Lower limb motion pattern recognition based on IWOA-SVM

Xiaoqi Li*, Yunlong Yang, Haidie Chen, Yufeng Yao
State Key Laboratory of Robotics and Systems, Harbin Institute of Technology, Harbin, Heilongjiang

ABSTRACT

This paper presents a lower limb motion pattern recognition algorithm based on SVM model optimized by improved whale algorithm (IWOA-SVM). The purpose is to overcome the problems of low accuracy and low reaction speed of existing lower limb rehabilitation pattern recognition algorithms, nonlinear adjustment factor is combined with WOA to enhance the search ability and search speed of the algorithm. The collected surface EMG signals are used as the input of the motion pattern recognition system, and the motion pattern recognition is realized by combining the IWOA-SVM model. Simulation experiments on six test functions are carried out and compared with WOA. The results indicated that the search convergence speed and optimization accuracy of IWOA are improved. Experiments on the collected signal data suggested that the recognition accuracy is 94.12%, compared with WOA-SVM algorithm, PSO-SVM and GA-SVM. The results indicated that the recognition accuracy of this algorithm is improved by 4.02%, 8.82% and 6.64% respectively.

Keywords: Lower limb rehabilitation robot, pattern recognition, SVM, WOA

1. INTRODUCTION

Lower limb rehabilitation robot can provide more scientific and effective rehabilitation training for patients, so it has been widely concerned by scholars[1]. Through the analysis of the patient's motion information and the recognition of the patient's movement pattern, the degree of human-computer interaction of the rehabilitation robot can be further improved and the patient's initiative can be improved[2]. Surface electromyography (sEMG) has been widely used because it is easy to obtain, advanced and relatively stable[3]. The surface EMG signals of different action modes are collected from the human body by the acquisition device, and the features are extracted as the judgment basis of pattern recognition. The classifier is the main algorithm of pattern recognition. Its structure and parameter setting affect the classification results to a great extent. Support vector machine is often used in pattern recognition based on sEMG because of its simple structure, high robustness and ability to deal with small data sets[4-6]. SVM is a commonly used supervised learning method, the selection of parameters in SVM will directly affect its performance. Its parameters can be selected by appropriate intelligent optimization algorithm, so as to improve the performance of SVM.

Previous studies have indicated[7] that WOA algorithm has advantages over genetic algorithm (GA) and particle swarm optimization algorithm (PSO) in parameter optimization of SVM, but these algorithms have some problems, such as low search accuracy, easy premature convergence into local optimization, low iterative efficiency of descendants and so on[8-10]. For the above shortcomings, He[11] combines WOA algorithm with genetic algorithm, the accuracy of gait detection is improved by 4%. Dong[12] introduces tent chaotic mapping to WOA, the convergence rate of IWOA is improved. Yin[13] proposes a WOA algorithm based on external archiving strategy, the superiority of the algorithm is proved by simulation experiment. Elhosseini[14] proposes a Weight-Based adaptive algorithm, which improves the convergence speed of the algorithm and the ability to break away from local optimization. Sun[15] introduces chaos algorithm into WOA to improve the diversity and self-centrality of search objects. However, because the optimal parameters of SVM belong to multi-extremum problem, there are high requirements for the global search ability of the algorithm, so it is necessary to solve the problems of low convergence accuracy and easy to fall into local optimization for WOA.

This paper improves the traditional WOA and introduces a nonlinear adjustment factor to improve the global search ability and accelerate the local search speed of the algorithm. The collected surface EMG signals are used as the input of the motion pattern recognition system, and the motion pattern recognition is realized by combining the IWOA-SVM model. Simulation experiments on six test functions are carried out and compared with WOA. The results indicated that the

* lxq18845786401@163.com

Third International Conference on Computer Science and Communication Technology (ICCSCT 2022)
edited by Yingfa Lu, Changbo Cheng, Proc. of SPIE Vol. 12506, 125066C

convergence rate and optimization accuracy of IWOA are improved. Also compared with WOA-SVM, PSO-SVM, GA-SVM, it is found that this method can recognize motion patterns effectively.

