A Radial Basis Network-based Early Warning Algorithm for Physical Injuries in Marathon Athletes

Ruisheng Jiao[1], Juan Luo[2*]
College of Physical Education, Chizhou University, Chizhou, China[1]
College of Foreign Languages, Chizhou University, Chizhou, China[2]

***Abstract*—For marathon runners, a single injury may affect their lifelong athletic career, so their injury management is very important. The current injury management for marathon runners has a certain lag, and the current injury warning is mainly based on manual teams, which is costly and poorly automated. To solve these problems, the study proposes a marathon athlete physical injury warning algorithm based on inertia weight adjustment optimized radial basis network. Particle swarm optimization technology has also been incorporated into early warning algorithms. Finally, an athlete injury and disease early warning model is constructed based on the algorithm. The results of performance tests show that the algorithm has a minimum fitness function value of 0.13, which is significantly lower than the current algorithm used for comparison. In the test with real data, the MAPE of the proposed algorithm was as low as 7.598% and the agreement of the hazard score results with the expert human assessment reached 100%. The results of the study indicate the practicality of the algorithm to assist work teams and perform early warning of physical injuries in athletes. However, the high number of iterations required is a limitation awaiting resolution.**

Keywords—Radial basis neural network; exponentially decreasing inertia weights; early warning algorithm; sports injury; marathon; particle swarm; model building

I. Introduction

Marathon is one of the most popular athletic events. For marathoners, injury management and prevention are of the utmost importance. A single serious injury can end an athlete's career. However, there is a certain lag in the current injury management of marathon athletes. In addition, marathoner injury management is currently mainly through human analysis and decision making, which is costly and less automated [1]. To solve these problems, an early warning algorithm for physical injuries of marathon runners is proposed. The research gap of this study is focused on injury prevention for athletes. There are few studies focused on automation and algorithm applications, and there is still a large research gap in this field. Radial basis function neural networks have excellent approximation and global optimization capabilities, and are an effective tool for solving early warning problems [2]. Currently, there are few studies on the application of radial basis function networks in athlete injury prevention. This research can enrich these fields. To address the problem of balancing global and local search performance in radial basis networks, the Exponential Decreasing Inertia Weight (EDIW) strategy is introduced into radial basis networks. The physical injury warning algorithm for marathon runners is constructed based on the radial basis network optimized by EDIW, and it is hoped that this study will bring meaningful results for injury management and warning of marathon runners.

This article has a total of V parts. The second part is related works, which reviews the research achievements in relevant fields in recent years, laying a foundation for this research. The third part is methods, which introduces the design idea of the algorithm and the construction process of the model. The fourth part is the experimental results, which show the performance of the proposed algorithm in the experiment. The fifth part is the conclusion, which summarizes the results of this study.

II. Related Works

Radial basis function neural network is a type of feedforward neural network that has superior performance and has been widely used in the prediction and warning fields. Zijie N led a team to build a mobile platform control system integrated with two Radial basis function neural networks, one for identifying the system's state and the other for predicting the mobile platform's deviation angle based on existing data [3]. The experimental results showed that the application of this algorithm during longitudinal driving reduced the correction time by 1.4 seconds and the overshoot angle by 7.4 degrees compared to traditional control algorithms. Additionally, Wang H and their research team proposed a robot fault-tolerant control model based on Radial basis function neural network prediction, which estimated external disturbances using an RBFNN and automatically handled hazardous factors employing trajectory tracking techniques [4]. The experimental results showed that this RBFNN model could predict external disturbances with an accuracy rate of over 70% and effectively mitigate their impact using tracking and vibration elimination techniques. Furthermore, Lian X and other researchers proposed a sliding mode controller based on an adaptive Radial basis function neural network that introduced a track modeling approach with 12 degrees of freedom [5]. Through performance testing and comparative analysis, the algorithm was found to perform high-precision satellite capture and release tasks. Current Radial basis function neural network research tends to focus on practical applications, with limited research investigating performance optimizations of RBFNN itself. This study addresses its own performance limitations to some extent by optimizing RBFNN prior to its use in practical applications.

Injury management and prevention in athletes has long been an important research topic in the field of sports. Ye and

Di studied injury and fatigue in a large number of winter Olympic athletes and continuously monitored their psychological status for injury prevention in winter athletes [6]. The results of the study showed that there was a significant correlation between the adequacy of athletes' preparation activities and the rationality of training programs and athletes' injuries. Wang and his research partner developed a mutual information sports injury warning model based on an attribute parsimony algorithm, which was designed for youth athletics [7]. Simulation experiments found that the model was able to warn youth track and field athletes of injuries with 80% correctness, but the model suffered from a local optimal solution. Bahr led his team to explore the characteristics of athletes' injuries and diseases based on epidemiological research methods, and they reached consensus on a set of recommendations for the latest sports injury and disease research and proposed an athlete epidemiological research report list extension [8]. The study provided a systematic understanding of the causes of injury and disease in athletes and developed protective measures accordingly. Li used data fusion techniques to analyze and assess potential injury factors in various sports and based on this, developed a dynamic chain model for early warning of risk factors for sports injuries [9]. The study provides a reference for athletes to avoid and reduce injury risk and guarantee normal training and competition, and the authors also applied the research results to tennis training and achieved scientific results. Chia and her research team studied injury prevention in athletes from a social marketing perspective and proposed a strategy to implement athlete injury prevention efforts using a social marketing mix [10]. The team analyzed in detail the useful features of the social marketing mix, including elements such as product, price, and location, and provided high-value recommendations on the corresponding injury prevention programs. According to the analysis results of the literature in the field of athlete injury management, it is found that there is less research on the balance between local and global search capabilities, and the application of radial basis function networks in the field of sports is also relatively lacking. This indicates that there is not much research focused on automation and algorithm applications in this field, and there is still large research space. Therefore, the improved radial basis network is applied to injury warning for marathon runners, hoping to bring practically meaningful research results to these fields.

