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Article

Research on recognition of Wushu motion boxing method based on PSO-BP neural network

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Abstract: Wushu movement full hair is a kind of fitness activity, and it is one of the ways for people to cultivate their self-cultivation and sentiment. It is of great significance to use motion capture system and data gloves to capture human movement posture and guide boxing practice in real time. The research of this topic uses neural network technology to construct a complete recognition framework of martial arts movements. Firstly, the collected martial arts movements are sorted out and a database is constructed. Because of the inherent defects of traditional BP algorithm, this is also because during the training of the modified algorithm, The network converges slowly, and easy to receive local minimum constraints, so this topic uses particle swarm optimization algorithm to optimize the initial weights and improved neural network algorithm to improve the learning rate and increase the reliability of the algorithm. Finally, through the martial arts action boxing recognition framework for testing, it is determined that the proposed algorithm is more effective.

Keywords: neural network; Wushu action boxing; particle swarm optimization algorithm; identify the framework.

1. Introduction

Martial arts, as a treasure of traditional Chinese culture, is not only a way of physical and mental cultivation, but also an artistic expression that combines strength, speed, and technique [1]. Among the many movements in martial arts, boxing is highly favored by martial arts enthusiasts and professional athletes for its unique offensive and defensive skills and significant practical value. However, traditional martial arts action recognition mainly relies on manual observation and evaluation, which is not only time-consuming and laborious, but also susceptible to subjective factors, making it difficult to achieve objective and accurate evaluation [2]. With the rapid development of artificial intelligence technology, especially the widespread application of neural networks in pattern recognition, new ideas and methods have been provided for martial arts action recognition. Among them, Back Propagation (BP) neural network, as a classic feedforward neural network model, has strong nonlinear mapping ability and self-learning ability, and has achieved significant results in fields such as image recognition and speech recognition [3]. However, BP neural networks also have some inherent drawbacks, such as slow convergence speed and susceptibility to local minima, which to some extent limit their application in complex action recognition tasks [4].

In order to overcome these shortcomings of BP neural networks, researchers have begun to explore methods that combine optimization algorithms with BP neural networks. Particle Swarm Optimization (PSO), as a swarm intelligence based optimization algorithm, has been widely used in fields such as function optimization and neural network training due to its simplicity and strong global search ability. The PSO algorithm simulates the collective behavior of bird flocks foraging, continuously adjusting the position and velocity of particles to find the global optimal solution, thereby effectively improving the training efficiency and recognition accuracy of neural networks. Based on the above background, this article proposes a martial arts action boxing recognition method based on PSO-BP neural network. This method utilizes PSO algorithm to optimize the initial weights and thresholds of BP neural network, in order to improve the convergence performance and recognition ability of the neural network [5,6]. At the same time, based on the characteristics and kinematic parameters of martial arts boxing techniques, a complete set of motion feature extraction and recognition processes has been constructed. Through experimental verification, this method not only achieves accurate recognition of martial arts boxing movements, but also has high recognition speed and robustness, providing a new technical approach and theoretical support for the automation and intelligence of martial arts movement recognition.

2. Related research results of motion recognition methods

2.1. Action segmentation method

Action segmentation According to the technology adopted, the relative relationship of the objects processed in the time domain can be divided into two categories: Local action segmentation and global action segmentation. One strategy in the local action segmentation method is to use the physical continuity characteristics of human action to find the action boundary by searching for the corresponding speed, acceleration or curvature inflection point, and then divide the action part. For example, Ali and Aggarwal constructed an eigenvector about the human pose angles, based on which the action was segmented by calculating the similarity of the angle information between the pixels to the eigenvector in an action video [7]. Viewed the human action as a subunit containing the recessive velocity variables, and then used the constructed action model to achieve action segmentation by matching [8]. The method of using action continuity to achieve action segmentation is greatly affected by the constructed continuity model, which is usually difficult to achieve good robustness, so the method based on action continuity model often fails to meet the requirements in effect. Another strategy in the local action segmentation is the sliding window method, in which the segmented action information has been used to match the video frame by frame, and the matched frames are extracted to complete the segmentation [9]. For example, Integrate the existing action features into a multi-scale kernel function, then use the kernel function to model the unsegmented video, and finally complete the action segmentation by the kernel function similarity discrimination. Similarly, Lee et al. used the linear variation and proposed a video detection system to segment the targets in the scene by using a calibrated minimal video window [10]. Constructed the sliding window by calculating the scale-invariance characteristics of the video, and then segmented the action according to the similarity between the sliding window and the video to be segmented. Local segmentation methods generally perform action segmentation through matching and thresholding methods, lacking the statistical analysis and learning process, so the overall error is large.

