A Data Fusion Method of Information Teaching Feedback Based on Heuristic Firefly Algorithm

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Abstract. In order to obtain more accurate teaching feedback information, an information-based teaching feedback data fusion method is designed based on the heuristic firefly algorithm. Establish the entity network of the data to be fused, feedback the characteristic matrix of the data, and obtain the correlation degree of parameters such as grade grade grade, individual grade, class grade, and score rate of each question. The cosine similarity and basic similarity of different feedback data are obtained, and the data fusion entity framework is constructed on this basis. The data fusion method is designed based on the heuristic firefly algorithm, and the parameter dynamic control of the firefly algorithm is implemented to realize the information teaching feedback data fusion. The experimental results show that the number of data fusion categories is proportional to the fusion time. The more data categories to be fused, the longer the fusion time.

Keywords: Heuristic Firefly Algorithm · Teaching Feedback · Information Based Teaching · Data Fusion

1 Introduction

Teaching evaluation is based on teaching objectives, according to scientific standards, using all effective technical means to measure the teaching process and results, and give value judgments. It includes: the evaluation of students' academic achievements, the evaluation of teachers' teaching quality and curriculum evaluation. The information obtained from the evaluation can enable teachers and students to understand their own teaching and learning situation. Teachers can revise teaching plans and adjust teaching methods according to the feedback information. Students can improve learning methods according to the feedback information, improve the weak links in learning, so as to achieve learning goals. Teaching feedback, namely teaching information feedback, refers to the process in which both sides of education evaluate each other and transmit the evaluation information to each other in the process of teaching implementation. It is an important means to promote students' growth, teachers' professional development and improve teaching quality [1]. In teaching activities, such as students' homework, test paper, behavior, expression, language and even classroom atmosphere are all teaching feedback, and serve as the basis for monitoring and regulating the teaching process.

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Similarly, teachers' requirements and evaluation of learning activities are also fed back to students as the basis for testing and regulating their own learning behavior. How to carry out teaching feedback scientifically and effectively is a basic component of modern teaching. Its realization depends on the accuracy and timeliness of information obtained by both sides of education. The information-based teaching data mainly includes the overall objective data and the individual objective data. The overall objective data includes grade scores, average scores, class scores, average scores, individual scores, grade excellence rate, pass rate, low score rate, score rate of each question, discrimination, etc. The individual objective data includes individual score of each question, individual score change, individual knowledge point mastery, error analysis, etc. In order to judge whether the teaching process is suitable for the actual situation, it must design an objective, scientific and quantifiable data fusion system.

In this paper, the heuristic firefly algorithm is used to fuse the feedback data of information teaching. Based on the calculation of the correlation degree of the fusion data, a feedback data fusion method for information teaching is designed based on the heuristic firefly algorithm. Through the application of heuristic firefly algorithm, we hope to get more accurate teaching feedback results.

2 Establish Data Entity Network to Be Integrated

2.1 Calculation of Fusion Data Correlation

In recent years, the number of information teaching feedback data has been rising rapidly, and most of the data have been digitally saved. In the face of massive digital resources, how to quickly and accurately mine the connotation of these data, so as to maximize its fundamental content, has become a huge challenge in the field of information teaching research. When studying a feedback data of information teaching, we will make some inferences about the data. To understand the world, people need to distinguish different things and understand the similarities between things, while computers need to use unsupervised learning methods to distinguish things [2, 3]. The disorder of information teaching feedback data has brought a huge test to data analysis. Here, we describe the characteristics of the information teaching feedback data from the four most representative characteristics of the information teaching feedback data: grade score, individual score, class score, and the score rate of each question, and obtain the corresponding information of the information teaching feedback characteristics. In order to express the classified information teaching feedback data in a unified form, we establish the characteristic matrix formula of the feedback data (1):

$$K_m = \begin{bmatrix} a_1 & a_1 & a_3 & \cdots & a_m \\ b_1 & b_2 & b_3 & \cdots & b_m \\ c_1 & c_2 & c_3 & \cdots & c_m \\ d_1 & d_2 & d_3 & \cdots & d_m \end{bmatrix} \tag{1}$$

