

A study of tennis momentum based on a comprehensive evaluation model and a random forest model

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Abstract. When the situation of a tennis match changes, the player's performance and momentum on the court are always a topic of concern for the audience. How to correctly and intuitively show the player's current momentum and predict the player's future momentum change is always a great challenge. In this paper, the momentum evaluation model based on comprehensive evaluation and the momentum shift prediction model based on random forest are established to address the above two problems, respectively. Among them, the player momentum evaluation model can not only accurately calculate the real-time momentum of both players, but also intuitively show which player has an advantage and the degree of advantage at each moment. The Momentum Shift Prediction Model can predict the momentum changes of future players based on current and past match data. These two models can not only help tennis coaches to better arrange the match strategy but also help tennis players to correctly analyze the court situation and make correct judgments, which has certain practical value.

Keywords: Tennis Momentum, Comprehensive Evaluation Model, Random Forest Model.

1. Introduction

Rising star Carlos Alcaraz, 20, defeated Grand Slam player Novak Djokovic to claim the ultimate victory in the men's singles final at Wimbledon 2023. Things changed repeatedly in this match and when Djokovic won the first set by a wide margin of 6-1, Alcaraz took the second and third sets 7-6 and 6-1. As Alcaraz looked to be in control of the match, Djokovic changed the direction of the match again at 6-3. In the end, the tables turned again and Alcaraz won 6-4. All of this points to the fact that "players seem to have unpredictable momentum in their matches", which makes them show good strength, but it is not easy to figure out how momentum changes over time and predict future momentum changes. Aiming at these problems, this paper tries to establish a momentum evaluation and prediction model for tennis players to help the players adjust their condition according to the model results. At the same time, the popularization and application of the model in other ball fields is conducive to helping more athletes achieve better performance in competitions, which is an important basis for the development of competition strategies.

In previous studies on tennis players' on-court performance, tennis players' performance in the game is affected by a variety of factors. For example, Meier P, Flepp R, et al [1-2] emphasized the relationship between psychological factors of athletes and athletes' performance and momentum in tennis matches. At the same time, Monaci M G [3] concluded that tennis player's anger alters athletes' performance on the court. Although a tennis player's mental state during a match has a significant effect on his or her on-court performance, this evaluation method lacks consideration of time scales. The point-by-point performance analysis proposed by Cui Y et al [4] successfully extends the research on the evaluation of the on-court performance of tennis players. In addition, in previous studies on momentum prediction, it can be seen that the methods of momentum prediction and factor selection differ greatly. For example, Wilkens S [5] used machine learning to predict the outcome of a player's match for betting purposes, and Angelini G [6] proposed a weighted elo rating method incorporating financial concepts. To improve the accuracy of prediction, Bunker R et al [7-8] conducted a comparative study between machine learning methods and elo rating and finally proposed a new prediction method combining machine learning and elo rating. Lowrance M et al [9-

10] applied the player momentum prediction model of various methods to actual professional matches based on model theory and proved it has certain feasibility and practicality.

To quickly display the player's momentum in a tennis match in real-time and improve the accuracy of the player's momentum shift prediction, this paper explores the momentum evaluation model based on comprehensive evaluation and the momentum shift prediction model based on random forest. In the comprehensive evaluation model, we considered four factors, proposed 11 secondary indicators, utilized the entropy weighting method and TOPSIS method to get the momentum time series, and finally visualized the results. In the random forest model, we identify the turning point by time window and indicator function, then employ the random forest method to predict the momentum shift, and finally get better results by root mean square error verification.

2. Establishment of model

2.1. Integrated evaluation model

Comprehensive evaluation is a method that combines multiple indicators in the system to evaluate the participating units in general, and its essence is to transform multiple indicators into one indicator that can reflect the comprehensive situation for evaluation. For the tennis player momentum evaluation problem that needs to be solved in this paper, the comprehensive evaluation model based on the entropy weight method and TOPSIS can solve the problem well.

To evaluate the momentum of the tennis players at the moment t , this model selects the data of the first 4 rounds of both sides' exchanges at the moment t and the moment t as the scope of the investigation to establish the model. Referring to various previous research, this model combines the actual situation of tennis games when selecting indicators, and selects 11 evaluation criteria as shown in Table 1 from four dimensions of psychological quality, physical exertion, technical ability, and court form, and names them $x_1 \sim x_{11}$ from top to bottom.

