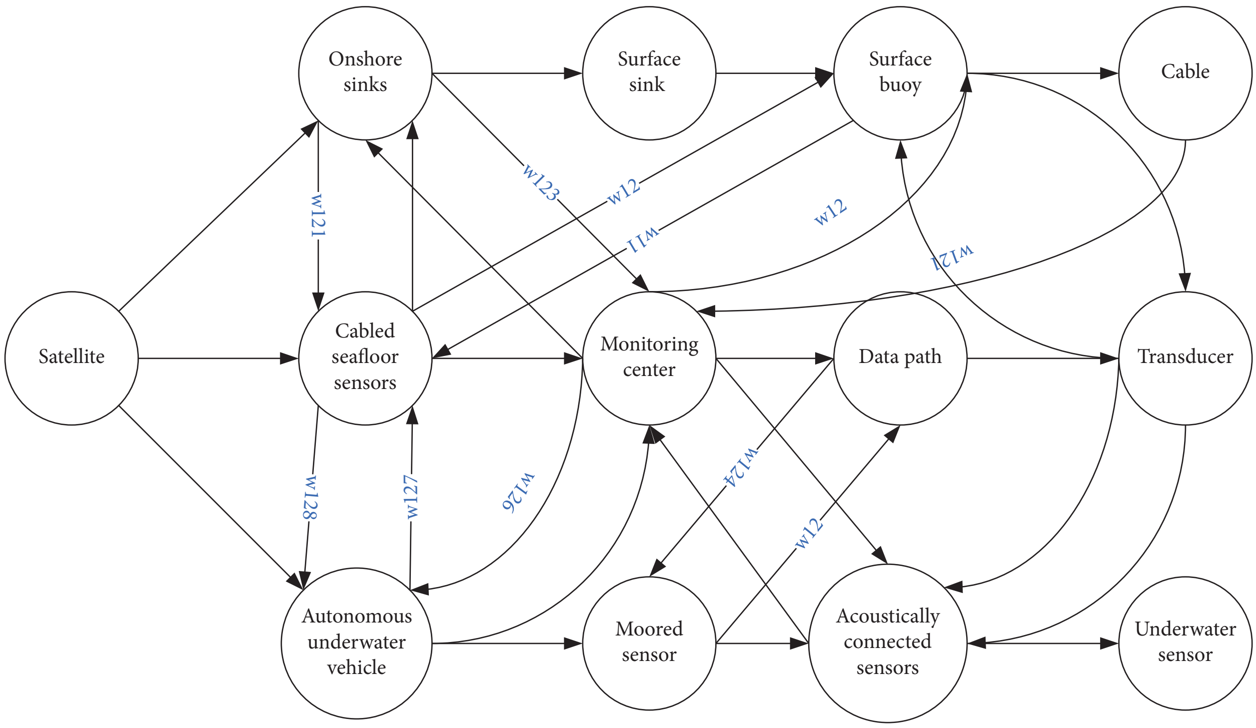

Figure 2: Technical route of predictive sensing model for underwater sensor network data.

the next cycle of underwater environmental emotion data for the data of this cycle, and this stage involves the edge layer as well as the cloud layer, so to get the underwater environmental emotion data situation timely and accurately; we propose a numerical prediction framework based on edge computing and deep learning; after getting the data in the edge layer, the data will be put into the deep learning algorithm for multilevel circulation to get the next cycle of underwater environmental emotion. Therefore, for the data transmission from the bottom node, exponential smoothing can be used layer by layer to weaken the effects caused by random factors and to determine the data trend to obtain more accurate prediction values. In this interaction, a two-way mechanism is designed to ensure accuracy, with the bottom node as the transmitter and the edge mobile device as the receiver, and to ensure the accuracy of the data, the bottom node discriminates the error and gives feedback to the receiver. In this framework, the edge settings are mainly taken care of by the computationally powerful base station and the surface buoy, with the AUV playing a supporting role. Parameterized sink velocity information, including the magnitude and direction of the sinking velocity, can be set. In addition, the implementation of the motion model is based on the case where the AUV is controllable. The velocity magnitude of the AUV and the magnitude and direction of the sinking velocity to which the AUV is subjected are known, and the direction of motion of the AUV is controlled to ensure that it is feasible to visit the target on the desired path.

