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Multi-sensor Data Fusion based on Fuzzy Theory and FWA-BP Neural Network

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***Abstract*—With the development of science and technology, there are more and more types of sensors, and their performance is getting better and better. But a single sensor is less effective in the perception of complex systems. In order to solve the problem of data access difficulties caused by the diversification of sensors, a new multi-sensor data fusion model is designed based on fuzzy theory and combining fireworks algorithm and back propagation neural network. The experimental results show that the accuracy of the model is up to 92%, the training time of the algorithm is only 90s, and the computational resources are less consumed, and the algorithm has 30 iterations. The computational time consuming of the model is relatively stable, mainly concentrated in the time range from 10ms to 20ms. Therefore, the proposed multi-sensor data fusion model has the advantages of less resource consumption, high accuracy and short computational time consuming, which provides new technical support for the development of the Internet of Things.**

Keywords*—*Fuzzy theory, back propagation neural network, fireworks algorithm

I. Introduction

With the acceleration of national industrialization and the rapid improvement of digital capabilities, sensor technology has also experienced rapid development. Nowadays, there are a wide variety of sensors with different functions, which are becoming increasingly diverse and complex. The advancement of this technology not only brings great convenience to people's production and life, but also highlights the importance of multi-sensor data fusion with the increasingly mature Internet of Things technology and the urgent need for the Internet of Things. The main methods of traditional multi-sensor data fusion include model-based, rule-based, and statistical fusion [1-2]. These methods face the problems of inconsistent and missing data when processing multi-sensor data, which may affect the accuracy and correctness of fusion results. Therefore, more and more people are paying attention to sensor data fusion [3]. Chen Linwei et al. proposed an axial piston pump fault diagnosis method based on multi-sensor data fusion deep residual shrinkage network learning to solve the problem that single sensor vibration information cannot fully express the fault feature information of the piston pump. This method can effectively extract the fault features of vibration signals, and the recognition accuracy is significantly higher than typical deep learning methods [4]. However, the related methods perform poorly in terms of redundancy, timeliness, and other aspects [5-6]. Given that this research innovatively combines Fireworks Algorithm (FWA) with Back Propagation Neural Network (BP) neural network for multi-sensor data fusion. Introducing polynomial least squares filtering for data smoothing and noise reduction to improve data quality. Using fuzzy membership functions to calculate the support between data and more accurately measure the interrelationships between data. Finally, use the Levenberg Marquardt (LM) algorithm to optimize the weights and thresholds of the neural network and reduce training errors. We hope to improve the accuracy and efficiency of multi-sensor data fusion through this series of innovative measures. The innovation of the research lies in the combination of fuzzy theory and neural network, making full use of the advantages of the two methods, improving the accuracy of multi-sensor data fusion and reducing the computational complexity of the algorithm. The contribution of the research is that the design algorithm can well eliminate the influence of the uncertainty brought by multiple information on data fusion, so as to obtain an accurate and complete description of the research objective or research environment, and provide support for the subsequent decision of data fusion.

II. Design of the Multi-sensor Data Fusion Model

A. Design of Data Fusion Structure based on Improved Fuzzy Support

The characteristics of multi-sensor data fusion mainly include complementarity, redundancy, timeliness, and low cost. In order to better cope with the complex and ever-changing multi-sensor data environment [7-8]. Research on combining fireworks algorithm with BP for multi-sensor data fusion [9]. FWA has strong global search capability and fast convergence, which can effectively find the optimal solution for data fusion problems [10]. Secondly, the BP neural network has excellent learning and mapping capabilities, which can deeply explore the internal connections between data. In the fireworks algorithm, feasible solutions are represented by the position of each fireworks. When fireworks explode, two types of Mars are generated: regular Mars and special Mars. Every time a fireworks explosion occurs, it produces a certain number of ordinary Mars and has a certain probability of producing a special Mars [11-12]. Ordinary Mars is generated in a random and uniform distribution around its original Mars, while special Mars is generated in a normal distribution near the original Mars. If the number of Mars generated in a certain iteration exceeds the expected number of Mars in each generation, the algorithm will screen based on the position of Mars and randomly retain the specified number of Mars to ensure the stability of the total number of Mars. The schematic diagram of the model structure is shown in Figure 1.

