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Design of dynamic load balancing algorithm for heterogeneous clusters based on energy consumption

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Abstract

In order to reduce energy waste and improve the dynamic load balancing of heterogeneous clusters, sensor technology is introduced into the Internet of Things technology to build a channel transmission model for heterogeneous clusters. Then use the dynamic weighting method to configure the output channel to complete the decomposition of the channel characteristics. In addition, based on the establishment of the channel fuzzy recombination structure model, the noise interference suppression method is used to suppress the multipath interference of heterogeneous cluster communication channels, and the equalization of the channel output is controlled by the baud interval equalization sampling method. At the same time, through the fuzzy balance configuration and spatial balance scheduling process, the dynamic load balancing processing of heterogeneous clusters is realized. The simulation results show that the method proposed in this paper has better balance for the load scheduling of heterogeneous clusters and reduces the bit error rate of the output signal. More importantly, the output balance and adaptive control capabilities of heterogeneous clusters have also been improved.

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Keywords: Internet of Things; Heterogeneous clusters; Node sensors; Dynamic load; Balancing algorithms; Data fusion algorithms

1. Introduction

With the development of communication technology, using heterogeneous cluster communication for big data transmission and load scheduling can effectively improve the reliability and security of data transmission [1]. However, when using heterogeneous clusters for information transmission, due to the interference of multipath characteristics of network communication channels, it is easy to lead to poor load balancing and scheduling ability of heterogeneous clusters. Therefore, it is necessary to design the load balancing control process of heterogeneous clusters to further improve the load balancing of heterogeneous clusters [2].

Relevant scholars have designed relatively mature load balancing algorithms, such as dynamic allocation technology based on nginx load balancing and multi index dynamic load balancing technology of data cluster

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system [3]. In addition, Tai Yingying et al. Proposed a dynamic load balancing algorithm based on improved weight. According to DS evidence theory, taking the factors affecting cluster performance as the judgment condition, the index weight is calculated by using the difference between historical data and threshold, and the basic trust function is constructed. At the same time, the trust function under judgment conditions is combined with load synthesis rules to achieve deep integration, so as to complete the dynamic load balancing of clusters. However, this method unifies the transmission model in order to build heterogeneous cluster channels, and the load balancing design has poor adaptability to heterogeneous clusters [4]. In addition, Wang Zhao et al. Also proposed a dynamic load balancing scheduling algorithm for streaming media clusters. The improved algorithm dynamically modifies the information feedback time by changing the number of cluster node tasks, and divides the information types according to the load of the cluster, so as to improve the load balancing effect of the cluster. However, the balanced scheduling ability of this method is not strong, and the bit error rate of the output signal is high [5]. Muhammad proposed a scheduler based on topology and traffic to optimize the resource use of heterogeneous clusters. Considering resource allocation, job calculation requirements, physical distance between communication nodes, etc., Muhammad controlled the load balance and optimized the resource use of heterogeneous clusters. However, the suppression effect of noise interference in communication channel is poor [6].

Generally speaking, the load balancing design of heterogeneous clusters is realized on the basis of channel balancing design, and then the load transmission balancing control process of heterogeneous clusters can be constructed [7]. Aiming at the shortcomings of traditional algorithms, this paper proposes a dynamic load balancing algorithm for heterogeneous clusters based on Internet of things technology. The ideas and innovations of the method proposed in this paper are as follows. Firstly, a heterogeneous cluster channel transmission model is proposed, and then the dynamic weighting method is used to configure the output channel, which fundamentally improves the output balance of the algorithm. At the same time, the noise interference suppression method is used to suppress the multipath interference of the channel, so as to reduce the bit error rate of the output signal. Finally, the load balancing design of heterogeneous clusters is realized by fuzzy balanced configuration and space balanced scheduling. The performance of the proposed method is tested through simulation experiments, and the conclusion of effectiveness is obtained. It has better load balancing effect on heterogeneous clustering, low bit error rate of channel output and good practicability.

