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RESEARCH ON THE APPLICATION OF APRIORI ALGORITHM IN THE TEACHING OF BALL SPORTS TECHNIQUES AND TACTICS

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Abstract. To address the problem that technical and tactical aspects of ball games have a large impact on match-winning, association rules are used to mine and analyse the data. Item constraint terms are added to the original Apriori algorithm to reduce the generation of redundant data, and the operational efficiency of the improved association rules is improved with the aid of the GSA-PSO algorithm to give full play to the fast convergence advantage of the hybrid algorithm. The experimental results show that the algorithm proposed in the study is more convergent than the Apriori algorithm, and the former has fewer iterations on average in the single-peaked function; the overall search accuracy is significantly improved. The algorithm is also less disturbed by the dataset than the Apriori algorithm, with an average running time of 19.23s, 21.54s and 25.61s for dataset sizes of 200, 500 and 1000 respectively. The deviation rate between the predicted and actual coaching strategies was less than 5% and the scoring tolerance rate was between 0.04 and 0.10. It indicates that the algorithm proposed in the study can improve the efficiency of data analysis, which is conducive to the development of a perfect ball sport technical and tactical scheme and promote the stability of ball sport technical and tactical development.

Key words: Apriori Algorithm, GSA-PSO, Association Rules, Sports Teaching, Tactics, Data Mining

1. Introduction. Since the founding of New China, the development of sports in China has grown from small to large and from weak to strong, and our country has become an important force with strong competitiveness in the international sports arena. Ball games are an integral part of sport, and many ball games are popular with our nationals. At the same time, in the process of modernising sports, the rules of ball games are constantly being updated, bringing certain changes and challenges to ball game techniques and tactics [1]. Techniques and tactics have a significant impact on the performance of athletes in the game, and the rapid and accurate development of ball sport techniques and tactics to guide the game is one of the key factors in winning the game. At the same time, with the strong development of computer technology, computer science is able to improve the efficiency and accuracy of data analysis, so information science techniques are being applied more and more frequently in sports [2]. Among them, association rule-based data mining is superior for the analysis of sports-related match data, and the Apriori algorithm is the most classical algorithm for association rules, but it is easy to fall into local optimal solutions and the number of scans of the most databases makes the efficiency of the algorithm greatly reduced [3]. Regarding the issue of the significant impact of technical and tactical skills on winning games in ball games, association rules are used to mine and analyze data. Optimize the Apriori algorithm to improve the efficiency of data analysis, facilitate the development of comprehensive ball sports technical and tactical plans, provide auxiliary support for improving the level of ball sports technical and tactical skills, and promote the stable development of ball sports technical and tactical skills.This study will optimize the Apriori algorithm by adding project constraints to the original Apriori algorithm, and utilize the GSA-PSO algorithm to improve the efficiency of association rules, fully leveraging the fast convergence advantage of hybrid algorithms. This is also the innovation of this study. To improve the efficiency of data analysis, promote the development of comprehensive ball sports technical and tactical plans, provide auxiliary support for improving the level of ball sports technical and tactical skills, and promote the stable development of ball sports technical and tactical skills.

2. Related Works. Data mining based on association rules can extract key data from a large amount of data and analyse it with high accuracy. The Apriori algorithm, as the most classical algorithm in association

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rules, is widely used in many fields. Many scholars have combined association rules to explore a large number of data mining, and have achieved a lot of research results.

Yang et al. constructed a data mining model based on the Apriori algorithm in order to solve the problem of quickly finding effective information from data materials, and the experimental results proved that the model can quickly mine effective information and promote the practicality and modernization of the university teaching management evaluation system [4].

Findawati et al. constructed a data mining model based on the Apriori algorithm in order to To uncover the potential value in the sales process of HPAI products, a data mining model based on an improved Apriori algorithm was designed, which can extract valuable information from the sales information of HPAI products and help sellers analyse the potential consumption demand for purchasing HPAI products [5].

In order to mine the potential behaviour of customers from the database, an association rule based on Apriori algorithm was established, which can more accurately mine the potential consumption behaviour of users and facilitate companies to develop more appropriate marketing strategies [6].

Luo et al. proposed an Apriori algorithm-based association rule in order to solve the problem of unreasonable medication use caused by redundant information in the medical industry. a data mining system based on Apriori algorithm, which can analyze and mine the correlation information in the data, so that the laws of rational drug use can be analyzed from the laws of drug use, dosage studies, etc. [7].

Liu et al. proposed a method and means based on Apriori algorithm and machine learning for the problem that the methods and means of volleyball technical prediction in China are relatively lagging behind Apriori algorithm and machine learning data mining algorithm, and the experiment proved that the algorithm can predict the score of volleyball matches with high accuracy based on the training data [8].