The underwater wireless sensor network involved, which consists of nodes statically placed at different depths in the ocean, collaboratively detects the ocean conditions. The UWSN is divided into two layers based on the node properties and locations, namely, the edge layer and the sensing layer. The edge layer consists of surface aggregation nodes, surface buoys, and mobile nodes AUVs configured with radio as well as acoustic transceivers; the sensing layer consists of common sensor nodes at the depth of the ocean.

When the data collected by the bottom node n_i per unit time has to be delivered to the aggregation node s_k, it will incur forwarding data energy consumption M_{send}; when n_i acting as a relay forwarding node, it will incur receiving data energy consumption M_{receive}; therefore, assuming that the energy value of the node n_i is E_{n_i}, the remaining energy value can be obtained as

$$E_{\text{rest}} = E_{n_i} + \frac{M_{\text{receive}} \cdot \sum_{i=1}^{N} n_i \cdot E_i}{M_{\text{send}}}, \tag{5}$$

when computing power allows, dynamic optimization using gradient descent can solve the constraints imposed by fixed values, where the loss function is expressed as the following equation:

$$\text{Loss} = \frac{\left(x_i - V_i^T\right)^2}{2}. \tag{6}$$

To minimize the energy consumption of underwater sensor nodes, that is, to maximize the residual energy of the network, it is urgent to satisfy

$$E_{\text{total}} = \sum \left[E_{\text{rest}} + \left(M_{\text{receive}} + M_{\text{send}}\right) \cdot n_i\right] + E_{\text{loss}}, \tag{7}$$

where E_{loss} is the nontransmission loss energy, to reduce the energy consumption of the underwater sensor node; that is, the value of needs to be E_{total} minimized; that is,

$$\frac{\mathrm{d}E_{\text{total}}}{\mathrm{d}t} = -\left(x_i - V_i^T\right)\frac{\partial^2 V}{\partial x^2} = 0. \tag{8}$$

From the above algorithm idea, it is clear that the AUV and the node use adaptive exponential smoothing to predict the data before the end of the T_{th} cycle, and the determination of the coefficient α in exponential smoothing is crucial to determine the relationship between the historical and predicted values, which determines the accuracy of the prediction, considering the computational capacity of the bottom node in the underwater environment, and the efficient determination of the coefficient value can reduce the energy consumption of the underwater bottom. Combining the data prediction model with underwater data transmission, the edge device is used to predict the estimated value of the next cycle of sensor readings, and the error threshold is used to determine the accuracy of the predicted value and thus whether the collected data need to be sent. This scheme saves transmission energy and extends the node lifetime [20]. Due to the weak computational power of the underlying nodes, the accuracy of the selected prediction model cannot be guaranteed, and in case of errors, the delay increases, and half the effort is made.

4. Design of a Wearable Sensor-Based Model for Evaluating Emotional Feelings in Underwater Environments

Context-aware technology has brought some impact on the interaction of mobile devices; for example, mobile devices can actively obtain contextual information, implicitly provide services to users, free users from some tasks, and have the remaining attention to deal with other tasks; the interface level may be "a thousand people," adaptive adjustment, and so on, which all pose new challenges to interaction design and interface design. This poses new challenges to interaction design and interface design. At the same time, it is also necessary to avoid the occurrence of phenomena or experiences such as information overload, low user involvement, and interruptions in traditional HCI systems.

