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A Distributed Sensor System Based on Cloud-Edge-End Network for Industrial Internet of Things †

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Abstract: The Industrial Internet of Things (IIoT) refers to the application of the IoT in the industrial field. The development of fifth-generation (5G) communication technology has accelerated the world's entry into the era of the industrial revolution and has also promoted the overall optimization of the IIoT. In the IIoT environment, challenges such as complex operating conditions and diverse data transmission have become increasingly prominent. Therefore, studying how to collect and process a large amount of real-time data from various devices in a timely, efficient, and reasonable manner is a significant problem. To address these issues, we propose a three-level networking model based on distributed sensor self-networking and cloud server platforms for networking. This model can collect monitoring data for a variety of industrial scenarios that require data collection. It enables the processing and storage of key information in a timely manner, reduces data transmission and storage costs, and improves data transmission reliability and efficiency. Additionally, we have designed a feature fusion network to further enhance the amount of feature information and improve the accuracy of industrial data recognition. The system also includes data preprocessing and data visualization capabilities. Finally, we discuss how to further preprocess and visualize the collected dataset and provide a specific algorithm analysis process using a large manipulator dataset as an example.

Keywords: data generation; Industrial Internet of Things (IIoT); data acquisition; distributed sensors; feature fusion

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1. Introduction

1.1. Background

In recent decades, the world economy has developed rapidly and entered the information age. With continuous innovation in communication technology, the Industrial Internet of Things (IIoT) has been growing rapidly. The IIoT integrates the industrial Internet, next-generation information technology, and industrial systems. It can effectively reduce production costs without compromising production efficiency, as shown in Figure 1. The IIoT is considered the foundation of the future industrial system. However, along with the increased productivity, the IIoT generates massive, high-dimensional, and heterogeneous real-time data. This poses challenges, especially for large enterprises or companies, as ineffective data processing can have detrimental impacts. To address these challenges, advanced technologies are needed to promote efficient and reliable IIoT networks [1].

These technologies encompass industrial data collection and storage, data conversion and transmission, data preprocessing, data visualization, and data analysis [2–4].

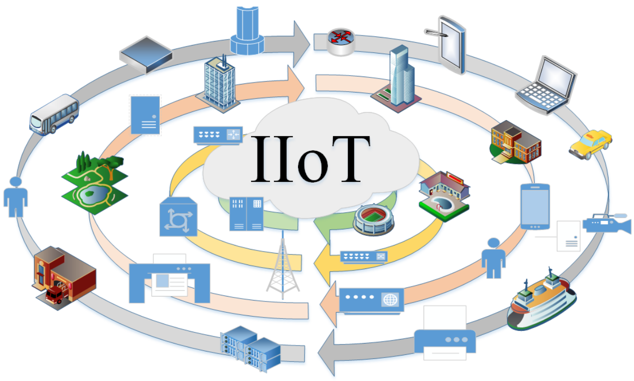

Figure 1. In the context of the Industrial Internet of Things, large amounts of multidimensional data have been generated.

The IIoT is driving the trend of processing data at the network edges to reduce latency and improve efficiency. However, this also requires careful data management outside the core data center to avoid data corruption and adverse effects. The continuous innovation of distributed sensor network (DSN) technology further advances the development of the IIoT. DSN technology overcomes many challenges posed by traditional on-site embedded industrial gateways connecting to industrial sites. Moreover, DSNs are widely used due to their significant advantages, such as flexible nodes, reliable transmission, multiple data transmission paths, and simple network layout [5]. In multisensor information fusion systems, both centralized and distributed architectures are commonly employed [6–9]. In a centralized data fusion structure, sensor data are sent directly to the data fusion center for processing, which minimizes information loss. However, it also has drawbacks, such as complex data interconnection, poor reliability, and high computing and communication resource requirements. In a distributed fusion architecture, each sensor has its own processor to process its own information and sends the processed data to the data fusion center for fusion [10].

1.2. *Challenges*

The biggest challenge at present is that current technologies and schemes cannot reasonably and effectively process the large amount of data generated in the industrial field. There are two technical schemes for processing industrial data at this stage. The first involves accessing industrial sites using embedded industrial gateways and collecting data through serial ports and servers [11–13]. The second scenario involves using a data terminal unit (DTU) to collect data and transfer them transparently to the cloud. However, both data collection schemes have many drawbacks:

- High complexity of development: IIoT devices come with various I/O mechanisms due to their different types and development protocols, leading to diverse interfaces for communication between hardware and software. The communication between different devices can result in varying data structures, posing challenges for data integration and processing.
- Low development reuse rate: The lack of standardization in software and hardware is a common challenge in the IIoT field. With diverse industrial environments, constant efforts are required to develop and adapt new hardware and software solutions, leading to resource waste and high costs.
- Poor maintainability and mobility: The reliance on gateways for data collection and storage in the IIoT can result in limited independence between devices and applications. This can lead to maintenance challenges in case of any issues.

- Poor privacy: The hardware equipment was acquired from a manufacturer. However, the cost was high and it is tightly integrated with the manufacturer's platform, which limits the user's control over data management.
- Datasets are too simplistic: Collecting data from different sensors using multiple devices can result in higher operating costs and more cumbersome processes.

