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Fuzzy Weighted Clustering Method for Numerical Attributes of Communication Big Data Based on Cloud Computing

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Abstract: It is necessary to optimize clustering processing of communication big data numerical attribute feature information in order to improve the ability of numerical attribute mining of communication big data, and thus a big data clustering algorithm based on cloud computing was proposed. The cloud extended distributed feature fitting method was used to process the numerical attribute linear programming of communication big data, and the mutual information feature quantity of communication big data numerical attribute was extracted. Combined with fuzzy C-means clustering and linear regression analysis, the statistical analysis of big data numerical attribute feature information was carried out, and the associated attribute sample set of communication big data numerical attribute cloud grid distribution was constructed. Cloud computing and adaptive quantitative recurrent classifiers were used for data classification, and block template matching and multi-sensor information fusion were combined to search the clustering center automatically to improve the convergence of clustering. The simulation results show that, after the application of this method, the information fusion performance of the clustering process was better, the automatic searching ability of the data clustering center was stronger, the frequency domain equalization control effect was good, the bit error rate was low, the energy consumption was small, and the ability of fuzzy weighted clustering retrieval of numerical attributes of communication big data was effectively improved.

Keywords: cloud computing; communication big data; numerical attributes; fuzzy weighting; clustering

1. Introduction

With the development of the economy, the progress of science and technology, and the improvement of talent technology, the development of wireless network mobile communication technology has been greatly promoted. With the increasing demand for internet communication, the process of improving the data transmission performance of wireless network mobile communication can help people to have a more comprehensive and clear understanding of the world, to pay attention to the dynamics of the world in real time, and to understand a more abundant amount of knowledge. In the new era, people cannot be separated from wireless network mobile communication data transmission. Whether in work or in daily life, wireless network mobile communication data transmission has penetrated into every corner and has promoted people's interaction. Wireless network mobile communication data transmission depends on optical cable optical fiber. Therefore, the superior performance of optical cable optical fiber communication transmission represents the top economic development and efficiency in the world [1]. In our country, at the end of 2017, the number of optical fiber access (FTTH/0) ports

reached 657 million, and the full function standardization of the first stage of the 5G network was completed in 2018. It is expected that in 2020, the optical fiber access (optical access) port will reach 657 million, with the full-function standardization of the first stage of 5G network having been completed in 2018. The experiment of the 5G mobile communication system in China has been carried out to promote the progress and development of society in the process of continuously improving the data transmission performance of mobile communication in a wireless network. It is necessary to optimize the clustering analysis of communication big data, establish the transmission fusion control model of communication big data, and combine big data mining method to continue the adaptive clustering of communication big data.

Fuzzy weighted clustering is a kind of unsupervised pattern recognition problem, which gathers things into groups according to their attributes, making the similarity within the groups as large as possible and the similarity between the groups as small as possible. Traditional clustering methods include C-means clustering and FCM soft clustering. With the increasing amount of data to be clustered, the efficiency of direct clustering with traditional methods is very low. High dimensional datasets involve spatial distribution, whereas the effectiveness of traditional clustering algorithm has strong dependence on the spatial distribution of samples. For example, C-means clustering has a better clustering effect when the feature space is a hypersphere, whereas it has a worse clustering effect when the feature space is a hypersphere, and FCM soft clustering has a better clustering effect when the feature space is an ellipsoid. In order to overcome the dependence of clustering efficiency on the spatial distribution of samples, a high-dimensional data fuzzy clustering algorithm based on genetic algorithm is adopted for the subset clustering of each high-dimensional communication big dataset. The purpose is to transform the fuzzy non similarity between high-dimensional samples into Euclidean distance between two-dimensional samples, that is, to transform the difference between high-dimensional samples into the difference between two-dimensional samples, so as to realize the mapping from high-dimensional samples to two-dimensional samples. Finally, the FCM algorithm can be used to cluster the two-dimensional samples.

