

Analysis and Improvement of the Application of Playground Sports Posture Detection Technology in Physical Education Teaching and Training

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Abstract

INTRODUCTION: The goal of human posture detection technology applied in the field of sports is to realise the indexing of sports norms, to provide scientific guidance for training and teaching, which is of great significance to improve the quality of sports.

OBJECTIVES: Aiming at the problems of incomplete features, low accuracy and low real-time performance of sports posture detection and recognition methods.

METHODS: In this paper, a method of sports pose detection based on snow melting heuristic optimisation algorithm of deep limit learning machine network is proposed. Firstly, by analyzing the process of motion pose detection, extracting the feature coordinates of Blaze-Pose and Blaze-Hands key nodes, and constructing the motion pose detection recognition system; then, optimizing the parameters of the deep extreme learning machine network through the snow-melt optimization algorithm, and constructing the motion pose detection recognition model; finally, through simulation experiments and analysis, the accuracy of the proposed method's motion pose detection recognition can reach 95% and the recognition time is less than 0.01 s.

RESULTS: The results show that the proposed method improves the recognition accuracy precision, robustness and real-time performance.

CONCLUSION: The problem of poor generalisation, low accuracy and insufficient real-time performance of the recognition application of the motion pose detection and recognition method is solved.

Keywords: sports posture detection, physical education and training, snow melting optimisation algorithm, deep extreme learning machine

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1. Introduction

Sport can improve people's physical fitness and well-being and can promote the development of various skills and abilities [1]. Currently, training in the field of sports is not scientific enough, resulting in people being vulnerable to exercise loss or insufficient training [2]. With the power of deep learning and the abundance of data, computer vision has made significant progress in various industries,

including human pose recognition and movement classification [3]. The application of deep learning algorithm based human posture recognition and movement classification technology in sports provides a new and effective solution for sports training and movement evaluation [4]. Sports teaching and training based on sports posture detection technology refers to the use of deep learning methods to analyse athletes' postures and movements, so that coaches and trainers can adjust the training plan and assess the effect of exercises in order to improve the efficiency and quality of sports training [5].

The goal of human posture detection technology applied in the field of sports is to realise the indexing of sports norms, to provide scientific guidance for training and teaching, and to improve the quality of sports is of great significance [6]. Therefore, it is a very meaningful task to study sports teaching and training methods based on sports posture detection technology [7].

Sports posture recognition refers to the use of three-dimensional or two-dimensional position of body joints, hand department joints and finger movement positioning, face and facial features position orientation to detect the movement state and performance [8]. At present, the application of sports posture detection technology in sports teaching and training, the construction of the playground sports posture detection effect analysis system, and the development of intelligent sports posture detection methods [7], are increasingly receiving the attention and research of experts in the field [8]. Sports posture detection effect analysis methods mainly include random forest, support vector machine, neural network, deep learning, heuristic optimisation algorithm and other methods [9]. Literature [10] extracted motion gesture detection features through questionnaires and other methods, and used the random forest method to construct a motion gesture detection method, which confirms the feasibility of intelligent motion detection technology; Literature [11] proposed an effect analysis method based on support vector machines by combing the analysis process of motion gesture detection and combining with machine learning algorithms; and Literature [12] designed a cloud-based multi-classification algorithm that has the ability to capture and analyse the leg and hip pressure features of human sitting state; literature [13] designed a Gaussian face algorithm and achieved significant accuracy on a face database; literature [14] used the KLT algorithm for face tracking, and trained a cascade classifier for face recognition, but the detection and recognition rate is low for people who are too high or too low; literature [15], after reflecting on the traditional sports gesture recognition method, discussed the joint position and face features as sports gesture recognition features, and proposed a neural network-based sports gesture recognition method; Literature [16] proposed three aspects of sports gesture recognition features, such as body joints, hand joints, and facial features, and meanwhile constructed a system for analysing the effects of sports gesture recognition, and proposed an effect analysis method based on deep learning algorithm; Literature [17] proposed a cascade classifier for detecting and recognizing faces, but the detection and recognition rate is low for tall and low people. analysis method; Literature [17] extracts posture features based on Mediapipe single person motion detection system, and proposes a human posture detection and recognition method based on support vector machine. In view of the above literature analysis, the existing motion posture detection methods have the following defects [18]: 1) the motion posture detection and recognition system is not comprehensive enough to influence the selection of features; 2) the motion posture detection and recognition method

lacks generalisation; 3) the effect analysis method is not sufficiently scientific and systematic and objective.

Extreme Learning Machines (ELM, Extreme Learning Machines) is a feed-forward neural network, first proposed by Prof. Guangbin Huang of Nanyang Technological University, Singapore in 2006, the algorithm has good generalisation properties as well as extremely fast learning ability [19]. Swarm Intelligence Optimization algorithms have been designed by simulating the behaviour of groups of insects, flocks of animals, flocks of birds and schools of fish or strategies for distributed interpretation problems [20]. With the increase of smart wearable devices, the accumulation of motion gesture data increases rapidly, and the construction of motion gesture detection and recognition models in the context of big data requires diverse intelligent optimisation algorithms combined with machine learning algorithms. The deep limit learning machine network method based on swarm intelligent optimisation algorithm makes the detection accuracy increase, and its application to the motion gesture detection and recognition problem becomes a research hotspot for experts and scholars in the field [21].

