Video Image Based Monitoring Method for Operation Status of Internet of Things Network Equipment

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Abstract. Conventional monitoring methods for the operation status of Internet of Things network equipment mainly use CBM (condition based maintenance) to obtain the early symptom characteristics of equipment, which is vulnerable to the impact of dynamic operation instructions, resulting in abnormal monitoring and early warning. Therefore, a video image-based IoT network device operational status monitoring method is designed. That is to say, the video image technology is used to process the monitoring information of equipment operation status. Combined with fuzzy logic, the monitoring framework of equipment operation status of the Internet of Things is constructed, and the monitoring algorithm of equipment operation status of the Internet of Things is designed, thus realizing the monitoring of equipment operation status of the Internet of Things. The experimental results show that the designed method for monitoring the operation status of Internet of Things network equipment based on video images has a good monitoring effect, can effectively warn, has reliability, and has certain application value, and has made certain contributions to improving the operation security of Internet of Things network equipment.

Keywords: Video Image · Internet of Things · Network Equipment · Operation Status · Monitoring Methods

1 Introduction

The Internet of things (IoT) concept was formally proposed and released by the International Telecommunication Union at the Information Society Summit held in Tunis in November 2005 [1, 2]. The Internet of Things refers to the realization of the interconnection of things and the formation of a highly intelligent information network based on the Internet and computer related technologies [3], which can realize intelligent identification and management, provide safe, controllable and personalized real-time online monitoring, positioning and tracing, alarm linkage, dispatching command, plan management, remote control, security prevention, remote maintenance, online upgrade statistical report, decision support and other management and service functions [4]. The Internet of Things realizes the Internet of Things and information exchange on the basis of the Internet. With the arrival of the 5G era, the application prospect is extremely broad [5, 6].

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In terms of equipment management, information technology is applied to implement equipment visualization and whole process management. Use information technology and means to strengthen the management of equipment [7]. The Internet of Things technology will play an irreplaceable role in data visualization, process control, real-time information collection and feedback and other management. At present, the existing equipment operation environment monitoring methods (regular manual inspection records) of each organization can only cover the normal working hours. At night and during holidays [8], the environment of the machine room may be out of control and can not be found in time, with great security risks and hidden dangers. In combination with the current situation and shortcomings of management, dynamic monitoring of the operating environment and real-time mastering of the data related to the equipment room environment will help to identify potential hazards as soon as possible [9], intervene in a timely manner, eliminate the crisis in the bud, ensure the smooth operation of equipment, ensure safety and reliability, and reduce the cost of maintenance support [10].

Now some large equipment manufacturers in the market are also monitoring the operating environment and status of equipment, but the data they collect are not open to customers [11]. Only by purchasing their warranty service will they open up some data sharing, which is a great economic burden for most organizations; Moreover, when manufacturers collect and transmit data, they may also involve information security issues in the process of information exchange between internal and external networks of institutions. In addition, the operation monitoring systems of different manufacturers are incompatible with each other. Therefore, it is difficult to achieve the two requirements of full coverage and low cost required by various institutions by using the environment and operation status monitoring systems of the original manufacturers of large equipment. Therefore, it is very necessary to design a set of general, low-cost and reliable equipment operation environment and condition monitoring methods on the basis of fully understanding and absorbing the existing mature technical solutions of various manufacturers and Internet of Things related technologies [12], and combining the suggestions and needs of large equipment users and engineering technology management personnel. Under the current background, this paper designs an effective monitoring method for the running state of Internet of Things network equipment based on video image technology, which has made some contributions to improving the running reliability of equipment.

2 Design of Monitoring Method for Operation Status of Internet of Things Network Equipment Based on Video Image

The overall framework for monitoring the operational status of IoT network devices based on video images is shown in Fig. 1.

Based on the above framework, specific monitoring methods are designed as follows.