Where, K_m represents the characteristic matrix of feedback data; a_m, b_m, c_m and d_m represent the information of grade score, individual score, class score and score rate of each question in m data [4]. For the information matrix of information teaching feedback characteristics, which includes grade scores, individual scores, class scores, and scoring rates of each question of the data, the correlation degree a_p of grade scores, the correlation degree b_p of individual scores, the correlation degree c_p of class scores, and the correlation degree d_p of scoring rates of each question are obtained from the four types of characteristics, and the correlation degree P_k between the matrices is obtained by weighting the four kinds of correlation degrees. Calculate the correlation degree of the four parameters, such as Formula (2):

$$P_k = \sqrt{\frac{f_s + \left(\frac{1}{t_1+t_2}\right)^2}{f_s + \frac{1}{t_1+t_2}}} \tag{2}$$

Where, P_k represents the fusion correlation degree of different information-based teaching feedback data; f_s represents the correlation coefficient of feature information; t_1 and t_2 respectively represent the fusion weight of the correlation degree. When calculating the correlation degree, the traditional method relies more on expert scoring, but the fusion method designed in this paper is an objective weight assignment method, which is only applicable to the case of fixed data samples. In the face of extensible data, the model needs to be updated constantly, so the time complexity is large.

2.2 Building an Entity Framework for Data Fusion

This paper proposes an entity matching framework that integrates structural information for multi-source heterogeneous data. This framework combines structural similarity with text similarity to more comprehensively measure the similarity of multi-source heterogeneous entities, and can quickly implement entity matching. The whole method is mainly divided into three modules, and the specific functions of each module are as follows:

The first is the data set preprocessing module, which is mainly used to clean, sort and format convert the original data, and generate the standard format data required by the subsequent process. In the face of multi-source heterogeneous data environment, a good data processing mode is the best start. In knowledge fusion, entity matching and data quality assurance are crucial. The quality of the original data will affect the final entity matching results. The final purpose of data preprocessing is to ensure the data quality of the input data of the subsequent process [5, 6]. Data quality can be measured from multiple dimensions, including whether the data format is standardized, whether the data is complete, and whether the data is accurate and timely. The pre-processing in this task guarantees the data quality mainly by ensuring the uniformity and regularity of the data format and minimizing the missing values in the data, which is the basic guarantee for the successful completion of subsequent tasks.

The second module is to build the dataset into a label graph, which aims to model the structural relationship between different entities and different attributes in the dataset. In this study, the dataset is used to build a label graph on the database. Combining the structure information in the graph, entity matching can be better performed. A method of entity matching will be further introduced in Chapter 4. Building tag graph is a core step of the method in this chapter. How to match entities on the database is a challenging task.

The third module is the evaluation of entity matching, which ultimately determines which entity records are matched based on the text similarity and the attribute similarity reflected by the tag map. The data is taken from the constructed label map. When entity matching is required, entity matching needs to be evaluated by combining the graph structure information and semantic attributes. If it meets the standard, entity matching will be performed [7]. In this step, the similarity evaluation of entity matching is set, and the knowledge fusion is implemented after the evaluation. Finally, the fused knowledge is presented on the Neo4j database, stored in the database, and stored in the form of graph structure.

Use MATCH syntax to read data from the database, and store all data in a temporary list. This step is to turn the problem into a Cypher query statement. You need to return different results according to your intentions. This method has a lot of scalability to this step, because the extracted node has attributes and relationships, which can be used for the integration of relationship information and the integration and extraction of node attributes. At this time, the cosine similarity and basic similarity of structural information can be obtained, and the comprehensive similarity formula (3) can be obtained:

$$b_{xyz}(p_i, t_i) = \begin{cases} \frac{1}{x_i}, \ ifd_s = 1 \\ \frac{1}{y_i}, \ ifd_s = 2 \\ \frac{1}{z_i}, \ ifd_s = 3 \end{cases} \tag{3}$$

Where, $b_{xyz}(p_i, x_i)$ represents the comprehensive similarity of x, y, z data under the two basic parameters of p_i and t_i; x_i, y_i and z_i represent the encoding vector of sampled data; d_s represents the embedded entity record result. With the above formula, you can first match the ACM and DBLP entity nodes in the DataFrame, merge the entity nodes, and retain their relationship [8, 9]. Although it is possible to fuse relationships, this paper only focuses on entity matching, so it is reserved in the label graph after the final output of the fusion. It can be clearly seen that entity matching can ultimately assist the completion of knowledge fusion.

