IEEE Access
Multidisciplinary ⋮ Rapid Review ⋮ Open Access Journal

Received March 26, 2019, accepted April 5, 2019, date of publication April 11, 2019, date of current version April 19, 2019.

Digital Object Identifier 10.1109/ACCESS.2019.2910191

Recognition and Analysis of Motor Imagery EEG Signal Based on Improved BP Neural Network

LONG LIU
College of Physical Education, Anyang Normal University, Anyang 455000, China
e-mail: liulong@aynu.edu.cn

ABSTRACT With the rapid development of neuroinformatics and related intelligent algorithms, the research of recognition and classification based on EEG signals is becoming more and more important and valuable. With the progress of science and technology, the related research of EEG signal recognition and processing has been gradually applied to rehabilitation medicine, intelligent information processing, and other cross-cutting fields. As one of the most important research directions in the field of the brain–computer interface, motor imagery EEG has a wide range of applications. At the same time, it shows a good application effect in the process of application practice. At present, the main EEG recognition and analysis algorithms always have some problems and defects in data processing, such as low signal-to-noise ratio, unclean noise filtering, and high data dimension. In this paper, based on the improved BP neural network algorithm, weight splitting technology is added to the traditional BP neural network algorithm. In order to solve the filtering problem, this paper uses the non-linear mapping function of the traditional BP neural network, and intelligently trains the small weight particles by combining the particle swarm filter algorithm, so as to improve the filtering performance of the whole BP algorithm. Based on the above two algorithms, the problem of low signal-to-noise ratio (SNR) and unclean filtering in EEG data processing caused by fast weight degradation in traditional BP algorithm can be solved. Finally, according to the actual data of brain–computer interface, this paper compares the improved BP neural network algorithm with the traditional BP neural network algorithm in recognition and analysis of motor imagery EEG signals. The experiment shows that the proposed algorithm has obvious advantages in recognition accuracy and analysis effect.

INDEX TERMS Keywords improved BP neural algorithms, motor imagery EEG signals, weight splitting technology, recognition accuracy, particle cluster filtering technology.

I. INTRODUCTION

Neuroinformatics is an interdisciplinary subject. It mainly studies the interdisciplinary integration between neuroscience and information science. At the same time, Chen *et al.* using advanced computer technology and scientific tools to realize the digitalization and graphical representation of EEG signals [1]–[3]. Neuroinformatics is widely used in rehabilitation science, biomedicine and pedagogy. Brain-computer interface technology is an important research means in the field of neuroinformatics. It mainly identifies individual EEG signals by computer technology or artificial intelligence algorithm, so as to realize the interactive communication between human brain and computer according to certain modes, Wei *et al.* have achieved some good results in this field [4]–[6]. Motion imagery EEG (motor imagery EEG) is an important field in the study of EEG. It has a wide range of applications [7]–[9]. However, there are still a lot of problems in resolving the signal-to-noise ratio (SNR) and filtering degree in the traditional algorithms for recognizing and analyzing motor imagery EEG signals. Therefore, it is very meaningful to apply advanced algorithms to the recognition and processing of motor imagery EEG signals in time, and it is also conducive to promoting the development of recognition and analysis algorithms, Fei and Jie have done a lot of work in this field [10], [11].

In order to solve the above problems, scholar Liu have carried out research and analysis, and he main driving points are set in solving their identification accuracy and filtering degree [12]. Austrian scholars have proposed a brain-electrical interface system for time-related de-synchronization of EEG signals, which mainly studies and

The associate editor coordinating the review of this manuscript and approving it for publication was Robertas Damasevicius.

analyses the perception, cognition and activity of the brain. This kind of research method has pioneered the research of EEG in medical rehabilitation, relevant research results can be seen in the [13]–[15]. American scholars have studied the development of EEG signals and computer systems for the spontaneous rhythm of motor sensation. The main purpose of this research is to convert the individual motor imagined EEG signals into two-dimensional motion instructions on the computer screen and corresponding mouse cursor movement control instructions. This method makes the research of EEG signals more detailed and implementable [16]–[18]. In order to solve the problem of the accuracy of the corresponding algorithm in recognizing and analyzing EEG signals of motor imagery, relevant scholars have proposed to optimize BP neural network algorithm based on particle filter algorithm, which gives the general expression of particle filter algorithm, and proves the inevitability of particle degeneration in such algorithm. This method is used to process EEG signals of motor imagery. The algorithm proposed in this paper is also based on the improved algorithm [19]–[21].

In this paper, based on the improved BP neural network algorithm, weight splitting technology is added to the traditional BP neural network algorithm. In order to solve the filtering problem, this paper uses the non-linear mapping function of the traditional BP neural network, and intelligently trains the small weight particles by combining the particle swarm filter algorithm, so as to improve the filtering performance of the whole BP algorithm. Based on the above two algorithms, the problem of low signal-to-noise ratio (SNR) and unclean filtering in EEG data processing caused by fast weight degradation in traditional BP algorithm can be solved. Finally, according to the actual data of brain-computer interface, this paper compares the improved BP neural network algorithm with the traditional BP neural network algorithm in recognition and analysis of motor imagery EEG signals. The experiment shows that the proposed algorithm has obvious advantages in recognition accuracy and analysis effect.

This paper makes the following arrangements on the structure of the paper: The second section of this paper will specifically study and analyze the algorithm idea of BP neural network technology and the characteristics and difficulties of recognition and analysis of motor imagery EEG signals; the third section of this paper will mainly analyze the related work of recognition and analysis of motor imagery EEG signals based on BP neural network algorithm, and mainly analyze the current related recognition and analysis of motor imagery. At the same time, the advantages and disadvantages of EEG algorithm are pointed out, and the existing problems are pointed out. In the fourth section, the core idea of the improved BP neural network algorithm and its application principle in the recognition and analysis of motor imagery EEG signal are analyzed, and the experimental comparative data analysis is given. Finally, a summary of this paper is given.