2. SUPPORT VECTOR MACHINE (SVM)

Support vector machine was first used to solve the problem of binary linear classification. When solving a classification problem, basis for classification $x=\{x_1,...,x_N\}$, $y=\{y_1,...,y_N\}$[7] is given, where in each data contains a plurality of feature vector $X_i=\{x_1,...,x_N\}$[7]. The classification result is $y\in\{+1,-1\}$, which represents the positive class and the negative class respectively. Thus, an optimal hyperplane $w^T X+b=0$ separates the two categories correctly, makes the distance between any sample point to the hyperplane greater than or equal to 1, and ensures that the objective function $J(w)=\|w\|^2$ is minimum, so that the distance between the two categories is maximum. For the nonlinear classification problem, support vector machine uses kernel function to deal with it, and its function model is[16]:

$$f(X)=sign\left[\sum_{i=1}^{n} a_i^* y_i K(X_i,X_j)+b^*\right] \tag{1}$$

SVM maps the low-dimensional space to the high-dimensional space and classifies the linear inseparable data by using the kernel function $k(x_i,x_j)$. Ideally, each data point can be accurately distinguished by the decision surface, but this will lead to the over-fitting phenomenon that the accuracy of the training sample becomes higher and the test sample becomes lower because of the influence of a small number of points in the sample. The fault tolerance coefficient ξ_i tolerance can be introduced to balance the generalization risk and the empirical risk. In this case, the classification surface is the soft edge optimal hyperplane, and its discriminant function is as follows[16]:

$$y_i\left(w^T X_i+b\right)>1-\xi_i,\quad \xi_i>0 \tag{2}$$

At the same time, the penalty coefficient C is introduced for ξ, and the new objective function is expressed as follows[16]:

$$\Phi(w)=\frac{1}{2}\|w\|^2+C\sum_{i=1}^{n}\xi_i \tag{3}$$

The classification performance of SVM is related to two undetermined parameters: penalty coefficient C and kernel function parameter g, and the complexity of SVM classification algorithm is directly affected by the coefficient g.

3. OPTIMIZATION OF SVM PARAMETERS BY WHALE ALGORITHM

Mirjalili and Lewis proposed WOA algorithm in 2016, which is a swarm intelligence optimization algorithm[7]. By imitating the feeding mode of whales, the optimization algorithm is designed according to the predation behavior of whales in bubble nets.

3.1 Encircling prey

Take the individual with the current optimal solution in the population as the target point, the remaining search individuals continue to shrink toward the target point and update their position coordinates accordingly. The mathematical model is[7]:

$$\overrightarrow{X}(t+1)=\overrightarrow{X_p}(t)-A\cdot\left|B\cdot\overrightarrow{X_p}(t)-\overrightarrow{X}(t)\right| \tag{4}$$

where $\overrightarrow{X}(t)$ denotes the whale individual position vector. t denotes the current number of iterations. $\overrightarrow{X_p}(t)$ is the prey position vector. $\vec{A}$ and $\vec{B}$ are coefficient vectors, respectively[7]:

$$\vec{A}=2\vec{a}\cdot\vec{r_1}-\vec{a} \tag{5}$$

$$\vec{B}=2\vec{r_2} \tag{6}$$

In equations (5) and (6), $\vec{r_1}$ and $\vec{r_2}$ are random vectors of [0, 1] interval, respectively. $\vec{a}$ decreases linearly from 2 to 0[7].

$$\vec{a}(t) = 2 - \frac{2t}{t_{\max}} \tag{7}$$

where $t_{\max}$ denotes the iterative maximum value. By decreasing the value of vector $\vec{a}$, the population is simulated to get closer to its prey and contract and surround it.

3.2 Spiral updating position

During hunting, whales rise in a spiral from directly below their prey until they surround their prey. The mathematical model of the helix update position is[7]:

$$\overrightarrow{X}(t+1) = \overrightarrow{X_p}(t) + \overrightarrow{C'} \cdot e^{bl} \cdot \cos(2\pi l) \tag{8}$$

The role of b is to define the shape of the logarithmic spiral and is a constant. l is random in the interval [-1, 1]. In the process of whale hunting, the shrinking encirclement of prey and the rising pursuit of prey along the spiral path is simultaneous. Therefore, the probability p of choosing contraction enclosure and spiral update is 0.5, as shown in the following formula[7]:

$$\overrightarrow{X}(t+1) = \begin{cases} \overrightarrow{X_p}(t) - \vec{A} \cdot \left|\vec{B} \cdot \overrightarrow{X_p}(t) - \overrightarrow{X}(t)\right|, p < 0.5 \\ \overrightarrow{X_p}(t) + \overrightarrow{C'} \cdot e^{bl} \cdot \cos(2\pi l),\ \ p \geq 0.5 \end{cases} \tag{9}$$