Lu et al. established an association rule analysis identification method based on the Apriori algorithm in order to find effective combinations of acupoints for the treatment of diabetic gastroparesis, and the experimental results proved that the method was able to link acupoints and establish effective combinations of acupoints that could play a better role in the treatment of diabetic gastroparesis [9].

Li et al. proposed an Apriori algorithm data mining model in order to study the the effect of course sequencing on student performance, an Apriori algorithm data mining model was designed, and experimental results proved that the model was able to reveal the internal connections between various course clusters and provide guidance to students on course selection [10].

In order to establish the reliability of a new type of badminton interval training, a simulated match and evaluation game mechanism, and experimental results showed that the mechanism was able to effectively match athletes' training and rest intervals based on their physiological responses and time to exhaustion [11].

Wang et al. structured a mathematical model of the vertical height and horizontal speed of the basketball offensive line in order to improve the hitting rate of basketball players, and experimental results showed that athletes using the dominant hand is a higher hit rate, and the model improves the teaching results of teachers explaining basketball training techniques and tactics [12].

Zhao used complexity computer simulation to simulate a football field, combined with mapping software to draw the football and players to develop real-time tactics, and the experimental results showed that using complexity computer simulation for early school football overall play with high accuracy of passing and running, which can provide implications for the overall tactics of football [13].

Yuki et al. designed a data mining model combining clustering and association rule analysis in order to perform effective data mining in multi-objective topologies, and the experimental results showed that the model was able to obtain visualization results of the target space and promote optimization of multi-objective topologies [14]. Malik et al. structured a data mining scheme to generate vehicle paths in abnormal road event maps, a safety-authentication-based data collection scheme was designed to mine and analyse the data using association rules and VANET techniques, and experimental results showed that the scheme was able to predict the vehicle paths in abnormal situations and save time for emergency rescue [15].

As can be seen in the above, Apriori algorithms have important applications in various industries and data mining with Apriori algorithms can provide intrinsic connections between behaviours. Given the importance of tactical instruction in ball games to the outcome of the game, the Apriori algorithm will be used to mine data in ball games with a view to providing better tactical instruction in ball games.

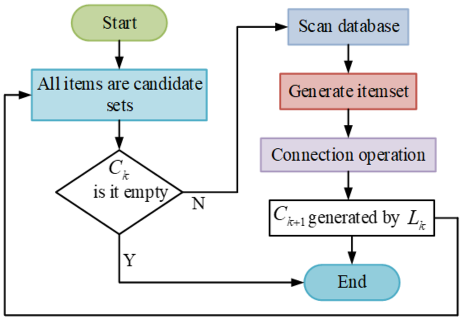


Fig. 3.1: Apriori algorithm flow chart

3. Application of Association Rule Mining Algorithm based on Apriori Algorithm in Sports Teaching.

3.1. Optimal Apriori algorithm under constraints. Data mining is the process of exploring large amounts of fuzzy random data for useful knowledge that can be used for information queries and management decisions, and predicting potential knowledge patterns with the help of relevant intelligence techniques and computer science to provide users with sound decisions. Data mining can be divided into descriptive and predictive according to its functions, of which association rule mining, as one of the important branches, can grasp the relationship between data in the database and find the set of frequent and satisfying support attributes, and subsequently, according to the preset confidence level, the eligible rule relationship can be derived [16]. Specifically, the association rule uses Support and Confidence to filter and filter the set of items preceding and following for the attributes of the data set, and then sets a threshold to achieve the data mining purpose [17]. Where the support and confidence of $(A \rightarrow B)$ is calculated as shown in equation ref3.1.

$$\begin{cases} Support(A \rightarrow B) = P(A \cup B) \\ Confidence(A \rightarrow B) = P(B|A) \end{cases} \tag{3.1}$$

Equation. 3.1 represents the proportion of$A$ and B contained in the set of instances Y and the probability of occurrence of Y in the instances containing A, where the mathematical expression for satisfying the threshold set by the association rule is shown in Eq. (3.2).

$$\begin{cases} \text{Support}(A) \geq \text{Min\_Support} \\ \text{Confidence}(A) \geq \text{Min\_Confidence} \end{cases} \tag{3.2}$$

In equation 3.2, A is a frequent item set when the support of the item set A is greater than or equal to the minimum support; the lift in the association rule is shown in equation 3.3.

$$Lift(A \Rightarrow B) = \frac{P(B|A)}{P(A)} \tag{3.3}$$

Equation 3.3 is defined as the ratio of the confidence of the rule to its support. When the confidence level of the item set is greater than or equal to the minimum confidence level, the association rule obtained is a strong association rule [18]. Association rules can include numerical, unidimensional, and single-layer depending on the problem situation, and the Apriori algorithm is the most widely used among numerical rules [19]. The Apriori algorithm is implemented as an iterative algorithm with layer-by-layer search to react to the correlation between transactions, and the implementation flow of this algorithm is shown in Figure 3.1.