III. Radial Basis Network-Based Physical Injury Warning Algorithm Construction for Marathon Runners

A. Radial Basis Network Model for EDIW Optimization

Radial basis networks belong to feedforward neural networks and have excellent approximation and global optimization capabilities [11]. In addition, radial basis networks have a simpler structure compared to other feedforward networks and are therefore widely used in approximation, classification, and regression problems [12]. The marathon runner physical injury warning algorithm is based on a special radial basis network, and the topology of this network and its difference from the ordinary radial basis network are shown in Fig. 1.

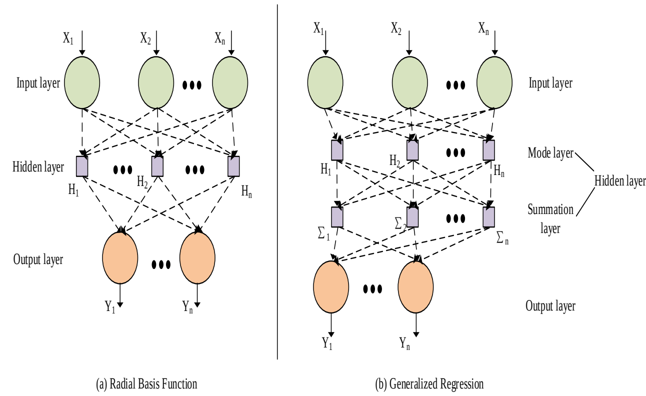

Fig. 1. Radial basis function network model.

Fig. 1(a) shows the structure of the ordinary radial basis network. Fig. 1(b) shows the adopted special radial basis network, which is based on nonlinear regression and is called generalized regression network. The difference from the ordinary radial basis network is that the hidden layer of the generalized regression network is a two-layer structure, i.e., the mode layer and the summation layer [13]. The mode layer is activated using a radial basis Gaussian function, while the summation layer performs direct and weighted summation of the output values of the mode layer, respectively [14]. This structure allows radial basis networks to optimize the warning effect by eliminating the need to adjust the connection weights and only changing the smooth factor to affect the activation function of the mode layer [15]. Current particle swarm optimized radial basis networks have received attention for their stronger global search capability and computational efficiency, and therefore damage warning algorithms also use particle swarm optimized generalized regression radial basis networks [16]. However, the global search and local exploration capabilities of such optimization networks are often not easily balanced, so how to adjust the inertia weights of the algorithm and achieve the best balance is a key issue for such networks [17]. In this study, an EDIW-based strategy is proposed, and the operational flow of the radial basis network model optimized by this strategy is shown in Fig. 2.

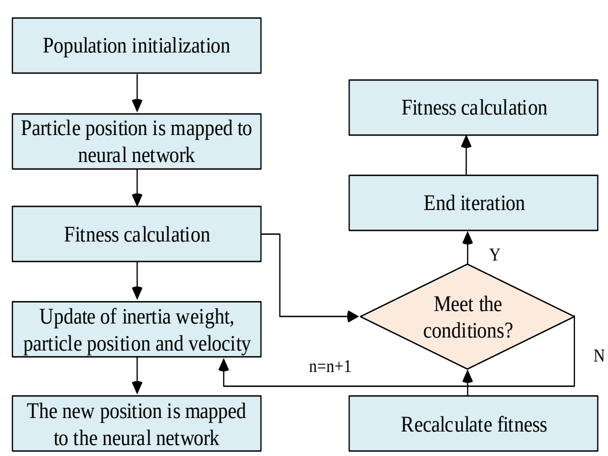

Fig. 2. Operation process of EDIW optimized RBF network model.

In this operational flow, the particle population is first initialized and the positions of the particles are mapped to the radial basis network. After that, the fitness is calculated and the inertia weights and particle positions and velocities are updated, and then the new values are mapped into the radial basis network. The mathematical expression of the EDIW strategy is shown in Eq. (1).

$$\omega(n) = \frac{n(\omega(\max) - \omega(\min))}{N} \tag{1}$$

In Eq. (1), n is the number of iterations of the neural network, and N is the maximum number of iterations. $\omega(\max)$ and $\omega(\min)$ are the maximum and minimum initial inertia weights, respectively. According to the mathematical properties of the EDIW expression, it is a linear function with the decline as shown in Eq. (2).