2.2. Related research on statistical methods

Turk and Pentland use eigenfaces to detect and recognize faces, and each face can be represented by a projection weight vector. Compare the weight vector of the test image with the weight vector of the training image to determine which training image is closest to the test image [11]. They further found that the projection vectors of face images are obviously different from those of non-face images, so they gave a method to determine whether there is a face in the image. In the experiment, a database of 2500 face images were used. Each type of face includes three different changes in illumination brightness, face direction and face size, and the recognition rates of these three changes are 96%, 85% and 64%, respectively. The most common statistical classifiers include minimum distance classifiers, nearest neighbor classifiers, Bayes classifiers and classifiers based on support vector machines.

The concept of intrinsic face can be extended to intrinsic eye and intrinsic mouth. Just as intrinsic face can be used to detect the existence of face, intrinsic eye and intrinsic mouth can be used to detect eyes and mouth. Pentland created an image set of 7562 images of 3000 people and classified them by sex, race and age. Experiments show that the recognition rate for adult whites and blacks is 90% and 95% respectively, while the recognition rate for Asian adults is only 80% [12].

2.3. Neural network method

Artificial neural network can be used for pattern recognition because of its parallel operation mechanism and distributed global storage of patterns, and it is not affected by pattern deformation. Neural network method for face recognition can train images with strong noise and partial defects, and this nonlinear method is sometimes more effective than linear method.

Kohouen was the first to apply neural network to face recognition, which used the association ability of network to recall faces. When the input image is noisy or some images are lost, it can also recall accurate faces [2]. Recently, Ranganath and Arun put forward a radial basis function network (RBFN) for face recognition, and Lin put forward a neural network based on probability decision for face detection, eye location and face recognition. It consists of three parts: Face detector is used to determine the position of face in the image; The eye locator can generate a meaningful feature vector at the location of the eye, and the face area includes eyebrows, eyes and nose but does not include mouth; The third part is Facebook recognizer. This system has achieved good recognition effect through a small database [13]. Lawrence et al. proposed a convolution neural network for face recognition [14].

To sum up, the human action is a signal with infinite degrees of freedom. When using the robot vision and machine learning technology for action recognition, the recognized capacity of the action objects tends to be infinite, so each action recognition method is tested in a certain action database. Due to the different action databases, the robustness and practicality of many methods will vary with the selected databases. At the same time, the database used for action recognition is becoming more and more complex and larger, and the scene is no longer a single fixed background scene. Therefore, realizing the accurate identification of actions in multiple different action databases is a hot issue of action recognition, and completing the evaluation of the robustness of action recognition methods in more complex action databases is an important future research direction and an important aspect of this work.

3. Construction of Wushu boxing recognition model based on PSO-BP neural network

3.1. PSO-BP neural network

Traditional neural networks have limitations in data analysis, and their universal applicability is accompanied by uncertainty. Although the BP algorithm optimizes the network through gradient correction error function, the initial weights are randomly generated, which affects the stability of the training results. To overcome this limitation, we introduce Particle Swarm Optimization (PSO) algorithm to optimize the initial weights of BP neural network. It is necessary to strictly explain the mathematical derivation of PSO-BP integration, covering the speed, position updates, and fitness function design of PSO, to ensure rigor and coherence. At the same time, the parameter selection criteria for PSO-BP neural network need to be better demonstrated, including hidden layers, number of neurons, learning rate, inertia weights, etc., and the optimal combination should be determined through experiments and theoretical analysis. Finally, it is necessary to analyze the convergence of PSO-BP neural network, prove that it can converge to the global or approximate optimal solution under reasonable parameters, and explore the influence of initial conditions, data distribution, and noise level on convergence, providing theoretical support and practical guidance for algorithm applications.