3 Data Fusion Method Design

Although the existing controller placement algorithm can obtain an approximate optimal controller placement scheme in a limited time, its shortcomings of poor search breadth in the early stage and low convergence accuracy in the late stage make the dynamic scheme obtained by solving is not ideal in terms of integrated transmission delay and controller load index. In this chapter, the algorithm based on firefly is improved from two aspects: static parameters and initial parameters.

3.1 Parameter Dynamic Control of Firefly Algorithm

The initial settings of the three key parameters α, β, γ in the firefly algorithm are static, but these three key parameters largely determine the performance of the algorithm. In the early stage of the algorithm, it is necessary to increase its randomness and improve the search breadth of the algorithm. In the later stage of the algorithm, it is necessary to reduce the randomness and improve the convergence accuracy of the algorithm. Therefore, this section will introduce a dynamic parameter strategy to improve the algorithm from three aspects: dynamic light attraction, dynamic attraction factor and dynamic random parameters.

Dynamic light attractiveness determines the attractiveness of different deployment schemes to other deployment schemes during the implementation of the algorithm. In order to improve the global search ability of the algorithm and avoid falling into the local optimal solution, it is necessary to reduce the attractiveness of deployment schemes with small differences in the early stage of the algorithm and improve the attractiveness of deployment schemes with large differences. Select the appropriate constants g and p. Where, g divides the algorithm into early stage and late stage, and p is the late stage static parameter of the algorithm. The dynamic light attraction parameter is expressed by the piecewise function shown in Formula (4):

$$R(\alpha) = \begin{cases} g \times T_i - \alpha, g \times T_i \leq g \times T_i \\ p, \alpha > g \times T_i \end{cases} \tag{4}$$

Where, $R(\alpha)$ represents a piecewise function of the dynamic light attraction parameter; T_i represents the number of iterations of the algorithm. After the optimization goal is determined, each deployment scheme will converge to the optimization goal. In order to improve the early random search ability of the algorithm and avoid falling into local optimization, and to improve the convergence speed of the later algorithm, the deployment scheme attraction factor based on the number of iterations is proposed, as shown in Formula (5):

$$R(\beta) = \begin{cases} \dfrac{\beta}{T_i}, \beta < g \times T_i \\ p, \beta \geq g \times T_i \end{cases} \tag{5}$$

Where, $R(\beta)$ represents the piecewise function of the dynamic attraction factor; p Divide the algorithm into early stage and late stage. The essence of random parameters is to provide a perturbation strategy for each deployment scheme in the process of convergence towards the optimization goal, so as to enhance the global search capability. A dynamic random parameter based on the number of iterations is proposed, which can achieve better convergence accuracy in the later stage of the algorithm, such as Formula (6):

$$R(\gamma) = \sqrt{\frac{h_u \times (\gamma - g \times T_i)}{T_i}} \tag{6}$$

Where, $R(\gamma)$ represents the function value of dynamic random parameter; h_u is the perturbation parameter of the algorithm. Through the above three formulas, an approximate optimal controller placement scheme is found in an iterative manner. First, confirm the placement scheme of each parameter and the moving target, and update the control coordinate vector of each scheme with the improved coordinate vector. Then, the coordinate vector of the updated placement scheme is calculated, and the comprehensive transmission delay and mapping relationship are obtained. Then, judge whether the load of each parameter optimization scheme meets the preset conditions, and randomly generate the scheme that does not meet the load constraints. Finally, the control coordinate with the lowest DELAY value and its corresponding mapping relationship are output.

3.2 Design Data Fusion Algorithm

In order to verify the effectiveness of the controller placement algorithm based on the improved firefly algorithm, after initializing the control scheme, random control coordinates can be generated according to the specific topology information, and the mapping relationship and comprehensive transmission delay of the initial control scheme can be calculated at the same time. The control algorithm is determined according to the input, and the approximate optimal control placement scheme in the entire solution space for iteration can be obtained. Design the data fusion algorithm shown in Fig. 1.