$$LD = \frac{\omega(\max) - \omega(\min)}{N} \tag{2}$$

The LD in Eq. (2) is the weight reduction. The inertia weights have two main roles for the motion damage warning algorithm, one is to adjust the influence of the historical velocity on the current velocity, and the other is to balance the global detection and local search ability. Therefore, at the beginning of the iteration, the inertia weights should decrease at a faster rate to ensure that the particle swarm can search the region where the feasible solution is located more quickly. At the later stage of the iteration, the inertia weight decreases at a significantly slower rate, thus limiting the step size of particle updates, which allows the particles to increase their ability to search for the optimal solution in the region of feasible solutions. Based on this theory, an EDIW strategy based on control parameters is proposed, as shown in Eq. (3).

$$\omega(n) = \exp(-\frac{Con * n}{N}) * (\omega(\max) - \omega(\min)) + \omega(\min) \tag{3}$$

In Eq. (3), Con is the control parameter whose value is always greater than 0. The strategy adds this parameter to the normal EDIW and uses it to change the drop in inertia weights. The decrease is affected by the variables Con, $\omega(\max)$ and $\omega(\min)$. Provided that the maximum and minimum initial inertia weights remain unchanged, the decrease in the weights according to the change in Con is shown in Eq. (4).

$$\left|\Delta\omega(n, Con)\right| = \frac{\exp(-\frac{Con * n}{N}) * (\omega(\max) - \omega(\min)) * Con}{N} \tag{4}$$

In Eq. (4), $\Delta\omega(n, Con)$ indicates how much the weight decreases with Con. The drop in weight becomes smaller as the number of iterations goes up. Assuming $n = N$, the expression of $\left|\Delta\omega(n, Con)\right|$ becomes Eq. (5).

$$\left|\Delta\omega(n, Con)\right| = Con * (\omega(\max) - \omega(\min)) * \exp(-Con) \tag{5}$$

The derivative function analysis of Eq. (5) is shown in Eq. (6).

$$\Delta' = \exp(-Con)(Con - 1)\begin{cases} > 0 & x < 1 \\ = 0 & x = 1 \\ < 0 & x > 1 \end{cases} \tag{6}$$

According to Eq. (6), when the value of the control parameter is greater than 1, the decline of the weights gradually converges to 0 with the increase of the control parameter. The maximum value of the decline is $\frac{1}{e}$, when the value of the control parameter is 1. So far the algorithm has achieved the design of the inertia weights with the number of iterations. The rate of decrease of the inertia weight decreases with the increase of the number of iterations. At the beginning of the iteration, the inertia weights are larger, which leads to the fact that the particles will retain more of the historical velocity. It is easy to see that the output results of the algorithm under this model are greatly influenced by the control parameters, so the values of the control parameters are important to ensure accurate results. Depending on the number of iterations, the selection of the control parameters also needs to satisfy different conditions. When $n = N$, the control parameters must be such that the inertia weights can reach or converge to $\omega(\min)$, and the inertia weights at this time are shown in Eq. (7).

$$\exp(-Con) = \frac{\omega(n) - \omega(\min)}{\omega(\max) - \omega(\min)} \tag{7}$$

In this case, the inertia weights are taken as shown in Table I.

TABLE I. INERTIA WEIGHTS

Con	**1**	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**
ω(max) =0.7 ω(min) =0.2	0.384	0.265	0.233	0.209	0.204	0.201	0.201	0.200	0.200	0.200
ω(max) =0.9 ω(min) =0.2	0.458	0.295	0.234	0.211	0.205	0.202	0.201	2.01	0.200	0.200
ω(max) =0.7 ω(min) =0.3	0.445	0.354	0.320	0.309	0.303	0.301	0.300	0.300	0.300	0.300
ω(max) =0.9 ω(min) =0.3	0.521	0.379	0.329	0.313	0.305	0.302	0.301	0.300	0.300	0.300
ω(max) =0.7 ω(min) =0.4	0.514	0.446	0.419	0.405	0.402	0.400	0.400	0.400	0.400	0.400

When $0 < n < N$, the control parameters need to be taken in such a way that the weights fall faster and then slower. In this case, the values of the control parameters can lead to large differences in the drop curves of the inertia weights, and it is necessary to test the drop curves with different parameter values to determine the optimal parameter values.

B. Construction of Injury Influencing Factors Model and Injury Warning Algorithm for Marathon Runners

Most sports injury events in marathon runners are not triggered by a single factor, but by a plural number of influencing factors acting together [18]. Therefore a correct analysis of the influencing factors is the basis of the early warning algorithm. According to the definition of sports injuries, the risk factors that induce this type of injury can be classified as internal and external factors [19]. Internal factors refer to the physical condition of the athlete, including age, muscle strength, injury history, etc. External factors are environmental factors other than the athletes themselves, including terrain, weather, etc. [20]. However, the model of injury influencing factors from internal and external factors only lacks comprehensiveness, so stimulus-triggering factors were added as the third assessment dimension in the influencing factor model. Stimulus-predisposing factors are factors that amplify the likelihood of an athlete's injury while internal and external influences remain unchanged. When an athlete's internal or external influences are abnormal, the athlete is judged to be an injury prone individual [21]. Injury-prone individuals are significantly more likely to be injured in marathon sports than non-injury-prone individuals and require extra attention. When stimulus triggers are present, the likelihood of injury increases and the risk is higher for injury-prone athletes, at which point the algorithm needs to warn the athlete and their team in a timely manner. This study compiled injury-influencing factors for marathon athletes based on the opinions of a panel of professional track and field players and coaches, as well as a large number of actual situations in competition, as shown in Fig. 3.