3.1.1. BP neural network

With the deepening of neural network research, the research results of exploring the authenticity of data through this method are more and more abundant. However, most of the studies can also reflect the freedom of neural network through the practical application of the algorithm. After combing through the traditional neural network model, it is found that the main reference method of the model is conducted through data analysis and model construction. To further elaborate on the structure of the neural network, it is illustrated in **Figure 1** below.

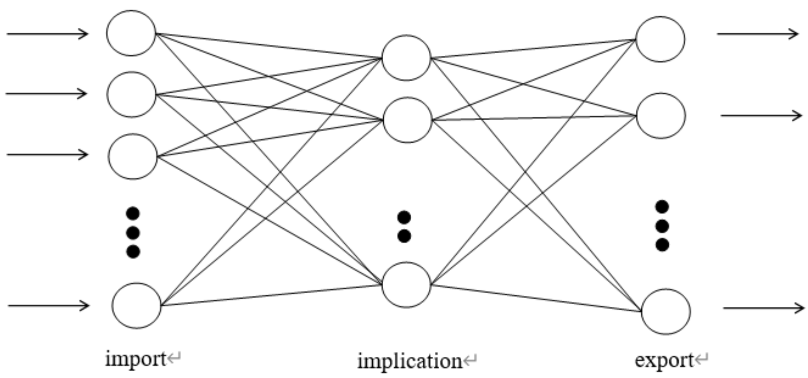

Figure 1. Model structure.

The transfer function is generally an S-type function as shown in Equation (1):

$$f(x) = \frac{1}{1 + e^{-n}} \tag{1}$$

Error function is shown in Equation (2):

$$E_p = \frac{\sum_i (t_{pi} - O_{pi})^2}{2} \tag{2}$$

After the above analysis, the constructed model is calculated through the propagation algorithm to obtain the error items in the model. The optimization of the neural network is mainly through two processes: One is the forward calculation, the other is the reverse calculation process is the model order calculation process; the reverse calculation is the data error from the hidden layer, and find whether the accuracy of the weight value is qualified.

The above algorithm, mainly through forward and reverse two ways to get the weight of the data, after determining the sample j, through the propagation algorithm for the sample, *i* represents the previous unit operation data, and *k* represents after an operation data, in order to more and more detailed operation process, through the way of illustration (**Figure 2**):

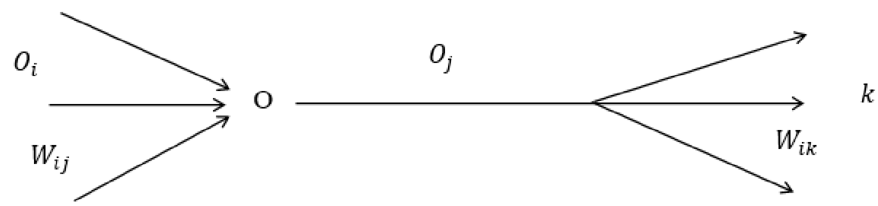

Figure 2. Algorithm structure.

When a sample is entered, the following calculations are made for each layer of samples from front to back, Equations (3) and (4):

$$net_j = \sum_i W_{ij} O_i \tag{3}$$

$$O_i = f(net_j) \tag{4}$$

The error under this sample is shown in Equation (5):

$$E = \frac{\sum_j (y_i - \hat{y}_j)^2}{2} \tag{5}$$

Because of the inherent defects of the algorithm, the convergence speed of the network is slow when training with the ordinary algorithm, and there is a problem of local minimum, in order to improve the shortcomings of the research in this topic, to get the new algorithm through the improvement way, to further improve the learning progress, and to improve the accuracy of the algorithm, the algorithm improvement is carried out by adjusting the learning speed.

Through the method proposed in this paper can reduce the local limitation of data operation, improve the accuracy of the operation results, mentioned, the weight of the operation results, through the optimization algorithm to revise the weight, modified in different ways, in the original data calculation process does not change the direction, the data calculation convergence, can reconsider the calculation process, Equation (6) is:

$$W(K+1) = W(k) + \alpha[(1-\eta)D(k) + \eta D(k-1)] \quad (6)$$

According to the above Equation (5) of the data, the convergence of the obtained calculation results can be reduced, and the training process of the above algorithm is reduced. Ordinary BP algorithm sometimes converges to local minimum, but momentum rule can successfully avoid local minimum and converge to global minimum.