$S_{min}C_k$ If all the items belong to the candidate set C_k, the algorithm is judged to be empty. If all the items are empty, the algorithm is terminated; otherwise, the database is scanned and the frequent $(k+1)$ items are selected from the candidate set L_{k+1} , and the frequent items are generated from L_k . C_{k+1} is judged again. The Apriori algorithm can effectively improve its efficiency in processing the candidate frequent itemset C_k , but it is more susceptible to the impact of data redundancy which makes some phenomena not meet the user's expectation [20].

The teaching of ball technology is limited by the level of information technology, and some of the important match-related data is only used in statistical analysis, and less consideration is given to the deeper analysis of the data and the correlation between winning and losing matches. In addition, the traditional Apriori algorithm has the disadvantages of being time-consuming and having a lot of rules, which makes it difficult to improve the efficiency of data analysis and cope with large matches. Therefore, we propose an improved algorithm that uses user interest as a constraint term to improve the problem of generating a large candidate set. Algorithm of Constrained Association Rule Mining based on Item, ACARMI) [21]. The ACARMI algorithm introduces thresholds to avoid the problem of the Reorder algorithm having a large number of candidate itemsets in the initial stage and the Direct algorithm generating too many in the later stage, achieving the accuracy and efficiency of data mining, thereby improving the efficiency of data analysis, facilitating the development of comprehensive ball sports technical and tactical plans, and promoting the stable development of ball sports technical and tactical plans.Firstly, by introducing the constraint , the mathematical expression is shown in equation (3.4), so that the support and confidence of the association rule contain a certain weight of the item set X, Y.

$$\begin{cases} C = e_1 \vee e_2 \vee e_3 \vee e_4 \vee e_n \\ e = a_1 \vee a_2 \vee a_3 \vee a_4 \vee a_m \end{cases} \tag{3.4}$$

In equation 3.4, $e_1 \vee e_2 \vee e_3 \vee e_4 \vee e_n$ is the Boolean expression for the constraint and is the set form. Unlike the original association algorithm which frequently computes the database, the constraint only scans the subset associated with the constraint and generates the set of transactions that meet the constraint, the computation of which consumes the time process shown in equation 3.5.

$$\begin{cases} t = |D| * (\lambda + 1) * \tau + |D| * \tau \\ t' = |D| * \tau + |D'| * (\lambda + 1) * \tau + |D| * \tau \end{cases} \tag{3.5}$$

In equation 3.5, D' is the set that meets the constraint, τ is the time consumed by a single processing transaction, λ is the maximum length of the frequent item set, and τ is the direct scan time and the filtered time. When $t' < t$ is used, then equation 3.6 is satisfied.

$$|D|/|D'| < \lambda/(\lambda + 1) \tag{3.6}$$

The data is collated to obtain the approximate rate of data reduction, as shown in equation3.7.

$$Fil\_Ratio = (\frac{|D| - |D'|}{D}) > \frac{1}{\lambda + 1} \tag{3.7}$$

The ACARMI algorithm avoids the problems of the Reorder algorithm having too many candidate items in the initial stage and the Direct algorithm having too many in the later stage by introducing a threshold to achieve accuracy and efficiency in data mining. The computational flow of the ACARMI algorithm is shown in Figure 3.2.

In Figure 3.2, the ACARMI algorithm generates the candidate item set with the minimum length frequent item set in the initial stage of the operation, and then during the scanning of the database, the iterative generated item sets are processed separately, i.e. iterations less than the maximum length are processed with the Direct algorithm and vice versa, the item sets generated in the previous cycle are sorted and subsequently new candidate item sets are generated with the Reorder algorithm [22]. This keeps its candidate item set small overall, thus achieving a guarantee on the efficiency of the algorithm.