Aiming at the problems existing in the current sports posture detection and recognition method, this paper proposes a sports posture detection and recognition method based on the swarm intelligence optimisation algorithm to improve the deep limit learning machine network. The main contributions of this paper are:

- (1) through the problem of sports posture detection and recognition, selecting sports posture features, and analyzing the characteristics of sports posture features.
- (2) carrying out the construction of sports posture detection and recognition structure system;
- (3) optimizing the parameters of the deep limit learning machine network by using the swarm intelligent optimization algorithm, and proposing the sports posture detection and recognition method based on the intelligent optimization algorithm optimizing the depth of the extreme learning machine network under the condition of big data;
- (4) carry out experimental analysis of sports posture detection and recognition by means of sports teaching and training data, and the experimental results verify the effectiveness of the method proposed in this paper, and at the same time improve the precision and real-time performance of sports teaching and training evaluation.

2. Human Movement Posture Detection Process

2.1. Blaze-Pose

In order to extract the human posture detection recognition features, this paper adopts the Blaze-Pose human posture detection method [22]. The inference flow of the Blaze-Pose method is shown in Figure 1.

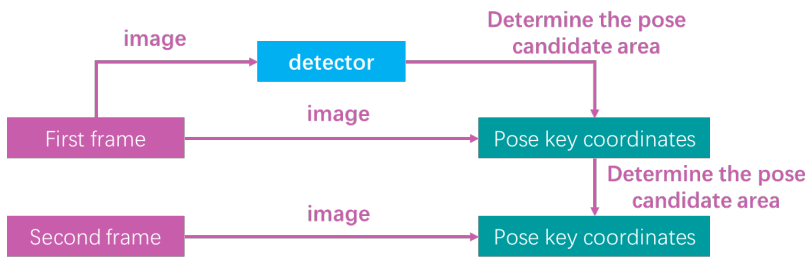


Figure 1. Flowchart of Blaze-Pose reasoning

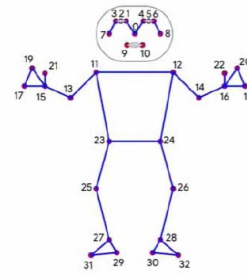


Figure 2. All key points of Blaze-Pose

The Blaze-Pose human pose detection method consists of a lightweight face detector and a pose tracker, where the pose tracker completes the prediction of 33 key coordinates of the human body, determines whether a human body exists in the current frame, and fine-tunes the

candidate frame region of the previous frame to be used for the prediction of the current frame. Blaze-Pose All the key points are shown in Figure 2, and the specific description is shown in Figure 3.

No	Blaze-Pose output format	No	Blaze-Pose output format	No	Blaze-Pose output format
0	Nose	11	Right shoulder	23	Right hip
1	Right eye inner	12	Left shoulder	24	Left hip
2	Right eye	13	Right elbow	25	Right knee
3	Right eye outer	14	Left elbow	26	Left knee
4	Left eye inner	15	Right wrist	27	Right ankle
5	Left eye	16	Left wrist	28	Left ankle
6	Left eye outer	17	Right pinky knuckle #1	29	Right heel
7	Right ear	18	Left pinky knuckle #1	30	Left heel
8	Left ear	19	Right index knuckle #1	31	Right foot index
9	Mouth right	20	Left index knuckle #1	32	Left foot index
10	Mouth left	21	Right thumb knuckle #1		
		22	Left thumb knuckle #1		

Figure 3. Classification of Blaze-Pose key points

The structure of Blaze-Pose is a lightweight convolutional neural network architecture that uses a combination of generating heat maps as well as regressing the output of the network to predict key points.

2.2. Blaze-Hands

In order to extract more detailed gesture features, this paper adopts the Blaze-Hands method [23]. Blaze-Hands consists of two models, the first is hand detection, which is used to predict the hand prediction frame, and the second is the hand keypoint detection model, which is used to predict the hand skeleton, including 21 keypoints, and the distribution of the keypoints is shown in Figure 4, and the specific numbering description is shown in Figure 5.

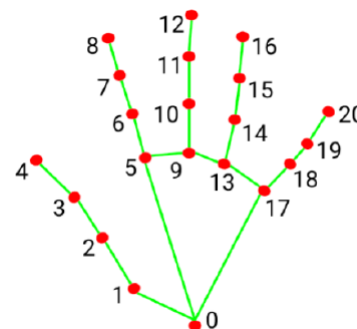


Figure 4. Distribution of Blaze-Hands critical points

No	Blaze-Hands output format	No	Blaze-Hands output format
0	Wrist	5	Index_finger_MCP
1	Thumb_CMC	6	Index_finger_PIP
2	Thumb_MCP	7	Index_finger_DIP
3	Thumb_IP	8	Index_finger_TIP
4	Thumb_TIP	No	Blaze-Hands output format
No	Blaze-Hands output format	13	Ring_finger_MCP
9	Middle_finger_MCP	14	Ring_finger_PIP
10	Middle_finger_PIP	15	Ring_finger_DIP
11	Middle_finger_DIP	16	Ring_finger_TIP
12	Middle_finger_TIP		
No	Blaze-Hands output format		
17	Pinky_MCP		
18	Pinky_PIP		
19	Pinky_DIP		
20	Pinky_TIP		

Figure 5. Description of Blaze-Hands key point numbering

The Blaze-Hands framework uses a palm detector, which inputs a full-width image and detects the palm part of the hand first instead of the whole hand, while masking the fingers in self-obscuring situations such as clenched fists, to obtain a palm detection frame; when the Blaze-Hands framework uses a hand keypoint detection model, it inputs an image of the hand cropped to the hand by the hand detector, and predicts the high-quality 2.5D coordinates of the 21 keypoints at the location.