Based on the training process passed as described above, Training on the data in an adaptive way, it is found that the application of this method can simplify the training time. Traditional neural network algorithms are not efficient for data learning in terms of convergence and learning rate, it needs to be improved. When the selection of the two indicators is not accurate, the correction to the data will change more, and will even affect the overall training results. In view of this, this topic optimizes the traditional algorithm by improving the algorithm. Equation (7) is:

$$W(K+1) = W(k) + \alpha(k)D(k) \quad (7)$$

If the direction does not change after the calculation, it represents an excessive reduction in this operation, in this case, the corresponding data can be added; On the contrary, it shows that the operation is added too much in this time, and the data can be reduced appropriately, which is also the process of adaptation and adjustment in this topic.

Regarding the segmentation of training test data, this study follows the standard practice of randomly dividing the dataset into a training set and a testing set, typically with a ratio of 70% training set and 30% testing set, to ensure that the model can both fully learn and effectively validate.

3.1.2. Particle swarm optimization algorithm

Particle Swarm Optimization (PSO) is a swarm-based evolutionary computation technology. It was first proposed as a nonlinear continuous function optimization method, but it can also be extended to discrete binary cases and applied to combinatorial optimization problems. From the perspective of methodology, PSO mainly originates from the theory of artificial life and the phenomenon of birds or fish clustering; From the perspective of social cognition, PSO applies the following simple truth: Every individual in the group can benefit from the past experience and the discovery of neighboring individuals, and its theoretical basis mainly includes the following three basic factors: (1) the evaluation of stimulus; (2) the comparison with neighboring individuals; (3) Imitation of the leading neighbor.

Particle Swarm Optimization (PSO) is an optimization technique based on swarm intelligence, inspired by the aggregation behavior of birds or fish. It seeks the optimal solution through individual experience sharing and mutual learning. In this study, PSO was used to optimize the initial weights of the BP neural network.

The specific parameter settings for PSO include particle count, maximum iteration count, inertia weight, learning factor, etc. The selection of these parameters has a significant impact on the performance of the algorithm. In this study, we set these parameters based on experience and validated their effectiveness through experiments. Specifically, the number of particles is set to 30, the maximum number of iterations is 100, and the inertia weight and learning factor are adjusted according to the specific properties of the problem.

Regarding the cross validation procedure, although this study did not directly implement complete cross validation (such as k-fold cross validation), we indirectly evaluated the model's generalization ability by running multiple experiments and observing the stability of the results. In addition, we further optimized the model performance by adjusting the parameters of PSO and BP neural networks.

The calculation process of the optimization algorithm (PSO) used in this paper can analyze the data more easily, which shows the following aspects during the operation: The unit speed of the optimization algorithm is different, and the different unit positions are also different; The values obtained will also change after determining the unit, which are as follows: First, the direction of the unit generally does not change; second, each unit will gradually get close to the optimal solution; and finally, the optimal solution of the data can be gradually obtained through the optimization algorithm. The algorithm used in the project is more superior, which is also because the algorithm eliminates the local restrictions, and the calculation process and location determination can be realized through simple calculation. In addition, the PSO can make each unit gradually close to the optimal solution, and record the current training path. After the change of the corresponding strategy, the algorithm has a more effective operational function.

The basic PSO algorithm can be summarized as follows:

Step 1: Initializing each particle in the particle swarm by adopting randomly generated positions and velocities in the whole search space;

Step 2: Find the fitness value of each particle at the current position. Equations (8) and (9) are as follows:

$$Fitness_i = f(x_i), i = 1,2,\cdots,N \tag{8}$$

Step 3: After determining the velocity and position of particles, the inertia weight is determined as follows:

$$\omega = \omega_{max} - \frac{\omega_{max} - \omega_{min}}{I_{max}} \times I \tag{9}$$

Step 4: If the termination criteria have been met, if the resulting value is less than a certain threshold or the maximum number of iterations has been reached, terminate the calculation, otherwise go to step 2.

3.1.3. Determination of initial weight of neural network based on PSO

Considering the complexity of neural network error surface and sensitivity to initial weights and the advantage of PSO in global search, a method for determining initial weights of neural network based on PSO is proposed. Its main idea is to train neural network with PSO algorithm firstly, and then use the algorithm to search locally when the weights are located near the spatial global optimum or near the global optimum, so that it can quickly converge to the final optimal value. This combination of their advantages, not easy to fall into local minima, with high accuracy, and fast convergence. This method, which uses PSO to determine the initial weights of neural network and then uses the traditional neural network algorithm based on gradient information, is called PSO-BP hybrid algorithm.