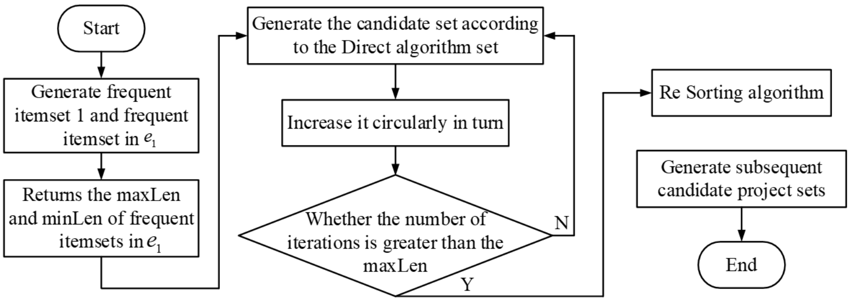


Fig. 3.2: Calculation flow of acami algorithm

3.2. Construction of an Application System for Teaching Sports Techniques and Tactics under the GSA-PSO-Apriori Algorithm. Ball sports competitions require high timeliness and therefore require good processing efficiency when using association rules for tactics development and related data analysis requirements. In order to further improve the efficiency of the Apriori algorithm in scanning data, the study relies on the Gravitational search algorithm-Particle swarm optimization (GSA-PSO) for the extraction of association rules, optimising the fast convergence characteristics of the hybrid algorithm Apriori algorithm, i.e. converting the original data into a binary format type and calculating the adaptation values for each particle. The rules are then mined with the aid of the GSA-PSO algorithm in order to update the particles and optimise the conditions [23]. The GSA algorithm considers that the mutual attraction between particles is proportional to their own mass and inversely proportional to the distance, which can improve the adaptability and applicability of the algorithm. inversely proportional to the distance, and can obtain the particle with the largest inertial mass after iteration, whose mathematical expression is shown in equation 3.8.

$$F_{ij}^d(t) = G(t)\frac{M_i(t)M_j(t)}{R_{ij(t)}+\epsilon}(xj^d(t) - xi^d(t)) \tag{3.8}$$

Equation 3.8 is the mathematical expression for the particle i acting on the particle j in the same dimensional space d and time t, where x_i^d is the position of the particle i in d dimensional space, M_i, M_j is the particle and its gravitational mass, ϵ is a constant, and $R_{ij}(t)$ is the Euclidean distance of the particle i, j in time. The mathematical expression for the Euclidean distance there is shown in equation 3.9.

$$R_{ij}(t) = ||X_i(t), X_j(t)||^2 \tag{3.9}$$

In Equation 3.8, $G(t)$ is the gravitational constant at the moment of t. To ensure the randomness of the gravitational search algorithm, by setting a random number taking values in the range [0,1], as shown in Equation 3.10.

$$F_i^d(t) = \sum_{j=i,j\neq i}^{N} rand\dot{F}_{ij}^d(t) \tag{3.10}$$

If the gravitational mass value is set equal to the inertial mass value in GSA, the sum of the current velocity of the particle and its acceleration is the velocity of the particle at the next moment, i.e. the mathematical formula for the position and velocity of the particle is shown in equation 3.11.

$$\begin{gathered} v_{id}(t+1) = randv_{id}(t) + a_{id(t)} \\ x_{id}(t+1) = x_{id}(t) + v_{id(t)} \end{gathered} \tag{3.11}$$

In Equation 3.11, $a_{id}(t)$ is the acceleration of the mass in the dimensional space [24][24]. In the traditional particle swarm algorithm, each particle in the population represents a feasible solution in the optimization

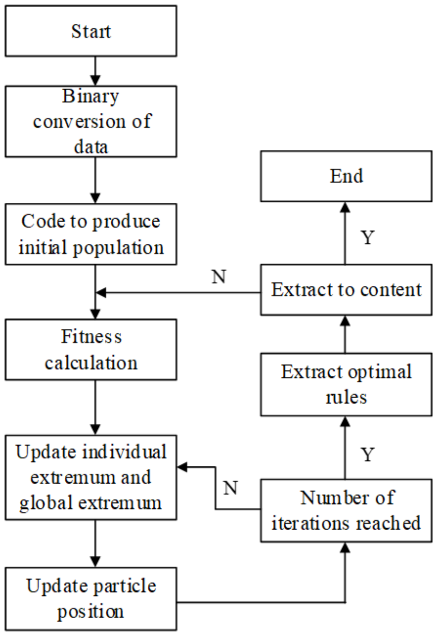


Fig. 3.3: Flow chart of gsa-pso algorithm mining association rules

problem, and the dimensionality and population size of each particle are D and N, respectively, which are calculated as shown in Equation 3.12.

$$\begin{cases} v_i(t+1) = w\dot{v}_i(t) + c_1 r_1(t)[pbest_i(t) - x_i(t)]c_2 r_2(t)[pbest_i(t) - x_i(t)] \\ x_i(t+1) = x_i(t) + v_i(t+1) \end{cases} \tag{3.12}$$