2.1 Operation Status Monitoring Information Based on Video Image Processing

Generally speaking, the research foundation of video image recognition technology is a large number of sample video images, whether it is traditional image processing methods or image recognition methods based on deep learning [13]. Especially for the mouth tag

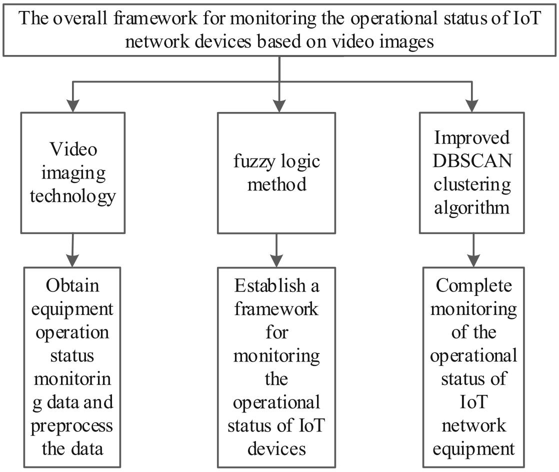

Fig. 1. Overall framework diagram for monitoring the operational status of IoT network devices based on video images

detection model, to achieve a good detection effect, there must be a large number of parameters as the support, and the premise to ensure the accuracy of these parameters is that they can be obtained only through a large number of data sample training, so the amount of data in the training set must be increased. If noise data is added to the original data set. It can also improve the robustness of the detection model.

Data enhancement is a method often used in the absence of data samples. It uses existing images to flip, shift, add noise and other operations to generate more images, so as to ensure that the detection model has a better generalization effect. There are two ways to enhance data: offline enhancement and online enhancement. The offline enhancement method is to operate directly on the original data set, which is often used for the lack of sample data set before training. The online enhancement method is to operate the batch data after obtaining it, which is generally used on larger data sets. Now, many machine learning frameworks can support online enhancement, and GPU can also be used to improve the calculation puzzle and effect. The method designed in this paper has carried out gray-scale image conversion according to the operating characteristics of the device $F(i,j)$ as shown in (1) below.

$$F(i,j) = \max(R(i,j) + G(i,j) + B(i,j)) \tag{1}$$

In formula (1), $R(i,j)$, $G(i,j)$, $B(i,j)$ they represent different color components. Because the manually set threshold does not combine with the specific distribution of pixel gray values on the image, it is arbitrary, so it will lead to the integration of mouth tags and background. Therefore, this topic also uses OTSU method for segmentation, which can find a more reasonable value as the threshold between the two peaks of the gray distribution histogram. The core idea is that the threshold value found meets the following conditions: all pixels in the image are divided into two categories, one is all pixels less than or equal to the threshold value, and the other is pixels greater than the threshold value. When the variance between the two categories of pixel values reaches the maximum, then the most appropriate threshold value is found, and the average pixel value at this time m as shown in (2) below.

$$m = m_0 \times \frac{n_0}{n} \tag{2}$$

In formula (2), m_0, n_0 represents the maximum and minimum pixel values respectively, n it represents the inter class variance of the monitoring and recognition pixel category combined with the above average pixel value to extract the equipment operating status characteristics g as shown in (3) below.

$$g = m \times (m_0 + n_0) + p_a \tag{3}$$

In formula (3), p_a represents the total number of pixels. Combined with the above formula, the OTSU method can be used to split the three devices. The effect picture is shown in Fig. 2 below.

It can be seen from Fig. 2 that the vertical encryption authentication gateway panel and background are both divided into black, and this level of adhesion cannot be separated using basic morphological operations (erosion and inflation).The main reason why the single threshold segmentation method can not effectively separate the mouth tag from the background is that the difference between the mouth tag and the background after graying is too small.

When there are multiple targets in the image, the single threshold segmentation method will cause the phenomenon that different mouthmarks stick to each other. The reason is that different mouthmarks may be in the same gray range. At this time, multiple thresholds must be calculated to distinguish each mouthmark from the background. Multi threshold segmentation is also called adaptive threshold segmentation, which is simply understood as calculating the threshold in each local area of the image, comparing the size relationship between the point in the area and the regional threshold to determine whether the pixel is classified as black or white, and the size of the area can be adjusted according to experience, so that multiple thresholds are calculated on an image, which is called multi threshold segmentation. This topic uses adaptive average threshold method and adaptive Gaussian threshold method to calculate the threshold value of each pixel, which means that the threshold value to be compared for each pixel is different. The basic idea is to calculate the average value of all pixels in the NXN region where the pixel is located, and then subtract the parameter C to obtain the threshold value of the point. The size of the NXN area can be adjusted to a range with the best effect after multiple comparisons. At this time, the adaptive threshold segmentation image of network equipment operation status monitoring is shown in Fig. 3 below.