With the advent of the intelligent era, implicit interaction has become an important research area of the human-computer interaction experience. By the evolution of traditional HCI systems to context-aware systems, the input and output of the system are implicit, and the original process of perceiving the environment by the user and adjusting the input according to the output is left to the context-aware computing system. The traditional interaction process is mostly command-based, in which the user actively and explicitly inputs commands through hardware devices such as key-win or touch, gesture, and voice, and the system/device performs the task according to the commands, which is called explicit interaction. Implicit interaction, on the other hand, has no explicit user instructions and is often referred to as invisible interaction, where the user no longer thinks too much about how to use the device or system during the interaction, but the wearable device actively and implicitly recognizes and analyzes the user's behavior and implicitly executes the analyzed concluding instructions. Interruptibility is an important topic in the field of computer-supported collaborative work and human-computer interaction. Broadly it refers to the condition that people are willing and able to handle interruptions even if they occur in a way that may interfere with the active process. Implicit interaction, on the other hand, has no explicit user instructions and is often referred to as invisible interaction, meaning that the user no longer thinks too much about how to use the device or system during the interaction; instead, the wearable device actively and implicitly identifies and analyzes the user's behavior and implicitly executes the analyzed concluding instructions. The subject has attracted more attention especially after the emergence of notifications as an interaction mechanism on smartphones. In context-aware systems, many tasks require judgments and commands from the user, and currently, the system chooses to use explicit ways to alert or ask the user to respond. If the output method is sporadic and inappropriate, it will not only cause disturbance to the user and interrupt the main task currently performed by the user but may also affect the user's attention situation and even mental emotions, reducing the efficiency and accuracy of the user in performing the task.

The wearable sensor-based human motion capture system consists of several sensor nodes fixed on the human limbs, convergence nodes, and the upper computer software as shown in Figure 3. The sensor nodes are worn on the human limbs, such as limbs, head, and chest, utilizing elastic bandages for capturing the motion data of each limb. To improve the comfort of wearing the system, the curvature is done on the back of the sensor node. The node is the bridge between the sensor nodes and the computer and is responsible for establishing, configuring, and managing the entire sensor node network and ensuring the synchronization of data from each node. The aggregation node collects the motion data of all the sensor nodes at regular intervals and then packages and sends the data to the computer according to a certain format or it can be stored offline in the memory card. The host computer software receives and parses the human motion capture data sent by the aggregation nodes, completes the reconstruction of the human motion in combination with the human kinematic model, and drives the 3D human model to display the human motion synchronously.

To meet the applications in different fields and scenarios, technical specifications such as the number of sensor nodes, data update frequency, and system latency should be fully considered during the system solution design [21].

4.1. Number of Sensor Nodes. The location and number of sensor nodes deployed on the human body are directly related to the level of granularity of human motion capture. To capture richer human motion information, the number of sensor nodes needs to be increased. However, too many sensor nodes increase the pressure on the system data transmission and processing, which affects the update frequency and real-time performance of the system. The