II. ANALYSIS OF BP NEURAL NETWORK ALGORITHMS AND RECOGNITION OF MOTOR IMAGERY EEG SIGNALS

This section mainly discusses the core idea of BP neural network algorithm, its working principle and its application in recognition and analysis of motor imagery EEG signals.

A. ANALYSIS OF BP NEURAL NETWORK

The core algorithm of BP neural network is gradient core deceleration method. Its main idea is that the core of gradient steepest descent method is to adjust the weights of each layer of the neural network to minimize the total error, that is, to achieve the minimum mean square error of reality and expectation. The learning process of BP neural network algorithm is a forward feedback learning process. In essence, it is a process in which errors propagate backwards while correcting the weight coefficients of each layer. Feedback learning runs through the adjustment of the connection mode, weight and threshold of each neuron, and the identification of the whole network. BP algorithm enables us to achieve the minimum of the given error function, so that we can get the relationship between input samples and output samples in BP neural network [22], [23]. The corresponding algorithm mainly divided into two stages: positive phase and reverse phase [24], [25].

BP neural network is essentially a forward feedback neural network, which mainly uses the error back-propagation algorithm to adjust the corresponding weights of each layer. The corresponding structure of Neural network is shown in Figure 1.

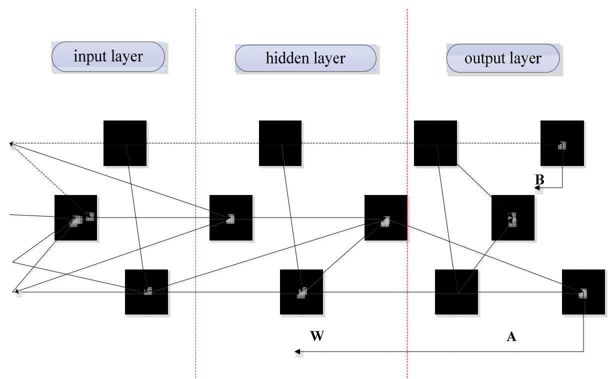

FIGURE 1. The corresponding structure of neural network.

B. ANALYSIS OF MOTOR IMAGERY EEG SIGNALS

Motor Imagery EEG signal is a predictive signal of a single individual before the actual movement. It is mainly produced by the brain when it is thinking. It is essentially a bioelectrical signal. By collecting and recognizing motion imagery signals, they can be transformed into easily recognizable waveforms, frequencies, amplitudes or image curves. In the process of recognition, EEG signals mainly go through data preprocessing, data feature extraction and classification, data feature recognition and brain state recognition. In data preprocessing, it mainly transforms a large number of biological behaviors of EEG signals into readable electrical signals, and filters the noise, invalid information and interference information effectively. In the filtering stage, the traditional BP neural algorithm adopts frequency-division filtering, and its corresponding classification of filtering frequency bands is shown in Table 1. After completing the pretreatment and classification, the data will be processed and analyzed. Finally, the feedback and summary of EEG data are given, and the analysis of the whole brain state is finally formed.

TABLE 1. **The corresponding classification of filtering frequency bands.**

Band range	Frequency values and characteristics
0.5-3HZ	Lethargy
4-8HZ	Drowsiness
8-13Hz	Resting state
13-30Hz	Tension and excitement
30-45Hz	Excited state

III. RELEVANT WORK ANALYSIS: RECOGNITION AND ANALYSIS OF MOTOR IMAGERY EEG SIGNALS BASED ON BP NEURAL NETWORK

This section will analyze and study the advantages and disadvantages of the current algorithms for recognizing and analyzing motor imagery EEG signals, and point out the existing problems in recognition and analysis of motor imagery EEG signals. With the development of neuroinformatics and related intelligent algorithms, the research of classification processing based on human EEG signals is becoming more and more important and valuable. Relevant research and development based on EEG signals have been gradually applied to rehabilitation medicine, intelligent information processing and other cross-cutting fields. As one of the most important research directions in the field of brain-computer interface, motor imagery EEG has a wide range of applications, and it shows good application effect in practice. At present, the mainstream classification algorithms of EEG signal processing always have some problems and shortcomings in EEG data processing, such as low signal-to-noise ratio, dirty filtering and high data dimension when processing EEG data. In this paper, based on the improved BP neural network algorithm, by adding weight splitting technology into the algorithm, and based on the non-linear mapping function of BP neural network, through the actual intelligent training of small weight particles, the filtering degree of the whole BP algorithm will be improved, thus resolving the signal-to-noise ratio of EEG signal processing caused by the fast weight degradation of the original BP algorithm. Too low, too much worry, not clean and other issues. Finally, according to the actual data of brain-computer interface, this paper compares the improved BP neural network algorithm with the traditional BP algorithm in the recognition and analysis of motor imagery EEG signals. The experiment shows that the proposed algorithm has obvious advantages in recognition accuracy and classification effect.

A. RELEVANT WORK 1: ANALYSIS AND RESEARCH OF RECOGNITION AND ANALYSIS ALGORITHMS OF EEG SIGNALS BASED ON MOTION IMAGINATION

In this section, we will discuss and compare the research results of current EEG recognition and analysis algorithms.

In the research framework of the whole system, a large number of scholars and research institutions follow the basic framework shown in Figure 2. In the framework shown in Figure 2, EEG signals mainly undergo data preprocessing, data feature extraction and classification, data feature recognition and brain state recognition. In data preprocessing, it mainly transforms a large number of biological behaviors of EEG signals into readable electrical signals, and filters the noise, invalid information and interference information effectively.