In order to solve the above problems, this paper proposed a new technical scheme based on the original scheme and combined with multisensor information fusion technology. The scheme is based on distributed sensor data generation and the fusion of a smart cloud edge network. The scheme is equipped with a data generation device, which is easy to install, has strong signal penetration, and has low delays and low energy consumption. Compared with traditional data collection schemes, this method has the following advantages:

- Low complexity of development:The data collection and transmission devices utilize a unified I/O mechanism, development protocol, and data format type, which enables efficient and accurate communication between the hardware and software due to the same model being used.
- High development reuse rate: Users can adjust the peripheral devices of the equipment to suit different industrial scenarios, without the need for a redevelopment of the hardware, communications, and software.
- Good maintainability and mobility: The dataset generator has a small and easy-to-install shape, with strong independence that eliminates the need for a gateway and simplifies later debugging and maintenance of the data collection process.
- Good privacy: The hardware equipment used in this scheme is self-developed, giving users complete control over the collection and transmission of datasets without any restrictions from intermediate manufacturers in terms of data storage and transmission.
- Diversity of datasets: The collection device is capable of collecting and storing data information from various sensors simultaneously. Afterwards, mature synchronization algorithms can be used to create a more standardized dataset.

1.3. Contributions

This paper presents a distributed sensor data generation and fusion system based on a cloud edge network. The main contributions of this work can be summarized as follows:

- This paper presents a distributed sensor self-network, which challenges the traditional edge sensor-central computer network method. It uses a three-level network approach that integrates cloud server platforms to optimize the network structure. It solves the problem of the high cost and low reliability of existing data collection schemes in the current Industrial Internet of Things environment.
- The scheme realizes the real-time monitoring of industrial field data and visualizes them in various dimensions, levels, and granularities. It helps enterprises make better decisions and manage industrial sites.
- The system is equipped with an advanced data preprocessing system that can use neural networks to clean, filter, and tag data. The system can generate complete industrial datasets and make them public, which solves the problem of the current lack of datasets in the Industrial Internet of Things.

The rest of this paper is structured as follows: In Section 2, we present the system model of the distributed smart cloud edge network. Section 3 describes the system architecture of the distributed sensor system. We then introduce the feature fusion of multisensor data from distributed sensors in Section 4. In Section 5, we summarize the main contributions and conclusions of this paper.

2. Related Works and Research Gaps

Multisensor information fusion technology has been widely adopted in industrial data processing [14,15]. The use of data fusion for data collection and processing has proven to be an effective solution for improving datasets. Deep learning, a complex machine learning algorithm, has made significant contributions to information fusion, data mining, and related fields [16–27]. By implementing complex machine learning algorithms through deep learning, improved performance can be achieved. Recently, deep learning has been utilized in developing and processing industrial data. In [28], data fusion technology is employed for processing industrial data, but the method does not guarantee an improvement in dataset accuracy. In [29,30], an end-to-end processing method for industrial datasets based on the convolution neural network is designed, but the method has a low convergence rate and difficulty in processing large data. In [31], a data monitoring algorithm based on the capsule neural network is presented, and in [32], a multiscale convolution recursive neural network is used for multi-industry data monitoring. Finally, in [33], a new mobile edge framework based on the Industrial Internet of Things is proposed.

3. System Model and System Architecture

The data acquisition and transmission model of the Industrial Internet of Things is one of the hottest issues in the current research field. We have broken away from the traditional way of networking, the "edge sensor-Central computer". As shown in Figure 2, a three-level networking model of distributed sensor self-networking and networking with cloud server platforms is presented. The model is composed of three parts: a dataset collector, repeater, and server. In this model, the most important part is the data collection module, which consists of two small modules. They are a wireless communication module and a data fusion module.

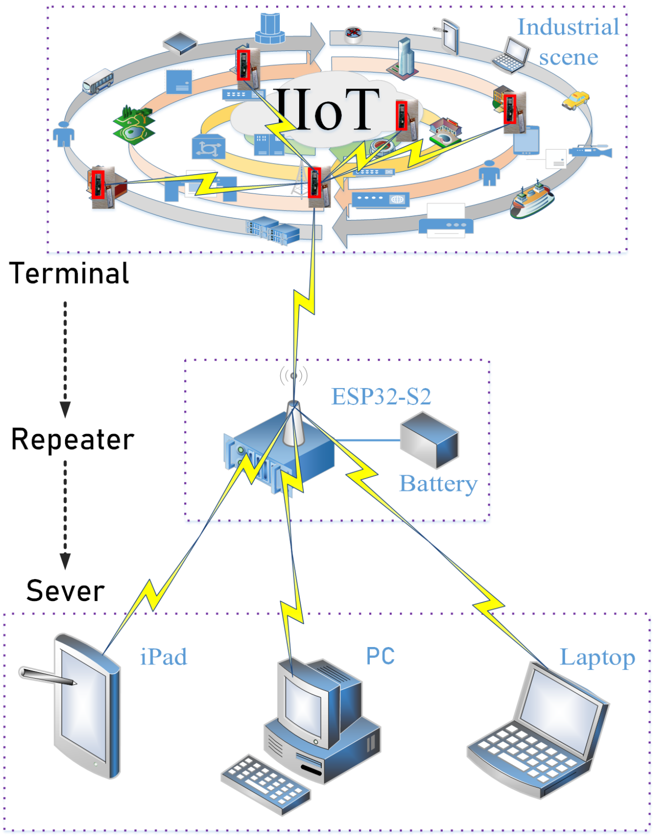

Figure 2. System model based on cloud-edge-end network.