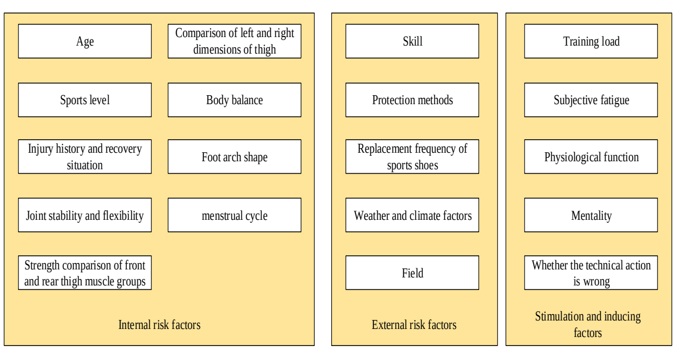

Fig. 3. Influencing factors of injury and disease of marathon athletes.

After importing the injury influencing factors into the radial basis network and training, the early warning algorithm is able to determine the injury risk of marathon runners by the input physical and other related information. The athlete's injury risk is classified as low, medium or high. The algorithm does not warn for low risk. For medium risk, the algorithm issues an alert and indicates the source of the risk to the athlete and his or her team. For high risk, the algorithm issues a warning and strongly advises the athlete not to participate in the competition or to take appropriate measures. The hidden layer activation function of the radial basis network is a Gaussian function, whose mathematical expression is shown in Eq. (8).

$$f_j(x) = \exp(-\frac{\|x - c_j\|^2}{2\sigma^2_j}) \tag{8}$$

In Eq. (8), $f_j(x)$ represents the output value of the j hidden layer node. x It is the independent variable and the input to the network. c_j is the center vector of the kernel function of the j hidden layer node. Under this activation function, the output of the radial basis network is shown in Eq. (9).

$$y_j = \sum_{j=1} \omega_{ij} f_j(x) \tag{9}$$

In Eq. (9), y_j is the output of the i th output layer node, and ω_{ij} is the connection weight between the i th and j th hidden nodes. Since the position vector of each particle in the radial basis network is composed of the function center, function width and connection weights, these three elements need to be defined [22]. First an error function needs to be defined, as shown in Eq. (10).

$$M = \frac{\sum_{q=1} E_q^{\ 2}}{2} \tag{10}$$

In Eq. (10), M is the error function and E_q is the error of the input sample. The definition of the error is shown in Eq. (11).

$$E_q = d_q - \sum_{j=1}^{3} \omega_{1j} \exp(-\frac{\|x - c_j\|^2}{2\sigma^2_j}) \tag{11}$$

Eq. (11) in d_q represents the value of the desired type of sample. The values vary according to the different athlete injury risk levels, 1 and 2 for low risk, 3 and 4 for medium risk, and 5 for high risk. According to the error function, the weights of the radial basis network output cells are shown in Eq. (12).

$$\omega_{1j}(m+1) = \omega_{1j}(m) - \eta \frac{\partial M(m)}{\partial \omega_{1j}} \tag{12}$$

In Eq. (12), $m+1$ is the value after iteration and m represents the current value of the individual variable. η represents the learning efficiency. The radial basis network implicit layer function centers are defined as shown in Eq. (13).

$$c_j(m+1) = c_j(m) - \eta \frac{\partial \eta(m)}{\partial c_j} \tag{13}$$

Eq. (13) in c_j is the center of the function. The width of the function is defined, as shown in Eq. (14).

$$\sigma_j(m+1)=\sigma_j(m)-\eta\frac{\partial M(m)}{\partial\sigma_j} \tag{14}$$

Finally, the fitness function of the radial basis network needs to be defined. The fitness function uses the relative error function between the actual output and the network output, and its mathematical expression is given in Eq. (15).

$$F=\frac{\sum_{r=1}^{R}\sum_{k=1}^{K}(\frac{y_{rk}-\dot{y}_{rk}}{\dot{y}_{rk}})}{R} \tag{15}$$

In Eq. (15), y_{rk} represents the first r output value of the k output neuron, and $\dot{y}_{rk}$ is its actual value. R is the sample size and K is the number of output neurons. In the practical application of the physical injury warning algorithm for marathon runners, it is first necessary to initialize the particle population and map its position into the radial basis network. After training, the radial basis network calculates the global extremes of the particles. After updating the weights, the particle fitness is calculated again and iterated continuously. If the population fitness after iteration is better than the last one, the iterated extreme value is used as the new extreme value. Keep iterating until the global extreme value meets the fitness filtering condition to output the prediction result.

IV. Performance and Application Effect Test of Physical Injury Warning Algorithm for Marathon Runners

The experimental hardware environment is a computer system with I7 processor and 8G memory, and the programming environment is PYTHON, and the experimental procedure is to test the theoretical performance of the early warning algorithm by simulating the environment and test data set, and finally to conduct the practical application test by using the data of real marathon runners' bodies and other related factors. Since the performance of the proposed warning algorithm is greatly influenced by the control parameters, the optimal control parameters need to be confirmed first. The inertia weight variation curves under different control parameters are shown in Fig. 4.