In this topic, the data collected by martial arts action boxing is trained through the improved algorithm. The specific calculation steps include the following points: First, the weights and threshold are obtained, and the determination is worthy to the new unit position, that is to say, each network weight and threshold is used as a particle swarm optimization. N Particle Swarm Optimization (PSO) is generated by the initial follow-up machine, and then according to the steps of PSO algorithm, using the infinite approximation ability of PSO algorithm, a vector close to the optimal position is searched as the initial weight and threshold of neural network.

3.2. Recognition of Wushu action boxing method based on neural network

After extracting features from face images by two-stage nonlinear feature extraction method, we use these feature vectors and corresponding teacher signals to train neural networks. As shown in **Figure 3.**

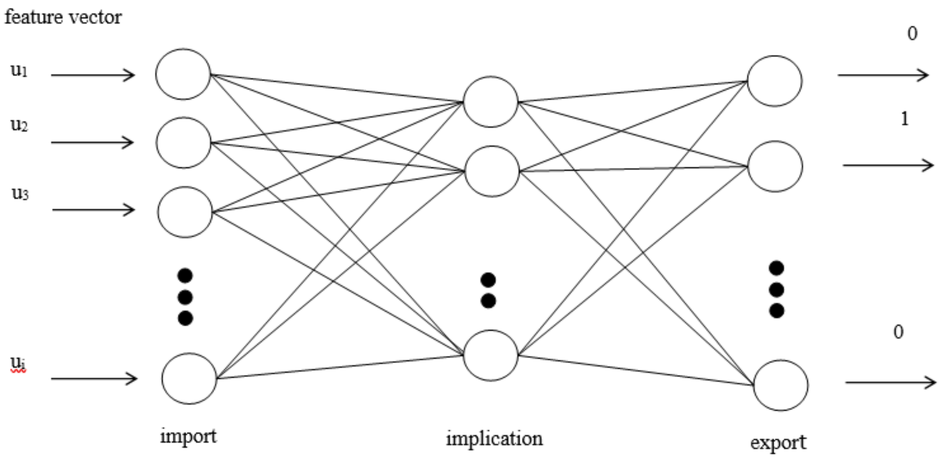

Figure 3. Classification of martial arts action boxing by neural network.

The neural network we use is a standard three-layer network. As for the selection of network layers, it is found that in the framework, the function operation can be trained through the data in the hidden layer, so as to reduce the error of the data, and enhance the accuracy of the training results, but this way further improves the training difficulty of the neural network training, and the efficiency is significantly improved. From the research results of practical application in neural network, it is found that increasing the data in the hidden layer can better observe the data in the model and get more accurate training results. This is also the accuracy of training results in most studies based on three-layer networks and then through the adjustment of this level. In the study of this subject, the data type of the hidden layer is uncertain. If the neurons at this level can have better units, the training process is more complex, and the training times need to be added accordingly, and then change the generalization of the computation.

It is more practical to train and compare different neuron numbers, and then add a little margin appropriately. Our experiments show that we can obtain satisfactory results when the number of neurons in the hidden layer is about half of that in the input layer. Therefore, the teacher signal can be expressed as: $out[0,0,0,\wedge 1,0,\wedge ,0]^T$ (the m-th element of the vector is 1).

The characteristics of the system training process are very obvious. Because it is nonlinear, the data operation results are affected by changing the initial weights, during this period, the convergence and efficiency are critical. Influenced by traditional neural networks, the initial weights are extremely susceptible to local constraints. Through the optimization algorithm proposed in this topic, —PSO, the above problems can be solved to some extent, and then the weight of the neural networks can be determined through the two learning methods mentioned above.

To sum up, the algorithm for training PSO-BP network can be simply described as the following process:

Step 1: Using particle swarm optimization algorithm (PSO) to give the initial weight of BP neural network which is close to the global minimum;

Step 2: Inputting training samples and expected outputs;

Step 3: Calculating the output layer by layer;

Step 4: Starting from the output layer, adjusting the weight value and reversely adjusting the error;

Step 5: If the error is less than the set value, ending; Otherwise, go to step 3 and continue learning.