3.1. Wireless Communication Module

The sensor module consists of multiple distributed sensors that are heterogeneous in nature. The module can gather data from various types of sensors, ensuring the reliability and richness of the data. By preprocessing and fusing different types of data, we can achieve more accurate results. For our study, we chose to use sound sensors and acceleration sensors, which we will experiment with, as outlined in [34]. To save channel resources and reduce costs, the local preprocessing and classification of sensor signals are necessary. The wireless signal $s(k)$ received by the hotspot can be expressed as

$$s(k) = x(k) + e(k), k = 0, 1, \cdots, N-1, \tag{1}$$

where $x(k)$is the collected data transmission signal, which transmits binary data and artificial noise. The binary data signal is mainly composed of an amplitude modulation (AM) signal, frequency modulation (FM) signal, two-phase shift keying (2FSK) signal, and four-frequency shift keying (4FSK) signal. $e(k)$ represents artificial noise in IDWSN and can be described as alpha-stabilized noise [35]. The wireless communication module uses the amplitude and phase of the electromagnetic wave to transmit information, including the binary data transmitted. Radio electromagnetic waves are a form of transmission of signals and energy that is used to transmit data between our sensors. The repeater receives the energy of the electromagnetic wave and obtains the transmitted binary data by identifying the amplitude and phase of the electromagnetic wave.

The advantage of the AM signal is that the receiving equipment is simple, but the disadvantage is that the power utilization rate is low, the anti-interference ability is poor, and the frequency band utilization rate is not high. The AM signal can be expressed as

$$w(t) = A\cos[2\pi f_c t + \phi(t) + \phi_0] \tag{2}$$

where A represents the instantaneous amplitude of the signal, ϕ_0 denotes the modulation phase, f_c stands for the carrier frequency, and θ is the carrier initial phase. The AM modulation signal can be represented as

$$A = m_0 + m_t \tag{3}$$

where m_T is the baseband modulated signal of the signal, and m_0 represents the dc component of the signal. The FM modulation signal is represented as

$$A = 1. \tag{4}$$

Digital modulation has better anti-jamming performance, stronger anti-channel loss, and better security. Its baseband waveform can be expressed as

$$w(t) = \sum_n a_n g(t - kT) \tag{5}$$

where $a_N$is the symbol parameter sent by the transmitter, $g(t)$represents the equivalent filter module in the transmission process. MPSK signals can be written as

$$w(t) = Ae^{j(2\pi f_c t + \varphi_i)} \tag{6}$$

where $varphi_I$ represents the phase modulation function and where the phase of the carrier is proportional to the instantaneous value of the modulated signal. The modulation function is given by

$$\varphi_i = \frac{2\pi i}{M}, i = 0, 1, \ldots, M-1. \tag{7}$$

Multiamplitude shift keying (MASK) signals are a type of digital modulation technique that uses multiple amplitude levels to represent digital data. This technique is commonly used to transmit digital information over various communication channels, such as radio, optical, and coaxial cables. MASK signals are widely employed in wireless communication, satellite communication, digital TV broadcasting, and other similar applications. MASK signals are represented as

$$w(t) = Ae^{j(2\pi f_c t)}. \tag{8}$$

Multifrequency shift keying (MFSK) signals are a digital modulation technique that uses multiple frequencies to transmit data. This technique is a form of frequency shift keying (FSK), where each symbol is represented by multiple frequencies, enabling higher data rates than traditional FSK. MFSK signals are widely used in various applications, including radio communication, satellite communication, and digital audio broadcasting. MFSK signals can be represented as

$$w(t) = e^{j(w_c t + 2\pi f_i t)} \tag{9}$$

where f_i represents the frequency of the modulation. The AM and FM spectra of single tone modulation are shown in Figures 3 and 4.

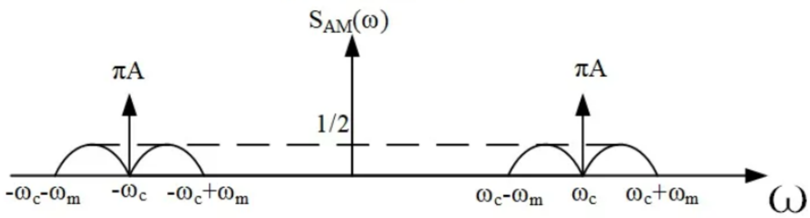

Figure 3. AM spectrum of monotonic modulation.

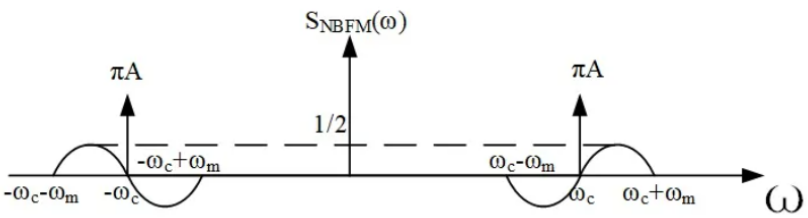

Figure 4. FM spectrum of monotonic modulation.

Distributed sensors are equipped with more powerful data processing units, enabling them to process data independently and filter out valid information. Additionally, they are equipped with high-power transmission antennas that rely on WiFi networks to transfer collected industrial data to a central computer in the cloud through a hotspot device. To ensure the uninterrupted operation of the sensor network for an extended period without replacing batteries, it is not practical for the collector to rely solely on battery power. We must also employ advanced power technologies, such as solar panels and lithium batteries.

The wireless communication module is capable of transmitting networked information and serves as the entry point for various smart terminals to access the Industrial Internet of Things. It plays a vital role in connecting the perception layer and network layer of the Industrial Internet of Things [36,37]. The wireless communication module serves as the system terminal, belongs to the hardware link at the bottom, and is irreplaceable. We connect a high-power external antenna to the wireless communication module to efficiently transfer industrial data to cloud servers using the 5G network.

3.2. Data Fusion Module

The data fusion module is responsible for preprocessing sensor data by cleaning up invalid binary data collected by sensors and integrating results from different sensors. Multisensor information fusion technology is suitable for processing multimodal data formats, enabling the fusion of different levels and forms of data information.

