Player Momentum Analysis in Tennis Match Based on Wavelet Analysis

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Abstract. Tennis matches are exciting and have many twists and turns, in which the energy that the players obtain from the match events and ultimately affect the match is called the player's momentum. In order to study the momentum change and match trend of tennis players in depth, this study establishes a momentum model related to players' match data reflecting players' match performance, and on this basis, using wavelet analysis method, establishes a wavelet sequence analysis chart as well as wavelet coefficient spectrograms, which analyzes the intrinsic characteristics of the player's full-court performance change in-depth from the point of view of the change of the time series. In order to verify the validity of the momentum model, this study conducted a multidimensional correlation analysis of the momentum data and the score data, obtained the strong correlation between the momentum data and the score data, and verified the non-randomness of the momentum data through the stochasticity test, thus proving the strong validity of the momentum model, which can provide a powerful support for analyzing and predicting tennis matches and adjusting the match strategy based on it.

Keywords: CRITIC, Momentum Model, Wavelet Analysis, Runs Test.

1. Introduction

Tennis, as a popular sport worldwide, has its unique charm due to its constantly changing rhythm and intense competitive environment. It not only tests the athletes' physical strength and skills, but also a battle of strategy and mentality. In this fierce competition, athletes need to constantly pay attention to the dynamics of their opponents and adjust their tactics and mentality to cope with various changes that may occur in the game. Behind this competition, there is an important factor called "momentum"[1] that affects the direction and outcome of the game.

The concept of "momentum" has a special significance in tennis. Due to the unique rules of tennis, players' performance in the game often fluctuates and changes. Sometimes, a player may perform well in a game, scoring consecutive points, forming a strong momentum that makes it difficult for opponents to cope with. And sometimes, when players are in trouble, they may reverse the situation by adjusting their tactics and mentality, bringing the game back to the balance.

The dynamic changes in tennis competition are not only affected by the competitive ability of players, but also profoundly affected by the elusive concept of momentum. Therefore, in addition to the analysis of the competitive ability of players, scholars have also been committed to quantifying and understanding the factor of momentum. However, due to the abstractness of momentum, it is indeed a challenging task to analyze how momentum is generated and changed by game events in sports and ultimately affects the results of the game. The goal of this study is to establish a mathematical model for quantifying momentum and in-depth analysis of tennis game data. It is expected that through this study, the law of momentum change in tennis competition can be more accurately revealed, providing tennis players and coaches with powerful data support and strategic guidance. When facing the constantly changing environment in the game, they can adjust their strategies in time according to these insights to better cope with challenges and ultimately improve their performance.

2. The Momentum quantitative scoring model

2.1. Data Preprocessing

In order to make the research more authoritative and accurate, this study begins with the 2023 Wimbledon men's singles tennis tournament data as the primary source of data for the study(https://www.comap.com/contests/mcm-icm).

The Wimbledon men's singles data used in this data record the detailed score data of many men's individual tennis competitions, including the most basic match labels, player names, game time points and scores, as well as important player performance data such as running data, return and serve direction, break serve, and errors. There are a large number of type variables that are difficult to calculate, and there are many missing values and abnormal values. The following will clean the data for these data problems.

(1) Data encoding

The data contains many categorical variables represented as strings. In order to make the model able to process such data effectively, it needs to be preprocessed by label encoding. The type and character variables in the tennis match data are encoded and simple values such as the serve direction are assigned to facilitate the subsequent processing of missing values. For each type of variable, we use natural numbers starting from 1 to encode one by one. Table 1 below will show the results of the coded data for the direction of the serve.

Table 1. "Direction of serve" data and coding results

variable name	direction of serve	post-conversion code
B	Body	1
BC	Body/Center	2
BW	Body/Wide	3
C	Center	4
W	Wide	5

(2) One hot coding

After the categorical variables are converted into data variables through data encoding, they still need to be further converted into dummy variables to be used in subsequent regression equation operations. The most classic method of converting type variables to dummy variables is one-hot encoding. One-hot encoding creates a Boolean column for each class in each single variable, where 1 represents the original class and 0 represents the rest classes [2]. The application of dummy variables in regression will be demonstrated by formulas in the following.

$$y_i = \beta_0 + \delta_0 F + \beta_1 x_{1i} + \beta_2 x_{2i} + \cdots + \beta_k x_{ki} + \mu_i \tag{1}$$

(3) Removal of outliers

A small number of outliers are present in most data due to issues such as statistical errors, data recording bias, and realistic contingencies. These outliers are very likely to have a significant impact on the final results, leading to significant deviations in the results. Therefore, the detection and removal of outliers is particularly critical and important in the data cleaning process.