It can be seen from Fig. 3 that although the adaptive threshold segmentation can have a good segmentation effect for the image with uneven lighting, there are two devices in the switch image. After the morphological operation, the two devices will stick together and cannot be separated. In this case, if you continue to use contour lookup to locate the device panel of the switch, two device panels will be selected by one contour. Therefore, the threshold based segmentation method is not ideal for separating devices from complex backgrounds.

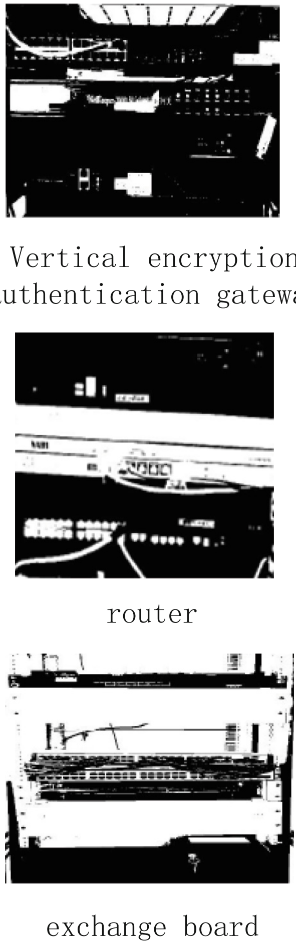

Fig. 2. Effect Diagram of Equipment Operation Status Monitoring

The basic idea of the region based segmentation method is to directly find the region of the mouth marking device. Starting from a group of original pixels, these original pixels grow from different regions, merge the pixels that meet certain conditions in their neighborhood into the region they represent, and repeat the merging process with the newly added pixels as new original pixels, The growth process is ended until no new eligible pixels can be merged. From this process, we can determine the appropriate original pixels of the monitoring image and determine the monitoring status. At this time, the processing flow of the operation status data of the video image device is shown in Fig. 4 below.

It can be seen from Fig. 4 that the gray level of the current area can be specified by marking on the image. The purpose of this operation is to make the "lake water" in this area rise from a certain height instead of starting from the "bottom of the lake"

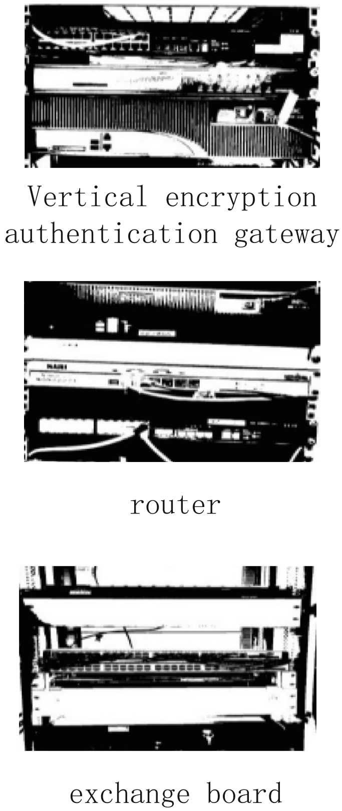

Fig. 3. Monitoring adaptive threshold segmentation image

in the process of submerging, so as to avoid the interference of some very small noise extremes.

This topic uses the watershed algorithm function provided in OpenCV to build a mouse interactive segmentation algorithm in the python environment. The three devices are divided by manual marking, which is the segmentation effect of the vertical encryption authentication gateway, router, and switch. The vertical encryption authentication gateway used the mouse to mark the panel before splitting, which was beyond the scope of the panel, so the panel and the environment were integrated. After comparison, it is found that in the case of accurate marking, the image segmentation effect based on the region is better than the threshold segmentation method. The mouth mark is roughly separated from the background, and the noise is reduced a lot. However, the manual marking has uncertainty in guiding the rules of region growth, so the segmentation effect cannot be guaranteed.