3.3 Search for prey (exploration phase)

During hunting, whales can not only narrow the encirclement during the spiral, but also swim randomly to search for prey. When $\left|\vec{A}\right| \geq 1$, the whales are slightly farther away from their prey, and the whales search their prey randomly according to each other's position, and then update the current individual's position according to the randomly selected location, so that the algorithm can conduct a global search. The mathematical model is[7]:

$$\overrightarrow{X}(t+1) = \overrightarrow{X_{rand}}(t) - \vec{A} \cdot \left|\vec{B} \cdot \overrightarrow{X_{rand}}(t) - \overrightarrow{X}(t)\right| \tag{10}$$

3.4 Improvement of whale algorithm

The WOA algorithm starts by assigning random location coordinates to individuals. In each iteration, when $\left|\vec{A}\right| \geq 1$, the prey is randomly searched, and the current individual position is updated according to the randomly selected location. When $\left|\vec{A}\right| < 1$, the current best path is selected to update the optimal individual location. The original adjustment factor $\vec{a}$ decreases linearly from 2 to 0 in the iterative process, which is difficult to deal with complex problems and is easy to fall into local optimization during optimization. For this problem, this paper proposes a nonlinear change strategy, which makes the adjustment factor $\vec{a}$ decrease slowly and then quickly from 2 to 0 in the whole iterative process, which improves the global search ability of the algorithm in the early stage of iteration and accelerates the local convergence speed in the later stage of iteration. The calculation formula of $\vec{a}$ after optimization is

$$a = a_{\max} - (3^{t/t_{\max}} - 1) \tag{11}$$

The whale algorithm is improved by changing the linear factor to a nonlinear factor to balance the global search and local development ability. The global search ability of the traditional whale algorithm is improved to prevent it from falling into local optimum. In this algorithm, the fitness is expressed by the correct rate of recognition during iteration. The fitness of the search particles can be calculated by the 5-fold cross-validation method to avoid over-fitting, and the iterative termination condition is to meet the requirements of the optimal fitness or the maximum number of iterations.

4. NUMERICAL EXPERIMENT AND RESULT ANALYSIS

In order to evaluate the performance of IWOA, six commonly used standard test functions are tested. Previous studies have indicated that WOA algorithm has advantages over GA and PSO algorithm in common standard test functions. This paper does not repeat verification, but only compares it with the standard WOA. The test function expression, variable range and theoretical minimum are exhibited in Table 1.

Table 1. Standard test function.

Function	Range	$f_{\min}$
$f_1(x)=\sum_{i=1}^{d} x_i^2$	[-100,100]	0
$f_2(x)=\sum_{i=1}^{n} i x_i^4 + random[0,1)$	[-1.28,1.28]	0
$f_3(x)=\sum_{i=1}^{n}[x_i^2-10\cos(2\pi x_i)+10]$	[-5.12,5.12]	0
$f_4(x)=-20\exp(-0.2\sqrt{\frac{1}{d}\sum_{i=1}^{d}x_i^2})-\exp(\frac{1}{d}\sum_{i=1}^{d}\cos(2\pi x_i))+20+e$	[-32,32]	0
$f_5(x)=(\frac{1}{500}+\sum_{j=1}^{25}\frac{1}{j+\sum_{i=1}^{2}(x_i-a_{ij})^6})^{-1}$	[-5,5]	1
$f_6(x)=4x_1^2-2.1x_1^4+\frac{1}{3}x_1^6+x_1x_2-4x_2^2+4x_2^4$	[-5,5]	-1.0316

In order to ensure the fairness of the simulation experiments, the experimental parameters related to the two algorithms are repeated with the same data, and the results are averaged. For each test function, each algorithm is run 20 times, and the search ability and convergence speed of the two algorithms are compared and analyzed. according to the standard deviation and average index of the running results. The results can be seen in Table 2. The IWOA proposed in this paper converges to the global optimal solution in all the six test functions, and its standard deviation and average are less than the optimization results of WOA. Therefore, compared with IWOA, traditional WOA is prone to poor robustness and insufficient search performance.

Table 2. Comparison of optimization results.