Table 1: Evaluation indicators

| Primary indicators | secondary indicators | description |
|----------------------------|--|--|
| Psychological quality | double fault count | A double-fault player will be more nervous. |
| | “untouchable shot” | increase self-confidence. |
| | number of unforced errors | Unforced errors indicate player anxiety. |
| | number of trips off the grid | Frequent trips to the net can negatively affect mood. |
| Physical exertion | number of breaks and holds | Break and hold serves can boost morale. |
| | serving speed | Serving speed will be slower when physical exertion is high. |
| Technical capability | Average distance run | The more physical a player is, the more agile he or she is. |
| | Score rate | A player who scores more points has a higher skill level. |
| Format (Current turn only) | number of ACE balls | Hitting an ace requires skill building. |
| | Whether or not to serve | In tennis, the serving team has a higher probability of winning the match. |
| | Whether or not there is an innings point | Players are affected in all aspects of their performance at set point. |

First, the indicators must be made consistent if the evaluation matrix is to be consistent with the subsequent modeling. The consistency of the indicators is achieved by selecting the negative indicator (x_1, x_3, x_4) and taking the reciprocal, while the positive indicator remains unchanged. After that,

min – max standardization is performed for each indicator, and the process can be expressed as follows

$$x'_i = \frac{x_i - \min(x_i)}{\max(x_i) - \min(x_i)} \quad (1)$$

where $\min(x_i)$ represents the minimum value in the player's x_i indicator data and $\max(x_i)$ is the maximum value in the player's x_i indicator data.

Secondly, after determining the evaluation matrix, this model applies the entropy weight method to determine the weight coefficients of the evaluation indicators. The entropy weight method determines the objective weights according to the magnitude of the variability of the indicators, and the information entropy of each feature is obtained through the input data as

$$E_j = -k \sum_{i=1}^m r_{ij} \ln r_{ij}, k = \frac{1}{\ln m}, j = 1, 2, \dots, n \quad (2)$$

to obtain the weighting coefficients for each indicator

$$w_j = \frac{F_j}{\sum_{j=1}^n F_j}, j = 1, 2, \dots, n \quad (3)$$

where E_j denotes the information entropy corresponding to the player's j indicator, w_j indicates the weight coefficient corresponding to the player's j indicator, r_{ij} is the i data corresponding to the player's j indicator and F_j represents an intermediate variable that satisfies the $F_j = 1 - E_j, 0 \leq F_j \leq 1$ relationship.

Finally, after obtaining the weights of the indicators for evaluating the tennis players at a given moment, this model obtains the player's momentum with the help of TOPSIS by obtaining the characteristic differences between the indicators and the positive and negative ideal solutions. For the performance of the i player at the moment t , the distance between him and the positive ideal solution is

$$C_i^+ = \frac{s_i^-}{s_i^+ + s_i^-}, i = 1, 2, \dots, n \quad (4)$$

where s_i^+ and s_i^- satisfy

$$s_i^+ = \sqrt{\sum_{j=1}^m (v_{ij} - v_j^+)^2} (i = 1, 2, \dots, n) \quad (5)$$

$$s_i^- = \sqrt{\sum_{j=1}^m (v_{ij} - v_j^-)^2} (i = 1, 2, \dots, n) \quad (6)$$

where v_j^+ represents the positive ideal solution of the player momentum problem and v_j^- denotes the negative ideal solution of the player momentum problem.

2.2. Random Forest Prediction Model

Step1: Defining the ‘Momentum Turning Point’. In tennis, momentum can be understood as the state of a side's performance in a match. Since this is a relatively subjective concept, we can quantify it.

$$Momentum_t = \sum_{i=t+k}^t (y_{p1_points_won_i} - y_{p2_points_won_i}) \quad (7)$$

where $Momentum_t$ represents the momentum at time point t , k indicates the size of the time window we chose, and $y_{p1_points_won_i}$ and $y_{p2_points_won_i}$ are indicator functions of how player 1 and player 2 scored at time point i .

In that question, we pick a time window k of 5 and set it so that when $Momentum_t$ is greater than 3, it is recognized that player 1 has good momentum at that moment. Conversely, when $Momentum_t$ is less than -3, player 2 has good momentum. This means that if a player on the trailing side wins 3 of the next 5 balls, the first of those 5 balls is considered to be the momentum turning point.

We thus create a new column at the end of the data table to mark momentum shifts. When a player's momentum shifts, we mark that moment as 1 and the rest of the moments as 0. Note that there are different sets of game data for different groups of players in the table, and we only select the same set of data for the same group of players when calculating momentum.

After analyzing and processing the data, we found a total of 230 momentum shifts, which we marked as 1.

