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Article

Method and practice of improving fitness training effect based on transfer learning from a biomechanics perspective

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Abstract: This study focuses on leveraging transfer learning technology to revolutionize fitness training from a cell and molecular biomechanics perspective. In the era of advanced biotechnology, understanding the minute biomechanical events within cells during exercise is crucial. We aim to apply computer-intelligent control concepts to fitness training, especially aerobics, by delving into the cell and molecular biomechanics. Via in-depth analysis of aerobics training's impact on cells and molecules and smart use of computer tech, a B/S mode simulation model integrating NET and SQL Server is crafted. This model offers a scientific framework for fitness training centered around cell and molecular biomechanics. The ID3 algorithm is then employed to dissect student sports test data related to cell and molecular changes, enabling personalized training plans based on individual cell and molecular traits. To enhance the model, the association rule algorithm is introduced. By scrutinizing extensive cell and molecular biomechanics training data, such as how mechanical forces influence gene expression and protein interactions, hidden patterns and correlative factors are unearthed. This refines the model's accuracy and practicality. During experimentation, comprehensive testing of the association rule algorithm in the context of cell and molecular biomechanics is carried out. Results confirm the viability of the computer-intelligent control-based aerobics training strategy, which effectively boosts fitness training effectiveness at the cell and molecular level. This research pioneers novel approaches for aerobics and other sports, providing valuable insights for optimizing training with respect to cell and molecular biomechanics.

Keywords: intelligent control; aerobic exercise; biomechanics; association rules; simulation model; score management

1. Introduction

With the rapid development of artificial intelligence technology, its application in various fields is becoming increasingly widespread. Especially in the field of sports training, the introduction of artificial intelligence not only changes the traditional training mode, but also greatly improves the training effect [1]. Li et al. [2] put forward a fitness action recognition model integrating ResNet, Transformer and transfer learning technology, and realized real-time processing of sports data and action recognition. Xiao et al. [3] put forward a feature analysis framework for identifying students' activities and monitoring health status based on smartphone accelerometer data through edge computing platform. Chen et al. [4] established a fitness database using a method based on deep transfer learning. After that, a deep neural network is used to detect the type and integrity of fitness actions [3]. Ataseven et al. [5] developed a body activity recognition framework based on deep transfer learning using acceleration data obtained by inertial measurement unit (IMU), and realized the automation of real-time body activity recognition. Aerobics, as a sports project that integrates fitness, entertainment, and competition, its innovative training methods and development are particularly noteworthy. Currently, aerobic training is no longer limited to a single mode, but requires more comprehensive and systematic research methods [6]. The exploration of intelligent training models is not only related to the attitude change of trainers, but also to a profound understanding of training objectives and the needs of trainees [7]. The widespread application of a relatively systematic effect makes the teaching and research of aerobics more scientific and efficient [8]. The computerized design of the aerobics training system has achieved precise control over the training structure, content, and time, reduced errors, and improved training quality [9]. The division between competitive aerobics and mass aerobics reflects the diversity and inclusiveness of aerobics [10]. The rapid development of competitive aerobics not only reflects the competitive level of Chinese athletes, but also demonstrates the influence of aerobics on the international stage. The popularization of mass aerobics has further promoted the development of the national fitness industry [11]. The application of artificial intelligence decision support systems in sports training provides new ideas and methods for the management of sports training in universities [12]. By combining artificial intelligence theory and computer decision-making methods, we can more accurately analyze the training status of athletes, develop personalized training plans, and thereby improve the fitness and athletic level of college students [13]. However, despite significant progress in the application of artificial intelligence in the field of sports training, it still faces many challenges [14]. Difficulties in acquiring knowledge, challenges in maintaining and updating knowledge, and improving the level of intelligent assistance in decision-making processes are all issues that we need to deeply study and solve [15].

Transfer learning, as an effective machine learning technology, has attracted more and more attention. The core idea of transfer learning is to transfer the knowledge learned in one domain to another, to improve the learning efficiency and effect of the model on new tasks. In fitness training, the application of transfer learning can significantly improve the training effect. For example, by analyzing and utilizing the training data of known athletes, it is possible to provide more precise and personalized training plans for new athletes. Therefore, this study aims to explore the application and impact of artificial intelligence in aerobics training, analyze the impact of intelligent training modes on trainers and trainees, and explore how to combine artificial intelligence decision support systems to improve the scientific and effective management of sports training in universities [16]. Transfer learning is applied to aerobics training, which constructs a more scientific training model by analyzing existing exercise training data in depth and combining individual physical characteristics. This method not only improves the personalized level of training but also effectively reduces the learning curve and adaptation problems that new athletes may encounter in the early stages of training. Through transfer learning, it is possible to extract experiences and strategies obtained in certain training modes and transform them into individual training plans, thereby optimizing training effectiveness. This offers a solid theoretical foundation for subsequent experiments and result analysis. This study is hoped to provide new decision-support methods for managing sports training in universities and promote the further development of aerobics [17].