F	WOA		IWOA	
	ave	std	ave	std
F1	3.1263E-73	2.19E-72	4.9866E-68	1.5578E-67
F2	0.0043019	0.0053914	0.004271	0.0041127
F3	1.8948E-15	1.0378E-14	0	0
F4	4.4409E-15	3.0944E-15	4.204E-15	2.0723E-15
F5	2.8987	2.9817	2.046	2.4874
F6	-1.0316	1.9779E-09	-1.0316	1.3434E-09

Figure 1 exhibited the convergence curves of two algorithms for six test functions. As can be seen from Figure 1, compared with WOA algorithm, IWOA has higher optimization accuracy and faster convergence speed.

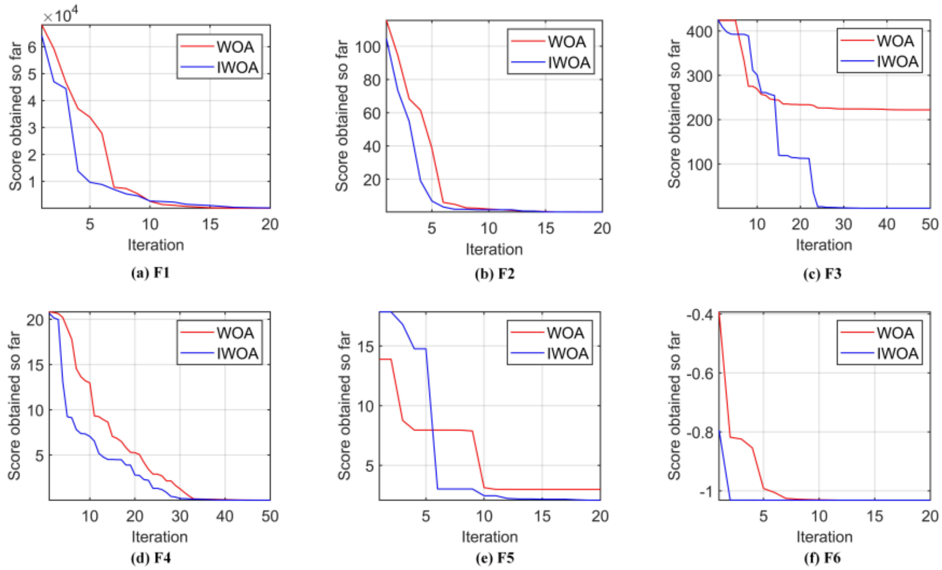

Figure 1. Comparison of six test functions in convergence curve.

5. PATTERN RECOGNITION EXPERIMENT AND RESULT ANALYSIS

In this section, we will verify the effectiveness of the proposed method., 13 healthy men took part in the experiment. The acquisition system was used to collect the surface EMG signals of 6 muscles under different rehabilitation movements. Each action was done 9 times, with an interval of 10 seconds every 3 times. Different movement intervals of 30 seconds to prevent muscle fatigue. The experiment is exhibited in Figure 2. Seven groups of features, such as wavelet coefficient, root mean square, variance and average absolute value, are extracted from the collected gait data after low-pass filtering, and the input signals are normalized to the interval of [-1, 1].

(a)electrode position (b)acquisition process

Figure 2. Schematic diagram of the experiment.

After preprocessing the collected data, a total of 30000 groups of data sets are obtained. In order to verify the advantages of IWOA-SVM model, the same training set and data set are used to classify EMG gesture recognition using WOA-SVM, GA-SVM and PSO-SVM models, and the four models are compared and analyzed. Table 3 lists in detail the parameter settings of the four classification models: IWOA-SVM, WOA-SVM, PSO-SVM and GA-SVM. In addition, the 5-fold cross-validation method is used to calculate the fitness of the search particles in the iterative process, and the final evaluation index is the correct rate of motion recognition. The results indicated that the recognition accuracy of the algorithm is improved by 4.02%, 8.82% and 6.64% respectively, and can effectively recognize the motion pattern.

Table 3. Results of each optimization algorithm.