The device recognition method based on template matching is simply to compare the existing device template with the image to be detected and find the matching mouth tag in the image. The device template starts from the upper left corner of the image. Each time it moves from left to right and from top to bottom in the unit of the upper left corner

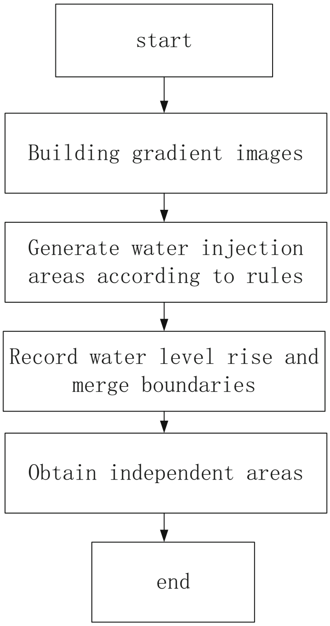

Fig. 4. Data processing flow of video image running status

pixel of the template, each time it reaches a pixel, it will take this pixel as the upper left corner vertex to cut an image of the same size as the template from the image to be detected and compare it with the template. At this time, the monitoring image matching degree $r(x, y)$ as shown in (4) below.

$$r(x, y) = \sum_{x,y} T(x, y) - I \tag{4}$$

In formula (4), $T(x, y)$ represents the abnormal state monitoring point, I it represents the calculation parameters of image matching matrix. The category prediction is multi label classification. The network structure replaces the Softmax layer originally used for single label multi classification with a classifier used for multi label multi classification. The category probability of object conditions is an array of probabilities. The length of the array is the number of categories detected by the current model. It means that when the prediction box considers that the object is currently included, the probability of each category in all categories should be detected. The probability of each category of POLO v3 algorithm is calculated separately by using the logical regression function (Sigmaid), so each category does not have to be mutually exclusive. Therefore, an object can be predicted to have multiple categories. After the above steps are processed, the monitoring data of the operation status of Internet of Things network equipment can be effectively obtained, which serves as the basis for the subsequent construction of the monitoring framework.

2.2 Build a Monitoring Framework for the Operation Status of IoT Equipment

The status of IOT node equipment has an important impact on the reliability of the IOT system and the safety of the monitoring environment. To solve this problem, this chapter will elaborate the overall framework of online monitoring methods for abnormal status of IOT node equipment, and study the theoretical basis respectively.

Compared with big data on the Internet, IoT data has its distinctive characteristics. Through the analysis of different IoT scenarios, this paper summarizes the characteristics of IoT data as follows: (1) IoT data is time series data with time stamps, usually including location information. These data are often numerical structured data, which is different from unstructured data such as text and pictures. (2) IoT data has massive high dimensionality. (3) The IoT data is streaming data. Streaming data is a group of sequential, large, fast, and continuous data sequences. Unlike static data, streaming data is an infinite dynamic data set that continues to grow over time. (4) The spatial distribution of IoT data sets has different characteristics from that of general data sets. Its spatial distribution is compact and dense, with a large amount of data closely overlapping, and only a small amount of data is distributed dispersedly, and the number is far less than that of densely distributed data. (5) IoT data also has the characteristics of multi-source heterogeneity, but at present this paper only analyzes the single observation characteristics of IoT sensors. (6) Finally, IoT data has very important relevance, that is, temporal correlation and spatial correlation.

Due to the above characteristics of IoT data, the processing of IoT data also has different processing requirements: (1) For IoT data, certain frequency reduction processing is required, and data users analyze the trend of data over a period of time rather than the data value at a specific time. (2) For Internet big data processing applications such as personalized recommendation system and user profile generation, only batch processing of data sets is required. (3) In the real-time processing of IoT data, it is usually calculated based on the time window and comprehensively analyzed by the time series of multiple node devices. (4) In the process of data processing of the Internet of Things, it is necessary to combine the real-time data collected at present with the historical data for processing to improve the data utilization. In view of the above characteristics, the monitoring framework of the operating status of the Internet of Things equipment built in this paper is shown in Fig. 5 below.