2. Dynamic load design of IoT sensors

2.1. Network structure design

In the ZigBee network, the number and types of sensors are relatively large and the data transmission protocols are also different, which leads to massiveness and heterogeneity of the collected data [8]. In order to reduce the redundancy of sensor data and improve the transmission efficiency of the network, a multiple layer data fusion algorithm in ZigBee sensor network is designed for different data transmission channels according to the characteristics of ZigBee network layering [9]. The whole design is divided into two parts. In the first part, a comprehensive average data fusion algorithm is adopted to fuse data between the data terminal node and the routing node, and in the second part, the neural network algorithm is applied to fuse data between routing node and coordinator node. The overall design block diagram is shown in Fig. 1.

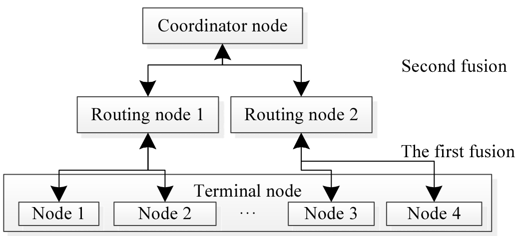


Fig. 1. Data fusion framework diagram.

A comprehensive average data fusion algorithm is used between the terminal collection node and the routing node in the first part, for which the terminal collection node is located at the bottom of the sensor network, with the largest amount of data and the highest degree of data redundancy, so that the network can utilize the computing power of the terminal node. Moreover, the fusion of data collected by terminal nodes through statistical functions can not only greatly reduce the redundancy of original data, but also the number of communications and transmission power consumption of the network, significantly improving the data transmission efficiency and survival time of the network. Meanwhile, it can also optimize the accuracy of the second data fusion in the later stage [10].

In the first part of data fusion, the operator of the data is added to the sensor network. The most basic 5 operators are listed in the paper, namely Max (maximum), Min (minimum), Sum (total), Number (number) , Ave (average) [11]. Here, the temperature value collected by the sensor node is used for data fusion, and the specific process is shown in Fig. 2.

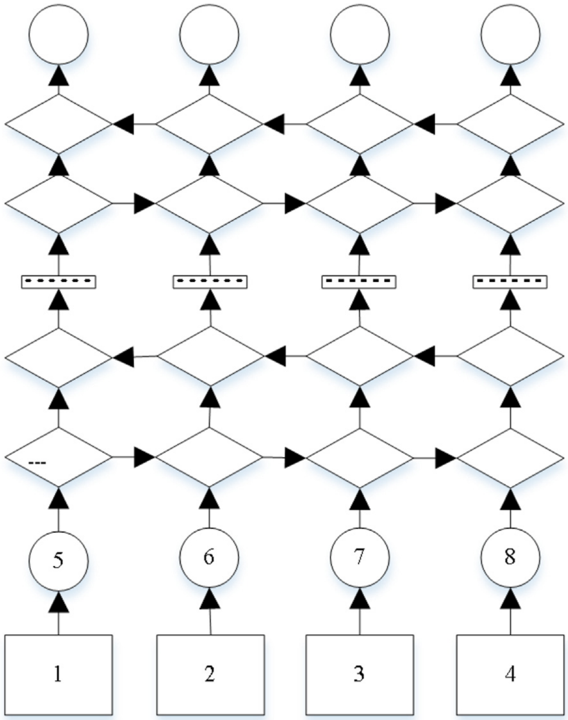


Fig. 2. Block diagram of node data fusion.

Since the entire network area divided into 4 areas is relatively large, as for temperature, the user only cares about the average temperature and maximum temperature of each network area. Here, the maximum temperature is taken as an example. After receiving the temperature data of the node, the routing node first judges whether it exceeds the set threshold temperature. If not, the temperature data transmitted by the previous routing node will be checked. If the data shows that it is not in the same network area as the routing node, then the two temperature data will be sent to the next routing node at the same time. If it is in the same area, then comparison will be conducted, and the highest temperature data will be sent to the next routing node. The temperature of all areas will be sent to the data gateway as this way [12]. Therefore, through the method, the number of node data transmissions can be greatly reduced, and the data transmission efficiency can be improved as well.