In reference [2], it was proposed that there are mode coupling and differential mode delay in the LMF method, and thus the adaptive equalization algorithm was used as the compensation mechanism. In order to reduce the complexity of the adaptive equalization algorithm in the long-distance LMF communication system, the frequency-domain equalization minimum average method based on variable step size was used to realize the mode decomposition multiplexing of multiple input and multiple output equalizers. After that, the equalization weight coefficient was modified by the least mean square adaptive algorithm of the frequency domain block, and the step factor was adjusted by the variable step function so that it could take into account the convergence speed and performance, and further use the fast Fourier transform to reduce the computational complexity. The simulation results showed that in the 112 g bit/s 1000 km small mode fiber channel communication system, the method could improve the signal Q2 factor by 3.7 dB and can be used in the 100 km small mode fiber communication system in the programmable field gate array under the same convergence. It can realize the signal demultiplexing in the system of modular division multiplexing, and realize the purpose of fast convergence and low steady-state maladjustment.

In reference [3], the 66 mode division multiplexing (MDM) system was demultiplexed by the unconstrained frequency domain equalization (FDE) of multiple input and multiple output, so as to eliminate the effects of mode coupling and differential mode delay on the signal. At the same time, unconstrained least mean square (fd-lms) algorithm and unconstrained frequency domain constant modulus algorithm (fd-cma) were used to demultiplex the MDM system, so as to prove the unconstrained FDE demultiplexing effect. Then, the performance of both unconstrained fd-lms and fd-cma were compared, and the results showed that unconstrained FDE demultiplexing performance and constraining of the FDE performance is similar, but the calculation method is simple.

In the mobile communication network, it is necessary to optimize the clustering processing of the text big data of the numerical attribute of the network communication big data, combine the clustering

attribute features of the data for fusion scheduling and classification recognition, improve the accurate positioning of the numerical attribute of the communication big data, improve the quantitative analysis ability of the numerical attribute of the communication big data, and study the clustering method of the characteristic information of the numerical attribute of the communication [4–6]. It has great significance in improving the information recommendation ability and big data information processing ability of mobile communication networks [7–9]. The multi-dimensional text information clustering processing of communication big data numerical attributes is based on the multi-dimensional feature extraction and association rule mining of the data, combined with the sensing data acquisition method to extract the association rule feature quantity of the communication big data numerical attribute multi-dimensional text information, as well as realizing of the multi-dimensional text data classification and recognition. In this paper, a big data clustering algorithm based on cloud computing was proposed. The cloud extended distributed feature fitting method was used to program and process the numerical attributes of communication big data. The mutual information features of big data numerical attributes were extracted, and the data classification was carried out by using cloud computing and adaptive quantitative recurrent classifiers. Finally, the simulation experiments were carried out to show the superior performance of this method in improving the clustering ability of numerical attribute feature information of communication big data [10–12].

2. Numerical Attribute Sampling and Feature Parameter Extraction of Communication Big Data

2.1. Communication Big Data Numerical Attribute Multi-Dimensional Text Feature Data Sampling

The construction of a network model is the basis of wireless network mobile communication data transmission, which has an important position, and is the guarantee of transmission performance. The main research field is the ad-hoc network, involving the use of mobile nodes for data transmission, and its structure is mainly a two-dimensional plane used to form a mobile node set. Each node is a relatively independent single signal channel, but at the same time, it should also conform to the overall standard of ordered random distribution [13–15]. In the network mode, the regular motion of the node set is used to carry out different signal transmission. On this basis, the node location and information corresponding to the corresponding symbols can be effectively found through the independence of the nodes, in which each node set is composed of nodes. In a mobile communication network, the multi-dimensional text information structure of communication big data numerical attribute is complex and the system coupling is strong. Through the classification of communication big data numerical attribute feature information, the optimal detection and classification recognition of big data numerical attribute is realized, and the multi-dimensional text information fusion method is used for the numerical attribute detection and intelligent analysis of community network communication. The multi-dimensional text feature data distribution structure model of communication big data numerical attributes is shown in Figure 1.

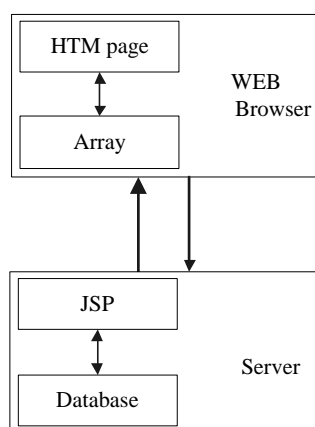


Figure 1. Numerical attribute distribution structure model of communication big data.