It can be seen from Fig. 5 that, on the whole, it can be divided into two key parts. The first part is the research on the online detection method of IOT node anomaly based on clustering, and the second part is the identification method of IOT node anomaly source based on fuzzy logic system. In the part of outlier detection, we first study the clustering method of outlier detection, propose a composite time series similarity measurement criterion, and propose an improved density based clustering algorithm. Secondly, the method of abnormal node detection based on clustering is studied. Using the time correlation of the IoT data, the method is divided into three steps: the division of the time dimension of the node data, the training phase, and the detection phase, to realize the detection of the abnormal status of each sensor node in the IoT application. In the part of anomaly source identification, firstly, the extraction method of node spatial correlation features is studied. By calculating the number of node spatial correlations, the geometric features of nodes are selected as the spatial correlation features. Secondly,

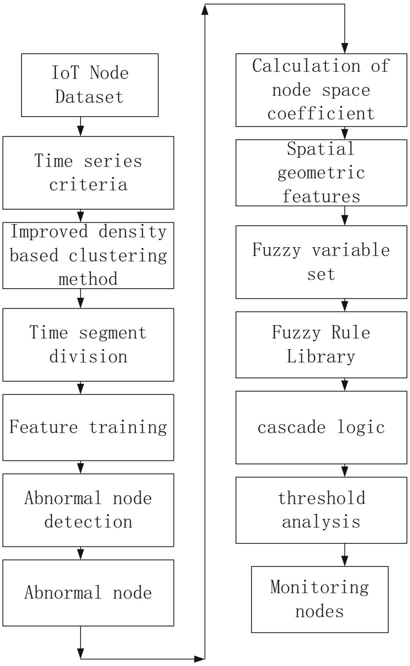

Fig. 5. Monitoring framework for operation status of IoT equipment

the fuzzy logic system that can evaluate the spatial correlation degree of nodes is studied, including the construction of fuzzy language variable set and fuzzy membership function, the establishment of temporal and spatial fuzzy rule base and the design of fuzzy logic system. Finally, the threshold analysis of the spatial correlation index of abnormal nodes output by the fuzzy logic system is carried out, and the identification of abnormal node types is realized by using the spatial correlation principle of Internet of Things nodes.

Unlike the lock step metric, the elasticity metric can compare two time series one to many. The most typical is the dynamic time adjustment DTW, which calculates the similarity between two time series by stretching or shrinking the time series to match. It is a similarity measurement method based on shape. It allows the points in the time series to be matched with equal length after self replication, which overcomes the problem that Euclidean distance cannot be matched due to the distortion of the time series; The time warping of dynamic window is introduced to improve the calculation efficiency and the accuracy of similarity measurement. However, DTW is very sensitive to noise and cannot be a measurement function. Therefore, Minkowski distance is introduced in this paper $Minkowsi\,Dis\tan ce : D$, the calculation formula is as follows (5).

$$Minkowsi\,Dis\tan ce : D = \left(\sum_{i=1}^{n} \left| s_{ij} - s_{io} \right| \right)^2 \tag{5}$$

In formula (5), n represents the device operation status features extracted by monitoring and identifying pixel categories combined with average pixel values, s_{ij} represents the monitoring metric Euclidean distance, s_{io} represents similarity parameters. At this time, we can assume the corresponding monitoring positions of different monitoring nodes, and the generated monitoring set $N_{EPS}(P)$ as shown in (6) below.

$$N_{EPS}(P) = dist(p, q) \tag{6}$$

In formula (6), $dist(p, q)$ represents the monitoring measurement object. DBSCAN introduces intuitive definitions of clusters and noise points in the dataset. While clustering data sets with arbitrary shapes, it is also possible to identify “noise data”. Select a point from the data set at random, start from the point, search all data points that meet the global density parameters and conditions and can reach the density of each other, and build them into a cluster. Objects that do not belong to any cluster are marked as noise points or outliers, Therefore, DBSCAN can be applied to abnormal data processing, and each monitoring node can be obtained by using the above designed operating state monitoring framework, effectively improving the reliability of monitoring.