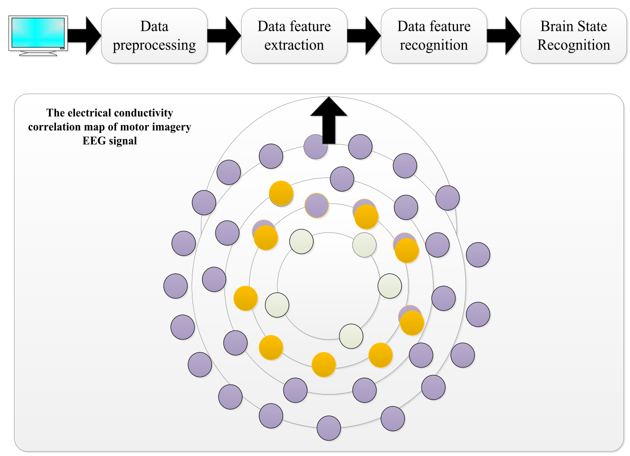

FIGURE 2. **The main flow chart and the electrical conductivity correlation map of motor imagery EEG signal.**

The corresponding Brain-Computer Framework for Algorithmic Recognition and Analysis is shown in Figure 3 below. In all the current algorithms, it basically follows such a system framework, which is a general framework:

Based on the above framework, a large number of scholars and research institutions have studied the recognition and analysis of motor imagery EEG signals.

1) RELEVANT RESEARCH ALGORITHMS AND LITERATURE ANALYSIS ON NOISE REMOVAL

Gursel and Balconi have developed a method for removing artifacts, such as Eye and EMG signals, in the process of signal acquisition and processing [26], [27]. Other mainstream methods of research institutions, such as common-space pattern recognition and analysis algorithms for motion imagery EEG signals, mainly use spatial filtering, bandwidth energy, Fourier transform, wavelet packet decomposition and other

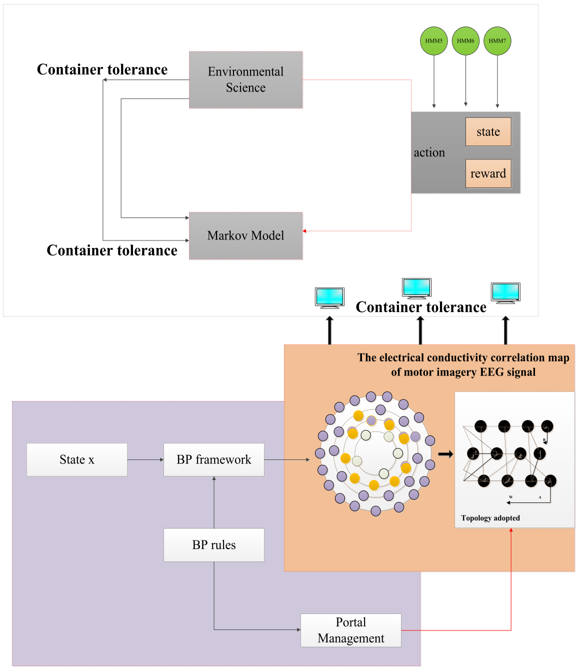

FIGURE 3. The corresponding brain-computer framework for algorithmic recognition and analysis.

technologies to find online classification and recognition algorithms for adaptive recognition algorithms. At the same time, it adds improved CSP algorithm and supervised learning algorithm to the hidden layer, which solves the problem of recognition accuracy to a certain extent, but the algorithm consumes too much computer and the algorithm is too complex.

2) ALGORITHMS AND LITERATURE ANALYSIS OF UNIVERSALITY ISSUES

In this regard, a large number of scholars have carried out research and analysis. Austrian scholars have proposed a brain-electrical interface system for time-related de-synchronization of EEG signals, which mainly studies and analyses the perception, cognition and activity of the brain. This kind of research method pioneered the research of EEG in medical rehabilitation. American scholars have developed and studied EEG signals and computer systems for the spontaneous rhythm of motor sensation. The main purpose of this research is to convert individual motor imagery EEG signals into two-dimensional motion instructions on computer screen and corresponding mouse cursor movement control instructions. This method makes EEG signal research more detailed and implementable. In order to solve the problem of the accuracy of the corresponding algorithm in recognizing and analyzing EEG signals of motor imagery, relevant scholars have proposed to optimize BP neural network algorithm based on particle filter algorithm, which gives the general expression of particle filter algorithm, and proves the inevitability of particle degeneration in such algorithm. This method is used to process EEG signals of motor imagery. The algorithm proposed in this paper is also based on the improved algorithm.

In this paper, based on the improved BP neural network algorithm, weight splitting technology is added to the traditional BP neural network algorithm. In order to solve the filtering problem, this paper uses the non-linear mapping function of the traditional BP neural network, and intelligently trains the small weight particles by combining the particle swarm filter algorithm, so as to improve the filtering performance of the whole BP algorithm. Based on the above two algorithms, the problem of low signal-to-noise ratio (SNR) and unclean filtering in EEG data processing caused by fast weight degradation in traditional BP algorithm can be solved. Finally, according to the actual data of brain-computer interface, this paper compares the improved BP neural network algorithm with the traditional BP neural network algorithm in recognition and analysis of motor imagery EEG signals. The experiment shows that the proposed algorithm has obvious advantages in recognition accuracy and analysis effect.

B. RELEVANT WORK 2: EXISTING PROBLEMS IN MOTION IMAGINATION EEG SIGNAL RECOGNITION AND ANALYSIS ALGORITHMS

Based on the comparative analysis of current algorithms, the current motor imagery EEG recognition and analysis algorithms mainly have the following problems:

1) ACCURACY OF RECOGNITION

Mainly when the EEG signal is more complex or the interference signal and clutter are more, the recognition accuracy of the whole system will be lower.

2) THE PROBLEM OF FILTERING DEGREE OF PRETREATMENT

In the process of signal acquisition and processing, a large number of auxiliary algorithms are needed to filter the signals to get the corresponding actions with the state of the brain. However, due to the external environment and the stability of EEG signals, the actual filtering effect is not ideal. At the same time, a large number of auxiliary algorithms will cause the whole algorithm to consume too much, resulting in the phenomenon of low efficiency.

3) THE PROBLEM OF LOW TRANSMISSION SPEED

In brain-computer system, the transmission rate of the whole system is mainly below 30 bits. In the case of long-term application, the corresponding transmission rate will further decline, which cannot complete the real-time control and communication of the whole system.