2. State of the art

The association rule algorithm, as an important technology in the field of data mining, has matured in research and application abroad. In the field of image processing and analysis, association rule algorithms provide strong support for fast image processing due to their efficient and accurate characteristics [18]. In recent years, with the rise of 3D technology, the application of association rule algorithms in 3D image processing has gradually received attention [19]. Foreign scholars actively explore the combination of association rule algorithms and 3D simulation technology, and have achieved significant results. However, although association rule algorithms have made some progress in 3D image processing, there are still many challenges in the application of dynamic 3D technology [20]. The establishment and development of dynamic training systems have become a hot research topic, which is of great significance for improving the real-time and accuracy of image processing and analysis [21]. Compared to foreign countries, China started researching association rule algorithms relatively late, but with the unremitting efforts of scholars, significant progress has also been made. Although the application of association rule algorithms in image processing is relatively mature, research in 3D image processing still needs to be strengthened. By introducing advanced foreign technologies, Chinese scholars have begun to explore the application of association rule algorithms in 3D image processing and have achieved certain results [22]. In the field of aerobic training, the combination of simulation technology and association rule algorithms provides new ideas for the research of aerobics training strategies. By studying the computer intelligent control of aerobics training strategies, it is possible to develop training plans more scientifically and efficiently, and improve the training effectiveness of athletes. In recent years, Chinese aerobics has achieved remarkable results on the international stage. The achievement of these achievements is inseparable from a deep understanding and research of the rules of competitive aerobics competitions. The competition rules of competitive aerobics are constantly developing and improving, providing clear guidance for the training and competition of athletes. By conducting statistical analysis on the selection of difficult movements in the World Aerobics Championships, we can further understand the development trends and technical characteristics of competitive aerobics, providing useful references for the training and research of aerobics in China [23]. In summary, the application of association rule algorithms in image processing and analysis has broad prospects, especially in the research of three-dimensional image processing and aerobic training strategies, which is of great significance. In the future, with the continuous advancement of technology and in-depth research, association rule algorithms will play an important role in more fields.

3. Methodology

3.1. Dynamic programming algorithm design for aerobics training

First, we describe the complete knapsack problem. Given n events, the importance of event I am wi, the value is VI, each event has infinite parts, and the existing knapsack capacity is w. What events should we do to maximize the total value of events in the backpack? For instance, it can be assumed that there are three aerobic training activities as follows: Activity A: Its worth is 10 points, taking 2 h; Activity B: Its worth is 15 points, taking 3 h; Activity C: Its worth is 40 points, taking 5 h. In this example, the trainer has a total time limit of 6 h. By applying a dynamic programming algorithm [24], a state transition equation is constructed to determine which activities to choose within the given time limit to maximize the total value. The core of dynamic programming is to store intermediate results, avoiding repetitive calculations and improving efficiency. By defining the state dp $[j]$ as the maximum total value with a time limit of j, this array can be populated through iterative calculations, ultimately achieving the maximum training value that can be reached within 6 h. This method enhances the optimization efficiency of the training plan and allows for flexible adjustments in the selection of activities according to different individual circumstances.

A mathematical expression is used to describe the problem, and the N element vector is found, $(x_1, x_2, ..., x_n)$, $max\,i\,mizep = \sum_{i=1}^{n} v_i x_i$ and the constraint conditions are satisfied: $\sum_{i=1}^{n} v_i x_i \leq w, x_i \in \{0,1,2, ... w/w_i\}$. The complete knapsack problem and the 0/1 knapsack problem are very similar in definition, with the main difference being that each item has an infinite number of usable items in the complete knapsack problem, while in the 0/1 knapsack problem, each item has only one. Therefore, when solving the complete backpack problem, we need to consider the possibility of each item being selected multiple times. For the complete knapsack problem, we can use dynamic programming methods to solve it. However, noting that in the complete knapsack problem, each item has an infinite number, we do not actually need a two-dimensional array to store the state, as each item can be selected multiple times. Therefore, we can optimize spatial complexity by using only a one-dimensional array dp $[j]$ to store states, where dp [j] represents the maximum value when the backpack capacity is j.

$$m(i,j) = max\{\, m(i-1, j-x, w_i) + x \cdot v_i, 0 \leq x \cdot w_i \leq j\} \tag{1}$$

The initial conditions for the iteration are as follows:

$$m(l,j) = x \cdot v_l, 0 \leq x \cdot w_l \leq j \tag{2}$$

Dynamic programming is an effective method for solving optimization problems, particularly suitable for tasks that have overlapping sub-problems and optimal sub-structure characteristics. In aerobics training, there is a need to select from multiple training items, each with its time and resource constraints. To maximize training effectiveness, the dynamic programming algorithm can be adjusted as follows. First, it is necessary to consider the characteristics of aerobics training. Typically, participants need to choose between multiple training items, such as jumping rope, running, swimming, etc., each with its corresponding importance (weight) and training effect (value). Therefore, each training item is regarded as an "item" in dynamic programming, where its weight represents the training time, and the value represents the training effect of the item. The pseudocode for the dynamic programming algorithm in aerobics training is presented in **Figure 1**.

```
function Knapsack(weights, values, capacity):
    dp = array of size (capacity + 1) initialized to 0
    for i from 1 to length(weights):
        for j from weights[i] to capacity:
            dp[j] = max(dp[j], dp[j - weights[i]] + values[i])
    return dp[capacity]
```

Figure 1. Pseudocode for dynamic programming algorithms in aerobics training.