2.3 Design the Operation Status Monitoring Algorithm of Internet of Things Network Equipment

Through the research on the clustering strategy for anomaly detection of IoT data, this chapter adopts the density based clustering method DBSCAN as the clustering method for anomaly detection, and further proposes an improved DBSCAN clustering algorithm against the defect of traditional DBSCAN that is sensitive to parameter values, and proposes a composite distance metric to comprehensively measure the similarity between IoT time series. After studying the clustering method of abnormal data detection of the Internet of Things, in order to study the online detection method of abnormal nodes of the Internet of Things, this chapter uses the time correlation of the data of the Internet of Things. Finally, based on the above work, this chapter proposes an online anomaly detection method for IoT nodes based on clustering. The method is divided into three parts: the division of the time dimension of IoT data, the training phase, and the detection phase. For each sensor node in the IoT application, online anomaly detection is carried out. The content block diagram of the design algorithm is shown in Fig. 6 below.

It can be seen from Fig. 6 that the principle of cluster analysis is to divide the sample set into several similar subsets according to the similarity of samples in the population. The sample items in the same subset are highly similar, but the sample items between subsets are not. Therefore, for the clustering task of time series mining, computing the similarity between time series is the focus of clustering algorithm, and reasonable time series distance measurement criteria have a direct and critical impact on the accuracy of clustering. IoT data is often a multimodal data stream, which is a multivariable time series composed of multiple time related variables. The time series generated by a single sensor node is generally a single variable time series, and different sensor nodes monitoring the same environmental variable generally collect data at a fixed frequency between nodes, so the time series of time stamps are of the same length. Only the single variable time series of sensor nodes are analyzed, and the observation time series of the same length can be designed at this time F_a, as shown in (7) below.

$$F_a = \{f_1, f_2 .. f_n\} \tag{7}$$

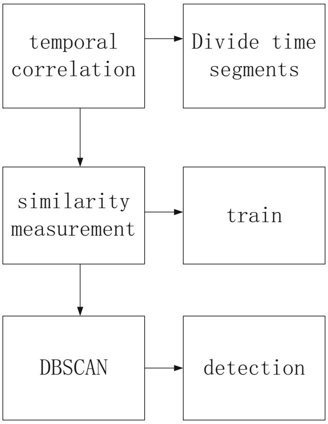

Fig. 6. Block Diagram of Operation Status Monitoring Algorithm

In formula (7),$f_1, f_2..f_n$ represent the observation node, and the difference amplitude of sequence status can be calculated according to the similarity relationship between time series d_{ij}, as shown in (8) below.

$$d_{ij} = \frac{1}{2}F_a + d \tag{8}$$

In formula (8), d represents the composite distance. The function can be estimated by combining the above formula, and the probability density obtained at this time $f(a)$ as shown in (9) below.

$$f(a) = \frac{d_{ij}}{p(f)} \tag{9}$$

In formula (9), $p(f)$ represent the dissimilarity function, which can generate effective equipment operation status monitoring algorithm by combining the above formula N, as shown in (10) below.

$$N = \|f(a) - d_{ij}\| * {}^1/_2(P_C + P_R) \tag{10}$$

In formula (10), P_C, P_R they respectively represent the correct and wrong operation status monitoring samples in the data stream. The clustering based online detection method of IoT node anomalies studied in this paper combines the time correlation of IoT data to detect abnormal data points in the sensor time series through the clustering method. According to the number of consecutive abnormal sample points in the time sequence, whether the corresponding sensor node is an abnormal node is judged. Therefore, the research of efficient clustering strategy to achieve anomaly detection of time series data points of the Internet of Things is the key to the implementation of anomaly detection methods of Internet of Things nodes.