Step2: Build decision tree. Randomly select a momentum change point from the original data set and select its feature data set.

$$D_t = \{(x_1, y_1), (x_2, y_2), \dots, (x_i, y_i)\} \quad (8)$$

where x_i is the feature vector and y_i denotes the corresponding label. In this manner all the feature datasets of the ball for the first 5 time points of that time point are then selected, note that the first 5 time points are selected here and not the last 5 time points (the starting period) because it is by finding the features of the data for the first 5 time periods that the prediction of the next turning points can be made.

$$D_i, (i = t - 1, t - 2, t - 3, t - 4, t - 5) \quad (9)$$

form a new subset. Utilize this subset to train a decision tree and divide each node using an optimization algorithm.

Step3: Build a random forest model to predict the results. Select the data of other momentum-changing points to form multiple decision trees in the way of step 1. The prediction result of our random forest can be expressed as

$$RF(x) = \frac{1}{T} \sum_{i=1}^T C_i(x) \quad (10)$$

where $C_i(x)$ denotes the prediction of a single decision tree given the input x and T is the number of decision trees.

In this way, we utilize 80% of the turning point data as the training set and 20% of the turning point data as the test set. We employ the training set to train the model and pass in the features and labels of the training set as parameters. Finally, we utilize the test set to make predictions and pass in the features of the test set to get the prediction results.

In addition, the Random Forest model is trained using the training datasets and the Random Forest calculates the importance of features for each decision tree. After training is complete, the importance of each feature can be obtained through the feature importance attribute. The higher the importance score of these features, the more important role they play in the prediction of the model.

Through the random forest, we get the importance ranking of features and display the importance of features through the visualization tool.

3. Results

3.1. Results and analysis of the integrated evaluation model

To visualize the effectiveness of the comprehensive evaluation model in solving the problem of momentum assessment of tennis players, the match between Carlos Alcaraz and Novak Djokovic in the men's singles final at Wimbledon 2023 is discussed as an example in this paper.

First, we show the results after filtering, interpolating, and normalizing the collected data, as detailed in Table 2.

Table 2: Data preprocessing results (partial)

| Number of double faults within the examination range | Speed of service within the examination range | Points scored within the examination range | Whether or not to serve in the round |
|--|---|--|--------------------------------------|
| 0 | 0.719 | 0.857 | 0 |
| 0 | 0.911 | 0.286 | 1 |
| 0 | 0.945 | 0.286 | 1 |
| 0 | 0.890 | 0.286 | 1 |
| 0.5 | 0.808 | 0.286 | 1 |

Secondly, we used Python language to write code to solve the weights of 11 indicators corresponding to the entropy weighting method, and the results are displayed in Table 3.

Table 3: Indicator weighting results

| | w_1 | w_2 | w_3 | w_4 | w_5 | w_6 |
|----------------|-------|-------|-------|----------|----------|-------|
| Carlos Alcaraz | 1.1% | 6.3% | 1.1% | 0.6% | 22.9% | 1.1% |
| Novak Djokovic | 0.8% | 10.9% | 0.7% | 1.5% | 21.6% | 1.7% |
| | w_7 | w_8 | w_9 | w_{10} | w_{11} | / |
| Carlos Alcaraz | 1.7% | 2.0% | 23.4% | 7.3% | 32.5% | / |
| Novak Djokovic | 2.6% | 3.2% | 9.7% | 10.5% | 36.8% | / |

By looking at the results, we can see that for both tennis players, the factors of mental quality and court format are weighted more heavily. This result suggests that players who participate in tennis matches should focus more on stabilizing their mindset during the match and creating a more favorable court format.

Finally, we will visualize the momentum of Carlos Alcaraz and Novak Djokovic's full game under TOPSIS evaluation in a time series, as detailed in Figure 1.