3.2. Improvement of dynamic programming algorithm

In the complete backpack problem, there are infinite items that can be used, while in the 0/1 backpack problem, there is only one item per item. If we really want to transform the complete backpack problem into a 0/1 backpack problem, theoretically, we need to create enough "copies" for each item so that the total number of these copies exceeds the backpack capacity limit. In this way, each "copy" can be regarded as an independent item in the 0/1 backpack problem. However, this transformation is not feasible in practical operation as it leads to a sharp expansion of the state space, making the problem difficult to solve. In addition, even if we can create enough "replicas", this transformation will lose the characteristics of the complete backpack problem itself, making the solution complex and inefficient.

In fact, we already have a simple and effective solution for the complete knapsack problem, which is to use one-dimensional dynamic programming. In this solution, we do not need to create multiple "copies" for each item, but directly use the state transition equation to calculate the maximum value.

The state transition equation is as follows:

$$m(i,j) = \begin{cases} max\{\, m(i-1,j), m(i-1,j-w_i) + v_i\}, j \geq w_i \\ m(i-1,j), \qquad 0 \leq j \geq w_i \end{cases} \tag{3}$$

The initial conditions for the iteration are as follows:

$$m(1,j) = \begin{cases} v_1, j \geq w_1 \\ 0, 0 \leq j < w_i \end{cases} \tag{4}$$

The basic idea of this method is to binary split the value and weight of each item, thereby transforming the complete knapsack problem into multiple 0/1 knapsack problems. Each split item represents a part of the original item, and its value and weight are the values corresponding to a certain digit in the binary representation of the original item.

The specific steps are as follows:

For each item, binary split its value and weight. For example, if the value of item *i* is vi and the weight is wi, we can split it into multiple items, and the value and weight of each item are the values corresponding to one of the binary representations of vi and wi.

For each item after splitting, we consider it as an independent item in the 0/1 knapsack problem. This means that each split item can only be selected once or not.

Use the dynamic programming algorithm of the 0/1 knapsack problem to solve this transformed problem. The state transition equation is the same as the 0/1 knapsack problem, except that the number of items increases (because each item is split into multiple).

The time complexity of this conversion method depends on the granularity of binary splitting. If split very finely, the number of items will be very large, resulting in a large state space and reduced algorithm efficiency. Therefore, in practical applications, we usually directly use dynamic programming algorithms for the complete knapsack problem, rather than transforming it into a 0/1 knapsack problem. The path planning based on BDP mode is shown in **Figure 2**.

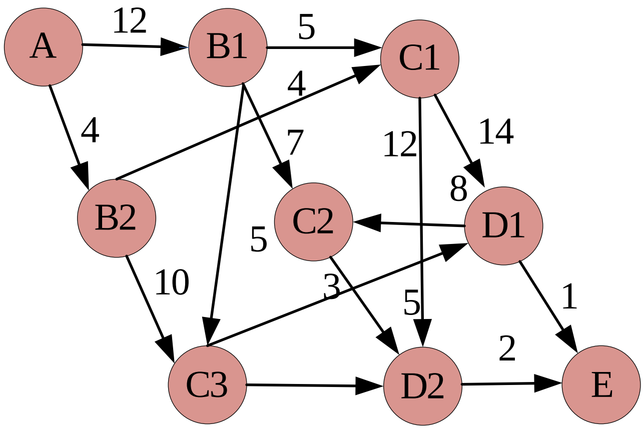

Figure 2. Path problem based on BDP mode.

In dynamic programming algorithms, NDP (usually referring to Non-deterministic Polynomial) algorithm is not a standard term and may be a misunderstanding or a specific context abbreviation. In the field of dynamic programming, we often hear about deterministic algorithms, which are used to solve problems with overlapping subproblems and optimal substructure characteristics.

When we say "every state transition involves optimization of the number of states", we refer to the process of dynamic programming, which effectively calculates and stores intermediate results (i.e. solutions to subproblems) to avoid duplicate calculations of the same subproblems and optimize the efficiency of the algorithm. The core idea of dynamic programming is to decompose the problem into smaller sub-problems and store the solutions of these sub-problems so that they can be reused when needed, rather than recalculated.

When calculating the current state, we usually rely on previously calculated states (i.e. solved subproblems). These resolved states (also known as "resolved states") provide us with the information needed to build the current state. By combining and extending these known states, we can gradually derive solutions to larger problems.

$$m(i,j) = \begin{cases} max\{m(i-1,j), m(i,j-w_i)+v_i\}, j \geq w_i \\ m(i-1,j), \qquad 0 \leq j \geq w_i \end{cases} \tag{5}$$

In dynamic programming algorithms, optimizing the number of states during the state transition process is an important strategy because it can significantly reduce the computational complexity of the algorithm, thereby improving its efficiency. By analyzing the original state transition equation, if a large number of invalid states are found, it is necessary to consider how to reduce the number of states involved in each state transition. Invalid states refer to states that do not contribute to the final solution or can be replaced by other states during state transition. The methods to reduce invalid states typically include redefining states, merging similar states, and utilizing the characteristics of the problem to prune.

Optimization of Dynamic Programming (ODP) is a general term for optimizing dynamic programming algorithms, covering various strategies to reduce the number of states in state transitions. The flowchart of the ODP algorithm is shown in **Figure 3**. Through ODP, we can design more efficient algorithms to solve practical problems. In ODP, a key step is to analyze the decision dependencies between states. By understanding the dependencies between states, we can determine which states are necessary and which ones are redundant, thereby retaining only those states that contribute to the final solution. The optimized state transition equation will involve fewer states, which means that the required computation for each state transition is reduced. This can not only accelerate the execution speed of the algorithm, but also reduce memory usage, as the number of states that need to be stored is reduced.