According to Figure 1, the output state characteristic quantity of the communication large data value attribute distribution set in the B model is $x_j = \{x_{1j}, x_{2j}, \dots, x_{mj}\}^T$, the sampling is carried out at a baud rate of more than two times, and the state characteristic distribution of the characteristic information of the communication large data value attribute characteristic information is $p(x_0)$. The joint feature mining results of the association rules of the text data are as follows:

$$P_{ij}(k) = \frac{(l_j(k) - l_i(k))\eta_{ij}(k)}{\sum_{j \in N_i(k)} (l_j(k) - l_i(k))\eta_{ij}(k)} \quad (1)$$

According to the symbol characteristic quantity of communication big data numerical attribute transmission, the information is reconstructed, and the bit sequence distribution of communication big data numerical attribute multi-dimensional big data transmission is obtained by using fuzzy data clustering analysis technology:

$$x(t) = \sum_{i=0}^p a(\theta_i)s_i(t) + n(t) \quad (2)$$

The semantic concept set of communication big data numerical attribute characteristic information is obtained, and rough set scheduling and frequent mining are carried out for the characteristic information of communication big data numerical attribute. According to the hierarchical characteristics of data aggregation tree, the classification state characteristic quantity of communication big data numerical attribute information is $z(t)$, and the rough concept distribution subset of data clustering center $S_i (i = 1, 2, \dots, L)$ that meets the convergence condition of semi-supervisory learning is

$$p(y|\alpha, \theta) = \sum_{k=1}^K \alpha_k p_k(y|\mu_k, \sum_k) \quad (3)$$

According to the above analysis, a grid clustering method is used to classify the communication big data numerical attribute feature information, and the small disturbance suppression method is combined to avoid the cluster center disturbance and improve the convergence of the clustering [16–20]. The specific schematic frame diagram is shown in Figure 2:

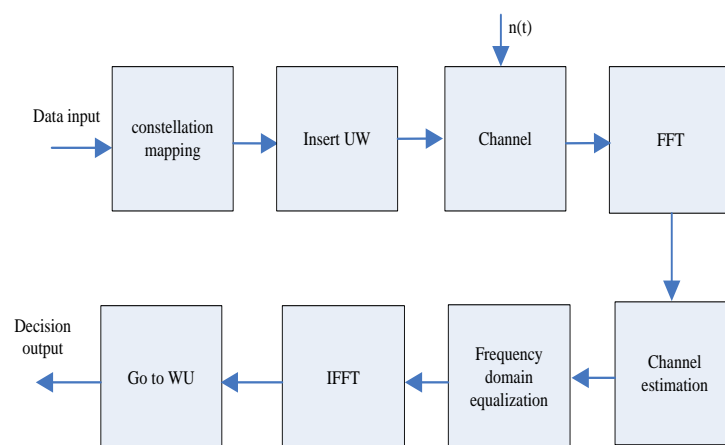


Figure 2. SC-FDE (frequency domain equalization) system model.

2.2. Communication Big Data Numerical Attribute Linear Programming Processing

The cloud extended distributed feature fitting method is used to process the numerical attribute linear programming of communication big data, and the mutual information feature quantity of big data numerical attribute of communication is extracted, which is described as follows:

$$P_i(t) = \sum_{n=1}^N \frac{A}{r} e^{-jkr} R_{in} \frac{1}{r} e^{-ikr} \tag{4}$$

The scalar time series of communication big data numerical attribute feature information is $x(t)$, $t = 0, 1, \dots, n - 1$, given the information flow of communication big data numerical attribute feature information. Given the vector group $x_1, x_2, \dots, x_n \in C^m$ (m-dimensional complex space), combined with the linear programming method, the finite set of communication big data numerical attribute feature information set distribution is obtained as follows:

$$\begin{aligned} \Sigma &= \text{diag}\{\max\{|\rho_1^+|, |\rho_1^-|\}, \dots, \max\{|\rho_n^+|, |\rho_n^-|\}\} \\ &= \text{diag}\{\rho_1, \dots, \rho_n\} \end{aligned} \tag{5}$$

$$\Sigma_1 = \text{diag}\{\rho_1^+ \rho_1^-, \dots, \rho_n^+ \rho_n^-\} \tag{6}$$

The fault location process of communication big data numerical attribute fuzzy weighted clustering is shown in Figure 3:

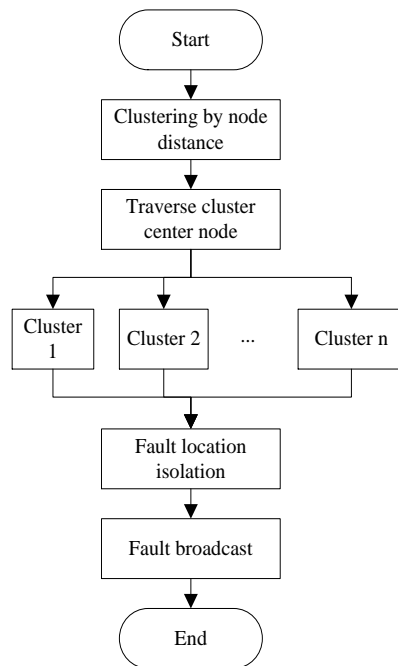


Figure 3. Fault location and identification process of intelligent feeder system.

The intelligent distributed feeder system automation management is the basic work for realizing the whole communication big data system automation management and power fault early warning, identification, and elimination. When the feeder system breaks down, it can quickly locate and isolate the fault points by using the system distributed topology structure and equation communication mode to restore the normal power supply in the non-fault area of the power grid quickly. The overall analysis of the distributed feeder topology system structure based on the peer-to-peer communication mainly includes the base station layer, the sub station layer and the terminal layer. The peer-to-peer network connection is used between each layer, as shown in Figure 4.

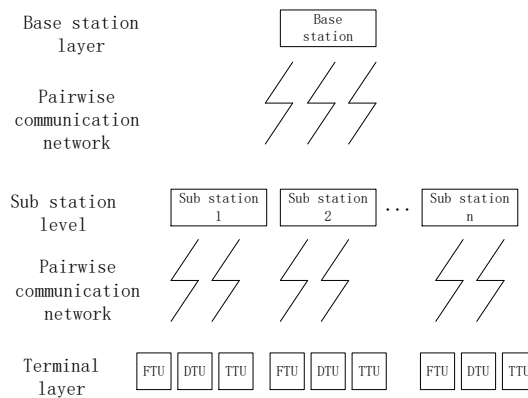


Figure 4. Distributed feeder communication big data architecture.

According to the different functions of nodes, the topology of the feeder system is divided into base station layer, sub station layer, and terminal layer. However, each node has the same position in the feeder system, which is not a subordinate relationship but a distributed parallel relationship. The nodes in the terminal layer are subdivided into feeder monitoring terminal (FTU), switching terminal (DTU), and distribution terminal (TTU). The base station layer acts as the control center of the system from the structural design, and is mainly responsible for the system broadcast and information summary of the power fault information. Similarly, the sub station layer nodes and the terminal layer nodes also have the system broadcast function of the fault information in the functional design; the nodes in the terminal layer are mainly responsible for the identification, measurement, and control of the fault within the area, and the terminal node itself has the function of the system broadcast. It can also package and transfer the node information to the sub station layer to improve the efficiency of power grid information transmission.

In the equal communication mode, the feeder topology system adopts the modular design, mainly including the central processing module, power module, bus communication module, switch module, and display module. The main module adopts the stm32h7 single chip and 32-bit bus system, and matches the hl2323ds communication chip. This structure design can not only meet the requirements of the feeder system topology on communication mode, but also improve the power fault information throughput of the distributed feeder system. The hardware connection design of the stm32h7 single chip microcomputer is shown in Figure 5.

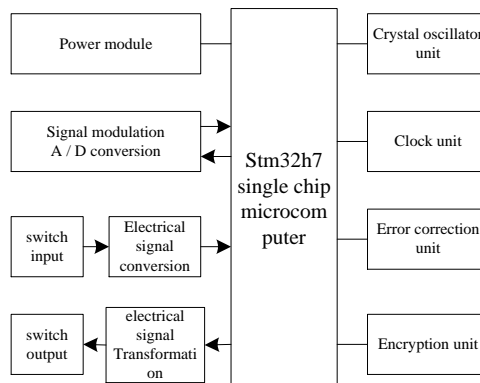


Figure 5. Logic structure of feeder system module.