3. Human posture detection and motion type recognition architecture

3.1. System architecture

Based on the human posture detection and recognition of sports teaching has training system structure is mainly divided into three parts, the structure is shown in Figure 6.

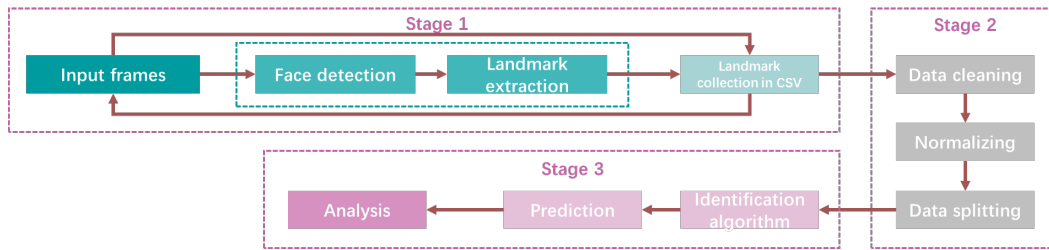


Figure 6. Human movement posture detection and action recognition

As can be seen from Figure 6, the first part uses Mediapipe to preprocess the image to obtain the coordinate information of each key point of the human body [24], as described in Section 2. The second part performs data cleaning and normalisation on the extracted coordinate data, the specific steps are shown in 3.2 and 3.3. The second part uses machine learning algorithms for predictive classification, the specific algorithm principles and steps are shown in Section 5.

3.2. Data cleansing

In this paper, only the x and y coordinates of the detector are considered, and the dataset collects all the human Blaze-Pose keypoints and Blaze-Hands keypoints in an image. Due to the blurring of the image, the detector does not send to detect the face, making the dataset input empty, for this reason it is necessary to be clear about these points and use the library function file for crawling and checking for null items. Data cleaning starts with searching for rows containing null items and removing their indexes.

3.3. Data normalisation

After removing the unwanted points, the x and y coordinates are normalised to fit the recognition system. In this paper, Z-Score method is used for normalisation as shown in equation (1):

$$\hat{x} = (x - \mu) / \sigma \tag{1}$$

Where, x denotes the original score, \hat{x} is the transformed z-score, μ denotes the mean of the score in the overall sample space, and σ denotes the standard deviation in the overall sample space.

4. Related technologies

4.1. Deep Limit Learning Machine

Extreme Learning Machine (ELM) is a single hidden layer feed forward neural network whose biggest advantage is its fast learning speed. For a hidden layer node the ELM can be expressed as equation (2):

$$f_{ELM}(x_i) = \sum_{j=1}^l \beta_j g(a_j x_i + b_j), i = 1, 2, \dots, N \quad (2)$$

$\beta_j = [\beta_{j1}, \beta_{j2}, \dots, \beta_{jn}]$ $a_j = [a_{j1}, a_{j2}, \dots, a_{jm}]$
 j b_j j $g(\cdot)$ Where denotes the output weight of the j th hidden layer unit, denotes the input weight of the j th hidden layer unit, denotes the bias of the j th hidden layer unit, and denotes the activation function of the hidden layer unit.

The ELM output error is equation (3):

$$E = \sum_{i=1}^N \|f_{ELM}(x_i) - y_i\| \quad (3)$$

$$= \|H(a, b) \cdot \beta - y\|$$

H β y Where, denotes the output of the hidden layer unit, denotes the output weight and denotes the desired output. a b H In ELM algorithm, by determining and is uniquely determined. The output weights are solved as equation (4):

$$\beta^* = H^{-1} \cdot y \quad (4)$$

H^{-1} H where denotes the Moore-Penrose generalised inverse matrix of the matrix.

A deep limit learning machine [25] consisting of multiple limit learning machine self-encoders outputs weights as equation (5):

$$\beta^* = H^{-1} \left(\frac{1}{C} + HH^T \right)^{-1} \cdot y \quad (5)$$

C represents the regular term coefficients. In order to reduce the complexity of training, two hidden layers are chosen in this paper, and the number of hidden layer units in each layer is learnt from the parametric experiments later.

4.2. Optimisation algorithm for snow melting

From a physical point of view, it is known that snow can be transformed into two forms: liquid and vapour, corresponding to the physical processes: melting and sublimation. The snow melting process and the optimisation mechanism are given in Figure 7. From Figure 7, it can be seen that during the melting process, snow is converted into liquid water, or snow is directly converted into vapour through the sublimation process. Meanwhile, liquid water can be converted to steam through transpiration. Based on the snow melting and sublimation behaviour, Snow ablation optimizer (SAO) [26] was proposed, which includes initialization, exploration phase, exploitation phase and dual population mechanism. The snow melting behaviour simulates the exploitation phase of the optimization process, and the sublimation and transpiration behaviours simulate the exploration phase of the optimization process.