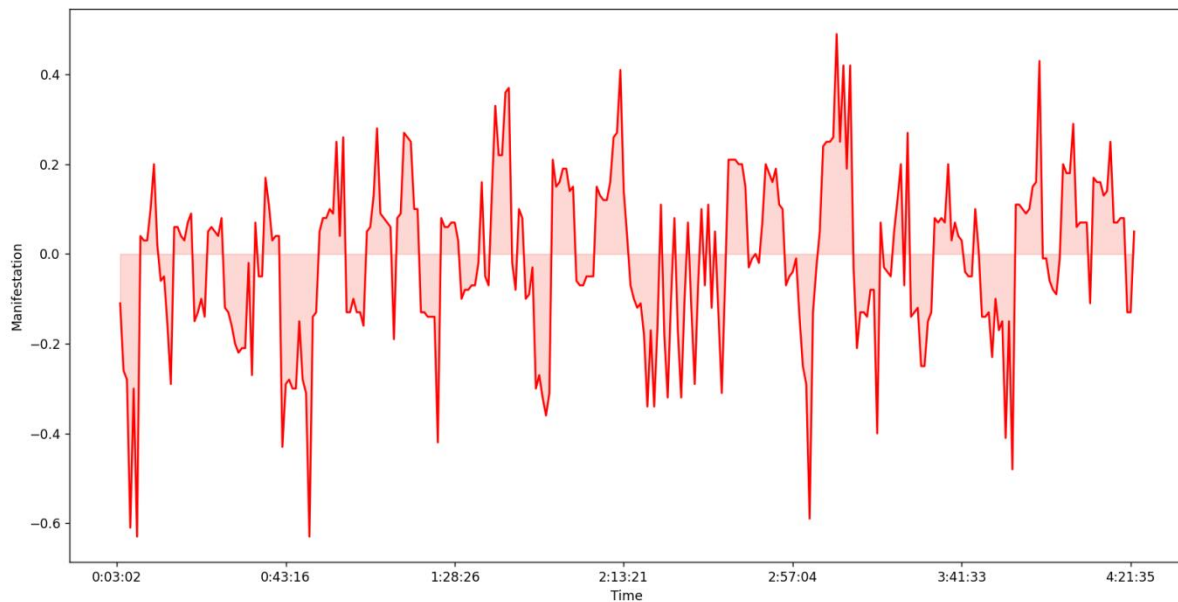


Figure 1: Momentum assessment results

In Figure 1, we can clearly and visually see the performance of the players on the field at each moment. A positive value means that Carlos Alcaraz performed better, while a negative value means that Novak Djokovic performed better. In addition, the displayed value's absolute value indicates how well the player performed.

Taking 0:43:16 as an example, we can see that Novak Djokovic's performance in the period before and after is extremely outstanding, and there is a big gap between him and Carlos Alcaraz. This period corresponds to the second game of the second set when Novak Djokovic scored consecutive points and hit several untouchable balls. As you can see, the modeled player performance generally matches the actual match.

3.2. Results and Analysis of Random Forest Modeling

3.2.1 Results of the Random Forest Prediction Model

In the above random forest prediction model, we applied 80% of the turning point data as a training set to train the model and passed the features and labels of the training set as parameters. Finally, we used 20% of the turning point data as a test set to make predictions and passed the features of the test set to obtain the prediction results as shown in Figure 2.

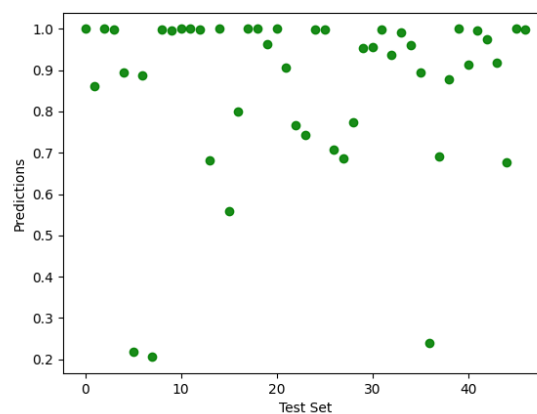


Figure 2: Forecast results

It can be seen that the vast majority of the predictions are in the neighborhood of 1, indicating that the predictions and the actual values largely match.

The advantage of this is that even if some of the decision trees are incorrectly predicted, the correct prediction results of the other decision trees will positively affect the final prediction results, thus improving the overall accuracy and robustness.

3.2.2 Main factors influencing changes in momentum

Through the random forest, we get the importance ranking of features and display the importance of features through the visualization tool (bar chart), as shown in Figure 3.

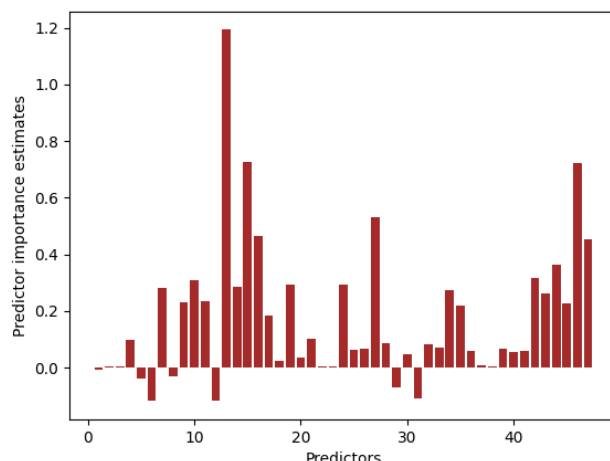


Figure 3: Characteristic Importance

In Figure 3, we can visually see the degree to which all factors contributed to the results, with the factors numbered 13, 15, and 46 particularly prominent, which means that their importance was very high.