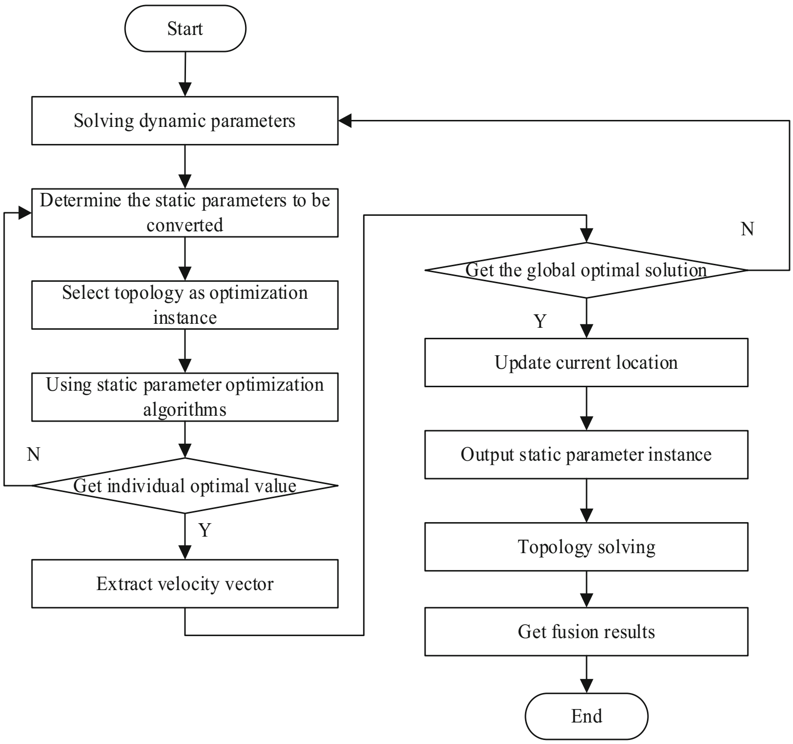

Fig. 1. Algorithm flow

First, calculate the optimal and worst controller placement schemes under the current iteration, and use the leadership strategy to update the coordinate vector of the controller placement scheme in the leadership. Secondly, for the controller placement scheme that is not in the leadership class, randomly select a controller placement scheme as the one, and find the update strategy of individual position according to the current scheme [10]. In this process, the loss function is shown in Formula (7):

$$f(x) = \sum_{i=1}^{n}\sum_{j=1}^{m} p_{\min} \times f_{ij}^{2} \tag{7}$$

Where, $f(x)$ represents the loss function of the algorithm after fusion; $p_{\min}$ is the minimum weighted index between fuzzy ribs; f_{ij} represents the correlation degree of the fusion center matrix. Constrain the correlation between the set fuzzy threshold and the initial fusion center. The principle of selecting the initial fusion center is to make the distance between the initial fusion centers greater than the set threshold, so that the fusion centers can be analyzed in multiple feasible regions in the next fusion algorithm. This process avoids the situation that the algorithm is easy to converge to the local minimum when the algorithm randomly obtains the initial fusion center.

4 Experimental Research

4.1 Experimental Environment and Experimental Data Set

The purpose of this experiment is to test the effectiveness of the information teaching feedback data and method designed above based on the heuristic firefly algorithm. In terms of hardware, the experimental environment of this paper is a single PC, its CPU configuration is Intel Core i7-8700 3.20 GHz, 32GB memory, and the operating system is Wndows10 Professional Edition. In terms of software, the experimental program is coded using MATLAB language based on MATLAB R2017a platform, and the subsequent experimental results are numerically analyzed using MATLAB R2017a platform.

Before the experiment, in order to quantitatively analyze the performance of the algorithm, it is necessary to experiment with the real information teaching feedback data set, including creating the training data set required for training and testing data set required for verification. In this paper, we collect data from the main Internet information teaching websites and build experimental data sets. When establishing the above two data sets, a large number of representative teaching feedback data were collected, and 1000 groups of representative data and their corresponding teaching feedback feature information were manually selected as the data source of the data fusion experiment of the heuristic firefly algorithm. Each group of data includes two different types of teaching feedback data and their corresponding characteristic information matrix. 1000 groups of data are divided into two parts, 500 groups are used as the training data set of the heuristic firefly algorithm, and 500 groups are used as the test data set of the algorithm.

Manually mark the collected characteristic information of various teaching feedback data. During the marking process, four markers are required to conduct Kappa test on the consistency of marking results, and the test results are shown in Table 1. The label results are based on the principle of complementarity, and the label information conflicts are based on the principle of high voting.