The number of iteration steps of the radial basis network is set to 1000 in Fig. 4, and the maximum and minimum initial weights are 0.7 and 0.2, respectively. Fig. 4 illustrates that smaller control parameters ensure that the inertia weights change slowly at the beginning of the network iteration, allowing the algorithm more space to find the ideal region while larger control parameters enable the algorithm to arrive at the minimum initial weight when it is iterating to the maximum number of iterations. When the control weights are above eight, the inertia weights drop too fast and reach the lower bound at 400 iterations. And when the inertia weight is less than six, the inertia weight decreases too slowly, and the lower bound is still not reached by the maximum number of iterations. In general, when the control parameter ranges from 6 to 8, the inertia weight decreases more satisfactorily. This experiment takes the middle number 7 as the control parameter of radial base network. After completing the control parameter setting, the simulation performance test of the warning algorithm was started. Firstly, experiments were conducted on the variation of the fitness function curve of the parameters with the number of iterations. In order to compare and determine the differences between the proposed algorithm and the existing algorithms, a normal radial basis network, a particle swarm optimized radial basis network and a linear decreasing inertia weight (LDIW) optimized radial basis network are used here as the comparison algorithms, and the results are shown in Fig. 5.

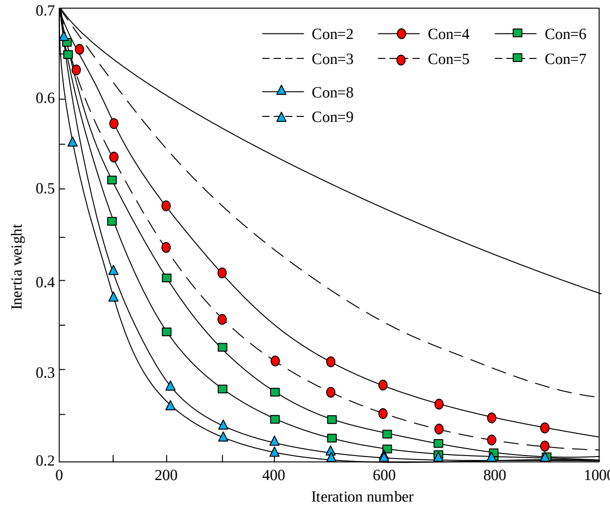

Fig. 4. Change of inertia weight under different control parameters.

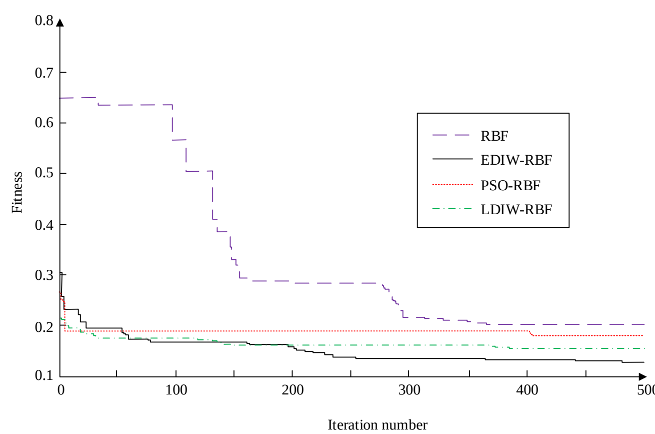

Fig. 5. Change of algorithm fitness function curve.

According to Fig. 5, it can be seen that the radial basis network without any optimization has the slowest convergence rate in terms of fitness, and the fitness that reaches stability after convergence is 0.22, which is greater than the other algorithms. The proposed EDIW optimized radial basis network shows a convergence speed very close to the other two optimized radial basis networks in the experiment and has the smallest fitness function value, which is 0.13. The four algorithms have the highest to lowest fitness function values in order of radial basis networks; particle swarm optimized radial basis networks, LDIW radial basis networks and the proposed algorithm. The results illustrate that the proposed early warning algorithm has the smallest neural network training error and shows the highest accuracy with negligible differences between the convergence speed and similar optimization algorithms. The next experiment trained the algorithm using time-series data of injury influencing factors of marathon runners, and the output obtained is shown in Fig. 6.

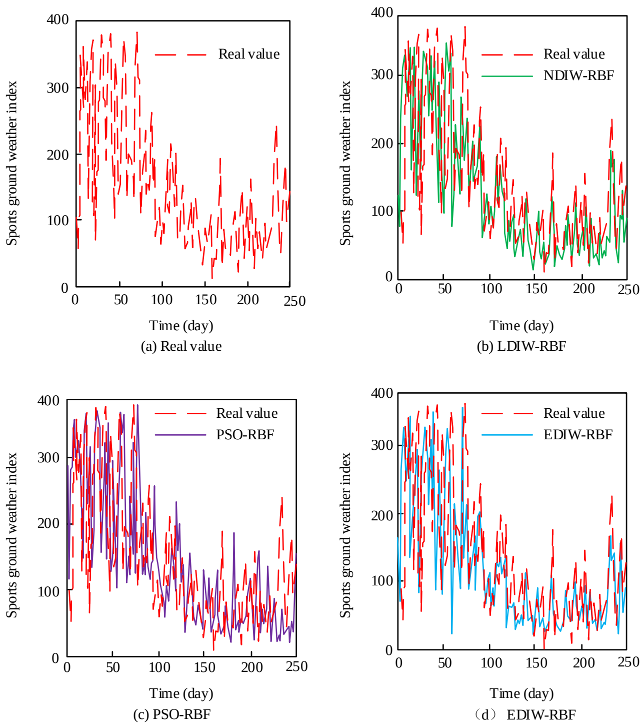

Fig. 6. Output curve of algorithm in training.