The neural network data fusion algorithm is used between the routing node and the data gateway in the second part, since the routing node ca n make optimization analysis according to the routing table and related decisions, so that the best data fusion scheme can be obtained [13]. What is more, through the first part of the data fusion algorithm, the redundancy of the original data has been greatly reduced. However, there is still a certain amount of data redundancy between the routing node and the data gateway. Therefore, with the help of the neural network data fusion algorithm, the data redundancy of the entire network can be reduced to a minimum [14].

The data fusion algorithm model of the second part is shown in Fig. 3.

The empirical characteristics are retained in the server database, while the data cannot be found in the database, and the accurate probability of the data cannot be obtained too. When a certain sensor data is sent to the database by the decision maker, the corresponding feature probability O_2 can be obtained, and the original sensor data will be

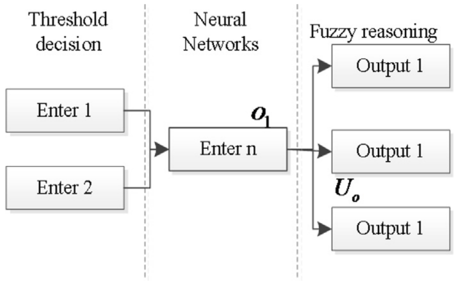


Fig. 3. Block diagram of neural network algorithm.

input into the feedback neural network. Meanwhile, the fitting feature probability O_1 of the original sensor data will be obtained. After the process, O_1 and O_2 are fused here at the same time, and finally the probability of the event U_0 neural network is obtained. Through the network, the data redundancy of the system can be further reduced as well [15].

2.2. Data transmission design

The terminal collection node is the terminal equipment of the ZigBee network node. In the system, it is mainly responsible for the information collection and transmission of the network sensor group. Moreover, considering the large temperature difference between day and night in the network environment and the difficulty of maintenance, the simplified functional equipment is adopted in the terminal collection node. Besides, in order to prolong the service life of the system, after integrating the cost and power consumption of the system as well as other factors, the PM2 sleep mode is usually adopted in the terminal collection node. During sleep, the terminal collection node will not send data to the parent node, and it cannot process the command of the parent node too. It can only be awakened through an external interrupt or timing. In addition, by adopting the sleep mode, not only can the power consumption of the terminal collection node be reduced, but also the data of the sensor group can be collected by setting external interrupts regularly, which greatly satisfies the system requirements [16].

After the terminal collection node is powered on, the device will be initialized first to check whether there is a network. If there is, the information about discovering the network will be fed back to the application layer by the network layer. Then, a signal request to join the network will be sent to the network with greater energy intensity through the network layer [17]. After successfully joining the network, the response signal of the successful joining will be fed back to the application layer by the network layer. Then a binding request will be sent to the coordinator to start data collection. Moreover, after the terminal collection node collects the data of the sensor group for data fusion, data transmission will be performed according to the data frame format specified by the ZigBee protocol stack. In addition, the format of the data frame is divided into the data frame header and the frame content. The data frame header is composed of data frame type, data source address, data destination address and so on, and the frame content is composed of data collected by the sensor group. Finally, when the data collection is completed, the transmission channel will be listened to. When the transmission channel is detected to be idle, the data will be sent [18]. The entire terminal collection node program flow is shown in Fig. 4.

2.3. Channel model and characteristic analysis

2.3.1. Heterogeneous cluster channel transmission model

In order to realize the dynamic load balancing design of heterogeneous clusters based on the Internet of Things technology, optical fiber sensing technology is used to construct the heterogeneous cluster channel transmission model [19]. The heterogeneous trunking channel transmission model is shown in Fig. 5.