Optimization method	Parameter setting	Optimal correct rate
IWOA	population size N=20. maximum iterations T=50 Shape parameters of logarithmic helix b=1	94.12%
WOA	population size N=20. maximum iterations T=50 Shape parameters of logarithmic helix b=1	90.10%
PSO	population size N=20. maximum iterations T=50 Learning parameters c1=1.5, c2=1.7. Weight factor w=0.8	85.30%
GA	population size N=20. maximum iterations T=50 Crossover probability 0.8. mutation probability 0.01	87.48%

7. CONCLUSION

In order to recognize the rehabilitation action pattern of patients, and then judge their movement intention, the pattern recognition algorithm based on IWOA-SVM has been applied in the new generation of rehabilitation robot. The nonlinear factor is introduced to improve WOA, and it is proved that IWOA has advantages over traditional WOA. Then two variables of penalty factor and kernel function parameters of SVM are optimized and compared with GA-SVM, PSO-SVM and WOA-SVM algorithms. The results indicated that the algorithm has high accuracy and convergence rate. It can jump out of the local minimum and effectively identify the motion pattern, which has the value for research and promotion. In the next step, the IWOA-SVM algorithm will be applied to the motion control of the robot to realize the real-time control of the rehabilitation robot according to the patient's movement intention.

REFERENCES

[1] Yao, Y. F., Yang, Y. L. and Guo, J. L., "A review of research on rehabilitation training robot after knee joint operation," Journal of Mechanical Engineering, 57(05), 1-18(2021).

[2] Liang, X., Wang, W. Q. and Hou, Z. G., "Human-computer interaction control method of rehabilitation robot," Chinese Science: Information Science, 48(1), 24-46(2018).

[3] Ding, Q. C., Xiong, A. B. and Zhao, X. G., "A review of research and application of motion intention recognition based on surface EMG," Journal of Automation, 42(01), 13-25(2016).

[4] Khan, S., Khan, A. and Farooq, O., "Selection of features and classifiers for EMG-EEG-based upper limb assistive devices—A review," IEEE Rev. Biomed. Eng., 13, 248-260(2020).

[5] Khairuddin, I. M., Majeed, A. P. P. A., Puzi, A. A., Razman, A. and Yusof, H. M., "The classification of movement intention through machine learning models: the identification of significant time-domain EMG features," PeerJ Computer Science, 7(1), (2021).

[6] Spiewak, C., Islam, M. R., Zaman, A. U. and Rahman, M. H., "A comprehensive study on EMG feature extraction and classifiers," Open Access Journal of Biomedical Engineering and Biosciences, 1(1), (2018).

[7] Mirjalili, S. and Lewis, A., "The whale optimization algorithm," Advances in Engineering Software, 95, 51-67(2016).

[8] Pan, Y., Xia, K., Wang, L. and He, Z., "A novel approach to oil layer recognition model using whale optimization algorithm and semi-supervised SVM," Symmetry, 13(5), 757(2021).

[9] Tang, N., Sun, J., Yao, K., Zhou, X., Tian, Y., Cao, Y. and Nirere, A., "Identification of Lycium barbarum varieties based on hyperspectral imaging technique and competitive adaptive reweighted sampling-whale optimization algorithm-support vector machine," Journal of Food Process Engineering, 44(1), e13603(2021).

[10] Nguyen, H., Bui, X. N., Choi, Y., Lee, C. W. and Armaghani, D. J., "A novel combination of whale optimization algorithm and support vector machine with different kernel functions for prediction of blasting-induced fly-rock in quarry mines," Natural Resources Research, 30(1), 191-207(2021).

[11] He, H. L., Zheng, J. B. and Yu, F. L., "Gait Detection of exoskeleton Robot based on improved whale optimization algorithm," Computer Application, 39(7), 7(2019).

[12] Dong, S., Bu, C. and Wang, Y., "Improved whale optimization algorithm based on the tent chaotic mapping and nonlinear convergence factor," Journal of Physics Conference Series, 1682, 012055(2020).
[13] Yin, X., Hou, Y. and Yin, J., "A novel SVM parameter tuning method based on advanced whale optimization algorithm," Journal of Physics: Conference Series, 1237, 022140(2019).
[14] Elhosseini, M. A., Haikal, A. Y., Badawy, M. and Khashan, N., "Biped robot stability based on an A–C parametric whale optimization algorithm," Journal of Computational Science, 31, 17-32(2019).
[15] Sun, W. Z. and Wang, J. S., "Elman neural network soft-sensor model of conversion velocity in polymerization process optimized by chaos whale optimization algorithm," IEEE Access 5 13062-13076(2017).
[16] Ai, Q., Zhang, Y., Qi, W., Liu, Q. and Chen, K., "Research on lower limb motion recognition based on fusion of sEMG and accelerometer signals," Symmetry, 9(8), 147(2017).