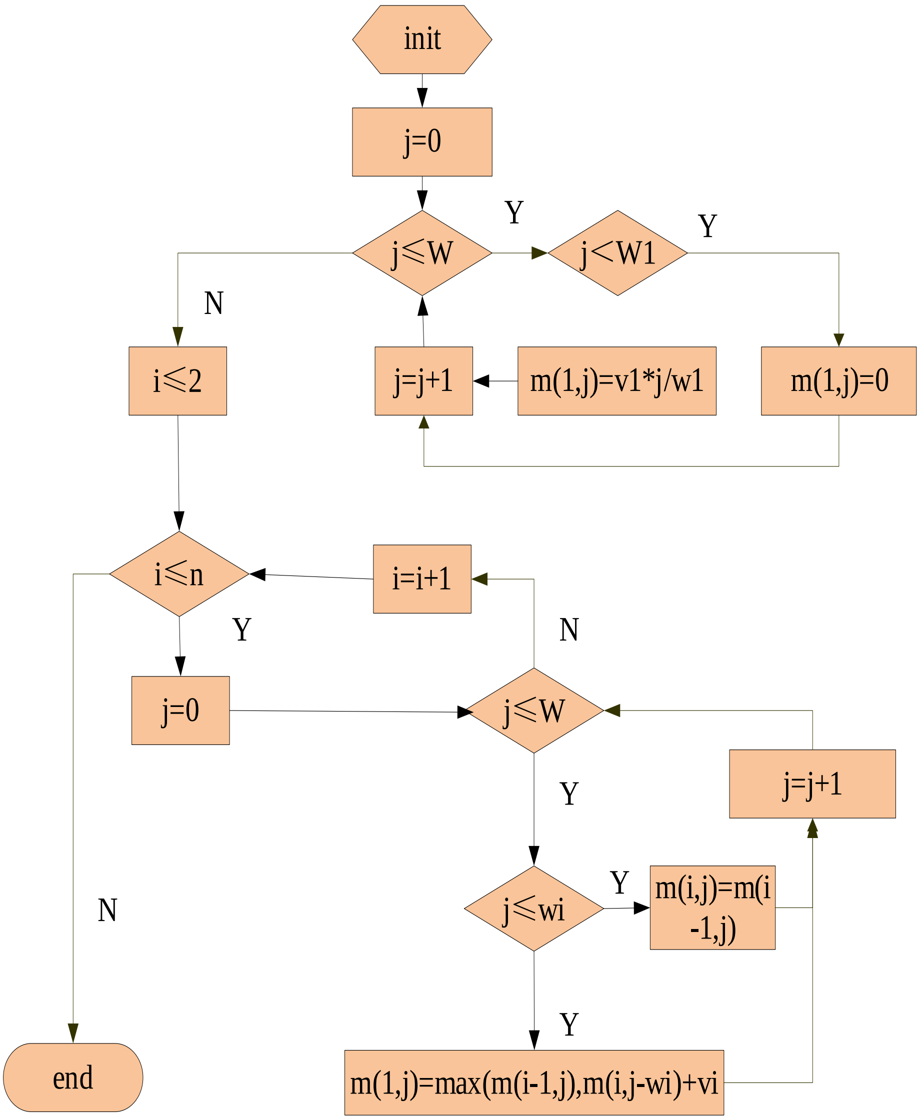

Figure 3. The flow chart of the proposed ODP algorithm.

In the optimization, the selection of *M* (k) value should be considered from the precision. In the initial iteration, the smaller *m* (k) value is selected, and the *M* (k) value is added after the iteration is added to reduce the error caused by the simulation. **Table 1** shows the effect of the *M* value on the iteration.

Table 1. The influence of the *M* value on the iteration.

m	***θ***	**step**	**time**
10	0.6354	95	0.04987s
100	0.6396	90	0.02735s
2000	0.6345	35	0.41764s
5000	0.6361	8	1.58391s

At the same time, the EM algorithm can be optimized from another direction, that is, the coordinate assent method, as shown in **Figure 4**. The straight line in the graph is the path of algorithm iterative optimization. We can see that every step will go one step towards the optimal value, and the progress path is parallel to the coordinate axis, because each step only optimizes a variable. This is equivalent to finding the extreme value of a curve in the X-Y coordinate system, but the curve function cannot be directly derived, so the gradient descent method is not suitable for use. So when setting a variable is fixed value, the other one can be obtained by derivation, so we can use the coordinate ascent method to fix one variable at a time, and to find the extreme value for the other, and finally approach the optimal extreme value. This principle corresponds to the realization of EM algorithm. In the *E* step calculation, θ is fixed and *Q* is optimized. When *M* step is calculated, *Q* is fixed, θ is optimized, and the extreme value is pushed to the maximum by alternating calculation.