In Fig. 6, Fig. 6(a) shows the actual values of the training data; Fig. 6(b) shows the superimposed images of the output of the radial basis network optimized by LDIW and the actual values; Fig. 6(c) shows the superimposed images of the output of the radial basis network optimized by particle swarm and the actual values; Fig. 6(d) shows the superimposed images of the output of the proposed algorithm and the actual values. It can be seen that the weather index of the sports field in this dataset reaches a maximum of 390 and a minimum of 11, showing an overall trend of significant fluctuations followed by a decrease. All three algorithms used in this session are able to restore the trend of the real data, but some errors can still be observed. To further compare the errors in a quantitative and visual way, the error images of the three algorithms in this session were drawn, as shown in Fig. 7.

In Fig. 7, Fig. 7(a) shows the error image of the particle swarm optimized radial basis network; Fig. 7(b) shows the error image of the LDIW optimized radial basis network; and Fig. 7(c) shows the error image of the proposed algorithm. It is not difficult to see that the training errors under all three algorithms show a trend from large to small. Before the 80th iteration, the error values of all three algorithms fluctuate more drastically. Both the radial basis network with particle swarm optimization and the radial basis network with LDIW optimization show an error of more than 250. The maximum error of the proposed algorithm, on the other hand, is 235, which shows an advantage in terms of the error maximum. After the 80th iteration, the errors of all three algorithms decreased significantly, indicating that the predictive stability of the algorithms for the test data increased with the number of iterations. The mean square error (MSE), root mean square error (RMSE) and mean absolute error (MAE) of the three algorithms in training were tested, and the three metrics of the proposed algorithms were found to be 2.521, 0.129, and 20684, which are the smallest among the three compared algorithms. This represents that the error of the proposed algorithm is the smallest of several algorithms. After completing the network training and related experiments, the actual accuracy of the early warning algorithm was further tested using real data sets, and the test results are shown in Table II.

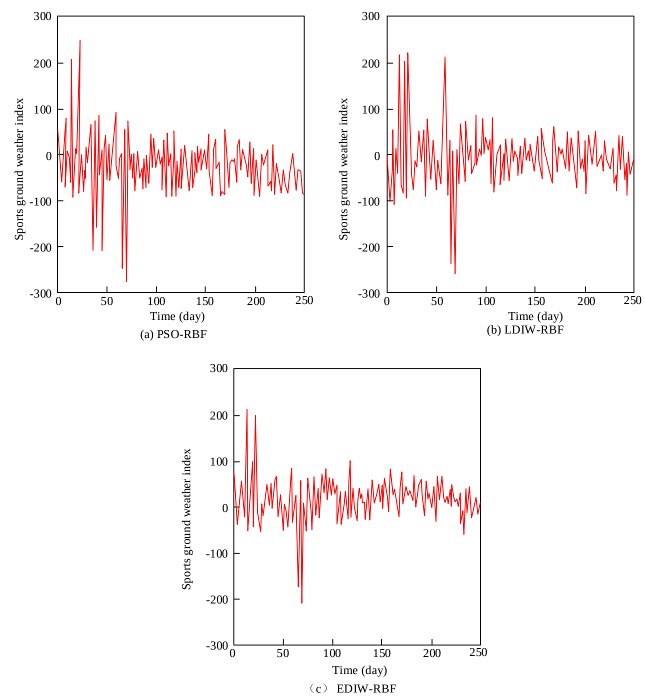

Fig. 7. Error comparison of different algorithms.

TABLE II. ALGORITHM ERROR TEST RESULTS UNDER REAL DATA

Case number	PSO-RBF	LDIW-RBF	EDIW-RBF	Actual value
1	224.34	223.14	234.75	231.50
2	247.48	245.87	236.61	223.00
3	241.01	250.63	241.11	281.00
4	247.00	248.47	241.75	215.00
5	249.63	246.33	239.07	247.00
Index	\	\	\	\
MAPE (%)	8.796	8.213	7.598*	\
MSE	6.846	5.268	4.996*	\
RMSE	0.011	0.010	0.008*	\

a. Note: "*" indicates that the error of this item is the lowest among the three algorithms.