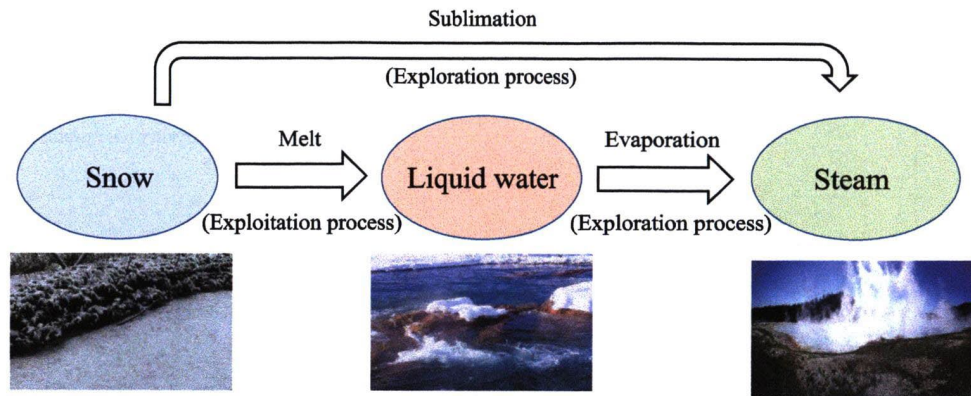


Figure 7. Schematic illustration of snow melting inspiration

Initialisation phase

In the SAO algorithm, the population initialisation is done using a stochastic strategy, which is modelled as follows:

$$Z = L + \theta \times (U - L) \quad (6)$$

L U θ $[0,1]$ where and denote the lower and upper bounds of the spatial solution and denotes the random number between.

Exploration phase

In the exploration phase, when snow or liquid water is transformed into vapour water, the search intelligences

show highly dispersed characteristics and have irregular movement characteristics. In the exploration phase, the behavioural situation is simulated using Brownian motion,

$$Z_i(t+1) = Elite(t) + \mathbf{BM}_i(t) \otimes \left(\theta_1 \times (G(t) - Z_i(t)) + (1 - \theta_1) \times (\bar{Z}(t) - Z_i(t)) \right) \quad (7)$$

$$Z_i(t) \quad \mathbf{BM}_i(t) \otimes \theta_1 [0,1] \quad G(t) \quad Elite(t) \quad \bar{Z}(t)$$

Where, denotes the i th individual in the t th iteration number, denotes the random vector of Gaussian distribution based on Brownian motion, denotes the dot product notation, denotes the random number between, denotes the current optimal solution, denotes the randomly selected individuals among the elite individuals, and denotes the location of the form centre of the population. $\bar{Z}(t)$ The specific calculation formula is shown in equation (8):

$$\bar{Z}(t) = \frac{1}{N} \sum_{i=1}^N Z_i(t) \quad (8)$$

$Elite(t)$ The elite group to which it belongs is represented in equation (9):

$$Elite(t) \in [G(t), Z_{second}(t), Z_{third}(t), Z_c(t)] \quad (9)$$

which searches for areas with potential. The position update formula for the exploration phase is as follows:

$Z_{second}(t)$ $Z_{third}(t)$ $Z_c(t)$ Where and denote the second and third best individuals, respectively, and denotes the location of the top 50% of individuals in terms of fitness values.

$$Z_c(t) = \frac{1}{N_1} \sum_{i=1}^{N_1} Z_i(t) \quad (10)$$

N_1 where indicates the number of individuals in the elite group, which is generally half the number of individuals in the group.

$\theta_1 \times (G(t) - Z_i(t))$ $(1 - \theta_1) \times (\bar{Z}(t) - Z_i(t))$ The behavioural diagram of the exploration phase is shown in Figure 8. and reflect the relationship between the individuals in the exploration behaviour.

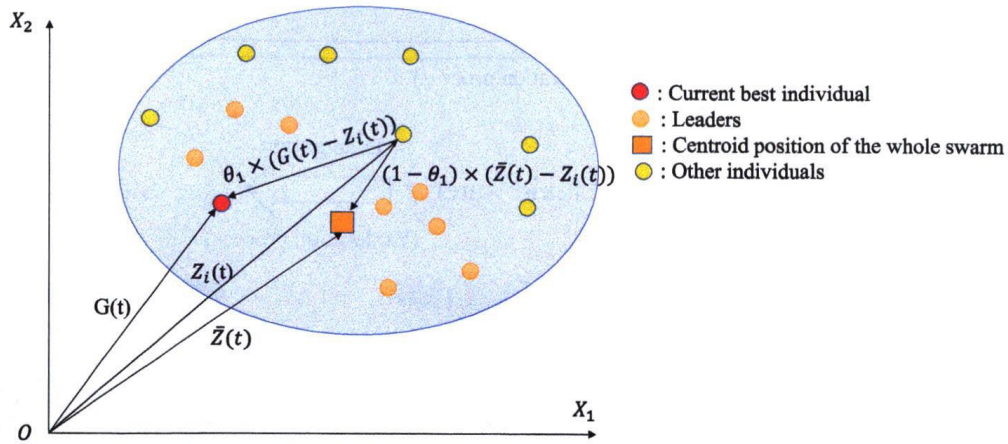


Figure 8 Schematic diagram of the exploration phase of the snow melting algorithm