The sensor technology is first used to design the anti-co-frequency interference of the ancient city of heterogeneous cluster transmission. Then, assuming that the transmission rule in the heterogeneous trunking transmission channel is h, the distributed particle filter detection model is j, and the input transmission signal in the Internet

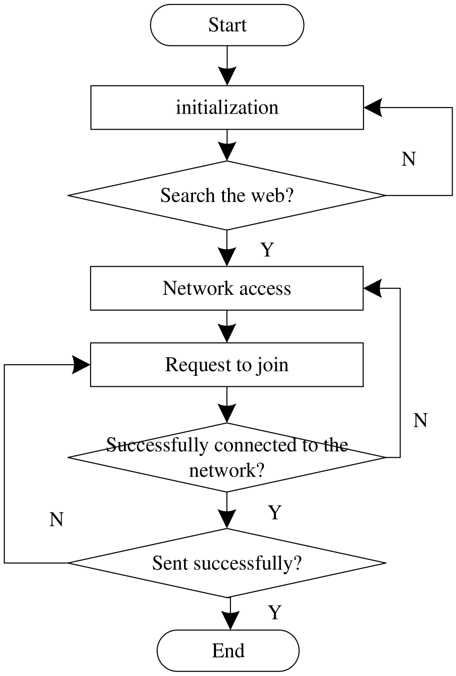


Fig. 4. Flow chart of terminal node sending data.

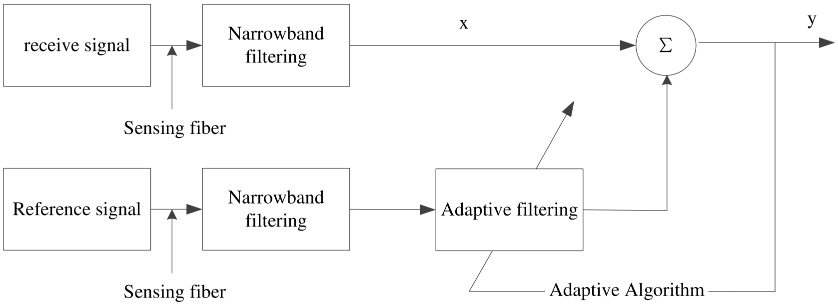


Fig. 5. Heterogeneous cluster channel transmission model.

of Thing is x, through the target's noise signal detection, the output spread spectrum signal in the heterogeneous trunking channel is:

$$y = \frac{x \times j}{h} \times n \tag{1}$$

In formula (1), n is the number of channels. Then the Grubbs criterion is used to perform output feature sampling and fuzzy equalization control of the heterogeneous cluster transmission channel. Meanwhile, the Time Reversal Mirror (TRM) recombination method is adopted to obtain the transmission function of the communication channel in the heterogeneous cluster, which is shown as follows.

$$T = \left(y \times \sum_{n} \frac{\alpha_n s_n}{f} \right) - \tau_n \times n \tag{2}$$

In formula (2), α_n is the expansion loss of the nth channel, and τ_n refers to the channel attenuation coefficient of the nth path. Besides, f represents the signal distribution in the channel within a limited time range, and s_n is the characteristic component of heterogeneous cluster transmission [20]. At this time, the impulse response of the multiple path channel transmitted by heterogeneous clusters can be obtained by combining the Grubbs criterion, which is shown as follows.

$$R = \left(\frac{T + E}{I}\right) \times t \tag{3}$$

In formula (3), I is the sampling interval, t refers to the time, and E indicates the channel extension component. The calculation process is as follows:

$$E = \frac{W_k}{T} \tag{4}$$

In formula (4), W_k is the bandwidth of the kth transmission node. On this basis, considering the offset l of the node position, the dynamic load model of the heterogeneous cluster can be obtained as:

$$F = \left(\frac{E \times \beta}{T}\right) \times t \tag{5}$$

In formula (5), β is the peak load. Then the heterogeneous trunking channel transmission model can be described as:

$$M = r \times \frac{k \times FT}{n} - Ln \tag{6}$$

In formula (6), L refers to the propagation loss of the heterogeneous trunking transmission communication channel (dB), and r is the weighting factor corresponding to the node.

2.3.2. Heterogeneous cluster channel feature decomposition

Based on the construction of the heterogeneous trunking transmission channel model, which is mentioned above, the noise interference suppression method is used to suppress the multiple path interference of the heterogeneous trunking channel and establish the heterogeneous trunking channel equalization model. Meanwhile, considering the multiple path characteristic measurement method, the transmission signal of the Internet of Things is analyzed to realize the decomposition of the channel characteristics of heterogeneous clusters [21].