Table II provides the error performance of the proposed algorithm and the two compared algorithms with the real data set and uses it to evaluate their actual accuracy. The proposed algorithm exhibits an RMSE of 0.008, MSE of 4.996, and

Mean Absolute Percentage Error (MAPE) of 7.598% in this session. The three errors metrics of the proposed algorithm are the lowest among the compared algorithms, which indicates that the actual accuracy of the proposed algorithm is better than the other two algorithms. This result further demonstrates the feasibility of applying the improved EDIW to the particle swarm radial basis function neural network, and its optimization effect is higher than other similar algorithms. Although the proposed algorithm has shown better performance than similar algorithms in predicting injury and illness factors in marathon runners, in reality most injury and illness risk factors management in marathon runners is still implemented by expert teams for human management. This management approach has proven to be effective, but consumes more human resources. Although the proposed algorithm can save labor cost, its consistency with expert team decision making still needs to be proven. Therefore, the experiments were conducted using the same set of athletes and race data, allowing the expert team and the algorithm to be evaluated separately, and the results are shown in Fig. 8.

Fig. 8(a) shows the results of the radial basis network with particle swarm optimization versus expert team decision making. Fig. 8(b) and Fig. 8(c) show the results of LDIW versus the output of the proposed algorithm versus the expert team decision, respectively. Although all three algorithms agree with the expert decision results in terms of the trend of the hazard level for different cases, only the hazard level scoring results of the proposed algorithm agree with the expert assessment by 100%. The agreement between the results of the particle swarm algorithm and the expert assessment is only 20%, while the agreement between the LDIW optimization algorithm and the expert assessment is 80%. This result indicates that the judgment of the radial basis network with particle swarm optimization has been very close to the judgment of experts who have worked in the industry for many years, which represents that compared to other algorithms, the learning effect of the radial basis network with particle swarm optimization is better, following the results of personal judgment by the close person.

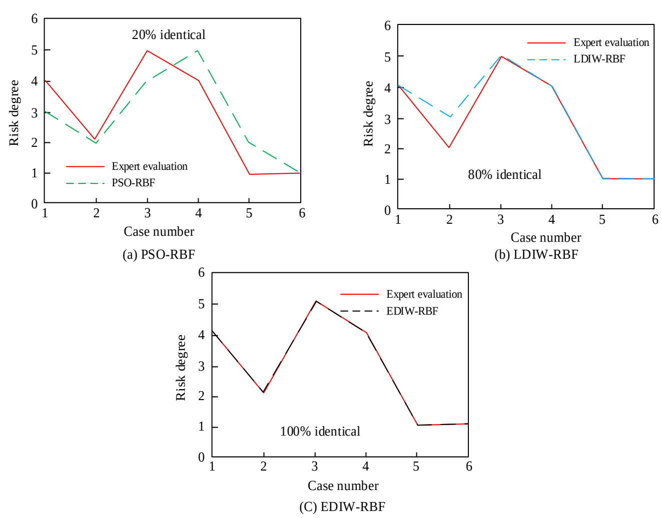

Fig. 8. Comparison between algorithm output and expert evaluation results.

V. Conclusion

To address the problems of lag and low automation in modern marathon tele-mobilization injury management, this study proposes a marathon athlete physical injury warning algorithm based on particle swarm radial basis neural network with EDIW optimization. The algorithm utilizes the EDIW strategy to optimize the search process of the neural network to ensure that the algorithm achieves an optimal balance between global search and local search. The minimum fitness function value of the proposed algorithm is 0.13, which is lower than the values of particle swarm radial basis network and LDIW radial basis network. In the training session of the neural network, the MSE, RMSE, and MAE of the proposed algorithm are 2.521, 0.129, and 20684, respectively, with lower errors than other comparative algorithms. In the test with real data, the MAPE of the proposed algorithm is as low as 7.598%, while the MAPEs of the LDIW radial basis network and the particle swarm radial basis network used as comparisons are both above 8.1%. In the comparison with the expert group's assessment, only the hazard score results of the proposed algorithm reached 100% agreement with the expert assessment. The experimental results demonstrate the practicality of this injury warning algorithm and its ability to enhance the automation of injury management for marathon runners. Although the construction of this algorithm has been successful, there are obvious limitations. Only when the number of iterations is high enough, the negative impact of parameter initialization of the proposed algorithm is small. However, this will lead to a large amount of computation, which leads to a high overhead of algorithm operation. In the case of a low budget, this algorithm may be difficult to apply to reality. How to reduce the computational complexity of the algorithm while ensuring performance is the focus of future research. In this regard, based on global optimization algorithms, using algorithmic search to find the most appropriate initial value, thereby reducing the amount of computation, is a promising direction.

Funding Statement

This research was supported by 2022 Youth Project of Anhui Provincial Philosophy and Social Science Planning: Research on the governance innovation of public service of sports for the elderly in rural communities in Anhui Province (Project No.: AHSKQ2022D132).

Data Availability Statement

The datasets used and/or analyzed during the current study are available from the corresponding author on reasonable request.

Conflicts of Interest

The authors declare no conflict of interest.

References

[1] T. E. Andersen, M. W. Fagerland, and B. Clarsen, “Assessing the cumulative effect of long-term training load on the risk of injury in team sports,” BMJ Open Sport and Exercise Medicine, vol. 8, no. 2, 2022, pp.1-20.

[2] W. B. Lian, B. H. Liu, and X. Q. Liu, “The backstepping control of high-speed train speed tracking based on rbf neural network,”

International Journal of Electrical Engineering: Transactions of the Chinese Institute of Engineers, Series E, vol. 28, no. 1, 2021, pp.35-42.