Multiple sensor information fusion (MSIF), also known as information fusion technology, initially had its roots in military applications. However, with the continuous improvement and upgrade of industrial systems, this technology has been extended to the civil field for use in medical diagnosis, mechanical fault diagnosis, air traffic control, remote sensing, intelligent manufacturing, intelligent transportation, industrial intelligent control, and criminal investigation. As a frontier technology, both military and civil systems are inclined to use data fusion technology for comprehensive information processing. In the era of knowledge explosion, data fusion technology plays a critical role as it helps to avoid the issue of rich data but poor information.

Data fusion is a multilevel automatic information processing process that utilizes information from various sources, modes, times, places, and expressions to obtain an accurate description of the perception object. Multisensor data fusion involves using different sensor observation information to automatically analyze and synthesize the observation information of multiple sensors obtained over time through a certain method to obtain more effective information.

This data collection model is based on the data layer fusion of multisensor information fusion technology. It involves collecting data from multiple sources, detecting and analyzing the collected data signals, and then fusing the data from multiple sensors. The Bayesian solution is used for data fusion, as shown in Figure 5, which requires that both sensors have available information [38].

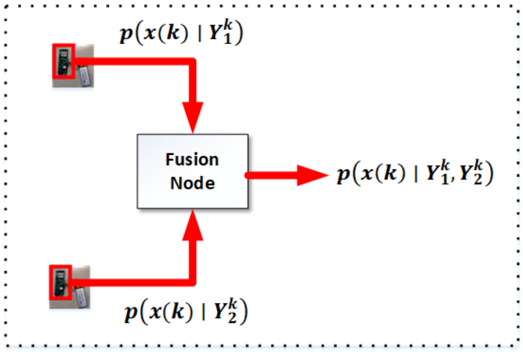

Figure 5. Schematic diagram of multisensor information technology in data layer fusion.

The probability density function can be expressed as

$$p\left(x(t) \mid Y_1^t, Y_2^t\right) = p(y_1(t) \mid x(t))p(y_2(t) \mid x(t))\frac{p\left(x(t) \mid Y_1^{t-1}, Y_2^{t-1}\right)}{p\left(y_1(t), y_2(t) \mid Y_1^{t-1}, Y_2^{t-1}\right)} \tag{10}$$

where $p(y_1(t) \mid x(t))$ and $p(y_2(t) \mid x(t))$, respectively, represent the available information of the two sensors. $p\left(x(t) \mid Y_1^t, Y_2^t\right)$ represents the result of the data fusion of two sensors at time t. $p\left(y_1(t), y_2(t) \mid Y_1^{t-1}, Y_2^{t-1}\right)$ represents the joint likelihood function of two independent sensors. The joint likelihood function of two independent sensors is the product of the likelihood functions of each sensor.

The most crucial step for fusion is to calculate the scores based on the data collected by the sensor

$$\frac{p\left(x(t) \mid Y_1^t\right)}{p\left(x(t) \mid Y_1^{t-1}\right)} \text{ and } \frac{p\left(x(t) \mid Y_2^t\right)}{p\left(x(t) \mid Y_2^{t-1}\right)} \tag{11}$$

Data layer fusion provides a wealth of accurate data and enables the easy extraction of data details without losing any information. It is essential to effectively and intelligently fuse the outputs of sensors to achieve optimal performance.

3.3. Hardware Architecture

As shown in Figure 6, the Inter-Integrated Circuit (I2C) is a communication protocol used to transmit data between integrated circuits on a circuit board. The ESP32-S2 is a low-power, WiFi-enabled microcontroller with a built-in 240 MHz Xtensa core, making it suitable for IoT applications. The use of I2C+ESP32-S2 technology provides a reliable and efficient way to collect, preprocess, and visualize data in industrial settings, as illustrated in Figure 7.