In equation 3.12, v_{t+1} and $x_i(t+1)$ are the velocities of the particles and their positions, $pbest_i$ is the local optimal solution of the particles. t is the number of iterations, w is the inertia weight, c_1, c_2 is the individual learning factor and social learning factor, and r_1, r_2 is a uniform random number in the range of [0, 1]. The combination of the GSA algorithm and the PSO algorithm can ensure the continuous improvement of particle memory while enhancing its ability to exchange information, so that the particles can enhance the ability of group information exchange while maintaining the original laws of motion, and its improved hybrid algorithm formula is shown in equation (3.13).

$$\begin{gathered} v_{id}(t+1) = r_1 v_{id}(t) + C_1 r_2 a_{id}(t) + c_2 r_3 (gbest_{id} - x_{id}) \\ x_{id}(t+1) = x_{id}(t) + v_{id(t+1)} \end{gathered} \tag{3.13}$$

In equation 3.13, v_{id} is the position of the particle at the moment, c_1, c_2 is the learning factor, r_1, r_2, r_3 is a random number in the range of [0,1], and $gbest_{id}$ is the best position of the group. By adjusting the value of the learning factor, the particle's own gravitational force can be balanced with the global exchange capacity, and thus improve the particle's performance in finding the best position. Figure 3.3 shows the flow chart of the GSA-PSO algorithm for mining association rules.

Figure 3.3 shows the key process of mining association rules using the GSA-PSO algorithm, which is the core part of the improved algorithm. When extracting rules with the GSA-PSO algorithm, data types such as the total number of particle populations, learning factor, maximum number of iterations and influence factor need to be input, and the recording of each particle position and new population is achieved with the help of the fitness calculation and particle optimal value update to ensure the extraction of optimal association rules. The

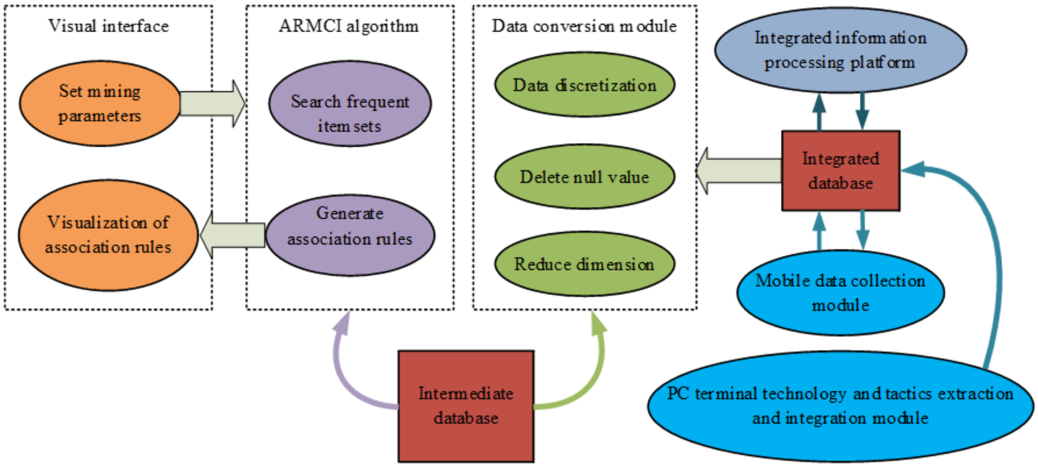


Fig. 3.4: Schematic diagram of the overall architecture flow of the system

GSA-PSO algorithm has improved the operational efficiency of the improved association rules, improved the efficiency of scanning data, achieved particle updates, and optimized conditions; The introduction of gravity search algorithm can ensure that the population particles fully exchange information, effectively improving the adaptability and applicability of the algorithm.The confidence and support degrees are used to adapt the degree function, and the influence factors are multiplied and summed to obtain the adaptation function, whose mathematical expression is shown in equation 3.14.