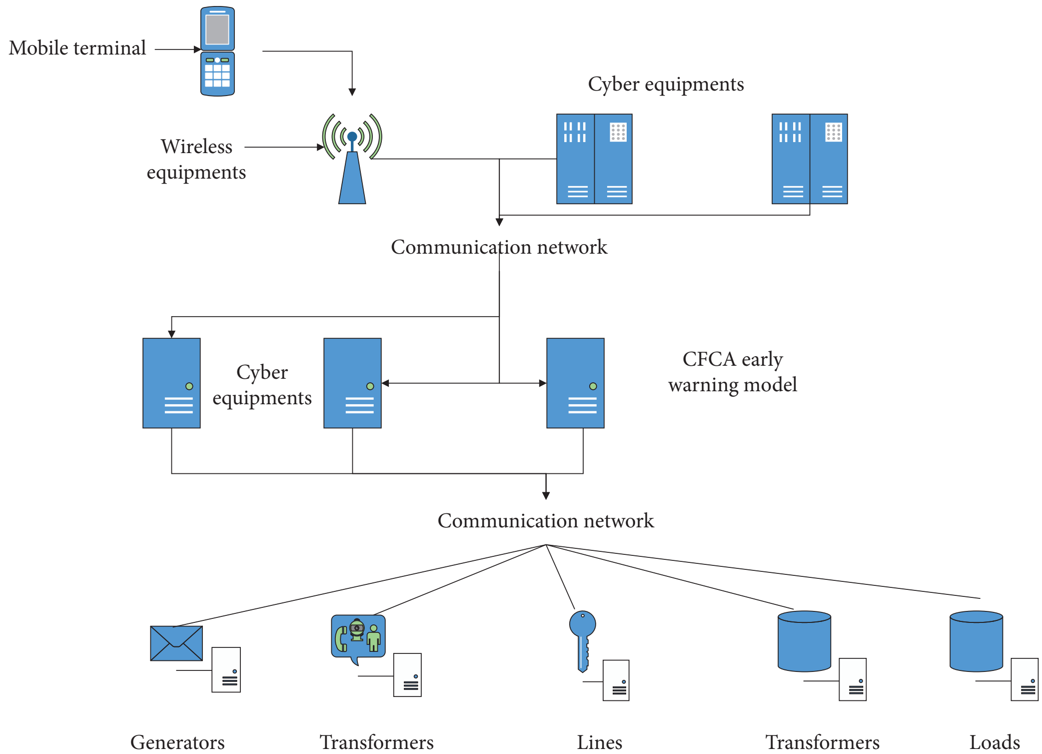

FIGURE 3: The framework of human motion capture system based on wearable sensors.

motion capture system designed in this paper can support up to 20 sensor nodes, which can be flexibly configured according to the application requirements to meet the needs of different users.

4.2. Frequency of Data Update. Typically, the human eye recognizes coherent images at a minimum speed of 24 frames per second, and coherent images at or above this speed will not feel jarring when viewed by humans. The higher the data update frequency, the higher the fluency of the captured human action but the greater the system data transmission and processing pressure. The data update frequency of the human motion capture system designed in this paper is divided into 50 Hz, 100 Hz, and 150 Hz. The communication network should be designed according to the maximum number of sensor nodes and greater update frequency to ensure sufficient network bandwidth and data throughput. Attitude and position solving are performed directly in the sensor module so that only the final results need to be transmitted without transmitting the raw sensor data, thus reducing the amount of data transmission and transmission latency.

4.3. System Delay. The time delay of the motion capture system contains the following components: transmission time from the sensor node to the aggregation node, data processing time at the aggregation node, transmission time from the aggregation node to the computer, and processing time at the computer. For motion capture systems, low latency and high response rate are critical metrics. The segmentation method based on simple thresholds is easy to implement, but it is prone to misclassification. If the threshold is set too small, the jitter of the limb will be recognized as a valid action segment; if the threshold is set too large, some actions with relatively small action amplitude will be ignored. To improve the success rate of human action segmentation, the sliding window threshold segmentation method is used to achieve the segmentation of action segments. In many application areas of motion capture, such as virtual reality and human-computer interaction, there is a high requirement for the latency of the system. The design latency of this system is less than 20 ms, so it is important to coordinate all aspects of the design and establish a precise time synchronization mechanism to compress the latency of each aspect to the maximum.

The data transmission of the system can be divided into two phases: the first phase is from the sensor node to the aggregation node, and the second phase is from the aggregation node to the host computer. The connection between sensor nodes and aggregation nodes is divided into wired and wireless solutions. The wired connection connects all the sensor nodes in series through cables, which can complete the data transmission and power supply of the sensor nodes at the same time. Sensor nodes do not require integrated charging modules and batteries, which can greatly reduce their size and weight. The wired connection has a fast and stable data transmission speed, and high data security is less susceptible to interference from the external environment and simple communication protocol. To facilitate the connection between the sensor node and the aggregation node, this design uses a four-prong headphone plug and socket as the connection interface. In the subsequent design, the sensor nodes can be combined with the clothes, and the connection cable can be embedded into the clothes, thus improving the comfort and convenience of wearing the system.

At the same time, to improve the reliability of the system data transmission, the corresponding transmission protocols are designed for each of the two data transmission stages. The data transmission from the sensor nodes to the aggregation node uses the UART interface, and one UART interface of the aggregation node can connect several sensor nodes in series. To prevent communication confusion, each sensor node has a unique address. The data transmission from the sensor nodes to the aggregation node uses a rotational communication mechanism. At each acquisition cycle, the aggregation node sends data transmission instructions to each sensor node in turn according to its address, the sensor node receives the instruction and compresses it with its address, and if the address matches successfully, it sends data to the aggregation node according to the instruction.