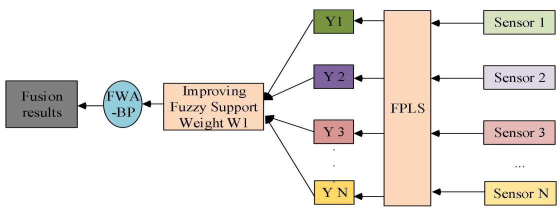

Fig. 1. Schematic diagram of the multi-sensor data fusion structure based on the improved fuzzy support.

Firstly, data is collected from multiple sensors, and filtered with polynomial least squares (FPLS) is used to smooth and denoise the collected data. Firstly, a fifth order polynomial is used to perform least squares fitting on every 10 data points within a specified time window as data within one window. After fitting, five parameters are obtained, which are used as weights. By using these weights, calculate the weighted average of the data within this time window, which is the result of filtering. Next, with one data point as the step size, gradually move this time window and repeat the above fitting and weighting process on each new window until the complete time series data is processed. In order to obtain mutual support between data, the study chose the logsig fuzzy membership function for support calculation. This function assigns weights to the data based on its support, and data with higher support will receive greater weights. Through this approach, it is possible to more accurately measure the interrelationships between data and optimize data processing and analysis. The characteristic of the logsig function is that its output value is between 0 and 1, which can well reflect the fuzziness and uncertainty of the data. Finally, the smoothing and denoising results obtained from polynomial least squares filtering are input into the FWA-BP model for further data fusion processing.

B. Main Steps and Optimization Design of the FWA-BP Algorithm

The first step is to determine the topology and transfer function of a BP in the algorithmic flow, which determines how the network processes the inputs and outputs the results. Next, the weights and thresholds are initialized for the BP neural network, which is a key preparatory step before training the network. Afterwards, the fireworks population is initialized, which is a set of individuals in a swarm intelligent optimization algorithm. Each individual fireworks' fitness value was calculated, assuming that the number of neurons in the output layer of the network is, and its fitness function is shown in Equation (1).

$$f\left(x_i\right) = SSE = \sum_{i=1}^{s}\left(t_i - y_i\right)^2 \quad (1)$$

In equation (1), t represents the expected output of the network, and y represents the actual output value of the network. Based on the fitness value, generate explosive sparks and Gaussian variation sparks to search for better solutions in the solution space. The main influencing factor of explosion operators is explosion intensity. In real life, when fireworks explode, a large number of sparks are generated, as shown in Figure 2.

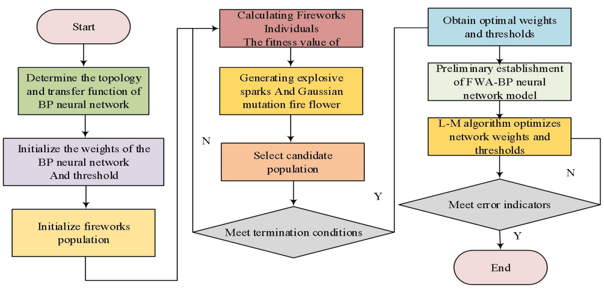

Fig. 2. Flow chart of FWA-BP model.