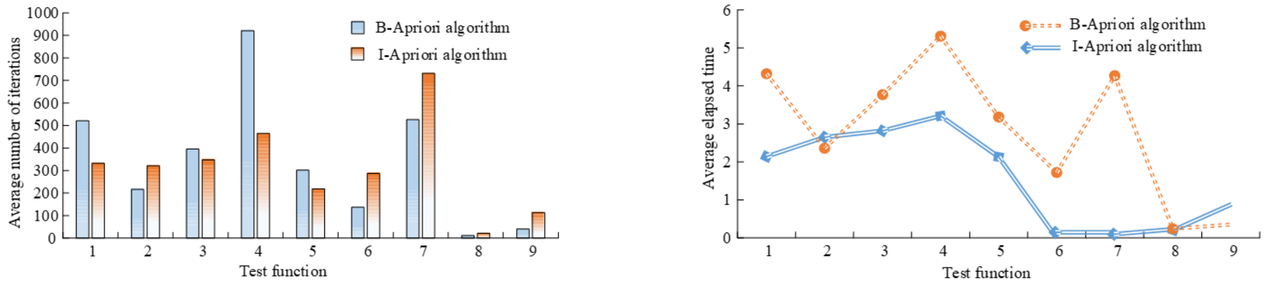
$$F(x) = aS(x) + bC(x) \tag{3.14}$$

In equation 3.14, x is the particle and a, b is the parameter of $S(x)$ support and $C(x)$ adaptation in a function that takes values in the range [0,1]. Each particle has its own velocity, position and fitness values, and the binary processing allows the particle swarm formula to be updated with the mathematical expression shown in equation 3.15.

$$\begin{gathered} v_{id}(t+1) = r_1 v_{id}(t) = c_1 r_3 (gbest_{id} - x_{id} \\ x_{id} = \begin{cases} 1, r_4 < sig(v_{id}(t+1)) \\ 0, r_4 \geq sig(v_{id}(t+1) \end{cases} \end{gathered} \tag{3.15}$$

In equation 3.15, $i(i = 1, 2, 3, \ldots, N)$ is the population size and the sig function takes values in the range (0,1). The velocity determines the maximum distance a particle can move in an iteration, with a larger velocity indicating a closer local search to the vicinity of the optimal solution. At the same time, the computer information platform is used to conduct data statistics on the scores, duration and errors of ball players during the competition, and this data is transferred to the back-end database. After pre-processing the data, improved association rule mining is introduced with a view to providing better decision analysis for athletic training of athletes and technical teaching of coaches. Figure 3.4 illustrates the overall architecture of the analysis system.

The system design consists of data collection, data conversion, algorithm implementation and visualisation interface. The pre-processing section converts numerical statistical information into Boolean data, and dimensionality reduction, constraint restriction and data type re-conversion make it possible to perform better association rule mining. The visualisation interface enables the presentation of relevant data results and thus provides strategic guidance to the user. At the same time, there are many different types of data, too many uncertainties and too many different attributes, so similar attributes need to be merged in the data processing phase to reduce the redundancy of frequent item sets.



(a) Average iteration times of Apriori algorithm before and after the experiment

(b) Time consumption of Apriori algorithm before and after the experiment

Fig. 4.1: Iteration times and execution time of Apriori algorithm before and after improvement

Table 4.1: Experimental Environment Parameter Settings

Parameter	Setting
Platform	Win7, MATLAB
Memory	4GB, CPU 1.8GHz
Population size	50
Maximum iterations	1000
Number of function runs	20

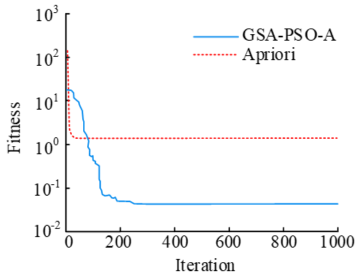
4. Analysis of the application of improved Apriori algorithm in the teaching of ball sports techniques and tactics.

4.1. Application Performance Analysis of the Improved Apriori Algorithm. After setting the maximum number of iterations, the data was counted for the number of iterations and execution time of the algorithm before and after the improvement of the Apriori algorithm. 50 experiments were conducted for each function value and the experimental results were counted as shown in Figure 4.1.

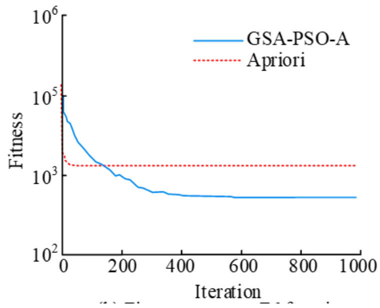
In Figure 4.1, the Apriori algorithm before the improvement is shown, and the Apriori algorithm after the improvement is shown. Test functions 1-9 are the minimisation benchmark functions that test the performance of the algorithm, where 1-4 are single-peaked functions and 5-9 are multi-peaked functions. Due to different peaks and test functions, the value of test function 8 is minimized.The results in Figure 5 show that the average number of iterations of the improved Apriori algorithm on the single-peaked function is less than that of the pre-modified algorithm, basically less than 500, but the difference in execution time is larger, indicating that the improved algorithm has better convergence on the single-peaked function and consumes less than 3 s. On the multi-peaked function, the number of iterations of the improved algorithm is higher than that of the pre-modified algorithm. This is because the improved algorithm performs particle swapping and global optimisation processes, but it takes less time to execute, essentially less than 2 s. Overall, the improved algorithm appears to be more effective for specific applications. The improved algorithm was then tested for fitness performance and the corresponding environmental parameters were set, as shown in Table 4.1.