Development phase

In the development phase, the search intelligences adopt a high quality development strategy around the optimal solution, relative to the highly dispersed features, and mainly simulate the conversion of snow into liquid water behaviour, i.e. snow melting behaviour. In the SAO algorithm, the snow melting rate is calculated by Eq. (11) and Eq. (12):

$$M = \left(0.35 + 0.25 \times \frac{e^{\frac{t}{t_{max}}} - 1}{e - 1} \right) \times T(t) \quad (11)$$

$$T(t) = e^{\frac{-t}{t_{max}}} \quad (12)$$

During the SAO development phase, the location is updated as in equation (13):

$$Z_i(t+1) = M \times G(t) + BM_i(t) \otimes (\theta_2 \times (G(t) - Z_i(t)) + (1 - \theta_2) \times (\bar{Z}(t) - Z_i(t))) \quad (13)$$

$M \theta_2 [-1,1]$ Where denotes the snowmelt rate and denotes a random number between. $\theta_2 \times (G(t) - Z_i(t)) (1 - \theta_2) \times (\bar{Z}(t) - Z_i(t))$ In this stage, under the effect of and, individuals search through the current optimal search particles and population centred areas to develop potential areas.

Dual Stock Mechanism

The balance between exploitation and exploration is very important. Liquid water is converted to steam to simulate the exploration phase. The algorithm gradually converges to the exploration search solution space as the irregular motion dispersion feature increases. In order to balance the exploration and exploitation phases, a two-population search mechanism is proposed in this section. $P_a P_b$ At the initial stage of the algorithm, the population is divided into two equal population sizes, respectively, and are used to represent the whole population and divide the population. $P_a P_b$ Population is mainly used for exploration and population is mainly used for exploitation. $P_a P_b$ As the number of iterations increases, the number of populations will decrease and the number of populations will increase, and the two-population mechanism is described in Figure 3.

Algorithm flow

According to the algorithm heuristic mechanism and optimisation strategy, the specific steps are as follows:

Step 1: Initialise the population parameters as well as the population position, set the maximum number of iterations and other parameters;

Step 2: Calculate the fitness value and record the current optimal individual;

Step 3: Calculate the snowmelt rate M;

Step 4: Randomly divide the population into two sub-populations based on the number of sub-populations;

Step 5: Subpopulation a carries out the exploration behavioural phase through the conversion of snow or liquid water to steam water, and subpopulation b carries out the exploitation behavioural phase through the conversion of snow to liquid water behaviour;

Step 6: Calculate the fitness value and update the optimal individual;

Step 7: Determine whether the number of iterations reaches the maximum number of iterations. If the maximum number of iterations is reached, carry out the output of the optimal solution and optimal value; otherwise, go to step 4.

According to the SAO algorithm steps, the SAO algorithm pseudo-code is shown in Figure 9.

Algorithm: Snow ablation optimizer (SAO)	
1	Initialization: the swarm Z, t=0, tmax, Na=Nb=N/2
2	Fitness evaluation
3	Record the current best individual G(t)
4	while t<tmax do
5	Calculate the snowmelt rate M;
6	Randomly divide the population P into two subpopulations Pa and Pb;
7	for each individual do
8	Update each individual's position;
9	end for
10	Fitness evaluation
11	Update G(t)
12	t = t+1
13	end while
14	Return G(t)

Figure 9. Pseudo-code of SAO algorithm

5. Process of Motion Attitude Detection and Recognition Method Based on Snow Melting Optimisation Algorithm Improved DELM Networks

Combining the snowmelt optimisation algorithm with the deep limit learning machine, this section proposes a motion pose detection recognition method based on the snowmelt optimisation algorithm optimising the deep limit learning machine network.

5.1. Coding Methods and Objective Functions

In order to improve the recognition and classification accuracy of the DELM neural network, the snowmelt optimisation algorithm is used to optimise the DELM neural network parameters, i.e., to optimise the weights and biases of the neural network's hidden layers, and this paper adopts the real number coding method to encode the parameters of the hidden layers, the specific coding method is shown in Figure 10. $l m m \times l + l (m_1 \times l_1 + l_1) + (m_2 \times l_2 + l_2)$

As can be seen from Figure 10, the coding region is mainly divided into the hidden layer weights and hidden layer bias, the coding dimensions of the two hidden layer units dimensional inputs are, and the coding dimensions of the two hidden layers are .

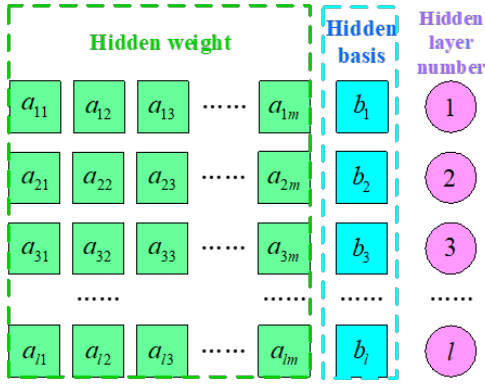


Figure 10 .Detection and recognition algorithm optimised coding method

In order to further improve the recognition classification accuracy of the DELM neural network, the classification recognition degree is calculated as the objective function of the SAO-DELM algorithm as follows:

$$\max f(a, b) = \frac{N_1}{N} \quad (14)$$

$f(a, b)$ denotes the value of the objective function, a is the DELM hermit layer weights, b is the DELM hermit layer bias, N_1 denotes the number of correctly identified classifications, and N denotes the total sample size, respectively.