Assume that the impulse response expression of the multiple path channel n in the transmission process of the Internet of Things transmission signal is:

$$S = \left(\sum_{n} n \times Mw\right) - dn \tag{7}$$

In formula (7), w refers to the information intensity of the transmission node, and d is the time delay of the multiple passage component. What is more, blind source separation is performed on the signal with a given confidence level, and the mutual information entropy dynamic weighting control method is introduced. In addition, considering the separability between classes, the multiple path extension component of the heterogeneous cluster channel is obtained as follows.

$$c = \frac{S \times M}{n} \tag{8}$$

On this basis, the distributed signals in different information transmission channels are reorganized, and the characteristic values of different signal distributions are obtained as follows.

$$z = \frac{\partial \times c\delta_n}{m} - \tau_n \tag{9}$$

In formula (9), ∂ is the intra-cluster dispersion, and τ_n and δ_n are the channel attenuation coefficient and frequency domain attenuation coefficient of the nth heterogeneous cluster transmission channel. m refers to the signal membership degree. Combined with the fuzzy equalization method and based on the K-means sparse feature decomposition process, the channel feature decomposition model of the heterogeneous cluster is obtained as follows.

$$P = (Mz - \rho) \times n \tag{10}$$

In formula (10), ρ is the width of the signal symbol.

In summary, through the above process, the feature decomposition of heterogeneous cluster transmission channels is realized, which lays the foundation for realizing load balancing and scheduling.

3. Dynamic load balancing algorithm design

Dynamic load balancing design is carried out based on what has been mentioned above, that is, when constructing the channel transmission model of heterogeneous clusters, the dynamic weighting method is used for the balanced configuration of heterogeneous cluster channel output [22].

3.1. Multiple path interference suppression on channel

A heterogeneous cluster channel equalization model is first established, and the baud interval equalization sampling method is used to control the output balance of the heterogeneous cluster channel. The received symbol signal x' is:

$$x' = \frac{(x+N)\,M}{\rho} \times n \tag{11}$$

In formula (11), N is the noise in the transmission process of heterogeneous trunking channels. In order to eliminate N, under the condition of minimizing the intra-class scatter, convolution is performed on the weighting factor r corresponding to the node and the received symbol signal x'.

$$X = x' * r \tag{12}$$

In formula (12), $*$ represents convolution.

On this basis, the clutter scattering suppression method is used for channel equalization design [23].

Assuming that the multiple path signal transmitted by the heterogeneous cluster is g_n, and the knowledge-constrained characteristic component of the clutter subspace is b, the heterogeneous cluster channel is suppressed by multiple path interference through spatial equalization sampling. The resulting suppression model is:

$$A = \left(\sum_n X P_n\right) + vn \tag{13}$$

In formula (13), v is the multiple path characteristic quantity of the heterogeneous trunking channel, and A refers to the output amplitude of the dynamic load. Based on this, load balancing can be designed according to the multiple path interference suppression results of heterogeneous trunking channels [24].

3.2. Load balance output

The baud interval equalization sampling method is first used to control the output equalization of heterogeneous trunking channels. Then, combined with the ambiguity balance configuration method, the dynamic load balance processing of heterogeneous clusters is performed. The balanced distribution sequence of symbols transmitted by heterogeneous clusters is:

$$H = X \times u \tag{14}$$

In formula (14), u is the frequency spectrum of the received signal. Combined with the passive time mirror reversal process, the dynamic load balancing transmission output of the heterogeneous cluster is:

$$Y = H \times t + e \tag{15}$$

In formula (15), e is the pulse train waveform that is pass-orthogonal. On this basis, based on the clutter subspace constraint method, the transfer function for dynamic load balancing control of heterogeneous clusters can be obtained, which satisfies:

$$Q = t \times \sum_n Y H n \tag{16}$$

Finally, combined with the Baud interval balanced sampling method, the output balance control of heterogeneous cluster channels is performed, and the dynamic load balance output model is obtained as follows.