4) STABILITY OF THE SYSTEM

Because of individual differences, time and environment differences, there is no efficient and universally applicable method for EEG signal processing. Many methods have their own particularities, so it is necessary to strengthen the research on signal processing algorithms.

Its corresponding algorithm and disadvantage list are shown in Table 2 below.

TABLE 2. The corresponding algorithm and disadvantage list.

Problems in Current Motion Imagination Analysis and Recognition Algorithms	Representational Solution Algorithms
Accuracy of Recognition	Common Space Algorithms
The problem of filtering degree of pretreatment	BP algorithm
The Problem of Low Transmission Speed	Fuzzy algorithm
The stability of the system	Clustering algorithm

IV. APPLICATION OF IMPROVED BP NEURAL NETWORK ALGORITHM IN RECOGNITION AND ANALYSIS OF MOTOR IMAGERY EEG SIGNALS

This section mainly discusses the application of improved BP neural network in recognition and analysis of motor neuroencephalogram signals.

A. CORE IDEA OF IMPROVED BP NEURAL NETWORK ALGORITHM

1) IMPROVED BP NEURAL NETWORK ALGORITHMS-ANALYSIS OF OPTIMIZED FEEDFORWARD COMPUTING PRINCIPLE

Compared with the standard BP neural network algorithm, the improved algorithm proposed in this paper mainly focuses on the improvement of feedforward calculation, which mainly solves the problem of low signal-to-noise ratio in the initial and processing problems of the traditional BP algorithm. The flow chart of the corresponding feedforward calculation is shown in Fig. 4. Compared with the traditional BP neural network algorithm, the improved BP algorithm adds feedforward design in the pretreatment stage. Its main function is to judge the error in advance when denoising, and adjust the error in advance when the error exceeds the threshold. This method can solve the error problem at the source, thus reducing the burden of later filtering.

In the above feedforward calculation, suppose that on the premise of sample B, its corresponding net (i) represents the input calculation formula of the first neuron, and its corresponding calculation formula is shown in formula 1 as follows:

$$net_i^n = w_{ij}o_j^p - \theta_i(i = 1.2.3\ldots n) \tag{1}$$

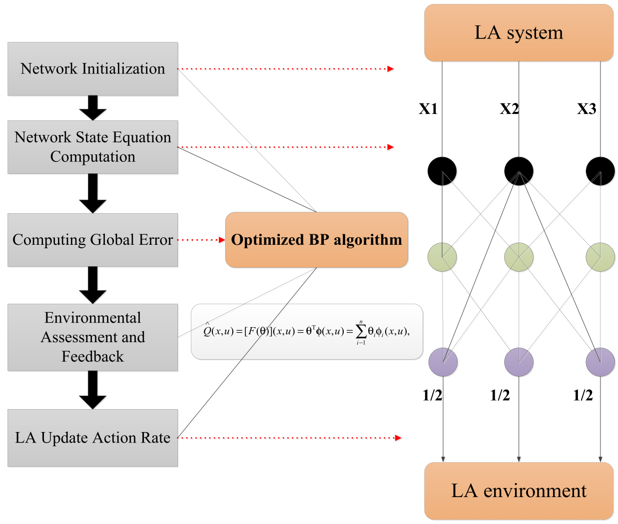

FIGURE 4. The flow chart of the corresponding feed-forward calculation.

The corresponding formula for calculating the output of the second neuron is shown in Formula 2.

$$o_i^n = g(net_i^n)(i = 1, 2, 3\ldots n) \tag{2}$$

The total input corresponding to the whole system is shown in Formula 3.

$$net_k^n = \sum_{i=1}^{n} w_{ij}o_i^n - \theta_k(k = 1, 2, 3\ldots L) \tag{3}$$

In this paper, the formula for calculating the quadratic error of each sample B is expressed as Formula 4.

$$J_p = 1/2k = 1\sum_{k=1}^{L}(t_k^n - o_k^n)^2 \tag{4}$$

In the feedforward calculation, that is, the whole improved BP neural network optimizes the weighting coefficients in the learning process. In order to further optimize the whole recognition network, w changes inversely according to the gradient of Jp function in actual change. The revised weighting formula is shown in Formula 5.

$$\delta_k^n = o_k^n(1 - o_k)(t_k^n - o_k) \tag{5}$$

The corresponding formula for calculating the hidden layer is modified to Formula 6 as follows:

$$w_{ij}(k + 1) = w_{ki}(k) + \mu\delta_i^n o_j^n \tag{6}$$

Based on the above improvements, the recognition accuracy of the whole system can be optimized. At the same time, it solves a lot of drawbacks caused by the stacking of a large number of traditional auxiliary algorithms.

For the filtering degree, the improvement of the whole algorithm is based on particle filter, because of the excellent filtering ability of the nonlinear system and the excellent learning performance of BP neural network. Based on the improved BP network algorithm, this paper proposes a particle filter algorithm which adjusts the weights. The main purpose is to combine BP neural network with standard PF algorithm and increase the weights of particles located at the tail of probability distribution. At the same time, the weights of particles with high weights are split after resampling step to increase the number of particles in the process of particle sampling. Sample, reduce errors. The structure of the corresponding particle filter algorithm group is shown in Fig. 5.

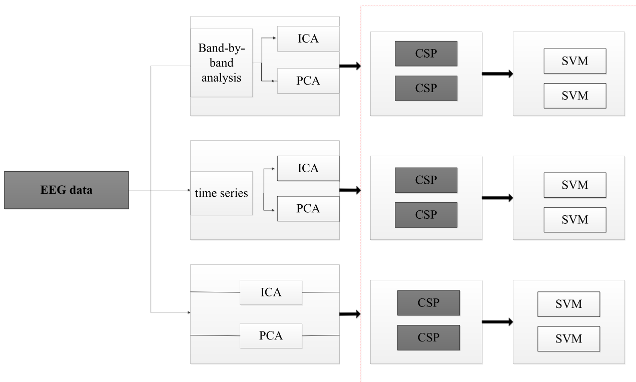

FIGURE 5. The structure of the corresponding particle filter algorithm group.