The most common method for effectively dealing with outliers is the triple standard deviation method, which is based on the principle of three times standard deviation to determine the range of outliers. In general, most (about 99.7%) of the data will fall within a range of plus or minus 3 standard deviations from the mean. Specifically, the lower limit is the mean minus 3 times the standard deviation and the upper limit is the mean plus 3 times the standard deviation. Any value that falls outside of this upper and lower limit will be determined to be an outlier.

In this paper, we utilized the triple standard deviation method to discriminate most of the numerical data. As a result, it was found that outliers existed in the data of bat swing, running distance and number of hits. In order to ensure the accuracy and reliability of the data, we decided to remove or place these outliers as null values and leave them for subsequent missing value processing. In this way, not only can we avoid the negative impact of outlier results, but also provide a more accurate and reliable data base for subsequent data analysis.

$$\sigma = \sqrt{\frac{\Sigma_{i=1}^{n}(x_i - \overline{x})^2}{n}} \tag{2}$$

$$|x_i - \mu| > 3\sigma \tag{3}$$

(4) Missing value processing

The impact of missing values on the data should not be ignored, so it is necessary to adopt appropriate processing methods for different types of data. As the data involved in this paper are time series data, direct deletion of rows containing missing values is obviously not desirable. At the same time, considering the differences between the data, we cannot take a one-size-fits-all approach to deal with all the missing values. For data such as the number of shots and the direction of serve receive in the type data, according to the playing habits of the top players, this kind of data is usually relatively fixed or in a certain fixed range. Therefore, for the missing values of these data, we adopt the method of filling in the plurality in order to maximize the preservation of the original characteristics of the data. As for the regular numerical data such as running distance, ball speed, etc., since they usually show a certain distribution pattern, we use the mean padding method to deal with the missing values. This can not only effectively fill the data gaps, but also maintain the overall stability of the data.

(5) Data standardization

The existence of a large amount of data with different scales in the data may lead to the key data cannot play a key role, at this time the data standardization will be particularly important, and its main purpose is to eliminate the scale differences between different features, so that each feature has the same weight in the data analysis. The standardized data can better reflect the real relationship between the data and improve the accuracy and reliability of the analysis results. In the process of data standardization, this paper will use specific mathematical transformation methods, such as Z-score standardization or Min-Max standardization, to convert the original data into a unitless uniform scale. Such processed data not only facilitates the calculation, but also eliminates the interference of outliers on the analysis results. For the dataset involved in this paper, we chose an appropriate standardization method according to the nature and distribution characteristics of the data. For the data with obvious skewed distribution, we adopted Z-score standardization, which converts them into a standard normal distribution with a mean of 0 and a standard deviation of 1 by calculating the mean and standard deviation of each data. For data with large ranges or outliers, on the other hand, we used Min-Max standardization, which scales the data to a specific range (e.g., between 0 and 1) to ensure that each feature has the same weight in subsequent analyses.

2.2. Introduction to the methodology

Given the abstract nature of momentum and its significant impact on the outcome of a match, this paper aims to quantify momentum by establishing a relational equation for match data and establishing it as a key metric for assessing athlete performance. Based on the general perception of first serve advantage, this paper explores the potential impact of momentum in depth and employs the kappa consistency test to correlate two types of categorical variables, namely, the winning side and the serving side. Based on this, this paper further selected several data indicators as the components of momentum, initially constructed the momentum expression, and visualized the momentum time series data.

In order to deeply study the law of momentum change over time, we applied the wavelet analysis method. Through the generated graphs, we were able to clearly identify the time periods when the athletes performed well. Ultimately, we utilized the momentum score, a comprehensive indicator, to provide a comprehensive assessment of the athlete's overall performance, which provided a strong support for the analysis of the tennis match process.

3. Momentum modeling and analysis

3.1. The correlation between serving and scoring

After performing data cleaning and processing, we develop a momentum scoring system that incorporates various influential factors to quantify the concept of 'momentum', thereby establishing a quantitative model for assessing momentum.

For whether the first serve has a higher probability of winning the match, we use kappa correlation analysis to calculate the correlation coefficient between server and point_victor, which denote the server and the scorer of the set, respectively.

The fundamental principle of Kappa analysis lies in evaluating the level of agreement among observers by comparing their actual observations with expected outcomes. The Kappa coefficient ranges between -1 and 1, where a value of -1 indicates complete inconsistency, 0 denotes random consistency, and 1 signifies perfect consistency. Typically, a Kappa coefficient exceeding 0.8 is considered indicative of strong concordance. The specific formula employed for computation is as follows:

$$k = \frac{p_0 - p_e}{1 - p_e} \tag{4}$$

$$p_c = \frac{a_1 \times b_1 + a_2 \times b_2 + \cdots + a_c \times b_c}{n \times n} \tag{5}$$

Where p_0 represents the overall classification accuracy, defined as the total number of correctly classified samples across all classes divided by the total number of samples.