5. Experimental Verification and Conclusions

5.1. Human Action Segmentation Based on Sliding Window Threshold Segmentation Method. Human action segmentation is the separation of valid action segments from continuous acquisition data, which directly affects subsequent action recognition and classification. The segmentation method based on simple thresholding is easy to implement, but it is prone to misclassification. If the threshold is set too small, the jitter of the limb will be recognized as a valid action segment; if the threshold is set too large, certain actions with relatively small action amplitude will be ignored. The underwater wireless sensor network is mainly based on acoustic waves as the physical carrier of wireless transmission, through the scattered in a wide range of static-dynamic sensor nodes to collect information, the functions of data acquisition, transmission, processing, and can be integrated. To improve the success rate of human action segmentation, the sliding window threshold segmentation method is used to achieve the segmentation of action segments. The segmentation threshold ξm can be determined by the amplitude of the pose fluctuation of the limb while remaining at rest as follows:

$$\ddot{x} = \frac{\delta y}{\delta x}\left(\gamma\sqrt{y^2 + x^2} + y^3 + c\right). \tag{9}$$

The motion window threshold segmentation method uses a sliding window with a width of γ and sliding step size c to determine the segmentation point of the human action. A binary state is defined by comparing the amplitude of the pose fluctuation within the sliding window with the segmentation threshold. When more than y y % of the sliding window exceeds the segmentation threshold, the state is defined as 1; when less than (100-y) % of the sliding window exceeds the segmentation threshold, the state is defined as 0; in other cases, the state of the current sliding window remains the same as the state of the previous window. A quantity percentage threshold y is a real number within 0–160, which can be determined experimentally. When performing human action segmentation, the start point of the action is determined first, and then the endpoint is determined. A change in the state of the sliding window from 0 to 1 is the starting segmentation point of the action, and a change in the state of the sliding window from 1 to 0 is the ending segmentation point of the action, as shown in Figure 4.

Next, the collected action sequences are initially screened to filter out the unqualified action sequences. Normally, the duration of normal actions should be kept within a certain range, and action sequences that are too long or too short, which may be irregular movements of the limb, should be discarded so that meaningless calculations can be avoided. Since the gesture measurements of human limbs are relative to the geographical coordinate system, the gesture motion sequences of the limbs will differ when the human body performs the same action in different orientations, and the relative motion of the limbs involved in the action is used to describe the human action. Based on the limb's gesture measurements, the sequence of joint angular motions corresponding to the body's movements $(X_1, \ldots, X_n)$ or the relative gesture motion trajectory of the limb can be obtained $(K_1, \ldots, K_n)$.

5.2. Validation of Human Emotional Feelings. In the user-related recognition experiments, multiple recognition tests were conducted for each experimenter separately, and then the average recognition rate of all experimenters was used as the final experimental result. A side-by-side comparison of Figure 5 reveals that the recognition rate based on the gestural gesture signal is the highest, which is due to the high accuracy of the gesture measurement based on multisensor fusion and the small reconstruction error of the gestural gesture trajectory. The recognition rate based on the acceleration signal is the lowest, which is because the changes in both the gesture and linear acceleration of the arm during motion affect the accelerometer measurement, and there is a large measurement noise and error in the gesture acceleration sequence.

By comparing Figure 5 vertically with the same number of nodes, the network life cycle of this algorithm is much higher than the other three algorithms. Our proposed algorithm updates the cluster head node every round so that the node with the highest energy is the cluster head, and each member node finds the closest cluster head node to itself, saving the energy consumption of forwarding data to the cluster head node and thus balancing the network energy consumption. In the user-unrelated gesture recognition test, the gesture samples of all experimenters are combined. For each gesture, 30 samples were randomly selected as training samples, and the remaining 270 samples were used as test samples. The user have different recognition rates for