The corresponding algorithm implementation steps are as follows. In the first step, the initialization technology of particle cluster is mainly realized. The probability of random sample occurrence is generated randomly according to the whole system. In the second step, we mainly realize the state prediction. According to the state equation, we extract particles assumed to be K-time at any time to update their weights. The corresponding updated calculation formula is shown in Formula 7.

$$\{X_{k|k+1}(i); i = 1, 2, 3, 4 \ldots N\} - p(X_\lambda | X_{\lambda-1}) \tag{7}$$

In the third step, particle splitting is mainly realized. Firstly, the weights of particles need to be arranged in matrix form, which can be divided into higher authority particle clusters and lower authority particle clusters. Then, the principle of substitution is adopted one by one, that is, the tail particles of lower weight particle matrix are replaced by the former one. In the fourth step, we mainly adjust the weights, mainly using the basic characteristics of BP neural network to adjust the weights. In the fifth step, resampling is the main method. Finally, the state estimation of the current time is carried out.

2) THE SECOND CORE TECHNOLOGY OF IMPROVED BP NEURAL NETWORK ALGORITHMS-PARTICLE SWARM FILTERING ALGORITHMS

In order to solve the problem of noise filtering in traditional BP algorithm, particle swarm optimization is added to the improved BP algorithm to optimize the noise filtering. Its main purpose is to combine BP neural network with standard PF algorithm. In the practical process of particle swarm algorithm, the particle located at the tail of EEG signal is enlarged, and then it is sampled. After the sampling, the particle with larger weight is split, so that the error of the whole system can be optimized and eliminated.

The operation flow of particle swarm optimization in BP neural network algorithm is as follows:

The first step is to initialize a large number of particles and make them produce corresponding probability distribution coefficients.

The second step is to carry out the state prediction operation. The corresponding equation is shown in Formula 8, where the corresponding K represents the corresponding time:

$$\{X_k(i) : i = 1, 2, 3 \ldots n\} - h(X_k | X_{k-1}) \tag{8}$$

At the end of the state prediction, it is calculated according to the latest state variables obtained. The corresponding calculation formula is shown in Formula 9.

$$w_k^i = w_k^{i-1} p(z_k | X_k), i = 1, 2, 3 \ldots N \tag{9}$$

The third step is to split the particles with larger weights. The rule adopted here is the iteration rule.

Step 4: Adjust the weight of particles. The main object of adjustment is the weight of the particles at the end of the matrix corresponding to the splitting process.

Step 5: Sampling the relevant particles. The weights of particles are compared with the preset thresholds. If the weights of particles are less than the thresholds, the sampling process will be re-conducted, otherwise the next step will be taken.

Step 6: Estimate the state value of the current particle, and the corresponding formula is shown in Formula 10.

$$x_k = \sum_{i=1}^{x} x_{k|k-1}^i w_k^{(i)} \tag{10}$$

Finally, based on the five steps mentioned above, the repetitive calculation is carried out according to the number of iterations set in advance to achieve the noise filtering effect of the whole system.

B. APPLICATION OF THE CORE IDEA OF IMPROVED BP NEURAL NETWORK ALGORITHM IN RECOGNITION AND ANALYSIS OF MOTOR IMAGERY EEG SIGNALS

Based on the two improved optimization algorithms proposed in section A, this section integrates them with the recognition and analysis system of motor imagery EEG signals, as shown in Figure 6.

In this system, the main basic algorithm is BP algorithm and its corresponding auxiliary algorithm is particle cluster filtering algorithm located in the hidden layer, which mainly solves the filtering problem in the process of system identification. The corresponding feed-forward improved algorithm mainly solves the recognition accuracy problem in the pretreatment process.

C. EXPERIMENTS AND DATA ANALYSIS

In order to reflect the variable control of the experiment, this paper also designs a comparison between the traditional

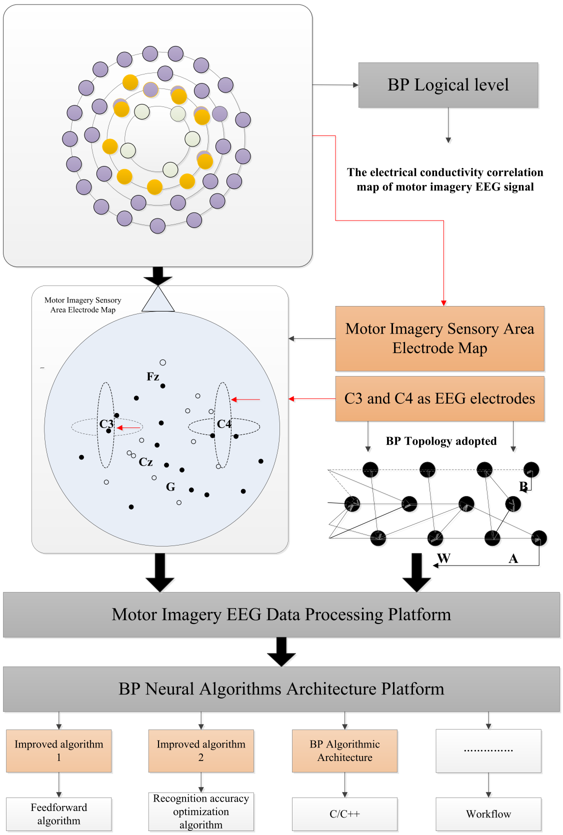

FIGURE 6. The corresponding model block diagram.

BP neural network and the improved BP neural network in the recognition and analysis of motor imagery EEG signals. The corresponding signal frequency band contains the whole frequency band. As shown in Figure 7, the filtered data of the corresponding hand movements at 8-12Hz and 12-16HZ frequencies are compared. It can be seen from the figure that the algorithm proposed in this paper has obvious advantages in filtering cleanliness.