The value of the global density parameter is related to the distribution of data points and the size of data. It requires scientific calculation algorithms and cannot be selected only based on experience. In view of this, this paper proposes an improved DBSCAN clustering algorithm that adapts to the selection of global density parameters. This algorithm analyzes the distance distribution of each sample point in the data set. Aiming at the characteristics of small amount of noise data and discrete distribution, combined with statistical thinking, it finds the best density parameter value applicable to the global cluster, Thus, a large amount of normal data and outlier data can be accurately separated. The algorithm is simple in operation, which solves the problem that traditional algorithms are sensitive to the selection of global density parameter values, makes up for the defects of DBSCAN, and improves the accuracy of clustering results.

3 Experiment

In order to verify the monitoring effect of the designed method for monitoring the running state of Internet of Things network equipment based on video images, this paper built an experimental platform, and compared it with the conventional method for monitoring the running state of Internet of Things network equipment based on digital twin technology and big data technology, and carried out experiments as follows.

3.1 Experiment Preparation

Combined with the experimental requirements, this paper selects the experimental sample data set. In practical applications, anomaly detection is usually an unsupervised learning task. Labeling abnormal nodes of the Internet of Things to obtain tagged data sets requires expert verification of the status of equipment of the Internet of Things nodes in turn, which is costly and difficult to achieve. Therefore, this paper proposes an experimental verification of online monitoring method for abnormal status of IOT node equipment by manually simulating the abnormal status of nodes using unlabeled real IOT data sets.

In the experimental step, the time and space correlation analysis of the data set is first carried out, and then the artificial simulation of the abnormal mode of the node when a fault or event occurs is injected into the node data to generate the fault node and event node. Then it is carried out according to the two aspects of node anomaly detection and anomaly source identification of the online monitoring method of node abnormal state, in which node anomaly detection includes training stage and detection stage. At the same time of node anomaly detection, the clustering results of the improved DBSCAN algorithm and the classical algorithm in the training phase are compared. Finally, the experiment verifies the anomaly detection ability and anomaly recognition effect of the online anomaly monitoring method.

The online monitoring method of abnormal state of IOT node equipment proposed in this paper is a general method, which is applicable to different IOT application scenarios. Here, the application scenario of the method is verified by the traffic monitoring system example. According to the traffic flow data set monitored by the traffic monitoring system PeMS of the California Department of Transportation through more than 39000 sensor stations deployed in the highway system of major urban areas in California. This paper

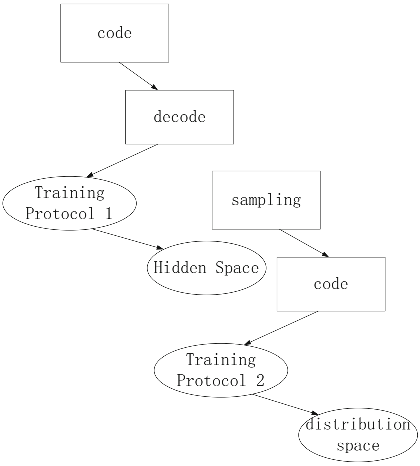

Fig. 7. Experimental data set training

selects a part of the monitoring data from PeMSD7 as the experimental data set, and then trains the data in this data set, as shown in Fig. 7 below.

It can be seen from Fig. 7 that data pre-processing is an essential and very important part of the anomaly detection process. Due to the instability of the automatic collection equipment and the variability of the environment, the selected traffic flow data set needs pre-processing work to clean, so that the data is neat and clean for subsequent data analysis.

First of all, this paper uses the Z-Core standardized method to standardize data and convert data of different orders of magnitude to the same order of magnitude. Secondly, the traffic flow data set is cleaned. Because it is difficult for sensor devices to synchronize, this paper uses linear interpolation to solve the problem of misaligned time points of data collected by different devices and missing data in the data set; For the wrong data in the data set, such as the data that obviously exceeds the normal range, such as the traffic speed is greater than 200 or negative, the threshold method is used to identify and the nearest neighbor interpolation method is used to repair.