$$\psi = \frac{Q \times Y}{H} \times nt \tag{17}$$

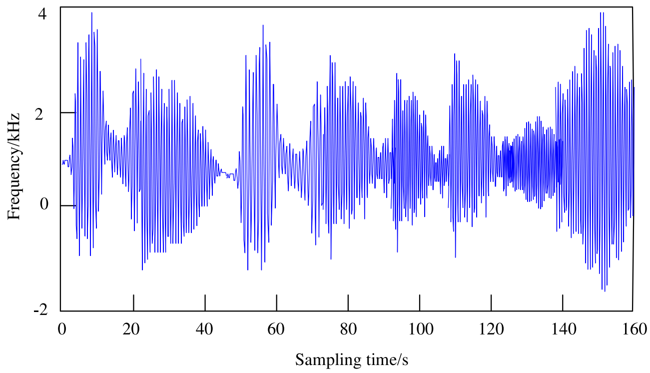


Fig. 6. Dynamic load signal wave forms of heterogeneous clusters.

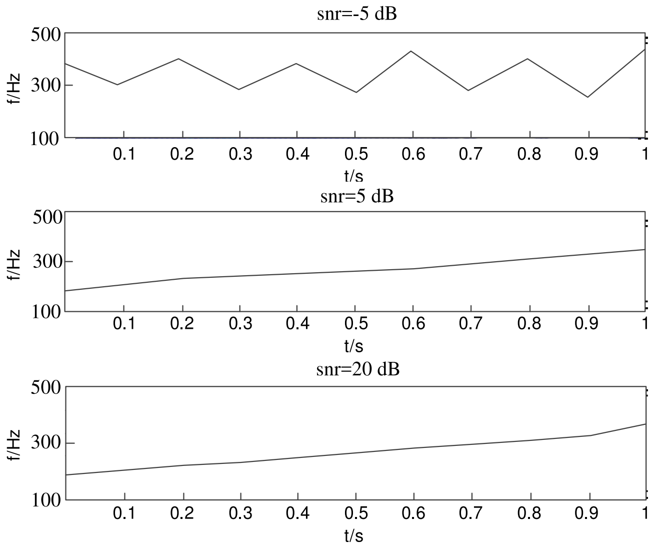


Fig. 7. Load balancing output.

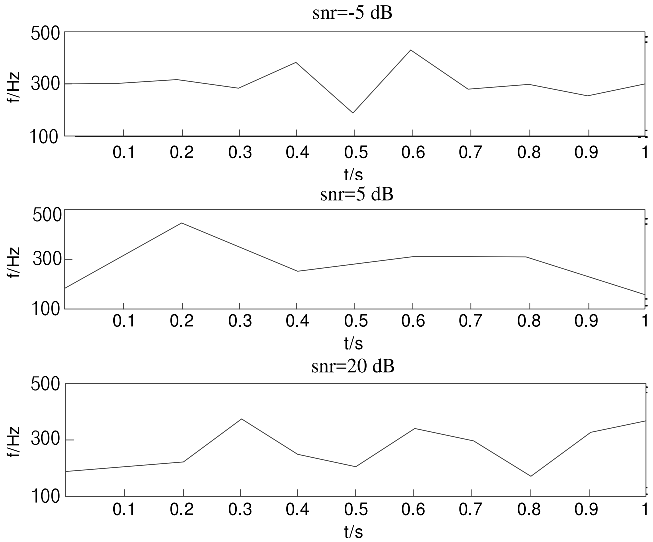
In summary, combined with the ambiguity balance configuration method, the dynamic load balance processing of heterogeneous clusters is performed, and the load balancing design of heterogeneous clusters is realized through spatial balancing scheduling [25].