After the network training reaches a stable state, the connection weights of the network are saved for later identification. The improved algorithm in this paper is used to identify martial arts action boxing, and its algorithm can be simply described as:

Step 1: Loading the eigenvector of the sample to be identified to the input layer node;

Step 2: Calculate the output of the hidden layer and the output layer, and judge the identification result according to the output of the node of the output layer.

4. Experimental results of martial arts action boxing recognition based on PSO-BP neural network

In the field of martial arts action recognition research, boxing, as a unique offensive and defensive technique with significant practical value, has always been a hot research topic. In recent years, with the rapid development of artificial intelligence technology, especially the widespread application of neural networks in pattern recognition, a new technological approach has been provided for the recognition of martial arts movements and boxing techniques. This article proposes a martial arts action boxing recognition method based on PSO-BP neural network, and its effectiveness is verified through experiments. The following will provide a detailed introduction to the experimental design, process, results, and conclusion.

4.1. Experimental design

(1) Data collection and participant selection.

This article carefully selected 40 martial arts enthusiasts as participants, covering groups of different ages, genders, heights, and weights. Each participant provided 10 pictures of different martial arts boxing movements, which not only captured facial expressions, facial details, and changes in posture, but also covered various common boxing movements such as straight punches, hook punches, and swings, as well as complex combination movements. This diverse dataset provides strong support for the algorithm's generalization ability.

(2) Camera settings and recording conditions.

To ensure the quality and consistency of the images, we used high-resolution cameras for shooting. The position of the camera is fixed to ensure consistency in the shooting angle. During the shooting process, we adjusted the focal length and exposure of the camera to ensure moderate image clarity and brightness. In addition, we also recorded information such as lighting conditions, camera model and parameters during filming for subsequent data processing and image preprocessing.

(3) Image preprocessing steps.

In the image preprocessing stage, we first crop and scale the image to ensure consistency in size. Then, we performed grayscale processing to convert the color image into a grayscale image, in order to reduce computational complexity and improve processing speed. Next, we performed image enhancement processing, including contrast enhancement and noise removal, to improve the quality and clarity of the image. Finally, we performed image normalization to normalize the pixel values of the image to between 0–1, in order to reduce the impact of lighting changes on the recognition results.

4.2. Experimental process

(1) Algorithm selection and comparison.

To verify the effectiveness of the algorithm proposed in this article, we compared several other algorithms, including PCA + NNC, PCA + KPCA + NNC, ICA + NNC, etc. These algorithms involve steps such as feature extraction, dimensionality reduction, and classification to varying degrees, but differ from the algorithm proposed in this paper in terms of feature extraction methods and neural network training strategies.

(2) Experimental setup and data partitioning.

We randomly selected 300 images of martial arts movements and boxing from the image database for the experiment. To simulate the impact of different training set sizes on recognition results, we selected 3, 4, 5, and 6 images of each person as training samples, and the remaining images that were different from the training samples as recognition samples. In this way, we can evaluate the performance of the algorithm under different training set sizes.

4.3. Experimental results and analysis

(1) Algorithm comparison results.

Figure 4 shows the classification accuracy of different algorithms under different training set sizes. From the figure, it can be seen that the PCA + KPCA + PSO-BP algorithm proposed in this paper maintains the highest classification accuracy under different training set sizes. This indicates that the algorithm proposed in this paper performs well in both feature extraction and classification through the two-stage kernel feature extraction method (PCA + KPCA) and PSO optimized BP neural network.