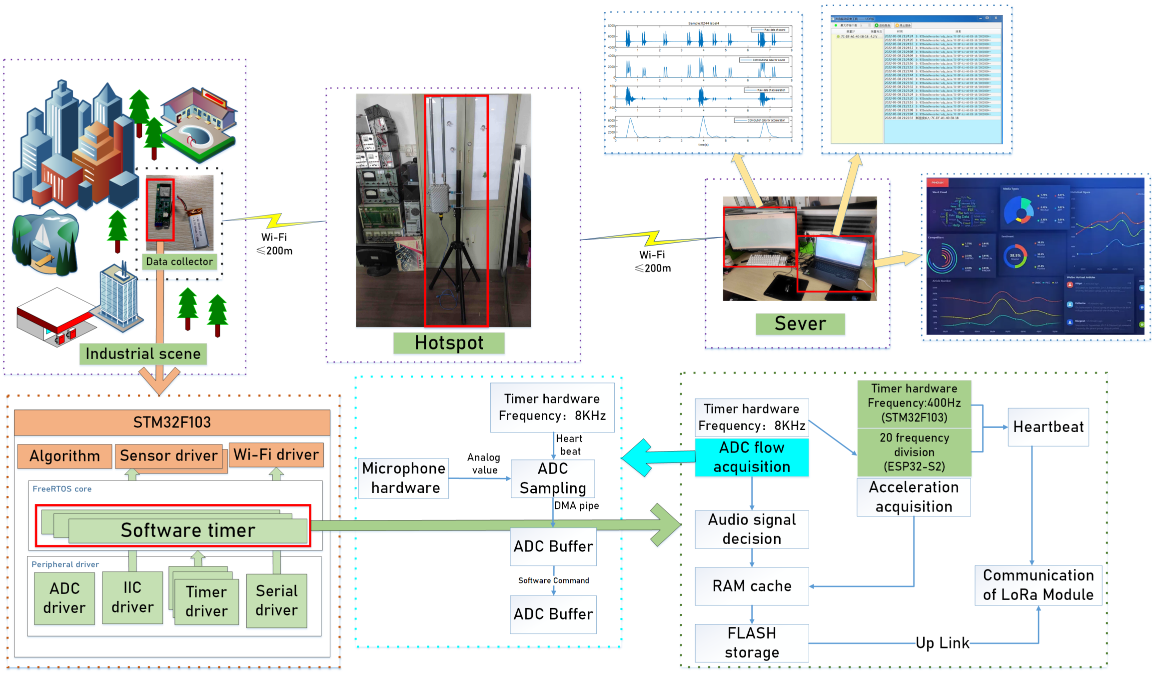

Figure 6. Schematic diagram of data acquisition in an industrial setting: IIC and ESP32-S2, with STM32F103 chip as the core collector and ESP32-S2 as the repeater.

Field studies are important to ensure that the data collection system is able to meet the needs of different industrial settings. The examples provided, such as industrial robot failure monitoring, large manipulator actuator failure monitoring, distributed smart gear box count monitoring, and the online working condition monitoring of a steam turbine generator set, demonstrate the versatility of the system in different applications [39]. In addition, the system can also be used in geographically challenging environments, where it may be difficult for humans to monitor the industrial scenes manually.

The dataset generator is designed to create a customized shell based on specific conditions. For instance, if the dataset is intended for underwater scene collection, the shell will be adjusted to account for waterproof performance, density, and other physical characteristics. Similarly, if the dataset is intended for the fault monitoring of a large manipulator actuator, the housing's fixed device will be upgraded to match the manipulator's specifications. The dataset generator can be installed at a specific location on the arm without disrupting its normal operation, and it can collect and transmit data as needed.

We evaluated several development board chips and ultimately chose the STM32F103 as the core chip for our dataset generator. The STM32F103 stands out for its powerful ARM core microcontroller, which features either 64 or 128 K bytes of flash memory. Additionally, the STM32F103 boasts low power consumption, built-in controllers, and other features that make it an ideal choice for our project. It offers numerous communication interfaces, including a Universal Serial Bus (USB) and a Controller Local Area Network (CAN), as well as seven timers and two ADCs. It also features a dual timer that allows us to collect sound signals at 4 KHz and acceleration signals at 800 Hz. Overall, the STM32F103 provides the necessary capabilities for our dataset generator while also minimizing power usage and maximizing functionality.

Figure 7. We have conducted field research on such scenarios as industrial robot fault monitoring, large mechanical arm actuator fault monitoring, distributed intelligent gearbox counting monitoring, online condition monitoring of steam turbine generator set, etc.

To collect sound signals, analog signals are first converted using operational amplifiers and then sampled through the MCU's built-in analog converter. For acceleration signals, an external three-axis acceleration sensor is used to collect and transmit data to the MCU via the I2C communication protocol. After analyzing the requirements of our users, we determined that the I2C protocol was sufficient for our needs. To support additional serial port protocols, we also added support for the DTU transfer module. This module can read data from subordinate devices and enable the system to interact with a wider range of devices. For ease of operation and configuration, we chose the JSON format as the configuration standard. This format is easy for users to read and modify and for programs to analyze.

FreeRTOS is a leading real-time operating system (RTOS) developed by major chip companies and distributed under the MIT open-source license. It offers excellent reliability and ease of use and includes a core and various libraries for Internet of Things applications across multiple industries.

While FreeRTOS is typically designed for use on a single core, the ESP32 processor is a dual-core chip with both a Protocol CPU and an Application CPU. Since both cores are identical and share the same memory, tasks can be run interchangeably between them.

The ESP32-S2 is an excellent choice for our data storage system, thanks to its long-range transmission capability of up to 200 m, as well as its low power consumption and excellent radio frequency performance. This repeater allows us to effectively transmit data to the platform over medium and long distances, making it an ideal choice for our dataset generator.

3.4. Software System

The software system plays a crucial role in processing, storing, and transmitting data. Improving the efficiency of data processing and transmission can significantly enhance the system's overall performance and reduce costs.

The data processing module comprises several components, including an ultrasonic receiver, a signal conditioning circuit, an A/D converter, a processing unit, and memory.

The ultrasonic receiver converts mechanical waves with frequencies greater than 20 kHz into another energy signal, possessing characteristics such as A high frequency, short wavelength, small diffraction, and good directivity. The signal conditioning circuit is responsible for converting the electrical signal from the slave sensor into a signal that complies with the A/D converter's input range. The A/D converter, as shown in Figure 8, digitizes the analog signal. The data processing unit performs appropriate preprocessing of the collected industrial data, filtering out unnecessary and redundant information and sending valid information to the central computer [40].

To convert the sound and acceleration analog data into digital data, we use an AD conversion module. The binary data are then sent to the buffer through the DMA pipeline, where the CPU processes and stores it in FLASH. Finally, the WiFi module is utilized to transfer data to the ESP32-S2 repeater and subsequently to the server for storage.