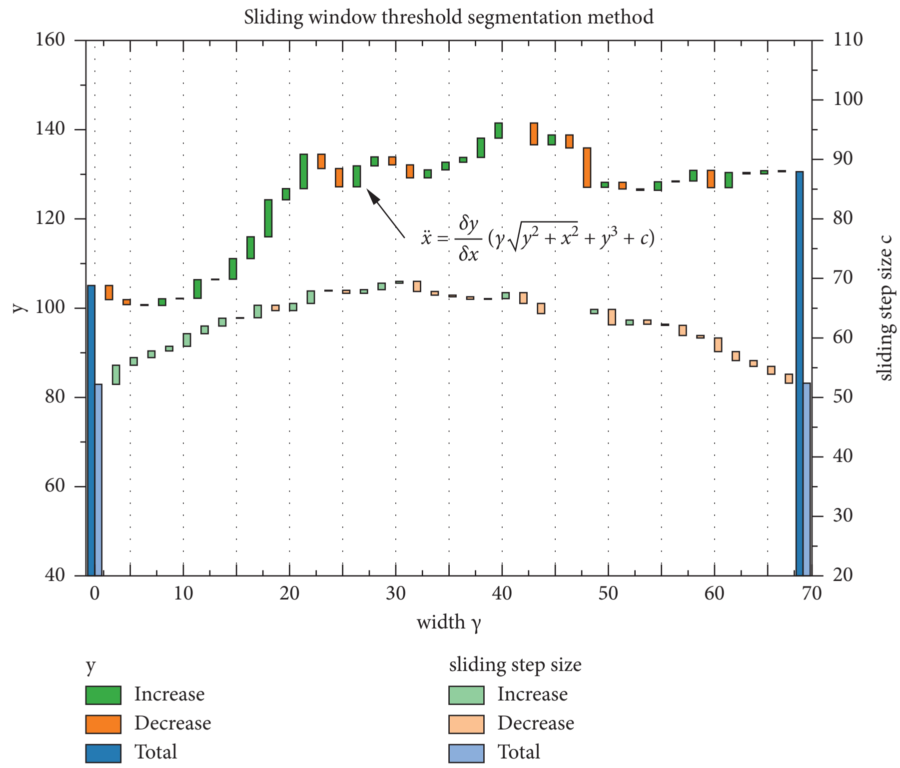

Figure 4: Human action segmentation based on sliding window threshold segmentation method.

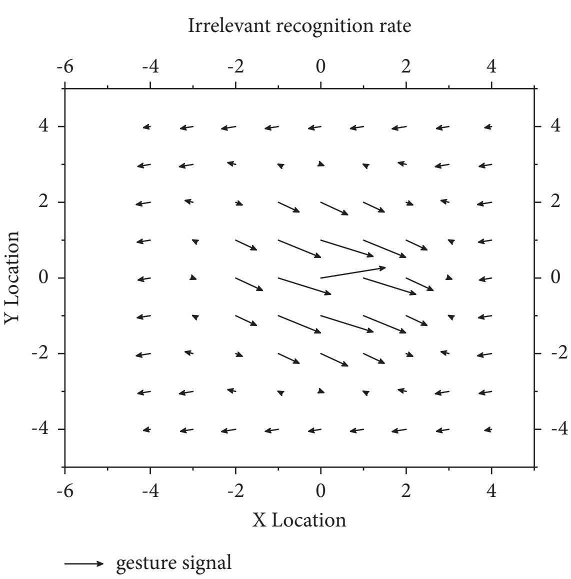

Figure 5: User irrelevant recognition rate.

different gesture signals and gesture templates. The comparison shows that, with the same gesture signal and gesture template, the user irrelevance recognition rate is somewhat lower than the user relevance recognition rate. Since the variability of gestures of different experimenters is much greater than that of the same experimenter, the gesture templates cannot characterize the gestures of all experimenters, and therefore a decrease in recognition rate occurs. The user irrelevant recognition experiments with gestural gesture signals and the ADBA time-series averaged template selection method had the highest recognition rate of 96.9%, a 2.3% decrease relative to the recognition rate used for irrelevance.

Based on the mature evaluation systems of usability, satisfaction, and user experience, combined with the relationship models of experience factors proposed by researchers for context-aware systems or other intelligent systems, indicators suitable for evaluating mobile context-aware systems are extracted.