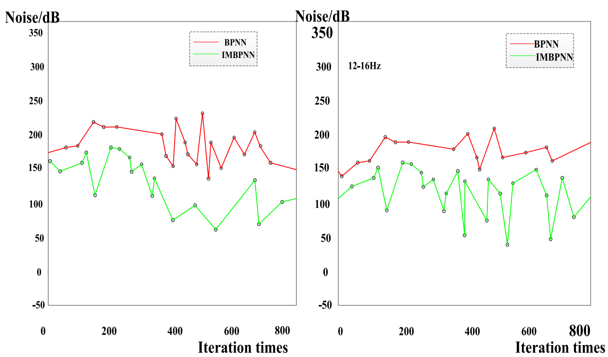

FIGURE 7. The filtered data of the corresponding hand movements at 8-12Hz and 12-16HZ frequencies.

As shown in Figure 8, the EEG signal processing atlas corresponding to the corresponding hand movements at 16-20Hz and 20-24Hz frequencies can also be seen clearly that the

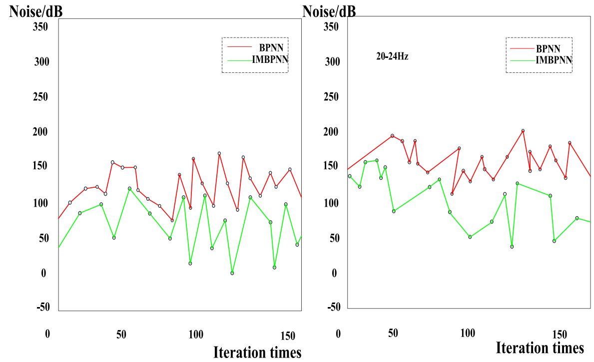

FIGURE 8. The filtered data of the corresponding hand movements at 8-12Hz and 12-16HZ frequencies.

corresponding algorithm proposed in this paper has strong advantages:

The recognition accuracy of the algorithm is mainly based on the typical frequency bands of 8-12HZ and 20-24Hz. The following accuracy statistics are made as shown in Table 3. It can be seen from the table that the proposed algorithm has great advantages in recognition accuracy.

TABLE 3. The following accuracy statistics.

Test number (20-14Hz)	Traditional BP algorithm	Improved BP algorithm
1	0.6667	0.8121
2	0.6444	0.8345
3	0.5456	0.8150
4	0.6154	0.7982
5	0.6667	0.7314
6	0.6243	0.8231
7	0.6712	0.5671

In order to further verify its recognition effect and anti-jamming ability in the actual recognition process, a large amount of spurious is added to the experiment in this paper. The corresponding variation factor figure is shown in Figure 9. The variation factor in the figure is random factor, and it acts on two different algorithms at the same time.

Based on the above factors, the recognition accuracy test is carried out. The corresponding test results are shown in Table 4. From the table, it can be seen that the proposed algorithm still has a strong recognition accuracy in the case of strong interference.

The corresponding cylindrical accuracy figure is shown in Fig. 10 In the process of precision experiment, the variable control method of experiment is strictly observed. In the same experimental environment, the traditional BP neural network algorithm is compared with the optimized BP neural network algorithm proposed in this paper in the recognition

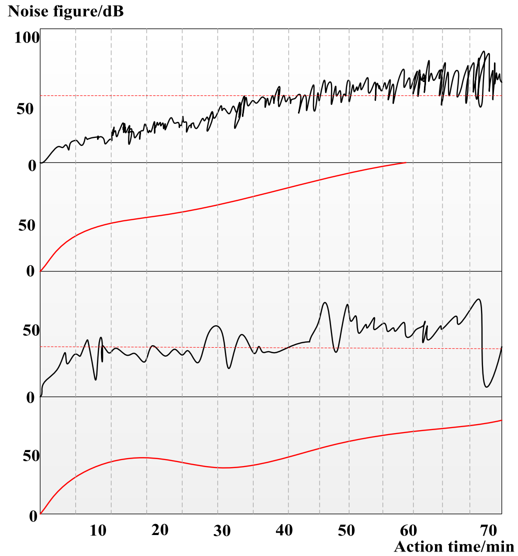

FIGURE 9. The corresponding variation factor figure.

TABLE 4. The corresponding test results.

Test number (20-14Hz)	Traditional BP algorithm	Improved BP algorithm
1	0.5167	0.7125
2	0.4144	0.7031
3	0.4154	0.8040
4	0.5154	0.6941
5	0.5061	0.7014
6	0.4243	0.8012
7	0.3912	0.6690

accuracy of EEG signals. From Figure 10, it can be seen that the proposed algorithm has a strong advantage in accuracy. As shown in Fig. 10, the accuracy of the optimized BP neural network algorithm proposed in this paper is about 10 percentage points higher than that of the traditional one.

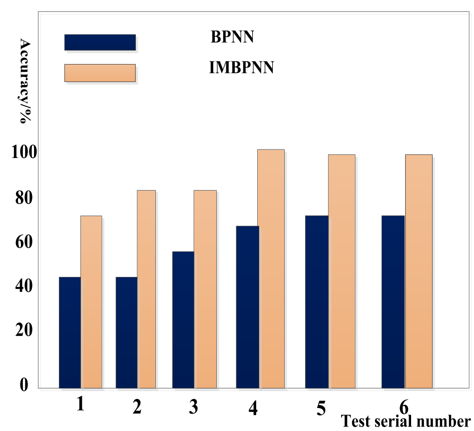

FIGURE 10. The corresponding cylindrical accuracy figure.