5.2. Steps and processes

The motion gesture detection recognition model based on SAO algorithm optimised DELM network is mainly

based on the mapping relationship between features and categories with motion gesture detection key point coordinate values as input and motion gesture type as output. The flowchart of the motion gesture detection recognition method based on the SAO-DELM algorithm is shown in Figure 11. The specific steps are as follows:

Step 1: Use Mediapipe to pre-process the image to obtain the coordinate information of each key point of the human body; perform data cleaning and normalisation on the extracted coordinate data; divide the data into test set, validation set and training set;

Step 2: Encode the initial parameters of DELM using SAO algorithm, and also initialise the algorithm parameters such as population parameters, number of iterations, etc.; initialise the population and calculate the objective function value;

Step 3: Calculate the snowmelt rate M ;

Step 4: Optimising and updating the individual logistics delivery solutions based on the exploration phase, development phase and two-population mechanism of the SAO algorithm;

Step 5: In each iteration, it is necessary to compare the objective function value of each candidate solution with the objective function value of the current global optimal solution and update the global optimal solution;

Step 6: Judge whether the termination condition is satisfied. If it is satisfied, exit the iteration, output the optimal DELM parameters, and execute step 8, otherwise continue to execute step 3;

$\theta^* = (a, b)$ Step 7: Decode the SAO-based optimised

DELM parameters to obtain;

Step 8: Construct the SAO-DELM recognition model, train the analysis model using the training set and input the test set into the model to get the recognition accuracy.

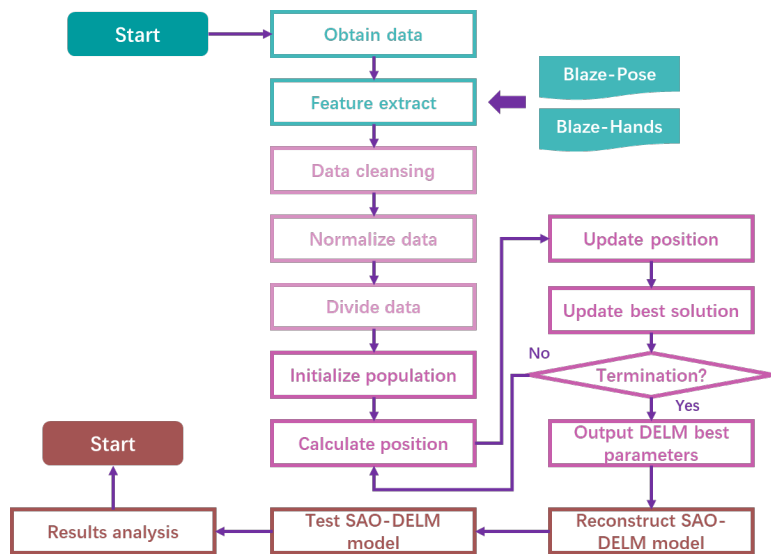


Figure 11. Flowchart of motion pose detection recognition based on SAO algorithm optimised DELM network

6. Experiments and results

In order to verify the accuracy and timeliness of the motion posture detection and recognition model proposed in this paper, five analysis algorithms are selected for

comparison with the sports teaching and training motion posture data as simulation data, and the specific parameters of each algorithm are set as in Table 1. the experimental simulation environment is Windows 10, CPU is 2.80GHz, 8GB memory, and the programming language Matlab2022a.

Table 1. Parameter settings of motion sensing posture detection and recognition method

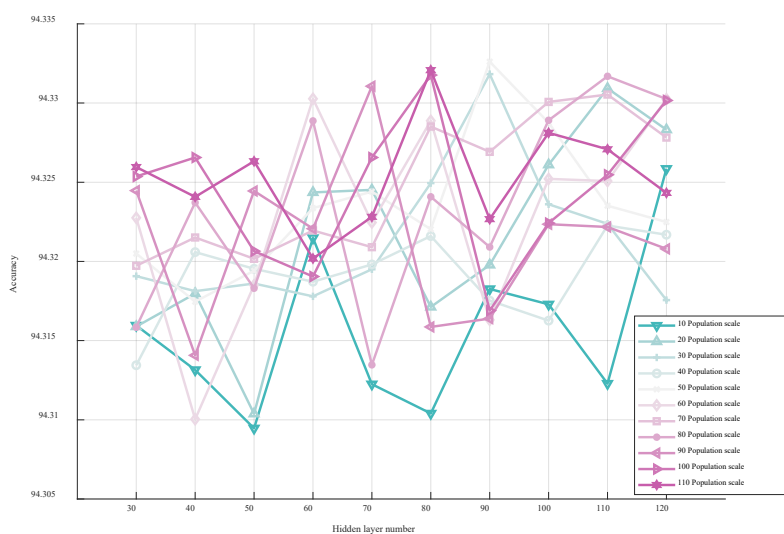
arithmetic	parameterisation
ELM	The number of hidden layer nodes is 50
DELM	Two hidden layers, see section 5.1 for reference analysis of the number of nodes in each hidden layer
GWO-DELM	Three cryptic layers, see section 5.1 for the reference analysis of the number of nodes in each layer, GWO parameter a decreasing from 2 to 0, and population size see section 5.1
SCA-DELM	Two hidden layers, see section 5.1 for reference analysis of the number of nodes in each layer, SCA parameter a decreasing from 2 to 0, population size see section 5.1
TLBO-DELM	Three cryptic layers, see section 5.1 for reference analysis of the number of nodes in each layer, with teaching factors of 1 and 2, and the number of populations in section 5.1
SAO-DELM	Three cryptic layers, see section 5.1 for reference analyses of the number of nodes in each layer, and section 5.1 for the number of populations