For the noise data in the data set, the local weighted regression LOESS method is used to smooth the noise in the traffic time series. Then, the data set is aggregated and preprocessed. The data interval of metadata is set from 30s to 5min. Therefore, the time series length of each node in the data set is 12672, including 288 data points every day. Finally, because the training phase of the anomaly node detection method in this article requires clustering of reasonable data features, the time correlation between daily traffic flow data analyzed in Sect. 5.3.1 was used in the experiment, 10 nodes with very large variance between daily data were artificially pre screened as abnormal nodes, and the data set of the remaining 218 nodes was taken as reasonable node observation data, After the experimental data processing is completed, the subsequent equipment operation status monitoring experiment can be carried out.

3.2 Experimental Results and Discussion

On the basis of the above experimental preparations, we can monitor the operation status of IoT equipment, that is, we can use the video image based IoT network equipment operation status monitoring method designed in this paper, the digital twin based IoT network equipment operation status monitoring method, and the big data based IoT network equipment operation status monitoring method to monitor, It is known that early warning is required when the monitoring risk value is higher than 0.5. At this time, the monitoring results of the three methods are shown in Table 1 below.

Table 1. Experimental Results

Equipment	Monitoring risk value	Early warning status of this method	Early warning status of monitoring method based on digital twin technology	Early warning status of monitoring method based on big data technology
Switch	0.4	No early warning	No early warning	No early warning
Router	0.6	Early warning	No early warning	No early warning
Firewall	0.6	Early warning	No early warning	No early warning
Bridge	0.7	Early warning	Early warning	No early warning
Hub	0.3	No early warning	No early warning	No early warning
Gateway	0.2	No early warning	No early warning	No early warning
VPN	0.8	Early warning	Early warning	Early warning
Network interface card	0.7	Early warning	No early warning	No early warning
WAP	0.4	No early warning	No early warning	No early warning
Modem	0.2	No early warning	Early warning	No early warning

From Table 1, it can be seen that in switches, routers, firewalls, bridges, hubs, gateways, VPNs, network interface cards, WAP, and modem devices, the video image based IoT network device operation status monitoring method designed in this article can effectively provide early warning, while the digital twin technology based IoT network device operation status monitoring method is effective in routers, firewalls, network interface cards, an early warning error occurs in the modem equipment, and the Big data based monitoring method for the running state of the Internet of Things network equipment has an early warning error in the router, firewall, bridge, and network interface card equipment. The above two methods cannot trigger the early warning when the risk value of the early warning is low. The above experimental results prove that the detection and early warning effect of the video image based monitoring and early warning method for the running state of Internet of Things network equipment designed in this paper is good, reliable, and has certain application value.

4 Conclusion

The emergence of the Internet of Things has provided a new mode and idea for the health monitoring and diagnosis of equipment. With the Internet of Things, information perception technology, network technology and intelligent computing technology can be integrated to complete real-time collaborative collection, intelligent processing, timely feedback and other functions of equipment health status information; Build a three-layer system framework of the perception layer, network layer and application layer, which can realize an intelligent and efficient monitoring and diagnosis mode integrating fault prediction, remote monitoring, remote diagnosis, online diagnosis and artificial intelligence. The real-time status information of the equipment is obtained through sensors, and the working status and operating environment information of the monitoring equipment are analyzed using advanced analysis technology, so as to obtain the health status of the equipment. Through the data resource sharing service of Ethernet distributed database, effective monitoring, diagnosis and prediction can be carried out according to the synergy and complementarity of multi-sensor data, which can process the monitoring data quickly and effectively. The model with superior classification performance is established, and the fault feature extraction technology is used to carry out fault diagnosis with the method of fuzzy recognition to evaluate the health status of equipment operation. According to the monitoring advantages of the Internet of Things, this paper uses video images to design a new monitoring method for the operating status of the Internet of Things equipment. In response to the problem of poor monitoring performance caused by low data sample size, video image processing technology was used to obtain equipment operation status monitoring data, and the data was preprocessed. Based on fuzzy logic, a monitoring framework for the operation status of IoT devices was established to improve the accuracy of monitoring results. The improved DBSCAN clustering algorithm was used to design the monitoring method for the operation status of IoT network devices. The experimental results show that the proposed method can provide effective early warning in different device states, which has made certain contributions to improving the operating reliability of network equipment.

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