The statistical analysis of the operational performance of the improved algorithm under different benchmark functions was carried out and the data collation results are shown in Figure 4.2.

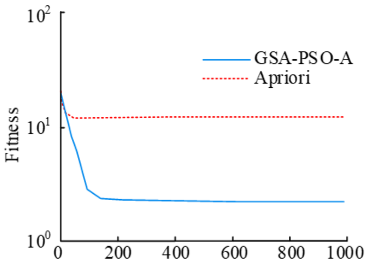
The results in Figure 4.2 show that the optimization results of the GSA-PSO-A algorithm on different benchmark functions differ, where the change in the fitness value of the GSA-PSO-A algorithm on the F2 function tends to decrease with the increase in the number of iterations, and the fitness value at 200 iterations is 0.055, which tends to be smooth at a later stage, much lower than that of the Apriori algorithm after



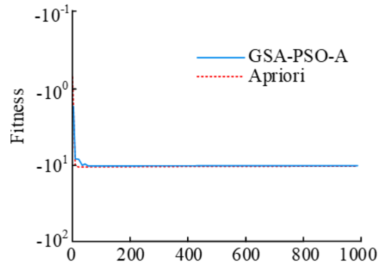
(a) Fitness Curve on F2 Function



(b) Fitness Curve on F6 Function



(c) Fitness Curve on F7 Function



(d) Fitness Curve on F9Function

Fig. 4.2: The performance of the improved algorithm under different benchmark functions

Table 4.2: Data Operation Results

/	/	Dataset Size	Average Number of Rules	Average Running Time	Support Threshold
Different Data Sets	Confidence Threshold	200	7.6	19.23	/
	Support Threshold	500	9.4	21.54	/
	Learning Factor	1000	12.7	25.61	/
Different Support Thresholds	Dataset Size	/	10.1	22.49	10%
	Confidence Threshold	/	9.1	19.87	15%
	Learning Factor	/	8.2	17.74	220%

smoothing. On the F6 function, the improved algorithm has a higher fitness value before 200 iterations than the improved algorithm, with a maximum value of over 1000, while the fitness value that plateaus at a later stage is 830. local optimum problem. Also with the help of MATLAB to achieve frequent item set and association rules mining run times 10 times, to get the run table under different data sets, the results are shown in Table 4.2.

The results in Table 4.2 show that the running time of the GSA-PSO algorithm is less affected by the number of databases, with the average running times of 19.23s, 21.54s and 25.61s for dataset sizes of 200, 500 and 1000 respectively, indicating that it can better adapt to the application effect of large datasets. While there is an inverse relationship between the change in support threshold and the number of association rules mined, which consumes more time, the improved algorithm proposed in the study can reduce the interference of some useless data during the run.

Table 4.3: Algorithm Mining Results after Introducing Constraints

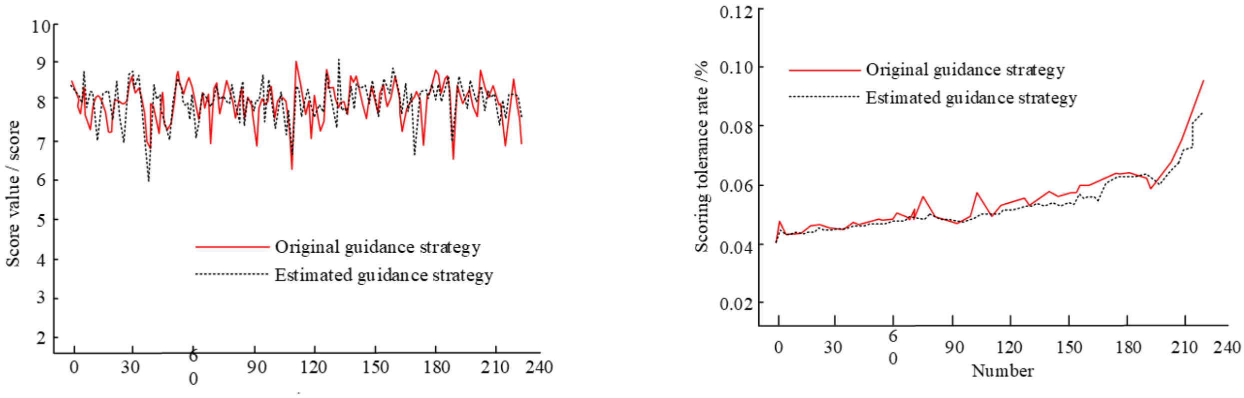
Rule	Support	Confidence Level
7-D Anti kill	15.38%	11.12%
5-J Anti high pair	8.97%	13.35%
4-J Medium high alignment	8.56%	16.27%
6-A Head block pair	8.54%	22.17%
6-A Far and straight	8.27%	30.98%
9-K Anti cross checking	8.02%	32.23%
11-J Anti blocking	7.11%	13.97%
12-L Anti blocking	6.75%	12.37%
4-L Reverse gear far	6.34%	34.56%
5-E Killing right	5.87%	13.08%
6-L Anti block	3.16%	36.27%
6-A Anti high school	16.28%	16.96%