Certain remarks on the extracted indicator categories can be used as a reference when naming factors distilled from multiple indicators in the later factor analysis. There is no absolute standard for selecting the values of the clinically sensitive features, and the main basis for our selection is the results of preexperiments and the feature sets used by researchers with better results in sentiment computing. If a large number of features are extracted, on the one hand, this will increase the difficulty of classification and lead to a "dimensional catastrophe," and on the other hand, an unselective increase in the number of features may lead to the inclusion of redundant and relevant features, which in turn may lead to erroneous experimental results. Energy consumption and acquisition is the most difficult problem to solve. Sensor nodes are randomly arranged underwater, and since node supply is only provided by batteries, replacing batteries to replenish power is difficult. At this stage of the study, the seven sets of features mentioned above were selected as the feature set to ensure the correctness of the final results. After the normalization process, all the obtained 84 sets of GSR values all fall between 0 and 1, and the

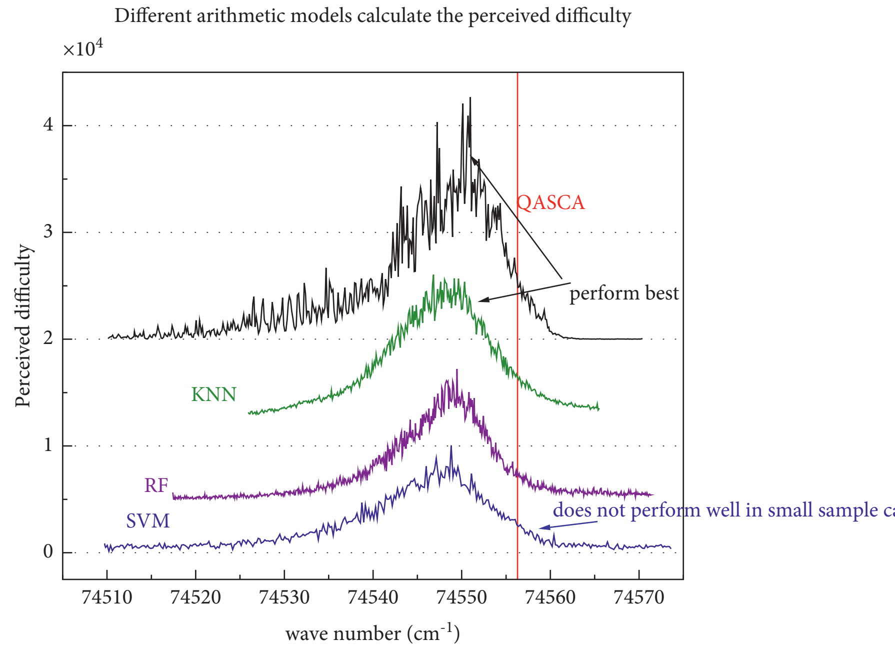

Figure 6: Different arithmetic models calculate the perceived difficulty of users.

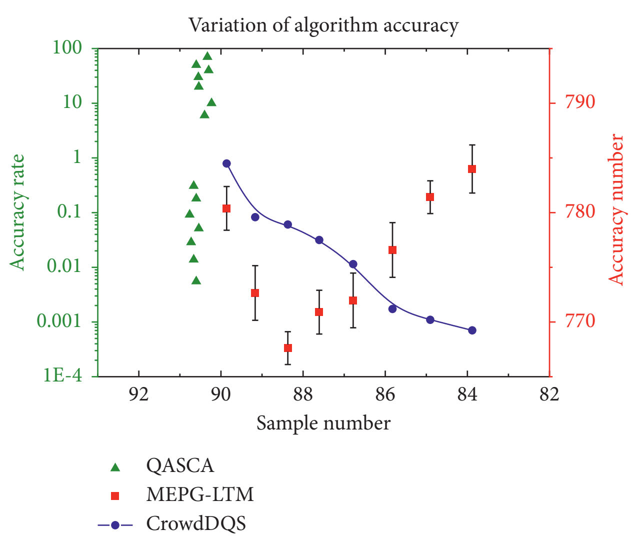

Figure 7: Variation of algorithm accuracy with the upper limit of task assignment.

variability of different experimental subjects can thus be offset, as Figure 6 shows.