In the fireworks algorithm, fireworks can make different fitness to produce different amounts of sparks [13] by adjusting the explosion intensity. The benefit of this practice is that it prevents the algorithm from falling into the local optimal solution, thus exploring and searching the entire possible solution space as much as possible. The number of fireworks generated by the explosion is shown in equation (2).

$$S_i = m\frac{Y_{\max} f\left(x_i\right) + \varepsilon}{\sum_{i=1}^{n}\left[Y_{\max} f\left(x_i\right)\right] + \varepsilon} \quad (2)$$

In equation (2), S_i is the number of sparks (new candidate solutions) that will be generated by the second fireworks (candidate solutions). This value is calculated based on the fitness value of the fireworks. m is a constant that represents the maximum number of sparks allowed to be generated in one iteration of the algorithm. $Y_{\max}$ is a constant used to control the influence of fitness values, which adjusts the weight of fitness values in calculating the number of sparks generated. $f\left(x_i\right)$ is the fitness value for the i fireworks (candidate solution). ε is a very small positive number used to ensure that the denominator is not zero, thus avoiding zero errors. $\sum_{i=1}^{n}\left[Y_{\max} f\left(x_i\right)\right]$ is the sum of weighted fitness values for all fireworks in the current population, with weights given by $Y_{\max}$. This sum is used to normalize the amount of sparks produced by each fireworks to ensure that their total does not exceed m. In order to expand the optimization space and increase the diversity of the population, and avoid getting stuck in local optima when fireworks explode. Displacement and mutation operations are required for explosive sparks. Using the method of random displacement to update the dimensions of sparks. When selecting candidate populations, roulette wheel selection is utilized to select individuals based on the proportion of their fitness value to the overall fitness value, forming the next generation population. Then determine whether the termination condition is satisfied. If not, return to the step of generating sparks to continue searching. If the termination condition is met, the optimal weight and threshold are obtained. When determining the amount of hidden layers, it is necessary to dynamically determine the network performance, assuming the amount of output layer nodes. The empirical formula is shown in equation (3).

$$n = \sqrt{s + p} + d \quad (3)$$

In equation (3), n represents the number of hidden layer nodes, s represents the number of input layer nodes, and d is the adjustment constant. With these optimal parameters, a preliminary FWA-BP model can be established. Afterwards, the L-M algorithm is used to further optimize the weights and thresholds of the neural network. The L-M algorithm combines the advantages of gradient descent and Newton's method. During the implementation process, the increment in the L-M algorithm is calculated based on the current weights and thresholds of the network, as well as the gradient information of the error function. Then, use this increment to update the weights and thresholds of the network. By continuously iterating this process, the output of the network will gradually approach the true value, thereby reducing training errors. At the same time, constantly assess whether the model meets the preset error indicators. If not satisfied, return to the L-M optimization step; If satisfied, output the final neural network model.

III. PERFORMANCE TEST AND APPLICATION EXPERIMENT OF THE FWA-BP ALGORITHM

In order to address the issues of complementarity, redundancy, timeliness, and low cost in multi-sensor data fusion, FWA-BP has been developed. To verify the effectiveness of each module in the model, the Intel Core i7-11800H central processor was installed A series of ablation experiments were conducted using Matlab 2017a software on the Windows 10 operating system with GeForce RTX 3070 graphics processor and 16GB of running memory. By setting up six experimental groups, key modules such as FWA, fuzzy logic, BP network, L-M optimization, and FPLS were removed, aiming to explore the contribution of each module to model performance. We comprehensively evaluated the performance of the model in the absence of different modules based on evaluation criteria such as iteration count, convergence time, accuracy, and computational resource consumption. Experimental group 6 served as the control group, retaining the complete FWA-BP model to demonstrate the performance of the model in its intact state. During the experiment, the adjustment constant for the number of sparks in the flower explosion was set to 30, the population size was set to 50, and the number of Gaussian variation sparks was set to 3. For the BP neural network module, its learning rate is set to 0.01, momentum is set to 0.9, and batch size is set to 200. By comparing the data of each experimental group, we can gain a deeper understanding of the impact of each module on model performance, providing strong support for further optimizing the model. The experiment outcomes are denoted in Table 1.