6.1. Parametric analysis

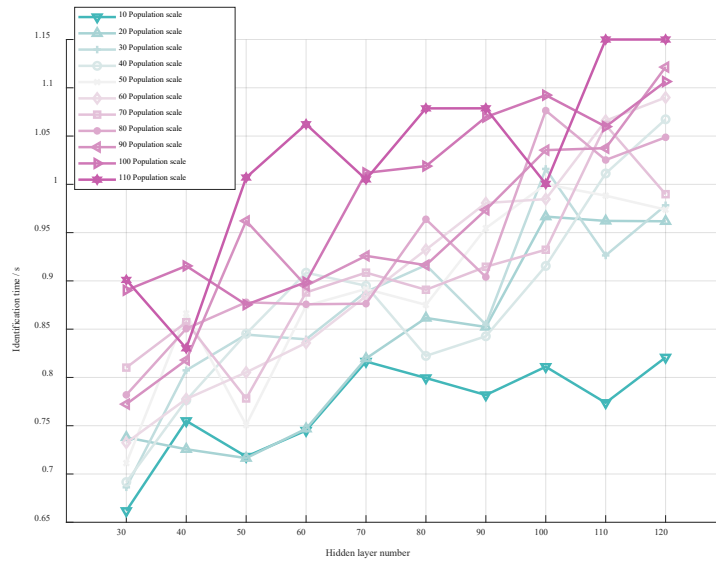
In order to obtain a suitable number of hidden layer nodes of the DELM network and optimise the population size of the algorithm, this section analyses the effect of different population sizes and number of hidden layer nodes on the recognition accuracy and recognition time of motion pose detection.

Figure 12 gives the effect of different number of populations and number of hidden layer nodes on recognition accuracy and recognition time. From Figure 12(a), it can be seen that as the number of populations increases, the recognition accuracy increases; as the number

of hidden layer nodes increases, the recognition accuracy increases. From Figure 12(b), it can be seen that as the number of populations increases, the recognition time increases; as the number of DBN hidden layer nodes increases, the recognition time increases. In summary, the increase in the population number with the number of hidden layer nodes of the motion pose detection recognition model based on the SAO-DELM algorithm is favourable to the increase in recognition accuracy, but the recognition time increases. In order to balance the contradiction between time and accuracy, the number of population should be selected as 60 and the number of hidden layer nodes as 60.



(a) Results of the impact on identification accuracy



(b) Results of the impact on recognition time

Figure 12. Effect of different number of populations and number of cryptic nodes on recognition accuracy value and recognition time

6.2 Comparative analysis of models

In order to verify the validity and superiority of the recognition method based on SAO-DELM algorithm for motion pose detection, SAO-DELM is compared with five other models such as ELM, DELM, GWO-DELM, SCA-DELM, TLBO-DELM, etc., and the recognition results of each model are shown in Figure 13 and Figure 14.

As can be seen from Figure 13, the accuracy of sports teaching and training movement posture detection and recognition based on SAO-DELM algorithm is greater than other algorithms. In terms of mean value, SAO-DELM algorithm is better than other algorithms, the accuracy rate

mean ranked in order TLBO-DELM, SCA-DELM, GWO-DELM, DELM, ELM algorithm. In terms of standard deviation, SAO-DELM algorithm is better than the other algorithms, and the standard deviation of accuracy rate is ranked in the order of TLBO-DELM, GWO-DELM, SCA-DELM, DELM, ELM algorithms; the recognition accuracy of the SAO-DELM algorithm is better than that of the GWO-DELM, SCA-DELM, and TLBO-DELM algorithms, which indicates that the SAO optimisation of the DELM recognition degree is better than the GWO-DELM, SCA-DELM, and TLBO-DELM algorithms. DELM recognition is better and SAO optimisation performance is better than GWO, SCA, TLBO algorithms.

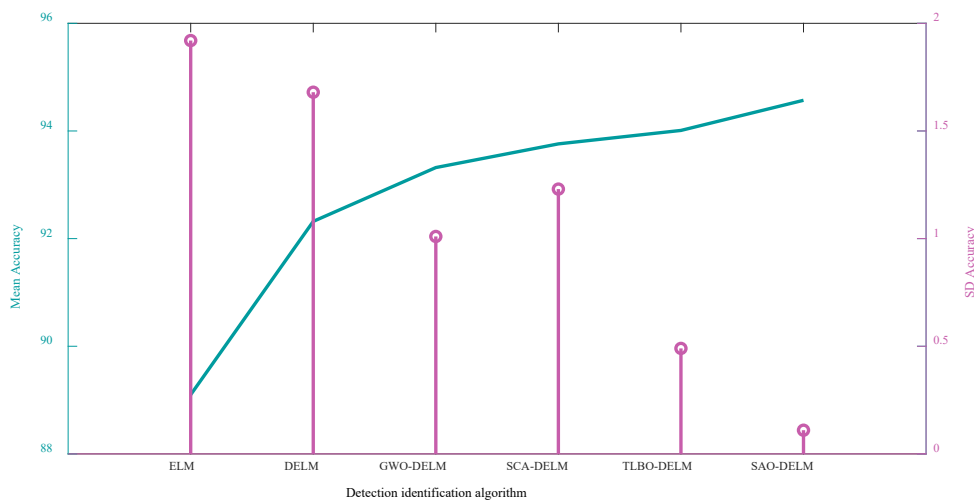


Figure 13. Comparison of accuracy analysis of motion pose detection recognition based on each algorithm