The stm32h7 single chip microcomputer is responsible for the control and information processing functions of the distributed feeder system. The chip is connected with other system modules through RS485 bus and can bus, and receives and transmits fault information of the feeder system, analog system calculation, control switch, and analysis message, among others. The stm32h7 single chip

microcomputer has good compatibility and rich interfaces. RS232 communication interface is selected as the bus communication module as the remote data exchange window with the sub station layer and the terminal layer. The operation information of each module of the distributed feeder system is displayed more intuitively through the display module. The stable operation of the distributed feeder system based on the equal communication requires a reliable power supply module. Because the design of the feeder system is mainly aimed at the overhead line, the AC power supply is selected to facilitate the stable operation of the information control system. Under the normal working condition, the working power supply of the distributed feeder topology structure is also responsible for the stable power supply of the PT line. The power module is also equipped with a battery as the standby power supply. When the AC power supply fails, the battery can guarantee the normal operation of the system for a short time.

The piecewise sample combination design of the fusion data is carried out [21,22], and when the time interval of association rule set feature extraction of communication big data numerical attribute feature information is $O(d)$ of $O(N^{1/d})$, data clustering space $sn\xi \rightarrow \tanh\xi$ obtains validation that the boundary value convergence condition of accurate clustering of communication big data numerical attribute feature information is satisfied.

$$\Delta E = -\eta \left[\left(\frac{\partial E}{\partial \omega} \right)^2 + \left(\frac{\partial E}{\partial b} \right)^2 \right] \quad (7)$$

If $C_o(x^*) = 0$, then

$$Y(P, Q, \beta) = Y[\text{red}(P, Q, \beta), Q, \beta] \quad (8)$$

Three kinds of kernel functions have been designed to represent the linear kernel function, random distribution characteristic kernel function, and uniform distribution kernel function of big data numerical attribute feature information clustering. The expressions are, respectively, as follows:

$$K(x_i, x_j) = \langle x_i, x_j \rangle \quad (9)$$

$$K(x_i, x_j) = (\langle x_i, x_j \rangle + 1)^d \quad (10)$$

$$K(x_i, x_j) = \exp(\|x_i - x_j\|^2 / 2\sigma^2) \quad (11)$$

According to the above three kernel functions, the linear programming design of accurate clustering of big data numerical attribute feature information is carried out, and the convergence control ability in the process of data clustering is improved by combining the semi-supervised learning algorithm.

3. Big Data Fuzzy Weighted Clustering Optimization

On the basis of using cloud extended distributed feature fitting method to deal with big data numerical attribute linear programming, the optimal design of big data fuzzy weighted clustering algorithm is carried out. In this paper, a big data fuzzy weighted clustering algorithm based on cloud computing was proposed. The mutual information feature quantity of communication big data numerical attribute is extracted, and the characteristic distribution value of geometric neighborhood (t, f) of communication big data numerical attribute clustering in nonlinear space is obtained.

$$f(x) = \begin{cases} f(x), x \in Lev f \\ a, x \in Lev f \end{cases} \quad (12)$$

Combined with fuzzy C-means clustering and linear regression analysis, the statistical analysis of numerical attribute feature information of communication big data is carried out. In the clustering space matrix (x_1, x_2, \dots, x_n) , the basis vector $G = [E_{k \times k} | A]$ of data fuzzy weighted clustering is obtained

in order to construct the joint disturbance feature equation group of communication big data numerical attribute feature information clustering.

$$\begin{cases} a(H_{ac}) = 1 - \frac{H_{ac}}{\max(H_{ac})+1} \\ \max(H_{ac}) = \log_2 k \end{cases} \quad (13)$$

On the basis of the above analysis of the boundary value convergence conditions for accurate clustering of numerical attribute characteristic information of communication big data, the stable convergence of the fuzzy weighted clustering mathematical model of the whole data is guaranteed. Using a semi-supervised learning method, the boundary solution vector function of numerical attribute feature information clustering of communication big data is constructed as follows:

$$w_{ji}(k+1) = w_{ji}(k) - \alpha \frac{\partial F}{\partial w_{ji}} \quad (14)$$

$$z_{kj}(k+1) = z_{kj}(k) - \alpha \frac{\partial F}{\partial z_{kj}} \quad (15)$$