Table 1. Consistency test of teaching feedback data

Serial No	Fusion type	Training Set	Test Set
1	A + B	0.865	0.896
2	A + C	0.835	0.885
3	A + D	0.874	0.815
4	B + C	0.896	0.834
5	B + D	0.907	0.875
6	C + D	0.815	0.865
7	A + B + C	0.867	0.836
8	A + B + D	0.905	0.845
9	A + C + D	0.789	0.901
10	B + C + D	0.869	0.875
11	A + B + C + D	0.875	0.869

As shown in Table 1, two, three and four data sets are randomly selected for fusion. On the training set or test set, the consistency test results of teaching feedback data in Kappa test are greater than 0.7, which shows that the marking results are valid.

4.2 Data Processing to Be Merged

First of all, we need to preprocess the data, and divide the information teaching feedback data into two types: overall objective data and individual objective data. The overall objective data includes 10 types of data, including grade grades, average scores, class scores, average scores, individual scores, grade excellence rate, pass rate, low score rate, score rate of each question, and differentiation, while the individual objective data includes individual score of each question, individual score change There are four types of data, including the mastery of individual knowledge points and error analysis.

In the second step, it is necessary to establish data sets to be fused for different samples. In the above 1000 groups of data, 500 of them are randomly selected as the training set, and the remaining 500 test set data are the verification values for the training model.

The third step is to conduct classified training on the overall objective data and individual objective data. Based on the training sample set, establish the nonlinear relationship between the objective data of information teaching feedback and its related achievements, knowledge point mastery, error analysis and other data types, so as to build a heuristic firefly algorithm model. According to different characteristics of information teaching feedback data, training and prediction are conducted separately in the overall objective data and individual objective data, and their root mean square error, correlation coefficient and deviation are calculated. Correlation coefficient, root mean square error and deviation, such as Formula (8)–(10):

$$\lambda(x, y) = \frac{\sum_{i=1}^{n}\sum_{j=1}^{m}\left(X_{ij} - X_n\right)\left(Y_{ij} - Y_m\right)}{\sqrt{\left(\sum_{i=1}^{n}\sum_{j=1}^{m}\left(X_{ij} - X_n\right)^2 \sum_{i=1}^{n}\sum_{j=1}^{m}\left(Y_{ij} - Y_m\right)^2\right)}} \tag{8}$$

$$RASE = \sqrt{\frac{\sum_{i=1}^{m}\sum_{j=1}^{n}\left(f_i - f_j\right)^2}{m \times n}} \tag{9}$$

$$P_m = \frac{d_h + d_k}{N} \tag{10}$$

Where, $\lambda(x, y)$ represents the correlation coefficient of x and y; X_{ij} and Y_{ij} represent the fusion frequency of data x and data y in two different data types respectively; X_n and Y_m represent the relative action frequency of data x and data y respectively. $RASE$ represents the root mean square error between the two information fusion and the original data; f_i and f_j represent two data to be fused respectively; G represents the data size. P_m represents the deviation value, d_h represents the word measurement value, d_k represents the absolute value of the average value, and N represents the number of measurements. The training results of overall objective data and individual objective data obtained through Formula (8)–(10) are shown in Table 2.

Table 2. Training Results

Comparison content	Overall objective data	Individual objective data
Correlation coefficient	0.92	0.91
Root mean square error	0.003	0.004
Deviation	−0.0006	−0.0005

In Table 2, models of both overall objective data and individual objective data can meet the fusion requirements, with correlation coefficients greater than 0.9, root mean square error less than 0.01, and absolute value of deviation less than 0.001. Therefore, in the model prediction of the heuristic firefly algorithm, after building the model, the prediction sample set can be input into the model for regression prediction.

The fourth step is to conduct the final processing of the data, convert the output predictive value from the sample dimension to the space-time dimension corresponding to the information teaching feedback data, and extract the objective data type to be verified according to the remaining data to verify the spatial expansion of the prediction results.

4.3 Selection of Experimental Parameters

When training the network structure of the heuristic firefly algorithm, there are many parameters that need to be adjusted. In this experiment, the learning rate, training times and data volume are taken as the adjusted object parameters. In the process of adjusting the network parameters of the heuristic firefly algorithm, the fusion accuracy is taken as the primary reference index.

For the training network, the initial learning rate is very important to the fusion accuracy, so it is selected as the primary parameter for adjustment. During the adjustment process, all 500 groups of data to be trained established above are selected for the training data set, and the other parameters are in the default state. All 500 groups of test data sets are selected to verify the accuracy.