As can be seen from Figure 14, the recognition time of sports teaching and training movement posture detection

based on SAO-DELM algorithm is less than other algorithms; in terms of mean value, SAO-DELM algorithm

is faster than other algorithms, and the ranking of time-consuming mean value is LBO-DELM, SCA-DELM, GWO-DELM, DELM, ELM algorithms in the order of time-consuming mean value; in terms of standard deviation, SAO-DELM algorithm is better than the other algorithms, the recognition time-consuming standard deviation ranking

in order of TLBO-DELM, GWO-DELM, SCA-DELM, ELM, DELM algorithms; SAO-DELM algorithm recognition accuracy is better than the GWO-DELM, SCA-DELM, TLBO-DELM algorithms, which means that SAO optimisation improves the recognition real-time.

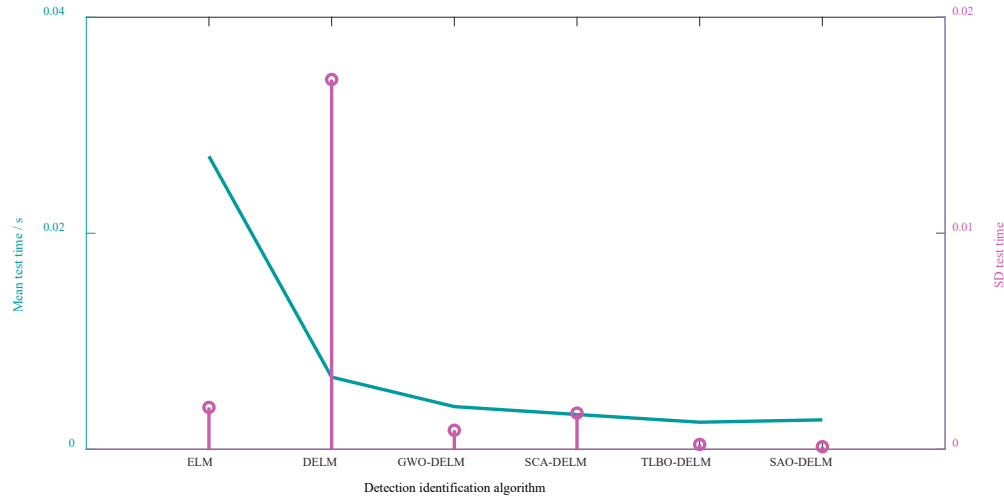


Figure 14. Comparison of recognition time analysis for motion pose detection based on each algorithm

From Figure 15, it can be seen that the SAO algorithm for optimising DELM network parameters converges faster and the convergence accuracy is better than the other algorithms. Figure 16 gives a comparison of the number of convergence iterations of optimised DELM parameters based on each algorithm. From Figure 16, it can be seen that SAO algorithm optimised DELM network parameters converge faster.

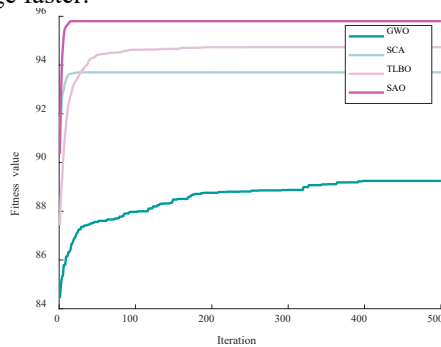


Figure 15. Comparison of convergence curves of optimised DELM parameters based on each algorithm

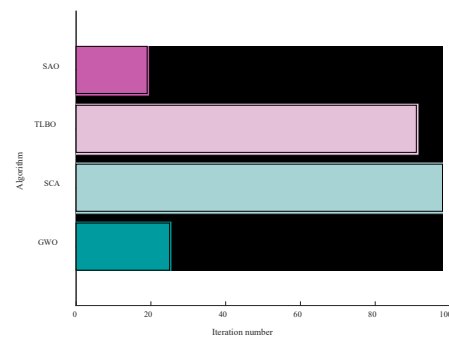


Figure 16. Comparison of the number of convergence iterations of optimised DELM parameters based on each algorithm

7. Conclusion

Aiming at the defects of incomplete features, low accuracy, and low real-time performance of motion gesture detection and recognition methods, this paper adopts snow melting heuristic algorithm and deep limit learning mechanism to construct motion gesture detection and recognition method. The method extracts motion gesture detection recognition features by analysing the motion gesture detection process. Using the SAO algorithm to optimise the DELM network parameters, construct a sports posture detection and recognition model. Simulation experiments are carried out using human posture data from sports teaching and training, and the following conclusions are drawn:

- (1) The SAO algorithm can improve the diagnostic accuracy of RF by comparing the recognition performance

of SAO-DELM with DELM, GWO-DELM, SCA-DELM, and TLBO-DELM algorithms;

(2) SAO-DELM recognition time meets real-time requirements.

The optimisation of the SAO algorithm used in this paper can easily fall into a local optimum, which makes the motion pose detection recognition model subject to certain limitations. In future work, the introduction of multi-strategy optimisation of the SAO algorithm will be considered to improve the efficiency of the algorithm.

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