Combined with fuzzy C-means clustering and linear regression analysis [23,24], the statistical analysis of big data's numerical attribute feature information is carried out, and the statistical feature equation is described as follows:

$$\dot{x}(t) = Ax(t) + Bx(t - d_1(t) - d_2(t)) \quad (16)$$

in which $x(t) = \phi(t), t \in [-h, 0]$. In order to realize data optimization clustering, a new training vector is input in a finite-dimensional space:

$$x(t) = (x_0(t), x_1(t), \dots, x_{k-1}(t))^T \quad (17)$$

For the method, the convergence constraint control of the iterative process is carried out by adopting the cloud computing and the adaptive quantitative recursive analysis, and the spatial clustering of the data fuzzy weighted clustering center is obtained as follows:

$$d_j = \sum_{i=0}^{k-1} (x_i(t) - \omega_{ij}(t))^2, \quad j = 0, 1, \dots, N-1 \quad (18)$$

wherein, $\omega_j = (\omega_{0j}, \omega_{1j}, \dots, \omega_{k-1,j})^T$. The fault location algorithm based on the network topology is used to form the topology tree structure of all nodes in the intelligent feeder network, and the cluster center is selected according to the optimal location of the nodes to form a number of node clusters [25–28]. During fault location, firstly traverse the cluster center node of each cluster. When the information is obtained from the cluster center node, there is abnormal node state in the cluster; then, traverse all nodes in the cluster, and then identify the location of the fault node and isolate the fault area, and synchronously transfer the fault information to other cluster center nodes [29–32]. When the clustering center satisfies the convergence condition of the semi-supervised learning, the detection statistic of the characteristic information of the large-data value of the communication satisfies the clustering convergence condition, and the implementation process of the large-data fuzzy weighted clustering algorithm designed in this paper is obtained, as shown in Figure 6.

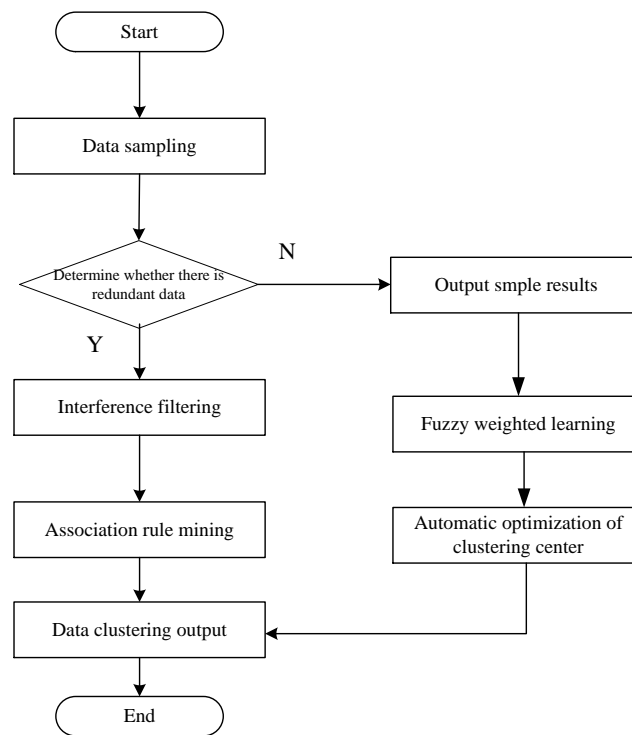


Figure 6. Data clustering output.

4. Simulation Experiment Analysis

In order to test the performance of this method in the clustering of numerical attribute information of communication big data and verify the effectiveness and feasibility of this method, simulation experiments were carried out. On the basis of the Deep Web database and MATLAB, we empirically designed a fuzzy weighted clustering algorithm. The attribute of the big data sample was set to 6, and the initial confidence level of data fuzziness was. The clustering was 95%, the critical value was 1.24, and the judgment threshold was 0.13. The embedding dimension of the feature space distribution was set to $M = 4$, the data length of the test sample was set at 2000 years, and the simulation time was 120s. The method of this paper was used to compare study [2] and study [3] for experimental and comparative analysis. The main parameters of the experiment are shown in Table 1.

Table 1. Simulation experiment parameters.