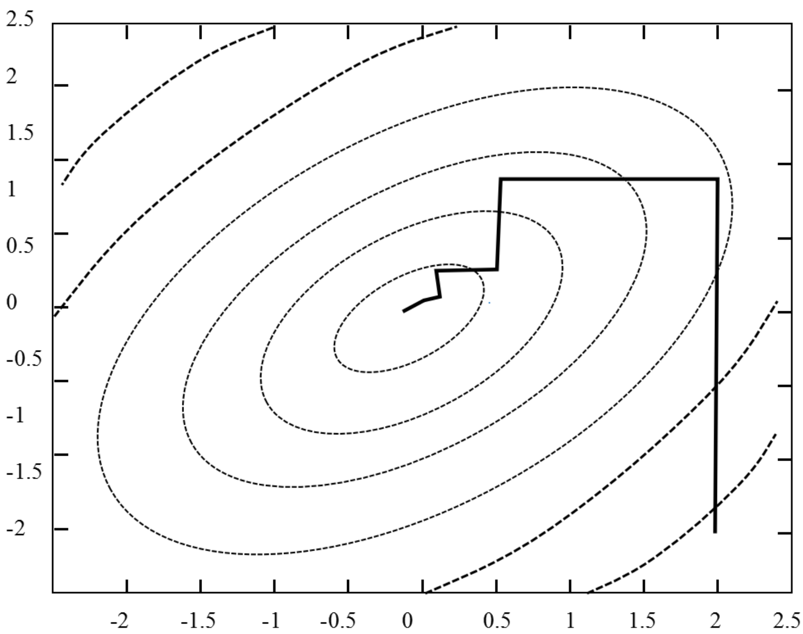

Figure 4. Optimization of EM algorithm by coordinate rising method.

The PX-EM algorithm, based on the standard EM algorithm, introduces additional parameters to adjust the covariance, thereby accelerating the convergence rate and improving the precision of data processing. The basic principle is to expand the parameter space so that the observed and complete data are consistent in dimensions, allowing for more efficient handling of complex data problems. The PX-E and PX-M steps of this optimization algorithm are calculated alternately, gradually reducing the error until the algorithm converges. In the data analysis of fitness training, the PX-EM algorithm has significant advantages over the traditional EM algorithm. The traditional EM algorithm is slow to converge when dealing with large-scale data or missing data, often leading to low computational efficiency. The PX-EM algorithm effectively addresses this problem by introducing additional parameters and optimizing the iteration process. Specifically, it can obtain more precise parameter estimation results in a shorter time, especially when handling the common problem of missing data in fitness training, showing better robustness and accuracy. This makes the PX-EM algorithm more rapid and precise in providing data support for the optimization of training effects when analyzing complex data such as aerobics training. The optimization through this algorithm allows for better capture of potential patterns in fitness training data and the improvement of training strategies based on these patterns. This is of significant practical value for handling large-scale sports data, particularly in situations where data missing is severe. In the algorithm, two conditions must be defined first, one is that there is a known transformation R, and $\theta = R(\theta^{*}, \alpha)$. When $\alpha = \alpha_0$, the extended model is selected to let the known observation data X does not have the information ofα. In the extended model, the parameters can be identified for the complete data. The optimization algorithm is in the form of the k+1iteration: the PX-E step, and the calculation of $Q\left(\varphi\middle|\varphi^{(k)}\right) = E\left(log\, p\,(z|\varphi)\middle|x, \varphi^{(k)}\right)$. In the PX-M step, the $\varphi^{(k+1)} = argmax_{\varphi}\, Q\,\left(\varphi\middle|\varphi^{(K)}\right)$, PX-E step and the PX-M step are calculated alternately, until the convergence is achieved.

4. Result analysis and discussion

4.1. Optimization results of the dynamic programming algorithm in aerobics training

In the teaching process, it is important not only to focus on the quality of teaching itself but also to optimize and manage aerobics training methods. Building on the foundation of dynamic programming algorithms, further discussions have been conducted on how to optimize aerobics training strategies by classifying and integrating different types of sports training environments. The experimental results shown in **Figure 5** indicate that optimizing the division of sports items through a bidirectional dynamic programming algorithm can effectively enhance the management efficiency of aerobics training data. Specifically, the bidirectional dynamic programming algorithm differs from traditional unidirectional dynamic programming by performing state transitions simultaneously from two directions, comparing data only at the intersection of states. Hence, it greatly reduces the number of states involved in the transition and optimizes the computational efficiency of the algorithm. This method is critical in the application of aerobics training because it can more efficiently analyze and classify training data under different training environments, aiding in the more precise formulation of personalized training plans.

Through this classification method, the intrinsic correlations of diverse training types can be revealed, offering strong support for personalized training in aerobics. In summary, the experiments in **Figure 5** not only demonstrate the significant effects of bidirectional dynamic programming in improving algorithmic efficiency but also offer innovative ideas for the management of aerobics training. By reasonably classifying and optimizing the management of training environments, more targeted training programs can be provided for students, thereby significantly enhancing training outcomes.