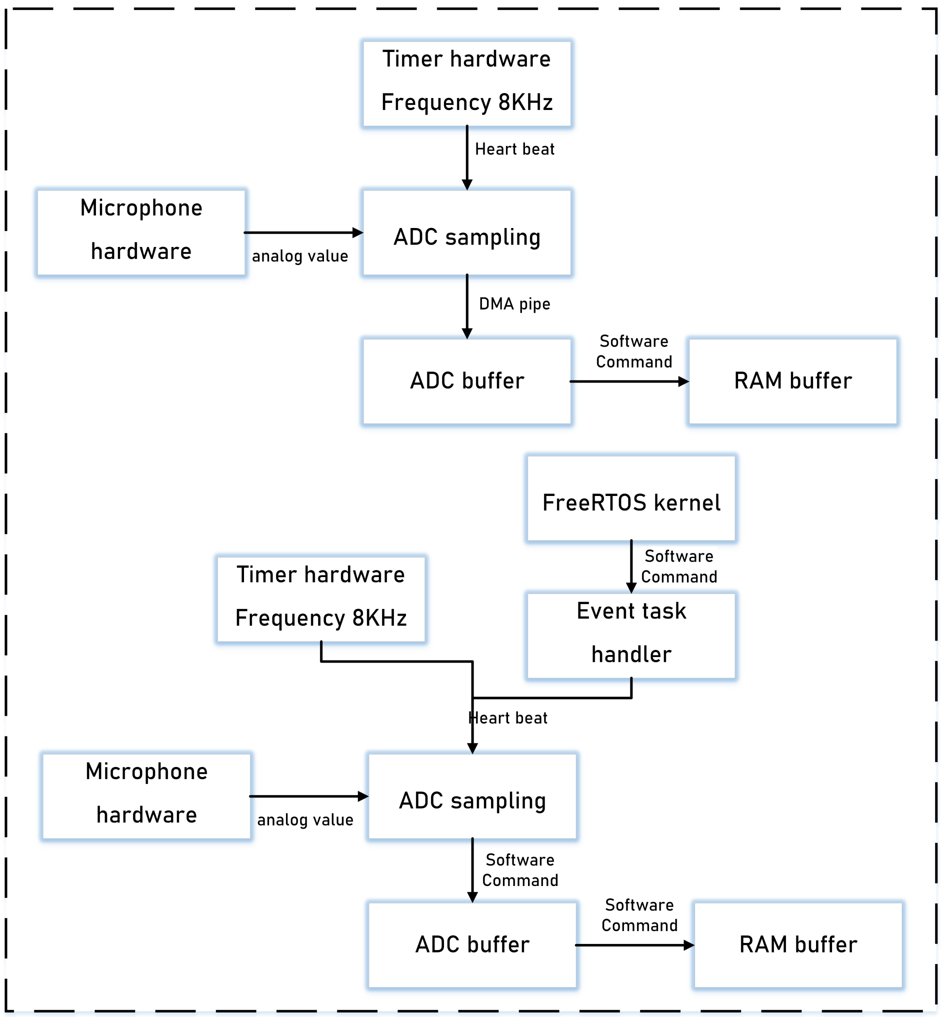

Figure 8. A/D and D/A conversion principle of data acquisition and storage process.

3.5. Data Preprocessing and Visualization

Data preprocessing is an essential step in data analysis, and it aims to clean, transform, and normalize data to prepare it for further analysis. In industrial applications, preprocessing techniques are used to reduce the impact of noise, missing values, outliers, and other anomalies in the data. Coordinated filtering is a common technique for removing noise from sensor data by taking the average of multiple sensor readings. K-means clustering can be used to group similar data points together, making it easier to identify patterns and anomalies. Singular spectral analysis is a method for decomposing time-series data into their underlying components, which can be used to extract trends and patterns. An LIN interpolation algorithm can be used to fill in missing values in the data, which is important for time-series data that have regular time intervals.

Visualization is another important aspect of data analysis, as it allows users to explore and understand the data. The system shown in Figure 9 has a data visualization module that allows users to interactively explore the data and generate visualizations, such as charts, graphs, and heatmaps. Data visualization tools can be used to identify patterns and relationships in the data and to communicate the results of the analysis to stakeholders. By using these tools, users can gain a deeper understanding of the data and make more informed decisions.

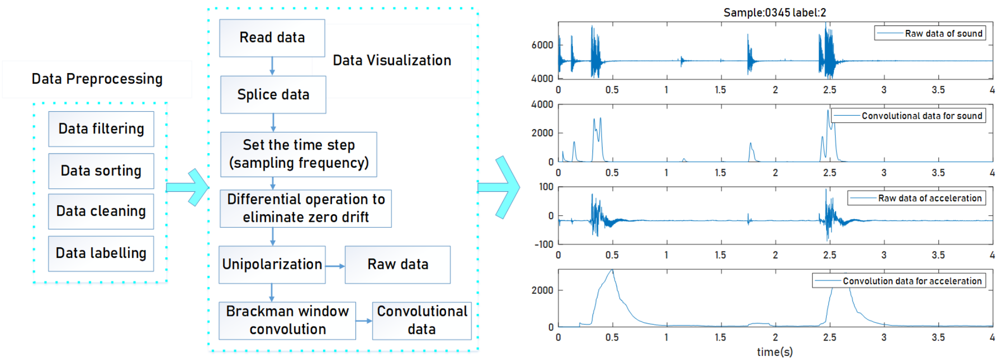

Figure 9. The system has the ability of data processing and display. This is the flow chart of dataset data preprocessing and data visualization.

It is great to see that the system is equipped with a comprehensive data preprocessing and visualization system. Data preprocessing is crucial to ensure that the collected data are accurate, complete, and consistent. By filtering, sorting, and cleaning the collected data, the system can generate high-quality datasets that can be used for further analysis. Additionally, the system can synchronize multisensor information using the finite state machine algorithm, which is a useful technique for integrating data from different sources.