Parameter Name	Description or Value
Total node value	400
Spacing between nodes	50–100 m
Queue control	Optimize queue
Experimental wireless channel model	MICAZE
Experimental time	Longest 900 s
Experimental range	1000 × 1000 m

According to the above simulation environment and parameter settings, big data fuzzy weighted clustering analysis communication big data numerical attribute μ executed one-dimensional text, and the original data distribution is shown in Figure 7.

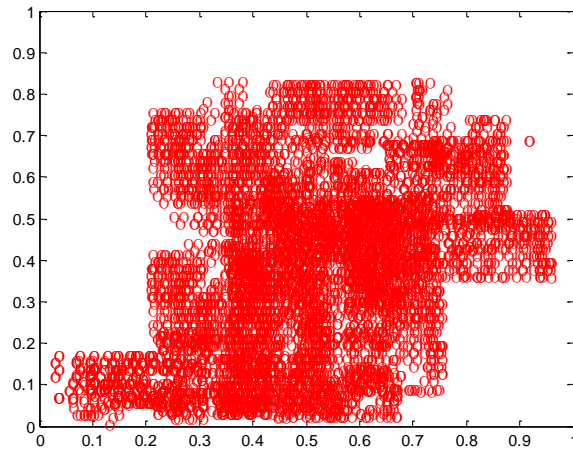


Figure 7. Raw data distribution.

Taking the data of Figure 7 as the research object, the fuzzy weighted clustering of the data was carried out, with the data classification being carried out by using cloud computing and adaptive quantitative recurrent classifiers. The clustering output results are shown in Figure 8.

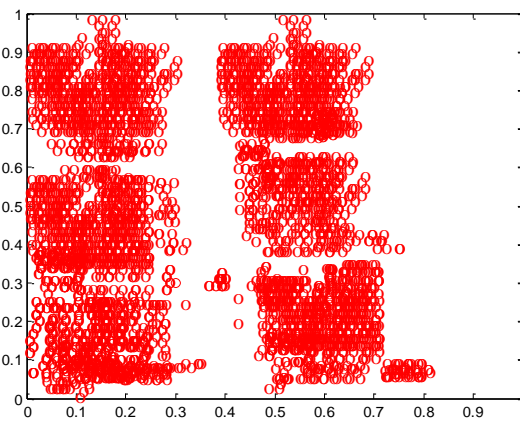


Figure 8. Big data fuzzy weighted clustering output.

Figure 8 shows that big data fuzzy weighted clustering can be effectively realized by using this method; the accuracy of data classification was high, and the error rate was small. The performance of big data fuzzy weighted clustering was tested by different methods.

The comparison results are shown in Figure 9. It can be seen from Figure 9 that the fuzzy weighted clustering error rate of big data was lower than that of the other two comparison methods after adopting this method, which proved that this method has obvious application advantages.

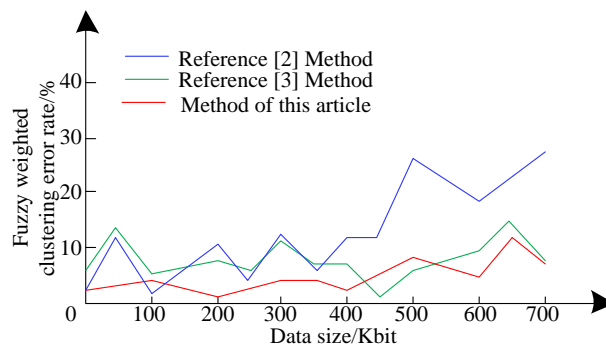


Figure 9. Performance comparison of fuzzy weighted clustering of data.

In order to test the effect of frequency domain equalization of communication security, this paper compared study [2] and study [3], and compared the performance of this method in the routing protocol that uses node location information to make decisions, finding that the performance of this method was better in the network with high dynamic topology caused by node movement. The comparison results of the average energy consumption of the three methods for successful transmission of a single packet are shown in Figure 10.

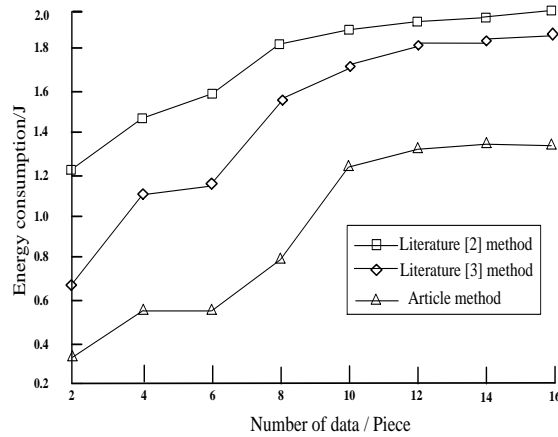


Figure 10. Comparison results of three methods of average energy consumption for successful transmission of a single packet.