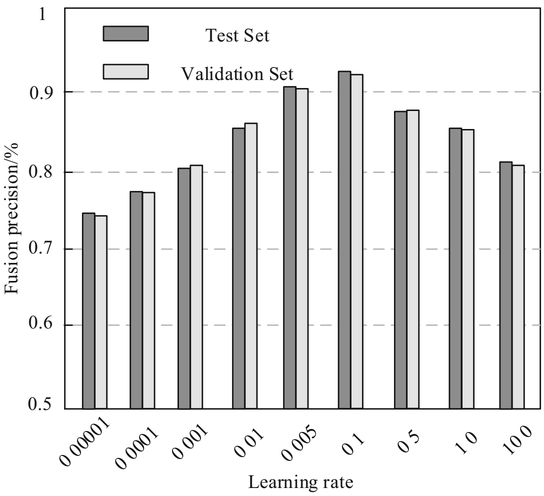

Fig. 2. Effect of learning rate on fusion accuracy

As shown in Fig. 2, the fusion precision difference between the test set and the verification set is small, so in the following experiments, the test set is selected as the experimental indicator. As the learning rate increased from 0.00001 to 0.1, the accuracy rate of the test also increased linearly, and the highest accuracy rate was 0.9325 near 0.1. Then, as the learning rate increases, the accuracy rate decreases slightly. Therefore, 0.1 is selected as the learning rate of the information teaching feedback data fusion method based on the heuristic firefly algorithm. After determining the learning rate, keep the learning rate at 0.1 and adjust the number of iterations of the algorithm.

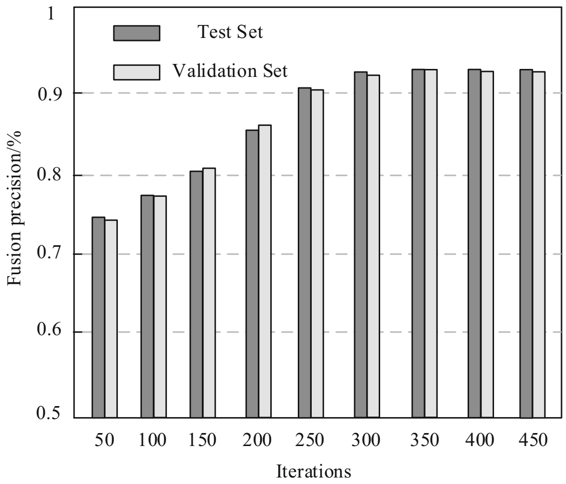

Fig. 3. Influence of Iteration Times on Fusion Accuracy

As can be seen from Fig. 3, with the increase of the number of iterations, the accuracy rate also improved significantly. When the number of iterations reached 300, the fusion accuracy of the algorithm reached 0.9374. After that, the number of iterations continued to grow, but the fusion accuracy of the algorithm did not change. It can be seen that 300 iterations were the peak value of the fusion accuracy in this experiment. Therefore, 300 was selected as the number of iterations in this experiment.

When the amount of test data is large, you need to set the learning rate to 0.1 and the number of iterations to 300.

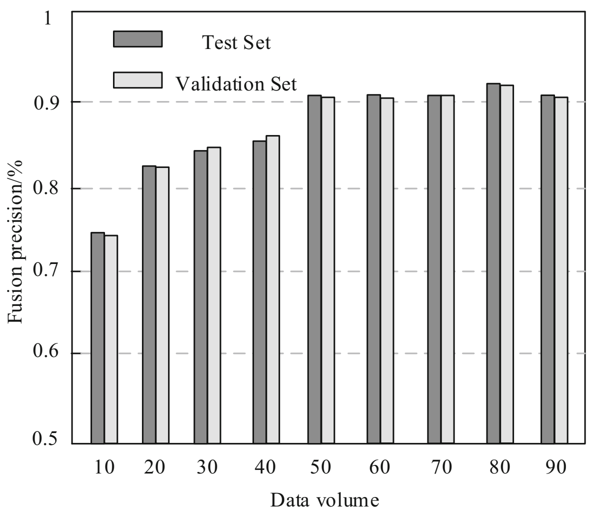

Fig. 4. Data volume

As can be seen from Fig. 4, when the data volume is 10, the fusion precision of the information-based teaching feedback data of the test set is 0.753. With the gradual increase of the data volume, the fusion precision of the information-based teaching feedback data is also growing. When the amount of data is 50, the fusion precision of the information teaching feedback data has exceeded 0.9, and when the amount of data is larger, the fusion precision of the information teaching feedback data sometimes increases, sometimes decreases, but is not less than 0.9. It can be seen that the amount of data selected for this experiment should be greater than 50.