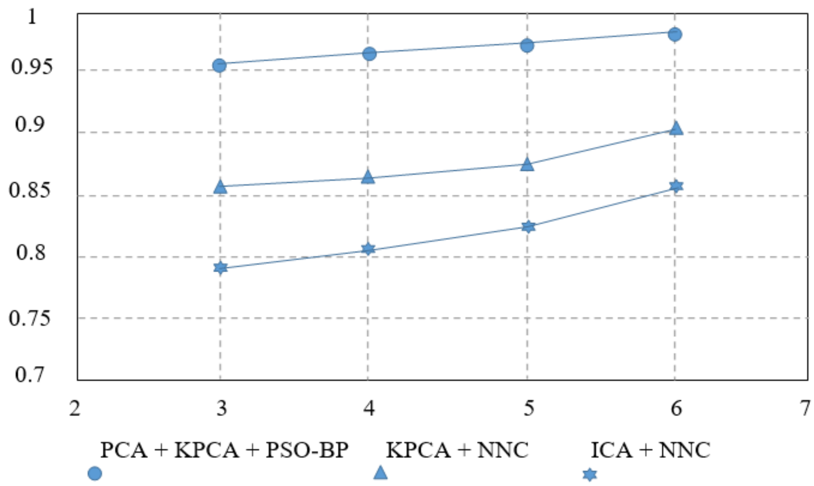

Figure 4. Comparison results of three algorithms.

(2) Identification results.

Table 1 lists the recognition results of three algorithms, including confirmation rate, recognition time, and recognition effect of incomplete samples. From the table, it can be seen that the PCA + KPCA + PSO-BP algorithm proposed in this paper achieves a recognition rate of 93.4%, which is higher than the other two methods. Meanwhile, through image preprocessing, although the recognition rate did not improve, the recognition time increased and the recognition effect of incomplete samples was better. This indicates that although image preprocessing has little impact on recognition rate, it can improve the robustness and applicability of the algorithm.

Table 1. Recognition results of three algorithms.

Algorithm	Recognition Rate	Algorithm in This Paper	Recognition Effect of Incomplete Samples
PCA + KPCA + PSO-BP	93.4%	2 min	Difference
Pretreatment + PCA + KPCA + PSO-BP	93.4%	2.8 min	Better
PCA + KPCA + PSO-BP + Minimum Distance	85%		Difference

In addition, we also attempted to combine the PCA + KPCA + PSO-BP algorithm with the minimum distance classifier, but found that its recognition rate decreased to 85%. This may be due to the high sensitivity of the minimum distance classifier to feature vectors, while the KL transform is greatly affected by external factors such as lighting, resulting in inaccurate feature vector extraction. Therefore, when selecting a classifier, it is necessary to fully consider its feature extraction method and the influence of external factors.

(3) Analysis of Algorithm Advantages.

The PCA + KPCA + PSO-BP algorithm proposed in this article performs well in the recognition of martial arts boxing techniques, mainly due to the following aspects:

1) Two level kernel feature extraction method: By combining PCA and KPCA, effective extraction and dimensionality reduction of image features are achieved, reducing the impact of redundant information on the classifier.
2) PSO optimized BP neural network: By using the PSO algorithm to optimize the initial weights of the BP neural network, the problem of local minima during neural network training is avoided, improving training efficiency and recognition accuracy.
3) High recognition rate and convergence speed: Due to the use of effective feature extraction methods and optimized neural network training strategies, the algorithm proposed in this paper performs well in both recognition rate and convergence speed.

5. Conclusion

This article aims to explore a martial arts action recognition method based on PSO-BP neural network, aiming to solve the problems of slow convergence and easy falling into local optima of traditional BP neural network in the field of action recognition. By introducing the Particle Swarm Optimization (PSO) algorithm, the initial parameters of the BP neural network were successfully optimized, significantly improving its convergence speed and recognition accuracy. In the experimental section, 40 martial arts enthusiasts with different characteristics were selected as samples, and each person provided 10 pictures of martial arts boxing movements to ensure the comprehensiveness and representativeness of the data. In the algorithm comparison, our proposed PCA+KPCA+PSO-BP algorithm demonstrated excellent performance, with a recognition rate of up to 93.4%, far exceeding other compared algorithms. In depth analysis of algorithm advantages reveals that the combination of PCA and KPCA effectively achieves image feature extraction and dimensionality reduction, providing high-quality feature vectors for subsequent recognition. By optimizing the initial weights and thresholds of the BP neural network through the PSO algorithm, the problem of local optima during training is avoided, improving recognition efficiency and accuracy. In summary, the martial arts action recognition method based on PSO-BP neural network proposed in this article not only has theoretical value, but also demonstrates significant superiority in practical applications, providing a new technical path and solution for the field of martial arts action recognition.

Author contributions: Conceptualization, JW and PL; methodology, JW and DL; software, SL and YS; formal analysis, JW, PL and DL; writing—original draft preparation, JW; writing—review and editing, SL and YS. All authors have read and agreed to the published version of the manuscript.

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