It can be seen from Figure 10 that in the comparison of the three methods for successfully receiving the average energy consumption of a single packet, the unit energy consumption of study [2] and study [3] was more, and the text energy consumption was the least, and thus the method in this paper is the best for the communication security frequency-domain equalization control effect. When the communication channel was weak, its noise had a great influence on the capacity of the communication channel. However, when the minimum mean square error equalization was used, the optimal energy constraint and frequency-domain equalization were controlled to ensure the optimal energy in the frequency domain equalization control, and the average energy consumption control of a single data packet was successfully transmitted. The communication channel information obtained by channel estimation was equalized in the frequency domain. The communication channel had three Rayleigh paths, and the specific communication channel equalization energy control results are shown in Figure 11.

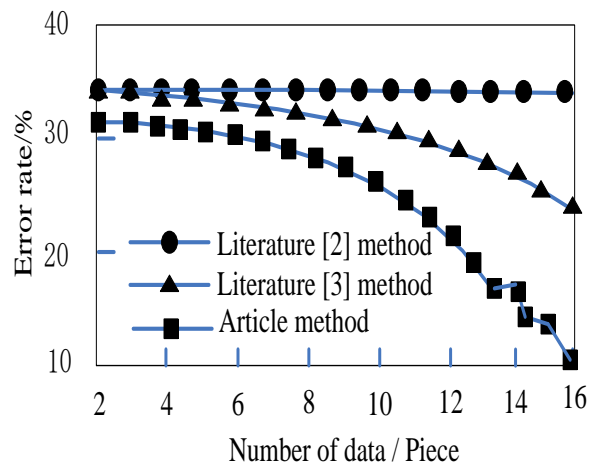


Figure 11. Results of communication channel equalization energy control.

It can be seen from Figure 11 that the bit error rate of the communication channel control conducted by study [2] and study [3] was higher, whereas that of the communication channel equalization energy control conducted by this method was lower, showing a downward trend. Using this method to balance the energy of the communication channel can optimize the system well, and its security performance is good. Because of the small energy loss, the life of communication network can be greatly extended.

From what has been discussed above, the information fusion performance of big data numerical attribute information clustering processing was better, the automatic search ability of data clustering center was stronger, and the fuzzy weighted clustering retrieval ability of communication big data numerical attribute was improved. This method had good application value in cloud computing analysis and clustering of communication data.

5. Conclusions

In this paper, a big data clustering algorithm based on cloud computing was proposed. The cloud extended distributed feature fitting method was used to process the numerical attribute linear programming of communication big data, and the mutual information feature quantity of communication big data numerical attribute was extracted. Combined with fuzzy C-means clustering and linear regression analysis, the statistical analysis of big data numerical attribute feature information was carried out, and the associated attribute sample set of communication big data numerical attribute cloud grid distribution was constructed. Cloud computing and adaptive quantitative recurrent classifiers were used for data classification, and block template matching and multi-sensor information fusion were combined to search the clustering center automatically to improve the convergence of clustering. The simulation results showed that the information fusion performance of big data numerical attribute feature information clustering processing was better, and the automatic search ability of data clustering center was strong, which improved the fuzzy weighted clustering retrieval ability of communication big data numerical attributes. This method had good application value in cloud computing analysis and clustering of communication data.

Author Contributions: H.D. and J.Z. a big data clustering algorithm based on cloud computing is proposed in this study. H.D. processed the numerical attribute linear programming of communication big data, and the mutual information feature quantity of communication big data numerical attribute was extracted by the cloud extended distributed feature fitting method. J.Z. and C.S. Combined with fuzzy C-means clustering and linear regression analysis, the statistical analysis of big data numerical attribute feature information was carried out, and the associated attribute sample set of communication big data numerical attribute cloud grid distribution was constructed. H.D. and J.Z. did the experiments, recorded data, and created manuscripts. All authors read and approved the final manuscript.

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