For further visualization, we categorize them to get the results in Table 4. It can be seen that the players' serving factors (serving side, ace, break, etc.), hitting factors (hitting times, surfing times, whether they hit irresistible balls, etc.), and running distance have a greater impact on the result, which is 89.5% in total. We can also summarize it as mental, physical, and technical factors. Therefore, the coach can use these factors to identify turning points in momentum and give the player confidence to play a beautiful counterattack.

Table 4: Classification of features

| features | contribution rate |
|--|-------------------|
| Serving Factors (whether to serve, aces, double faults, etc.) | 0.273414407 |
| Process factors (distance run, etc.) | 0.11660105 |
| Hitting factors (number of shots, netting, whether or not you hit an unstoppable ball, etc.) | 0.504705527 |
| Number of small games won | 0.105279016 |

3.2.3 Cross-validation of models with root mean square error

In our model, the outcomes are 0 and 1 variables, and the datasets we selected are all momentum turning point datasets labeled 1. This means that what we are evaluating is whether the mean of the outcome predicted by the test set can be close to 1. If it is closer to 1, the root mean square error is close to 0. The smaller the root mean square error, it means that the model fits the training and test data better.

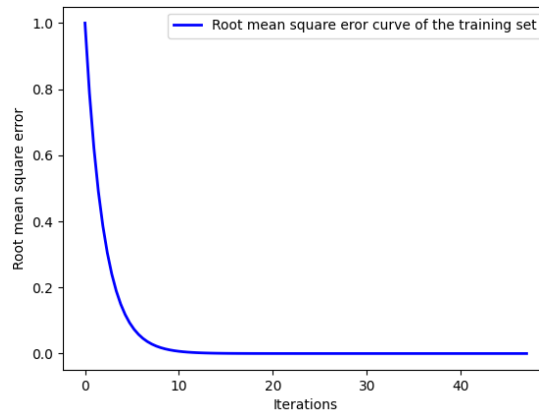


Figure 4:Root mean square error curve for the training set

As can be seen from Figure 4, the root-mean-square error gradually tends to 0 as the number of iterations increases, indicating that the predicted results of the model are in good agreement with the actual values. Through this process, we can more comprehensively understand the performance of the random forest model on different data sets, and ensure the generalization ability of the model.

4. Conclusions and outlooks

The main focus of this study is to address the issue of evaluating the real-time performance of players and predicting their momentum changes in tennis matches. Based on establishing 11 secondary indicators, a comprehensive evaluation model based on the entropy weight method and TOPSIS was established to evaluate and visualize the real-time performance of athletes. At the same time, this article establishes a random forest model based on identifying athlete momentum changes using time windows and indicator functions to solve the problem of predicting athlete momentum changes and conducts cross-validation on the model using root mean square error.

In terms of model results, the player performance evaluation model successfully outputs a time series graph of the performance of two contestants on the field after providing input of competition data. Based on the actual competition situation at that time, we found that the results of the evaluation model were completely in line with the conditions of the field. In addition, the athlete momentum transition prediction model, given a training dataset and completed training, can not only output the athlete momentum transition in the future time but also provide the main factors affecting the athlete momentum transition. In the subsequent root mean square error cross-test, the model performed well, and the predicted results matched the actual values very well. It can be seen that the above two models have certain application values for real-life tennis match scenarios.

Compared with various existing studies, the comprehensive evaluation model proposed in this paper not only has a higher computational speed but also takes into account the interrelationships between various influencing factors. This makes the model more in line with the complex situations in actual competitions and can provide a more comprehensive evaluation of the performance of players. In addition, the prediction model based on random forest can be applied to various data types and has a certain robustness to missing and outliers. It can also provide key factors that cause changes in player momentum to help athletes and coaches develop better strategies.

Although the model presented in this article has shown advantages in many aspects, there are still issues with the strong weight dependence of the comprehensive evaluation model, as well as the time-consuming and memory-intensive training of the random forest model. To address these issues, we can continue to study data preprocessing and code optimization to achieve faster computation speed and higher computational accuracy.

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