The visualization system is also an important component of the system as it allows users to monitor data in real-time and detect anomalies or issues with devices. With real-time monitoring, enterprises can maintain their devices in a timely manner and optimize their performance. Moreover, by making packaged datasets publicly available, users can contribute to the community and promote collaboration in the industry.

Finally, the system model's hardware independence is a significant advantage as it reduces the cost of manufacturing for enterprises. Overall, the system's data preprocessing and visualization capabilities, combined with its hardware independence, provide a powerful tool for enterprises to improve their operations and achieve better outcomes.

4. Specific Applications and Performance Analysis

DenseNet is a type of convolutional neural network that improves training by adding a DenseBlock module. The DenseBlock module concatenates the outputs of all previous layers to obtain the input for each layer. The architecture of DenseNet begins with a convolutional layer with a 7×7 kernel size and stride 2, followed by max pooling with a 3×3 kernel size and stride 2 [41]. The network then alternates between DenseBlock and transition layers. The last layer of the network is a global average pooling layer with a 7×7 kernel size [42], followed by a fully connected layer with 1000 units and a SoftMax classification layer. The basic structure of DenseNet is illustrated in Figure 10.

As shown in the Algorithm 1,the transition layer in DenseNet is composed of three parts: a batch normalization layer [43], a 1×1 convolution layer, and a 2×2 average pooling layer. Its purpose is to reduce the number of feature maps. Unlike traditional convolutional neural networks, which have L connections for an L-layer network, DenseNet's DenseBlock module allows the output of the previous layer to be used as input for each subsequent layer [44]. This means that the input for each layer is a concatenation of the outputs of all previous layers, resulting in a narrower network and fewer parameters. This is one of the key advantages of DenseNet over traditional neural networks.

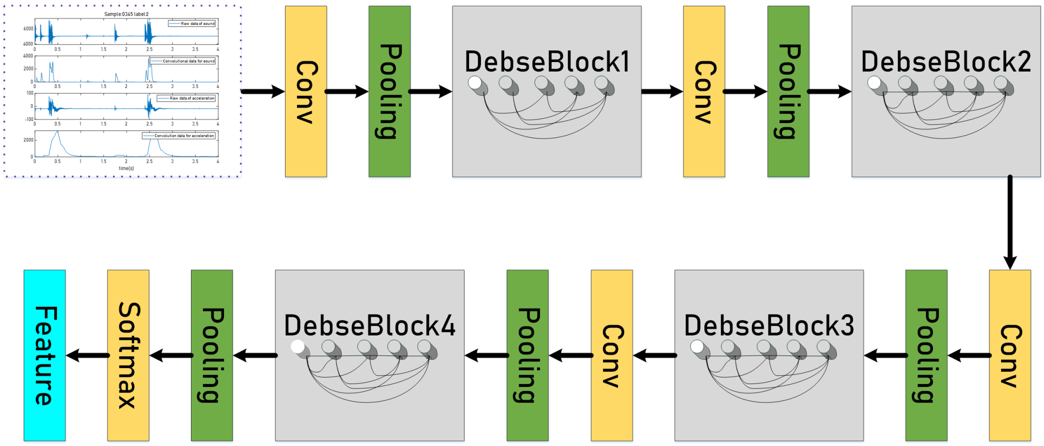

Figure 10. In the DenseBlock module, the output of all previous layers of this layer determines the input of each subsequent layer. This is the basic structure of DenseNet.

We propose an innovative feature fusion network [45], based on previous research, and present its architecture in Figure 11. Our network extends the original model by including several feature fusion layers. These layers are designed to combine the deep and shallow information from the input multisensor data [46], in varying degrees, to expand the amount of feature information and enhance recognition accuracy.

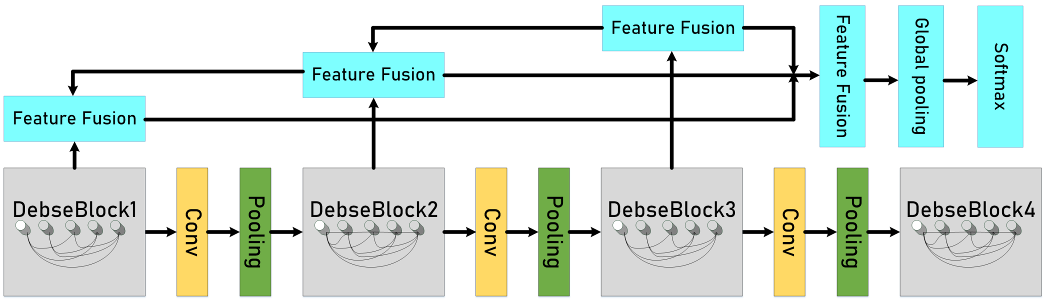

Figure 11. This paper introduces a new approach to feature fusion using a DenseNet-based network. The proposed network structure incorporates both shallow and deep information from the input multisensor data. Specifically, the feature fusion layer is designed to combine these two types of information in different proportions, allowing for a more flexible and effective feature representation.

Algorithm 1: Steps of Feature Fusion Based on DenseNet.

Input: Data sequence
Output: Data sequence after feature fusion
Put the feature matrix into the feature fusion network, set the number of convolution channels n and the number of convolution layers N in DenseBlock;
Convolution of input data tensorConvolution Layer: Kernel size [7 × 7];
Maximum Pooling: Core size [3 × 3];
DenseBlock: Alternating connection between DenseBlock and the transition layer;
Transition Layer: BN layer, [1 × 1] Convolution Layer and [2 × 2] Average pool layer;
Global Average Pool: [7 × 7];
Full Connections: 1000;
Classification Layer: SoftMax.