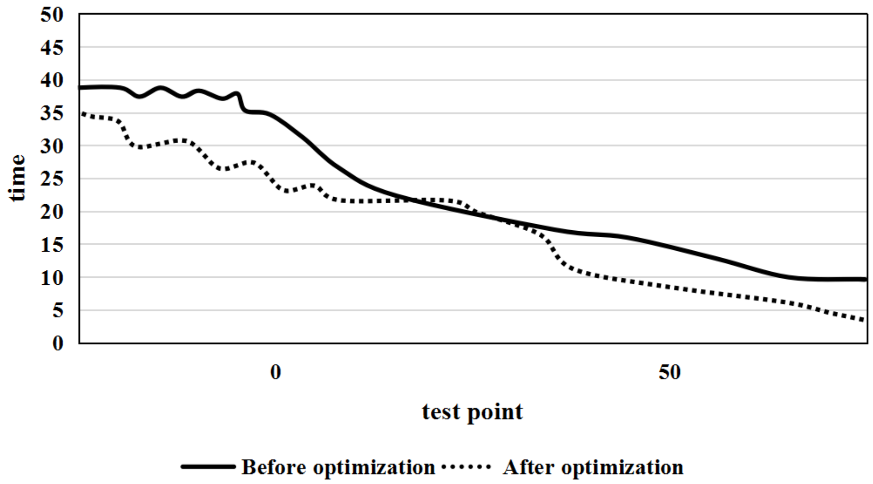

Figure 5. Experimental results of "Sports events division Divide" problem.

In the process of transforming and optimizing the training methods and methods of aerobics, aerobics training in various regions carries unique local characteristics. To manage and teach more effectively, we can use dynamic programming algorithms to classify and integrate these training methods with local characteristics. This not only reveals the inherent connections between various training methods but also provides strong strategic support for the development of aerobics training management in universities. We have conducted in-depth research and experiments on the optimization of aerobics training methods. **Table 2** shows the algorithm test results after improving the accuracy of the target test data. These scores represent the minimum total scores obtained after processing with the optimized algorithm on specific test data. Specifically, the scores are calculated by comprehensively assessing the participants' performance in various sports activities. The score for each test point is accumulated based on the participants' scores in different items, reflecting their overall performance level during the training process. The basic process of score calculation first records the participants' performance in multiple items, including rotation, bending, and jumping, among others. According to predetermined scoring criteria, the scores for each item are normalized to ensure that scores between different projects can be directly compared. Finally, the normalized scores for each item are added together to form a comprehensive score, indicating the lowest performance of the participants in this training session. The significance of these scores lies in the ability to more clearly assess the degree of improvement in training outcomes brought about by the optimization algorithm by comparing the changes in scores before and after optimization. When the amount of data processed is small, the change in scores is not significant; however, as the amount of data increases, the advantages of the optimization algorithm become more apparent, especially in large-scale data processing, where the effects of optimization are even more pronounced. The experimental data reveals that the optimized algorithm has significantly improved accuracy. It is worth noting that when the amount of data processed is small, the difference before and after optimization is not significant, because the number of states involved in each state transition is only an order of magnitude difference, not a multiplier or exponential difference. However, as the amount of data increases, the effectiveness of optimization algorithms becomes more significant, especially when dealing with large-scale data, where their advantages are more pronounced. The monotonicity technique used in this optimization process is not only efficient and practical but also has broad application prospects. But to master this technology, one needs to have a solid teaching foundation and application ability. In practical applications, we need to conduct in-depth analysis and judgment on the problems we are dealing with to ensure that the conditions for using optimization techniques are met, thereby effectively improving the efficiency of solving practical problems.

Table 2. Experimental results of "Sports events consolidation (minimum score)" problem.

Test point	test data	Output results	Running time		Efficiency increase ratio	Effect
			Pre optimization	After optimization		
1	4 5 9 6 1	39	0.03 s	0.03 s	0.00%	
2	6 3 4 6 5 4 2	61	0.03 s	0.03 s	0.00%	
3	10 2 9 3 1 0 1 6 8 3 9 4	178	0.04 s	0.02 s	100.00%	obvious
4	50 14 1 12 8 15 19 2 11 14 8 20 14 8 20 14 13 5 20 11 11 16 11 18 20 18 20 14 7 16 18 12 12 15 6 20 20 4 19 16 14 20 9 20 8 14 13 4 1 13 11 19 13 2	3572	0.03 s	0.03 s	0.00%	

4.2. Optimization of environment classification in aerobics training

To further explore the application of transfer learning in aerobics training, regression experiments are conducted to analyze the influence of different variables on fitness behavior. Then, after conducting experiments on transaction type classification and merging, a regression experiment is conducted to see the interaction between numerical values more intuitively. This study uses the partial least squares regression modeling of aerobics athletes' data on fitness training. The three variables of exercise plan, self-efficacy, and social support have explanatory and predictive abilities for exercise intention and behavior, and their role in intention to behavior. The experimental object of this study is 10 members of an Aerobics Team. The regression coefficient diagram, the standardized data, and the expression of the regression equation are drawn. It can be seen from the regression coefficient that self-efficacy variables play a very important role in the interpretation of the three regression equations. However, relative to the rotation and bending, the regression equation of the high jump performance is not ideal. The three variables are independent of the explanatory power. To better understand and improve self-efficacy and predict and interpret exercise behavior, this study constructs a partial least squares regression model as three variables to influence the change in Aerobics Athletes' training performance. The result, like **Table 3**, shows that all three groups of variables are on the rise. There may be a social expectation effect in the measurement. To investigate the accuracy of the three regression equation models, all the sample points are plotted in this study. The graph takes $(\hat{y}_{ik}, y_{ik})$ as a coordinate. $\hat{y}_{ik}$ is the prediction value of the I sample point (y_{ik}) in the K variable. In **Table 3**, if the point of the table is evenly distributed around the corner, the difference between the equation fitting value and the original value is very small. The result of this equation fitting is satisfactory. Through regression analysis results, it can be found that variables such as self-efficacy and social support significantly affect the transformation of exercise intentions and behaviors. This finding provides important support for optimizing personalized training plans using transfer learning techniques. Specifically, transfer learning can apply the patterns of influence of these variables to diverse training environments and individuals, enhancing the targeting and effectiveness of training. For example, when designing new fitness programs, training strategies can be adjusted based on known influential factors to better adapt to different individual needs. Such strategies enhance the scientific nature of training and provide effective references for a wide range of fitness programs.