TABLE I. FWA-BP MULTISENSOR DATA FUSION MODEL ABLATION EXPERIMENTS

Experimental group number	Iteration frequency	Convergence time to optimal solution (seconds)	Accuracy (%)	Computing resource consumption (Relative units)
1	50	120	80	15
2	40	100	85	20
3	60	150	88	25
4	80	200	90	35
5	45	110	83	18
6	30	90	92	22

By comparing the data of six experimental groups, the following conclusions can be drawn. In terms of accuracy, experimental group 6 (complete FWA-BP model) achieved the highest 92%, significantly higher than other experimental groups lacking modules. This indicates that each module contributes significantly to the accuracy of the model. Among them, the accuracy of experimental group 3 (lacking BP network module) was 88%, second only to the complete model, indicating that the BP network module is particularly crucial for improving accuracy. Secondly, in terms of convergence time, experimental group 6 also performed the best, converging to the optimal solution in just 90 seconds. And experimental group 4 (lacking L-M module) had the longest convergence time, reaching 200 seconds. This indicates that the L-M optimization module plays an important role in accelerating the convergence speed of the model. From the perspective of computing resource consumption, the computing resource consumption of experimental group 6 is 22 relative units, which is at a moderate level. Experimental group 4 had the highest consumption of computing resources, reaching 35 relative units, which may be related to the lack of L-M modules leading to slower convergence speed and increased consumption of computing resources. Furthermore, in terms of the number of iterations, experimental group 6 had the lowest number of iterations, only 30, indicating a high optimization efficiency of the complete model. And experimental group 4 had the highest number of iterations, reaching 80, further confirming the importance of the L-M module in the optimization process. The experiment fully verified the FWA-BP model's superiority in the field of sensor data fusion. To further verify that the model also performs equally well in practical application environments, the study introduced the Multi Sensor Data Fusion algorithm for Two Level Fusion (MSDF-TLF) proposed in reference [14]. As a comparison, the FWA-BP model and MSDF-TLF were used to fuse data from multiple sensors on electric vehicles. The experimental results are shown in Figure 3.

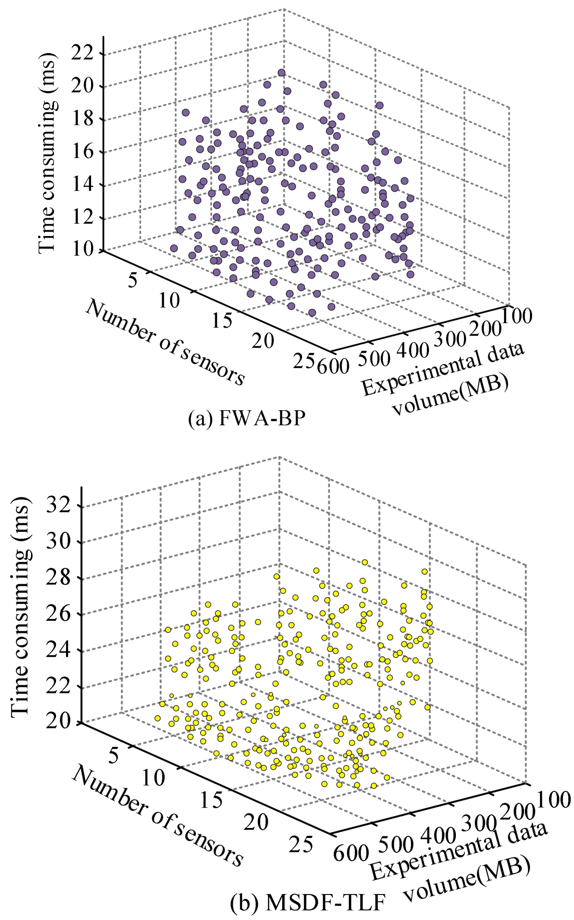

Fig. 3. Schematic diagram of the multi-sensor data fusion structure based on the improved fuzzy support.