[3] Z. Niu, P. Zhang, Y. Cui, and Z. Jun, "PID control of an omnidirectional mobile platform based on an RBF neural network controller," Industrial Robot, vol. 49, no. 1, 2022, pp.65-75.

[4] H. Wang, X. Zhou, and Y. Tian, "Robust adaptive fault-tolerant control using RBF-based neural network for a rigid-flexible robotic system with unknown control direction," International Journal of Robust and Nonlinear Control, vol. 32, no. 3, 2022, pp.1272-1302.

[5] X. Lian, J. Zhang, L. Chang, J. Song, and J. Sun, "Test mass capture for drag-free satellite based on RBF neural network adaptive sliding mode control," Advances in Space Research: The Official Journal of the Committee on Space Research (COSPAR), vol. 69, no. 2, 2022, pp.1205-1219.

[6] L. Ye and P. Di, "Optimizing the regulation and control of sports injury and fatigue of winter olympic ice and snow athletes based on injury prevention," Revista Brasileira de Medicina do Esporte, vol. 27, no. 2, 2021, pp.79-82.

[7] X. Wang and Y. Guo, "Attribute reduction algorithm based early warning model of sports injury," Informatica, vol. 45, no. 5, 2021, pp.561-657.

[8] R. Bahr, B. Clarsen, W. Derman, and K. Chamari, "International Olympic Committee consensus statement: methods for recording and reporting of epidemiological data on injury and illness in sport 2020 (including STROBE Extension for Sport Injury and Illness Surveillance (STROBE-SIIS))," British Journal of Sports Medicine, vol. 54, no. 7, 2020, pp.372-389.

[9] Y. Li, "Construction of intelligent campus tennis players' body data monitoring and injury warning system based on data fusion," Revista Brasileira de Medicina do Esporte, vol. 27, no. spe2, 2021, pp.46-49.

[10] L. Chia, C. W. Fuller, D. Taylor, and E. Pappas, "Mastering the topic, the message, and the delivery: Leveraging the social marketing mix to better implement sports injury prevention programs," The Journal of Orthopaedic and Sports Physical Therapy, vol. 52, no. 2, 2022, pp.55-59.

[11] D. Zhang, W. Feng, L. Wei, and X. Hu, "RBF neural network PID space vector control of linear servo load simulator," Mechatronic Systems and Control (formerly Control and Intelligent Systems), vol. 48, no. 4, 2020, pp.207-215.

[12] J. Zhang, H. Sun, Y. Qi, and S. Deng, "Temperature control strategy of incubator based on RBF Neural Network PID," World Scientific Research Journal, vol. 6, no. 1, 2020, pp.7-15.

[13] W. Huang and Y. Yang, "Water quality sensor model based on an optimization method of RBF Neural Network," Computational Water, Energy, and Environmental Engineering, vol. 09, no. 1, 2020, pp.1-11.

[14] X. Peng, H. Yu, X. Zhu, and Y. Li, "Electro-hydraulic proportional position control using auto disturbance rejection based on RBF Neural Network," Journal of Beijing Institute of Technology, vol. 30, no. 1, 2021, pp.121-128.

[15] H. Liu, B. He, P. Qin, X. Zhang, S. Guo, and X. Mu, "Sea level anomaly intelligent inversion model based on LSTM-RBF network," Meteorology and Atmospheric Physics, vol. 133, no. 2, 2021, pp.245-259.

[16] Q. Li, Q. Xiong, S. Ji, Y. Yu, and H. Yi, "A method for mixed data classification base on RBF-ELM network," Neurocomputing, vol. 431, no. 1, 2021, pp.7-22.

[17] J. Ostadieh and M. C. Amirani, "Introducing the hybrid 'K-means, RLS' learning for the RBF network in obstructive apnea disease detection using Dual-tree complex wavelet transform based features," Journal of Electrical Bioimpedance, vol. 11, no. 1, 2020, pp.4-11.

[18] C. Avinash, D. P. Loretta, Y. Heather, and E. Angelo, "Modeling time loss from sports-related injuries using random effects models: an illustration using soccer-related injury observations," Journal of Quantitative Analysis in Sports, vol. 16, no. 3, 2020, pp.221-235.

[19] M. Edama, H. Inaba, F. Hoshino, S. Natsui, and G. Omori, "The relationship between the female athlete triad and injury rates in collegiate female athletes," PeerJ, vol. 9, no. 4, 2021, pp.1-12.

[20] C. J. Xie and L. Tian, "Application of Nano-Composites in the recovery of sports ligament injury," OMICS International, vol. 83, no. 4, 2021, pp.235-242.

[21] J. Sabol, C. Kane, M. P. Wilhelm, J. C. Reneker, and M. B. Donaldson, "The comparative mental health responses between post-musculoskeletal injury and post-concussive injury among collegiate athletes: A systematic review," International Journal of Sports Physical Therapy, vol. 16, no. 1, 2021, pp.1-11.

[22] J. Xi and H. Jiang, "Infrared multispectral radiation-temperature measurement based on RBF Network." Infrared Technology, vol. 42, no. 10, 2020, pp. 963-968.