In order to further verify the advantages of the proposed algorithm in recognition and analysis of motor imagery EEG signals compared with the traditional BP algorithm, this paper also extracts EEG data and performs image processing based on EEG data. Fig. 11 and FIG. 12 respectively correspond to the data representation maps of traditional BP neural network algorithm in processing EEG data and the data representation maps of improved BP algorithm in processing EEG data proposed in this paper. Compared with Figs. 11 and 12, the improved BP neural network algorithm proposed in this paper has obvious advantages in the feature representation

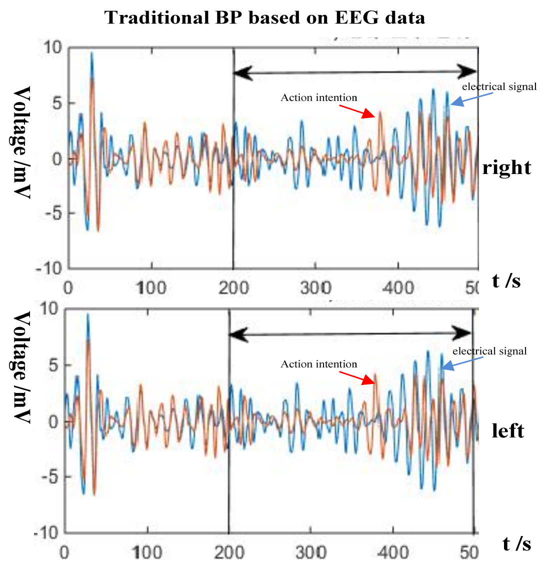

FIGURE 11. The data representation maps of traditional BP neural network algorithm in processing EEG data.

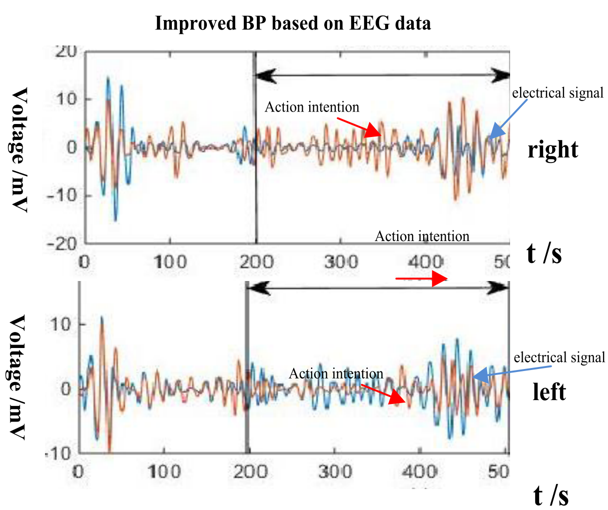

FIGURE 12. The data representation maps of improved BP algorithm in processing EEG data proposed in this paper.

of motor EEG signals, which also proves that the proposed algorithm has high accuracy in recognizing motor imagery EEG signals.

In order to further demonstrate the accuracy of the proposed algorithm in the recognition and analysis of motor imagery EEG signals, based on the measured data in Figure 11 and Figure 12 as shown in Table 5, the superiority of the proposed algorithm can be clearly seen from the table.

TABLE 5. The superiority of the proposed algorithm.

Experiment number	Accuracy of traditional BP algorithm	Accuracy of improved BP algorithm
Test 1	83.5%	93.5%
Test 2	81.2%	94.5%
Test 3	82.1%	92.6%
Test 4	78.9%	92.1%
Test 5	78.3%	93.5%
Test 6	81.8%	94.1%
Test 7	80.9%	95.1%
Test 8	83.1%	94.2%

In summary, the above data and corresponding charts show that the proposed algorithm has a strong advantage over the traditional BP algorithm in the recognition and analysis of motor imagery brain wave signals.

V. CONCLUSION

In this paper, based on the improved BP neural network algorithm and the traditional BP neural network algorithm, the weight segmentation technology is added. In order to solve the problem of filtering, this paper uses the nonlinear mapping function of traditional BP neural network and particle swarm optimization algorithm to train small-mass particles intelligently, so as to improve the filtering performance of the whole BP algorithm. Based on these two algorithms, we can solve the problem of low signal-to-noise ratio and unclean filtering caused by the fast attenuation of weights in traditional BP algorithm when processing EEG data. Finally, according to the actual data of brain-computer interface, the improved BP neural network algorithm is compared with the traditional BP neural network algorithm in the recognition and analysis of EEG signals in motion images. Experiments show that the algorithm has obvious advantages in recognition accuracy and analysis effect. Of course, the convergence and accuracy of the recognition and analysis algorithm for motor imagery EEG still have a problem that cannot be acquired at the same time. In the following research, this paper will focus on compatibility.

REFERENCES

[1] T. Chen and W. Xu, "Post-evaluation on financial support highway traffic project based on BP neural network algorithm," *J. Discrete Math. Sci. Cryptogr.*, vol. 21, no. 4, pp. 869–879, 2018.

[2] B. Xu, H.-C. Dan, and L. Li, "Temperature prediction model of asphalt pavement in cold regions based on an improved BP neural network," *Appl. Thermal Eng.*, vol. 120, pp. 568–580, Jun. 2017.

[3] A. Ghaemi, E. Rashedi, A. M. Pourrahimi, M. Kamandar, and F. Rahdari, "Automatic channel selection in EEG signals for classification of left or right hand movement in brain computer interfaces using improved binary gravitation search algorithm," *Biomed. Signal Process. Control*, vol. 33, pp. 109–118, Mar. 2017.

[4] W. Wang, M. Li, R. H. E. Hassanien, M. en Ji, and Z. Feng, "Optimization of thermal performance of the parabolic trough solar collector systems based on GA-BP neural network model," *Int. J. Green Energy*, vol. 14, no. 10, pp. 819–830, 2017.

[5] M. Amadeo, C. Campolo, A. Molinaro, and G. Ruggeri, "Content-centric wireless networking: A survey," *Comput. Netw.*, vol. 72, pp. 1–13, Oct. 2014.

[6] Z. Li and X. Zhao, "BP artificial neural network based wave front correction for sensor-less free space optics communication," *Opt. Commun.*, vol. 385, pp. 219–228, Feb. 2017.