According to the data shown in Figure 3 (a), it can be clearly observed that as system resources continue to increase, the computational time of the FWA-BP model shows a significant downward trend. This decline is not non-linear, but gradually slows down as resources increase, indicating a marginal diminishing effect. This also means that when the system resources reach a certain level, the contribution of increasing resources to reducing computational time will gradually weaken. In addition, as the number of sensors in the system increases, the computational time of the FWA-BP model also increases, but the magnitude of this increase is not significant. Overall, the calculation time of the FWA-BP model is relatively stable, mainly concentrated in the time range of 10ms to 20ms. From Figure 3 (b), it can be seen that the performance of the MSDF-TLF model is similar to that of the FWA-BP model. As system resources increase, their computing time also shows a decreasing trend, and the speed of this reduction is gradually slowing down, reflecting the law of marginal decrease. But unlike the FWA-BP model, as the amount of sensors increases, the computational time of the MSDF-TLF model increases more significantly. The overall time consumption is mainly concentrated between 20ms and 28ms, which is improved compared to the FWA-BP model.

In order to further verify the comprehensive performance of the model compared to other data fusion algorithms, the study introduced the algorithm proposed in reference [15] as experimental group 1, the algorithm proposed in reference [16] as experimental group 2, the algorithm proposed in reference [17] as experimental group 3, the algorithm proposed in reference [18] as experimental group 4, and the FWA-BP model as experimental group 5. Using model complexity (number of parameters), generalization ability (cross validation accuracy,%), robustness (accuracy under 1% noise,%), and real-time performance (time required to process a single data point, ms) as evaluation indicators, the experimental results are shown in Table 2.

TABLE II. COMPREHENSIVE PERFORMANCE PERFORMANCE OF THE FIVE DATA FUSION ALGORITHMS

group number	Number of parameters	Cross-validation accuracy rate (%)	Accuracy rate (%) at 1% noise	Time required to process a single data point (ms)
1	5000	82.5	78.1	15.2
2	4500	85.3	80.2	12.5
3	4800	83.6	79.5	18.9
4	5200	79.8	75.6	13.8
5	4700	88.9	84.3	11.1

According to the experimental results in Table 2, the comprehensive performance of five data fusion algorithms can be obtained. In terms of model complexity, the number of parameters in experimental group 5 (FWA-BP model) is 4700, which is relatively low and shows good model simplicity. In terms of generalization ability, the cross validation accuracy of experimental group 5 reached 88.9%, which is significantly better than other experimental groups. In the robustness test, experimental group 5 achieved an accuracy of 84.3% under 1% noise, ranking first among all experimental groups. In addition, from a real-time perspective, experimental group 5 requires the shortest time to process a single data point, only 11.1ms, indicating its efficiency. Overall, the FWA-BP model performs well in all four evaluation indicators, especially in terms of generalization ability and robustness, while ensuring good real-time performance. Therefore, it can be concluded that the FWA-BP model has better overall performance compared to other data fusion algorithms.

IV. CONCLUSION

This study conducted an in-depth comparative analysis of six different blockchain technology platforms to meet the needs of cross-border e-commerce application platforms when selecting the most suitable technology solution. By constructing an evaluation system containing multiple key indicators and using Monte Carlo simulation to explore the sensitivity of indicators, it was found that safety, logistics efficiency, product traceability, and customer service are key factors affecting the performance of cross-border e-commerce platforms. The sensitivity of security indicators is the highest, with an average sensitivity of about 85.3%, highlighting the core position of security in the evaluation of cross-border e-commerce platforms. The average sensitivity of logistics efficiency is about 75.6%, product traceability is about 78.2%, and the sensitivity of customer service indicators is about 81.6%. These three indicators also have a significant impact on platform performance. Furthermore, the LDAPANA method was used to comprehensively evaluate multiple cross-border e-commerce platforms, and the study found that the R3 Corda platform performed excellently in all indicators, ranking first with a comprehensive evaluation value of 0.90. In summary, this study indicates that when choosing blockchain technology for cross-border e-commerce application platforms, key considerations should be placed on indicators such as security, logistics efficiency, product traceability, and customer service. The R3 Corda platform performs the best in these areas and is the preferred technological solution. However, there may be certain limitations in the selection of experimental sample size and evaluation indicators in this study. Future research can further expand the sample range and add more detailed evaluation indicators to improve the comprehensiveness and accuracy of the study.

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