4. Simulation experiment and result analysis

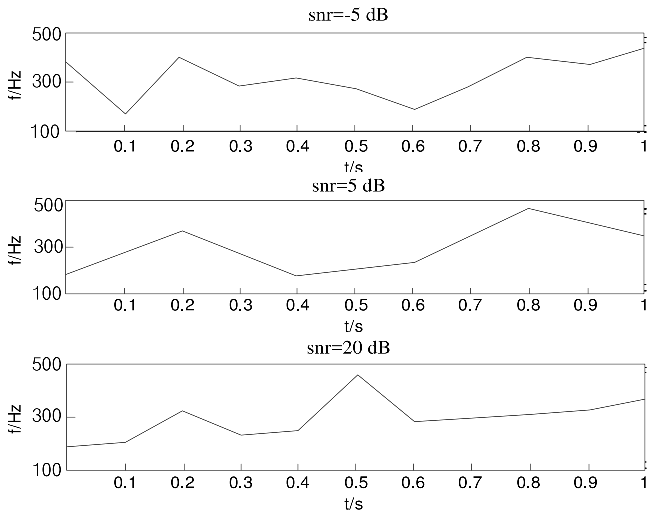
In order to verify the practical application performance of the dynamic load balancing algorithm for heterogeneous clusters based on the Internet of Things technology, the following simulation experiments are designed.

4.1. Experiment preparation

The experimental environment settings are as follows. The experimental simulation platform is MATLAB, and the Doppler frequency of the heterogeneous cluster transmission channel is 0.25. The signal output bandwidth is 24 Hz. Besides, the sensor network topology is a hierarchical structure, that is, a flat hierarchical network structure is adopted by the sink node, the gateway node and the sensor node. The time length of signal sampling is 1200 s, and the maximum number of iterations of the experiment is 200 times [26].



（a）Algorithm proposed in Literature [4]



（b）Algorithm proposed in Literature [5]

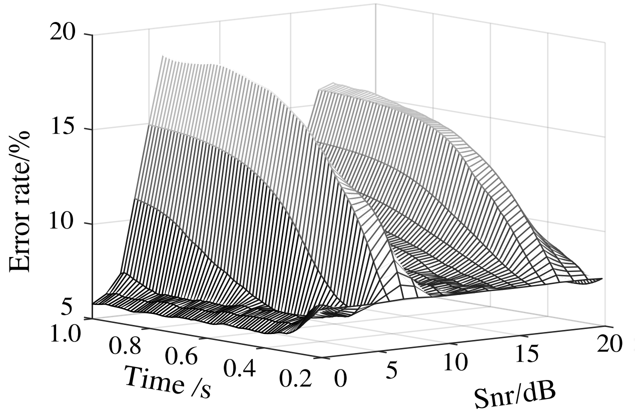
Fig. 8. Load balancing output of the two comparison methods.

4.2. Statistical results and analysis

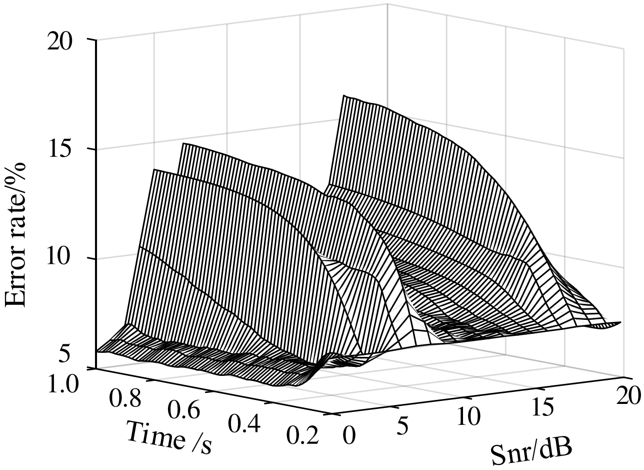
According to the simulation scenarios and parameter settings mentioned above, a heterogeneous cluster is designed for dynamic load balancing. The transmission signal waveform of the channel in the heterogeneous cluster is shown in Fig. 6.

The dynamic load shown in Fig. 6 is the research object. Combined with the channel multiple path interference suppression process, a heterogeneous cluster channel equalization model is established to realize dynamic load balancing control. The signal equalization output situation is shown in Fig. 7.