In conclusion, when the learning rate is 0.1, the number of iterations is 300, and the data volume is 50, the maximum fusion precision between the test set and the verification set can be obtained.

4.4 Time Efficiency of Data Fusion

In order to evaluate the time efficiency of the heuristic firefly algorithm designed in this paper to integrate the overall objective data and individual objective data in the information teaching feedback data fusion model, test and analyze it, and the experimental results are shown in Fig. 5.

As shown in Fig. 5, as the amount of data increases, the time required for data fusion also increases significantly, and it can be clearly seen that the fusion time required for overall objective data is less than that for individual objective data. Compared with the data fusion between different types, the time required for two types of data fusion is obviously less than that for three types of data fusion, while the time required for three types of data fusion is less than that for four types of data fusion. It can be seen that the larger the data volume, the longer the data fusion takes; The fewer data types, the faster the fusion.

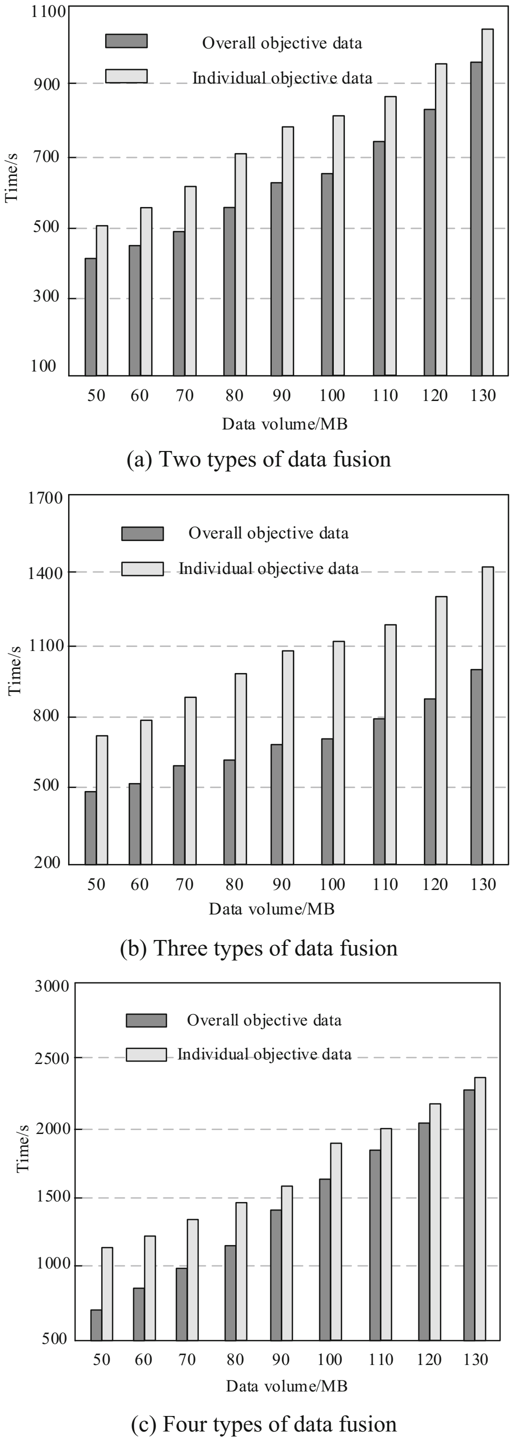

Fig. 5. Algorithm Running Time

5 Conclusion

From the perspective of classification of information teaching feedback information, according to its data characteristics in different fields, this paper conducts classification processing from multiple dimensions, and establishes the characteristic data matrix of information teaching feedback data. According to the experimental data, the optimal learning rate, iteration times, data volume and other parameters are obtained, and the algorithm running time of two types of data, three types of data, four types of data is obtained according to the different types of data fusion. It can be seen from the experimental results that the amount of data and the number of data types are in direct proportion to the fusion efficiency.

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2. 2022 General Project of Philosophy and Social Sciences Research in Colleges and Universities: Research on the Realistic Dilemma and Technical Appeals of Precision Funding in Colleges and Universities from the Perspective of Big Data (Project No.: 2022SJYB1050).

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