Table 3. Fitness training data.

NO	Exercise plan(x_1)	Self-efficacy(x_2)	social support(x_3)	Rotate(y_1)	Bend(y_2)	High jump(y_3)
1	91	36	50	5	162	60
2	89	37	52	2	110	60
3	93	38	58	12	101	101
4	62	35	62	12	105	37
5	89	35	46	13	155	58
6	82	36	56	4	101	42
7	67	34	60	6	125	40
8	76	31	74	15	200	40
9	54	33	56	17	251	250
10	69	34	50	17	120	38

This study mainly uses simulation experiments to verify the influence of aerobics and sports dance on the analysis results under the condition of different data missing rate. The first step is to produce a safety observation data vector Y, which obeys parameterθ , which is exponential distribution, normal distribution and lognormal distribution. At the same time, it generates the number of n that generates the same distribution as a constraint condition for $Y\,Y = (y_1, \cdots, y_n)$, and it is expressed as$X = (x_1, \cdots, x_n)$. Then the random missing distribution of the selected data is randomly distributed. When the equation is$x_j \geq y_j$, $z_j = r_j$ represents the value of the observed data. When the equation is $x_j < y_j$, $z_j = r_j$ represents the missing data. For the convenience of computing, the Z is arranged in an ascending order, and $Z =$

$(z_1, \cdots, z_k, z_{k+1}^+, \cdots z_n^+)$ is obtained, in which $z_{k+1}^+, \cdots z_n^+$ represents missing data. The EN algorithm is used to estimate the parameters, and the estimated value of the parameters is obtained. The maximum likelihood estimation (MLE) is used to get the estimated value of the complete observation data. Repeat the previous steps to get the sequence of parameter estimation. M represents the number of repeated computations, and then calculates the mean square deviation of different parameter estimation sequences, and uses the EM algorithm to estimate the accuracy of missing data. In the case of different deletion rate P, different initial values θ , and different observation data n, the algorithm's iterative process is carried out, and the algorithm results are compared and analyzed.

4.3. Optimization results of the EM algorithm

Table 4 demonstrates the impact of varying missing rates on the parameter estimation of the EM algorithm. These results have significant practical implications for the collection and analysis of fitness data. In the process of sports training and fitness assessment, data missing is quite common due to constraints in measurement equipment, testing conditions, and human factors. For instance, during large-scale fitness training or competition data collection, some athletes may experience data loss due to injury, absence, or equipment failure. How to effectively handle these missing data directly affects the accuracy of subsequent data analysis and the scientific nature of the training plans formulated. In **Table 4**, as the data missing rate increases, the estimation results of the EM algorithm gradually deviate from the true values, and the mean square error (MSE) remarkably increases. When the missing rate P is within 20%, the EM algorithm can estimate the missing data with relatively high accuracy, and its error is not much different from the MLE method. However, when the missing rate exceeds 20%, the estimation effectiveness of the EM algorithm significantly declines. It indicates that in the analysis of fitness training data, when the proportion of missing data is high, relying solely on the EM algorithm may lead to biased results. Especially, when the missing rate reaches above 30%, this bias becomes particularly noticeable. Therefore, in the actual collection of fitness training data, efforts should be made to minimize data loss, and use the EM algorithm for completion when the amount of missing data is low. For datasets with high missing rates, it is recommended to employ other more robust estimation methods or combine multiple algorithms to enhance the estimation accuracy. Additionally, when conducting data collection, effective strategies should be adopted to reduce the likelihood of data missing, such as improving the stability of testing equipment, enhancing the automation level of data recording, and strengthening data monitoring and real-time repair mechanisms to ensure data integrity and quality. By analyzing the estimation results of the EM algorithm under different missing rates in **Table 4**, the following practical recommendations can be drawn. In the collection and analysis of sports training data, efforts should be made to minimize data missing and employ the EM algorithm for handling missing data when the amount is low. Moreover, more appropriate estimation methods are selected when the missing rate is high, to ensure the accuracy of analysis results and the effectiveness of training plans. This provides data support and methodological guidance for the scientific management and precise decision-making of fitness training.