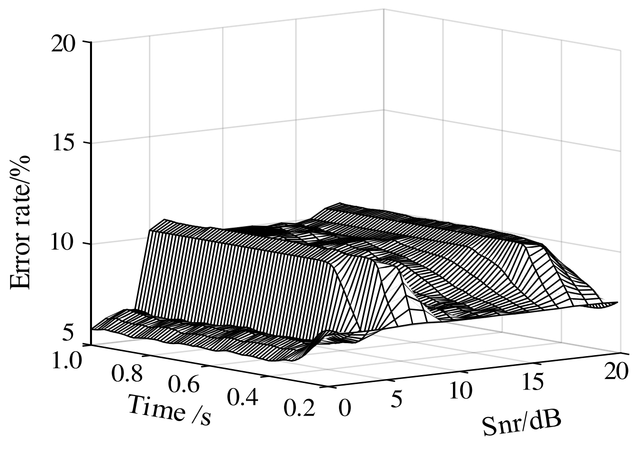
Analyzing Fig. 7, it shows that under different SNR environments, with the passage of experiment time, the frequency of the output signal under the proposed algorithm changes regularly and has small fluctuations. When the



（a）Algorithm proposed in Literature [4]



（b）Algorithm proposed in Literature [5]



（c）Algorithm proposed in the paper

Fig. 9. Comparison of bit error rate of channel output results under different algorithms.

signal-to-noise ratio is 5 dB and 20 dB, the frequency of the output signal increases slowly. When the signal-to-noise ratio is −5 dB, the frequency of the output signal changes regularly [27].

In order to further verify the effectiveness of the dynamic load balancing algorithm for heterogeneous clusters based on the Internet of Things technology proposed in the paper, the dynamic load balancing algorithm based on improved weights in literature [4] and the dynamic load balancing scheduling algorithm of streaming media clusters in literature [5], which are as a comparison, are introduced in the paper. The channel output of the methods in [4] and [5] is shown in Fig. 8.

Comparing Figs. 3 and 4, it can be seen that the algorithm proposed in the paper has better balance, since the baud interval equalization sampling method is adopted by the algorithm proposed in the paper to achieve effective control of the channel output equalization [28].

On this basis, when the environmental signal-to-noise ratio and time change, the changes in the bit error rate of the output results of the heterogeneous trunking channels under different algorithms are tested, and the comparison results are shown in Fig. 9 [29].

Analyzing Fig. 9, it can be seen that with the continuous change of the environmental SNR and time, the bit error rate of the output result in the heterogeneous trunking channel under different algorithms is also changing. After adopting the algorithm of literature [4] and literature [5], the bit error rate of the channel output result is relatively high. Among them, the error rate of the channel output result of the algorithm in the literature [4] is once close to 20% [30]. Therefore, by comparison, it can be seen that after using the algorithm proposed in the paper, the bit error rate of the channel output result is lower, which effectively guarantees the effectiveness and accuracy of heterogeneous cluster information transmission [31]. This is because the sensing technology is adopted by the method proposed in the paper to construct a unified heterogeneous cluster channel transmission model, and before the dynamic load balancing of heterogeneous clusters is realized through the ambiguity balancing configuration and spatial balancing scheduling process, the noise interference in the communication channel is suppressed, thereby improving the effect of the balancing processing.

5. Conclusion

In order to solve the problems of poor load balancing and scheduling ability and high bit error rate of channel output when traditional methods transmit information in heterogeneous clusters, a dynamic load balancing algorithm for heterogeneous clusters based on Internet of things technology is proposed.

(1) Under Grubbs criterion, the output characteristic sampling and fuzzy equalization control of heterogeneous clustering transmission channel are completed, and the heterogeneous clustering channel equalization model is established. Combined with the multi-path feature measurement method, the channel transmission signal is analyzed, and the confidence level is separated from the blind source.

(2) A mutual information entropy dynamic weighted control method for adaptive equalization control is introduced. Using the fuzzy balanced configuration method, the dynamic load balancing of heterogeneous clusters is processed, and the load balancing design of heterogeneous clusters is realized through spatial balanced scheduling.

(3) Through experimental analysis, it can be proved that the algorithm proposed in this paper has better load balancing ability and scheduling ability for heterogeneous clusters, can ensure that the bit error rate of channel output is always maintained at a low level, can meet the needs of practical applications, and lay a good foundation for communication transmission.

Declaration of competing 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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