To reduce redundancy in the feature fusion network, we have designed two structures for fusing features [47]. The first structure combines the outputs of two convolution layers, input layer 1 and input layer 2. Input layer 1 is a shallow convolution layer used for classification, while input layer 2 is a deeper layer in the network. To increase the dimension of features in input layer 2 [48], we use deconvolution layers. In the second feature fusion structure, we combine the previously fused features, controlling the size of the features through convolution. We employ a cell operation layer that uses splicing to combine feature maps of the same size, ensuring that the spliced feature map maintains the same size as the original map, but with the number of channels equal to the sum of input channels. To avoid data overload, we use smaller convolution kernels to reduce the number of feature channels. Algorithm 2 summarizes the steps of feature fusion based on DenseNet.

Algorithm 2: Acoustic wave width algorithm.

Input: Data sequence
Output: Number of MWEs

for *Follow pointer* $\neq$ *Forward pointer* **do**
    Recognition results and accuracySet simulate acceleration clock;
    TimerGenerate dataset path;
    Load acceleration data;
    Circular pointer zeroing;
    Convolute with the specified size;
    Enter the recognition algorithm and record the results;
    if *No mark on the upper bound of the interval* **then**
        Judge whether the upper bound threshold of the interval is reached;
        Maintain follow pointer.
    end
end

Applications of the IIoT Data

We use the scheme proposed in this paper and the two previous schemes to collect data from large-scale mechanic industrial sites [49]. Through many test analyses in different scenarios, it is concluded that the cost of accessing industrial sites to collect data using an embedded industrial gateway is three to four times that of the scheme proposed in this paper, and the effectiveness of the data is not advantageous. The method of data collection using a data terminal unit is similar in cost and data validity to the scheme in this paper. Its disadvantage is that it is extremely complex to develop, can only collect a single dataset, and has poor privacy.

In order to further measure the performance of the system proposed in this paper, we applied the scheme to the industrial site of a large manipulator and collected data for several large manipulators. We collected a total of 890 acceleration and sound data generated during normal operation. We can improve the algorithm for collecting datasets to identify potential problems and make necessary adjustments to the arm.

In the first test, we focused solely on the data collected by the sound sensor and designed an algorithm called the acoustic wave width (AWW) algorithm, which is based on the working frequency of the manipulator. The AWW algorithm calculates the total wavelength of the machine's working interval and counts the acoustic convolution data that reach a predetermined threshold. In the first test dataset, there were 890 Operator Work Events (MWEs). There were 7 error detections and 17 missed detections in the AWW algorithm, and its accuracy was 97.30%.

To improve the accuracy and stability of working state recognition for large-scale manipulators, we incorporated acceleration data to assist in detection in addition to the sound sensor. This approach eliminates the noise interference caused by collisions between surrounding arms. To solve the asynchronous problem of the two sensors, we designed a finite state machine detection (FSMD) algorithm. The FSMD algorithm matches the asynchronous sound characteristics with the acceleration characteristics by dividing the present-state (PS) and sub-state (SS). This process filters out any mismatched noise signals [50].

The results of the second test on the previous dataset show that the large manipulator worked 890 times normally. The AWW algorithm combined with the FSMD algorithm had 5 error detections and 12 missed detections, and its accuracy rate was 98.09%, which has significantly improved. The state table of the finite state machine algorithm is shown in Table 1.

Table 1. State table of FSMD algorithm.

Accelerate PS	Sound PS	Accelerate SS	Sound SS	Accelerate Output	Sound Output	MWE Output
0	0	0	0	0	0	0
0	0	0	M	0	0	0
0	0	1	0	0	0	0
0	0	1	M	0	0	M
1	N	0	0	0	0	N
1	N	0	M	0	0	N
1	N	1	0	0	0	N
1	N	1	M	0	0	N

In the third experiment, we used the feature fusion network designed in this paper to process the dataset. There was one error detection and three missed detections in the preprocessed dataset, and the accuracy rate was 99.56%, which improved significantly. By observing and comparing the data of three times, it is clear that the sonic algorithm can effectively detect the working data of a large manipulator. However, the accuracy can be significantly improved by adding the finite state machine algorithm. At the same time, the feature fusion network designed in this paper can further improve the recognition accuracy after preprocessing the dataset. Therefore, the system can successfully realize real-time monitoring and fault data detection of the industrial site. In addition to the tests mentioned above that demonstrate the feasibility of the system, we have also tested it in an industrial setting using a large shooting arm and reached consistent conclusions. The system device has a high accuracy rate, and it can be further improved through the implementation of specific algorithms and special networks. We plan to conduct experiments with it and compare more data, as well as develop more algorithms for different scenarios.

5. Conclusions

With the development of 5G technology, the IIoT has been promoted more and more rapidly. While increasing productivity, it also generates massive, ultra-high-dimensional, complex, and heterogeneous real-time data. We need advanced technology to promote efficient and reliable IIoT networks. Combining the idea of multisensor information fusion, this paper breaks away from the traditional network mode of an "edge sensor-Central computer". A three-level networking model based on a distributed sensor self-network and cloud server platform is presented. We implement monitoring data collection for a variety of industrial scenarios that require data collection. The system can process and store critical information in time, reduce data transmission and storage costs, and improve the reliability and effectiveness of data transmission. At the same time, a feature fusion network is designed to further expand the amount of feature information and improve the accuracy of industrial data recognition.

The system model improves the efficiency of modern chemical plant production to a certain extent and also reduces costs. Visualization ensures the safety and maintenance of the plant. It can be said that it provides an important basis for enterprise development and optimization. In the future, we will continue to experiment and design algorithms for different scenarios, as well as improve the system's data processing ability and accuracy in different scenarios.

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