Table 4. The influence of different missing rates on the estimation of EM algorithm.

p	**5%**	**10%**	**15%**
EM	5.2218374	5.3847892	5.6424283
MLE	5.1526353	5.0984624	5.1386302
MSD	0.1003726	0.2483628	0.4735274
p	20%	25%	30%
EM	5.7236482	6.0738438	6.4278492
MLE	4.9327384	5.0043742	5.0037461
MSD	0.8326382	1.8933734	2.7444392
p	35%	40%	45%
EM	6.8938843	7.7483213	8.8538323
MLE	5.1438348	5.1993746	5.0327634
MSD	6.1264839	9.7363482	16.374939

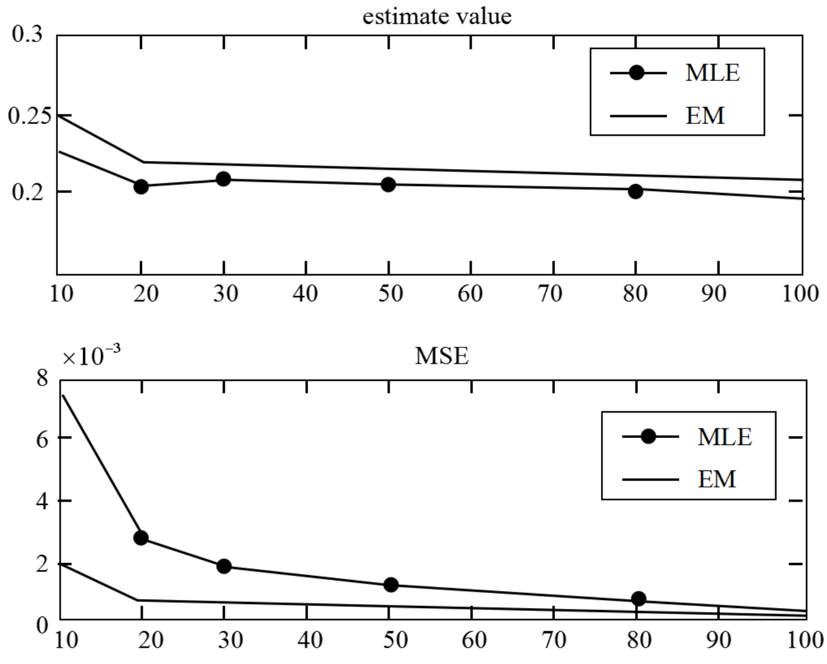

Figure 6. The effect of the number of different observational values on the parameter estimation of the exponential distribution EM.

The effect of the number of observed values on the estimation of the exponential distribution of EM parameters is shown in **Figure 6**. When the total observation data is not large, such as $n < 20$, the estimation results of the EM algorithm and maximum likelihood algorithm are quite different for the estimation of complete data. At this time, the effect of the EM algorithm is not very good. When the full observation data $n = 30$, the estimation result of the EM parameter is better, but if the number of observations n continues to increase, the effect of the EM algorithm is not good. That is to say, when the EM algorithm is used to estimate the missing data, the effect of the algorithm is improved by not increasing the number of observations. When the missing rate P is relatively small, the EM algorithm's MSE is smaller than the MSE of the MLE of the complete data, which means that using the EM algorithm to estimate the observed value of missing data has better algorithm advantages.

5. Conclusion

This study optimizes fitness training methods through a dynamic programming algorithm based on transfer learning, which holds significant practical application value. Specifically, fitness coaches and athletes can apply the following strategies during the training. (1) Optimization of training plans: Utilizing dynamic programming algorithms, fitness coaches can design personalized training plans based on the athletes' individual characteristics and training needs. It ensures that each athlete trains at the most suitable intensity and content, thereby maximizing training effectiveness. (2) Data-driven decision-making: By implementing association rule algorithms, coaches can analyze a vast amount of training data to identify key factors affecting training outcomes. This allows coaches to formulate more scientifically sound and reasonable training strategies, adapting more quickly to the training needs of athletes. (3) Real-time monitoring and feedback: The developed computer intelligent control model can be used in conjunction with real-time monitoring systems, assisting coaches and athletes in obtaining immediate feedback on training effectiveness. This real-time capability makes the training process more flexible and efficient, enabling swift adjustments to training content and intensity to ensure the achievement of training objectives. (4) Enhancement of athletes' self-efficacy: The optimized algorithms not only provide coaches with effective training tools but also help athletes strengthen their sense of self-efficacy, increasing their training enthusiasm and proactivity, thus improving training outcomes. In summary, this study offers new perspectives and methods for fitness training and also provides valuable references for the training optimization of other sports. It is believed that fitness coaches and athletes can achieve greater efficiency and effectiveness in their daily training by implementing these optimized algorithms.

In the analysis and study of related investigations, the situation of data is often incomplete under the influence of various actual conditions. The incomplete data not only bring about a deviation in the direction of investigation and analysis but also have a great influence on the results of the research. The maximum expectation algorithm is an intelligent model that specializes in the analysis of incomplete data. Therefore, this study proposes a data analysis algorithm based on the maximum expectation algorithm, which combines data analysis with aerobics and sports dance, and provides a scientific decision basis for investigation and analysis. This study first expounds on the similarities and differences between the maximum likelihood method and the EM algorithm and analyzes the structure and the implementation process of the EM algorithm. The optimization improvement scheme is proposed for the M-step process which has the main influence factor in the algorithm step. The E step is integrated to improve the accuracy of the algorithm. The coordinate ascent method is used to find the best estimation value effectively, and the PX-EM algorithm is used to optimize the EM algorithm's slow convergence period. Finally, the simulation test of the optimized

EM algorithm proposed here is mainly to verify the impact of different missing data rates on the real evaluation results. The experimental results show that the mathematical model based on the maximum expectation algorithm for missing data can provide a good basis for scientific decisions. Of course, the results also show that there is an improved space for the optimization of the maximum expected algorithm, so further improving the accuracy of the M step is the direction of the future research.

Ethical approval: Not applicable.

Informed consent: Informed consent was obtained from all subjects involved in the study.

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