4.2. Analysis of Application Effects. When performing data mining, the minimum support and minimum confidence were entered and constraints were set to make the results of the analysis. Also to reduce the impact of uncertainty on the results of sporting competitions and to reduce the loss of value knowledge, the minimum support and minimum confidence were set to 4% and 10% respectively and the derived results were collated as shown in Table 4.3.

Table 4.3 shows the algorithm mining results after introducing constraint conditions, which can have a certain impact on tactics and teaching when combined with rules.The association rules in Table 4.3 are represented as 'number-letter-behaviour', for example '7-D reverse kill pair' represents an event where the player hits the ball from zone 7 to zone D and the technical means is a reverse kill pair and the 'score loss "The probability of the event occurring at the same time as the 'loss of point' event was 11.12% and the support level was 15.38% indicating that the ball player was aware of the consequences of this event resulting in a loss of point. The results in Table 1 show that the probability of a player hitting the ball from zone 6 to zone L with a technical means of back-blocking being the highest for this event to occur in conjunction with a 'lost point' event was 36.27%, while only 3.16% of players were aware of this issue. The support results showed that the players' strategy of using backhand attacks was more successful, therefore, in the later stages of sport teaching, the training of targeted technical characteristics should be strengthened to improve their professional skills and abilities, taking into account the probability of losing points. To further validate the effectiveness of the application of the association rule proposed in this study, the data of ball players' participation in a sports season in a certain year was used as experimental data for application analysis and the differences were compared with the original strategy formulation, and the degree of effectiveness of its application was indicated by a rating value of 1-10, and the results are shown in Figure 4.3.

The results in Figure 4.3 show that the improved association rule algorithm proposed in the study can effectively analyse the technical movements of ball players, and the scoring results between its proposed guidance strategy and the original guidance strategy are similar, basically between 7-9 points, and the overall change is relatively smooth, with a small fluctuation range and a deviation rate of no more than 5%. And the scoring tolerance rate between the predicted strategy and the original strategy is basically between 0.04-0.10, which means that the improved algorithm can better meet the realistic requirements and has better application results.

5. Conclusion. At present, there are many statistical data of ball games. Association rules can be introduced into the statistical data of ball games to analyze and obtain the rules related to the winning factors of the game. Improve the most classic Apriori algorithm in association rules, and study the extraction of association rules with the help of gsa-pso, so as to further improve the efficiency of Apriori algorithm in scanning data. The experimental results show that the fitness of the proposed algorithm tends to decline with the increase of iteration times in the corresponding parameter environment, and the F2 function is 0.055; It is 830 in F6 function, and the overall search accuracy has been significantly improved, avoiding the algorithm



(a) Score Value (b) Scoring Error

Fig. 4.3: A comparative study on the guiding strategies of ball players in competition

falling into the local optimization problem. And the average running time of the proposed algorithm when the data set size is 200, 500 and 1000 is 19.23s, 21.54s and 25.61s respectively, which is less disturbed by the data set. Through the application analysis of this algorithm, it is found that it can make a better correlation analysis of athletes' actions and loss of points in the guidance teaching, in which area 6 hits area L and the technical means is anti blocking. The probability of this event and "loss of points" event is the highest, reaching 36.27%, while only 3.16% of athletes are aware of this problem. At the same time, the deviation rate between the predicted guidance strategy and the actual guidance strategy is no more than 5%, and the scoring tolerance rate is basically between 0.04-0.10, which has good application value and effect. It shows that the proposed algorithm can help coaches make targeted training plans and assist in on-the-spot decision-making, and has very important practical value.The algorithm proposed in the study can improve the efficiency of data analysis, facilitate the development of comprehensive ball sports technical and tactical plans, and promote the stable development of ball sports technical and tactical plans.

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