Analyzing the above results can find that, compared to RF and SVM algorithms, KNN and QASCA algorithms have the best performance, and the overall correct recognition rate of the user's emotional state by a dermal electrical signal is maintained at about 60% and 70%, considering that, in the process of research, the average weight method is used for the feature selection of dermal electrical signal, and then the features are weighted with different weights. The performance of SVM is the worst, mainly because SVM is suitable for machine learning with a huge sample size and does not perform well in small sample cases. As for the prediction of H user affective states, it was found that the best performance was obtained for the prediction of perceived difficulty and relatively poor for the judgment of perceived stress and interest level.

In Figure 7, we compare the performance of various online task assignment algorithms on the Bluebird dataset when the task assignment limit is changed from 10 to 100. We can observe that QASCA possesses optimal performance. Specifically, the accuracy of QASCA first increases rapidly as the capacity increases and then slowly decreases as the capacity exceeds 50. We also note that its number of allocations first increases and then rapidly decreases after reaching a peak. One possible reason for this is that as the upper limit of tasks that users can accept grows, highly qualified users will complete more tasks. Since observations from high-quality users can significantly improve the quality of the data, low-quality users will be assigned fewer tasks, so the number of assignments decreases from 1438.1 (capacity = 50) to 686.3 (capacity = 100). The significant reduction in task assignment results in only a slight decrease of 0.176% in the accuracy of QASCA.

Compared to QASCA, we find that MEPG-LTM uses only 81.77% of the number of tasks assigned by the QASCA algorithm at a capacity of 50 and achieves a higher accuracy (0.832% higher) than the QASCA algorithm. When the capacity is 100, the accuracy of MEPG-LTM is 0.285% higher than the accuracy of the QASCA algorithm, while the number of tasks assigned to the MEPG-LTM algorithm is only 39.69% of QASCA at this time. Compared with the suboptimal performance comparison algorithm CrowdDQS, MEPG-LTM shows a significant disadvantage in both accuracy and number of assignments. For how to predict the next cycle of water quality data after obtaining it at the edge and how to efficiently transmission to the cloud layer, we can consider the neural network of deep learning with higher accuracy. However, due to the complexity of water quality prediction, only one neural network model often cannot completely solve the problem. To improve the reliability of data prediction, in the case of sufficient computing power at the edge layer, a combined prediction model is introduced, which can further improve. To improve the reliability of data prediction, in the case of sufficient computing power in the edge layer, a combined prediction model is introduced, which can further improve the accuracy of water quality data.

6. Conclusions

With the rise of IoT, the scope of cloud computing is becoming more and more extensive, it is gradually difficult to meet the demand of timely response of the bottom layer and to bear the pressure of the high load of data transmission, and the volume size and the number of types of underwater data are increasing. In this thesis, distributed edge computing is introduced to solve the problems of energy consumption, timely response, and evaluation of the emotional feeling of the underwater environment in the bottom nodes. To avoid the use of acoustic communication data transmission from the bottom sensor nodes to the AUV, a data prediction acquisition mechanism based on edge devices and bottom sensors is proposed. The problem of underwater energy consumption is mathematically problematized based on the environmental structure of the underwater bottom sensors, and the adaptive exponential smoothing algorithm and the idea of bidirectional prediction are elaborated to develop the first level of underwater data transmission. The proposed scheme is proven to maximize the residual energy of the nodes. Aiming at the heterogeneity of devices in the IoT environment, the ARMA prediction models with extended Kalman filtering algorithm between AUV and aggregation nodes are used to carry out two-way prediction, the selection of parameters and error analysis are introduced in detail, and the experiments show that the prediction effect is good and the accuracy is high. Meanwhile, comparing the schemes of AUV-assisted data collection, multihop routing, and DBP and discussing them in terms of node mortality, node energy consumption, and time delay, the results all show that the two-level prediction transmission scheme performs well and is, on balance, more suitable for data prediction transmission in underwater sensor networks, so that the required data can be obtained at the edge end.

Data Availability

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

Conflicts of Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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