[7] Y. Shu and G. H. Xu, "Multi-level dynamic fuzzy evaluation and BP neural network method for performance evaluation of Chinese private enterprises," *Wireless Pers. Commun.*, vol. 102, no. 4, pp. 2715–2726, 2018.

[8] H. Fei and L. Zhang, "Prediction model of end-point phosphorus content in BOF steelmaking process based on PCA and BP neural network," *J. Process Control*, vol. 66, pp. 51–58, Jun. 2018.

[9] Y.-X. Zhang, D.-Y. You, X.-D. Gao, and S.-J. Na, "Automatic gap tracking during high power laser welding based on particle filtering method and BP neural network," *Int. J. Adv. Manuf. Technol.*, vol. 96, nos. 1–4, pp. 685–696, 2018.

[10] F. He and L. Zhang, "Mold breakout prediction in slab continuous casting based on combined method of GA-BP neural network and logic rules," *Int. J. Adv. Manuf. Technol.*, vol. 95, nos. 9–12, pp. 4081–4089, 2018.

[11] T. Jie, H. Zhang, D. Wu, and D. Yuan, "QoS-constrained medium access probability optimization in wireless interference-limited networks," *IEEE Trans. Commun.*, vol. 66, no. 3, pp. 1064–1077, Mar. 2018.

[12] J. Liu, T. Zhang, X. Song, and J. Xing, "Enhanced red emission of 808 nm excited upconversion nanoparticles by optimizing the composition of shell for efficient generation of singlet oxygen," *Opt. Mater.*, vol. 75, pp. 79–87, Jan. 2018.

[13] Y. He *et al.*, "Optimizing microwave-assisted hydrolysis conditions for monosaccharide composition analyses of different polysaccharides," *Int. J. Biol. Macromolecules*, vol. 118, pp. 327–332, Oct. 2018.

[14] S. Wang, H. J. Kim, J. Chen, D. E. Laughlin, G. Piazza, and J. Zhu, "The effect of *in situ* magnetic field on magnetic properties and residual stress of Fe-based amorphous film," *IEEE Trans. Magn.*, vol. 54, no. 6, Jun. 2018, Art. no. 2001008.

[15] R. Wang, X. Peng, J. Zhang, and K. B. Letaief, "Mobility-aware caching for content-centric wireless networks: Modeling and methodology," *IEEE Commun. Mag.*, vol. 54, no. 8, pp. 77–83, Aug. 2016.

[16] X. Yu, J. Han, L. Shi, Y. Wang, and Y. Zhao, "Application of a BP neural network in predicting destroyed floor depth caused by underground pressure," *Environ. Earth Sci.*, vol. 76, no. 15, p. 535, Aug. 2017.

[17] L. A. Moctezuma and M. Molinas, "EEG-based subjects identification based on biometrics of imagined speech using EMD," in *Proc. Int. Conf. Brain Inform.* Arlington, TX, USA: Springer, Dec. 2018, pp. 458–467.

[18] K. Singh, A. Gupta, and T. Ratnarajah, "QoS-driven resource allocation and EE-balancing for multiuser two-way amplify-and-forward relay networks," *IEEE Trans. Wireless Commun.*, vol. 16, no. 5, pp. 3189–3204, May 2017.

[19] E. K. Kalunga, S. Chevallier, Q. Barthélemy, K. Djouani, E. Monacelli, and Y. Hamam, "Online SSVEP-based BCI using Riemannian geometry," *Neurocomputing*, vol. 191, pp. 55–68, May 2016.

[20] A. Korik, R. Sosnik, N. Siddique, and D. Coyle, "Decoding imagined 3D hand movement trajectories from EEG: Evidence to support the use of mu, beta, and low gamma oscillations," *Frontiers Neurosci.*, vol. 12, p. 130, Mar. 2018.

[21] Y.-H. Liu, S. Huang, and Y.-D. Huang, "Motor imagery EEG classification for patients with amyotrophic lateral sclerosis using fractal dimension and Fisher's Criterion-based channel selection," *Sensors*, vol. 17, no. 7, p. 1557, 2017.

[22] E.-R. Symeonidou, A. D. Nordin, W. D. Hairston, and D. P. Ferris, "Effects of cable sway, electrode surface area, and electrode mass on electroencephalography signal quality during motion," *Sensors*, vol. 18, no. 4, p. 1073, 2018.

[23] P. Gaur, R. B. Pachori, H. Wang, and G. Prasad, "A multi-class EEG-based BCI classification using multivariate empirical mode decomposition based filtering and Riemannian geometry," *Expert Syst. Appl.*, vol. 95, pp. 201–211, Apr. 2018.

[24] J. Li *et al.*, "A unified canonical correlation analysis-based framework for removing gradient artifact in concurrent EEG/fMRI recording and motion artifact in walking recording from EEG signal," *Med. Biol. Eng. Comput.*, vol. 55, no. 9, pp. 1669–1681, Sep. 2017.

[25] N. O. Gursel, L. Gumusel, and Y. Yang, "A biologically inspired approach to frequency domain feature extraction for EEG classification," *Comput. Math. Methods Med.*, vol. 2018, Jan. 2018, Art. no. 9890132.

[26] M. Balconi, L. Cortesi, and D. Crivelli, "Motor planning and performance in transitive and intransitive gesture execution and imagination: Does EEG (RP) activity predict hemodynamic (fNIRS) response?" *Neurosci. Lett.*, vol. 648, p. 59, May 2017.

LONG LIU was born in 1976. He received the bachelor's degree from Chengdu Sports University, in 2005, the master's degree from Zhengzhou University, in 2012, and the Ph.D. degree from the Panyapiwat Institute of Management, in 2017. He is currently an Associate Professor with the College of Physical Education, Anyang Normal University. He is also a Researcher with the Guangxi Vocational Academy, for performing arts, and a Fellow of the Siam Think Tank, Thailand. He has published more than 10 papers, two of which were included in EI and two were included in SCI. In addition, he has published four monographs and participated in six provincial-level projects as a major author. His research interests include sports management and motion imagination EEG signals.