$a_1, a_2 \cdots a_c$ $b_1, b_2 \cdots b_c$ represent the total number of samples and the total number of predicted samples, respectively.

The kappa correlation coefficient yielded a value of 0.347, indicating a significant positive correlation.

3.2. Definition of momentum

3.2.1 Index selection

Based on the close correlation between first serve and scoring, this paper carries out an in-depth discussion and further selects several key data indicators. These indicators cover the important performance of players in the game, and also fully consider the physiological and psychological factors of players. The momentum expression is quantified through the comprehensive use of these data indicators, so as to visualize the performance of athletes in the game.

(1) ***Excellent performance (good ball) indicators***

This type of indicator shows the number of ACES, winners and breaks of serve played by players, which is their unstoppable and come-back performance. These three types of balls are very able to motivate players, encourage players, increase their morale and momentum, and the data of each such ball is regarded as one point.

$$H_t = ace + winner + break \tag{6}$$

Ace, winner and break represent the number of three types of balls respectively.

(2) ***Running indicators***

The athlete's physical fitness is an important factor affecting the game. High intensity running not only means physical consumption, but also reflects the strength gap between the two sides. The opponent's frequent pulling makes the athlete's running increase, and the mood will also change. At the same time, due to the large differences in the running indicators, in order to accurately reflect the influence of the running momentum among players, the average value of the outlier was calculated to be 12.868 meters (0.236 after standardization).

$$\bar{S}=\frac{\Sigma(S_i^1+S_i^2)}{t} \tag{7}$$

$$\Delta S_i^k=\left|S_i^k-\bar{S}\right|\ k=1,2;\ i=1,2,3\cdots \tag{8}$$

$$S_t^{k_1}=if(\Delta S_i^{k_1}<\Delta S_i^{k_2}) \tag{9}$$

Where, $\bar{S}$ and S_i^k are the average distance run by all players and the distance run by one player respectively. In contrast, if $\Delta S_i^1>\Delta S_i^2$ an increment of one momentum point is allocated to the first player at that specific moment in time.

(3) ***Failure indicators***

There is no doubt that mistakes in international competitions have a significant impact on our mentality and our emotions, thus affecting our momentum. We choose two-shot mistakes and unforced mistakes as indicators and regard the number of mistakes as reducing momentum.

$$J_t=doublefault+unferr \tag{10}$$

Where *doublefault* and *unferr* indicate double error and unforced error respectively.

(4) ***Oppressive indicators***

In the game, the greatest influence on the momentum is to show a strong pressing force, which can greatly reduce the momentum of the opponent and promote the momentum of the opponent. We use the number of consecutive wins to embody this pressing force, and regard three consecutive goals as a great crushing indicator score plus one.

$$Y_t=if(pointwon_i+pointwon_{i-1}+pointwon_{i-2}) \tag{11}$$

In the formula, point-won indicates the score, and i denotes the number of games in which the score was obtained. The selection of indicators is shown in Table 2.

Table 2. Indicator selection

Index	Selection variable
Excellent performance indicators	p1_ace, p1_winner, p1_breakpt….
Running indicators	p1_distance_run, p2_distance_run
Failure indicators	p1_double_fault, p1_unf_err…
Failure indicators	point_victor
Oppressive indicators	sever

3.2.2 Selection of CRITIC weights

The impact of various game situations on player momentum is unique, and the corre-sponding weights must be established during the data operation process for quantifying mo-mentum. Due to unknown correlations and indicator importance, subjective weight determi-nation methods often result in significant deviations.

CRITIC method is considered as a better method to obtain weight than entropy method and standard deviation method. This method can not only calculate the correlation between indicators, but also well analyze the impact of correlation between indicators on weight. It is a method combining independence weight coefficient method and coefficient of variation method, which is similar to most objective weight methods. The CRITIC method uses the proportion of information entropy to calculate the weight [3], which can be expressed as:

$$C_j=S_j\times R_j, W_j=\frac{C_j}{\sum_{j=1}^{p}C_j} \tag{12}$$

Finally, in order to facilitate the calculation of momentum data, the nonlinear parameter optimization is further carried out, and the values of α, β, μ, ν, λ are finally simplified (0.15, 0.2, 0.25, 0.25, 0.15).

3.2.3 Smoothing Processing

After determining the weight, the data of the time point of the single ball can be calculated, but due to the wide selection of indicators, the amplitude of momentum change is too frequent. Considering that the mentality of all players is generally stable in reality, the momentum will not change sharply in a short time, it is decided to convert the calculated momentum value into the average value of three consecutive momentum, reduce the ups and downs of momentum, and reduce the actual impact of each factor.

The smoothing of momentum can be roughly represented as shown in Fig. 1 Momentum time series data variation.

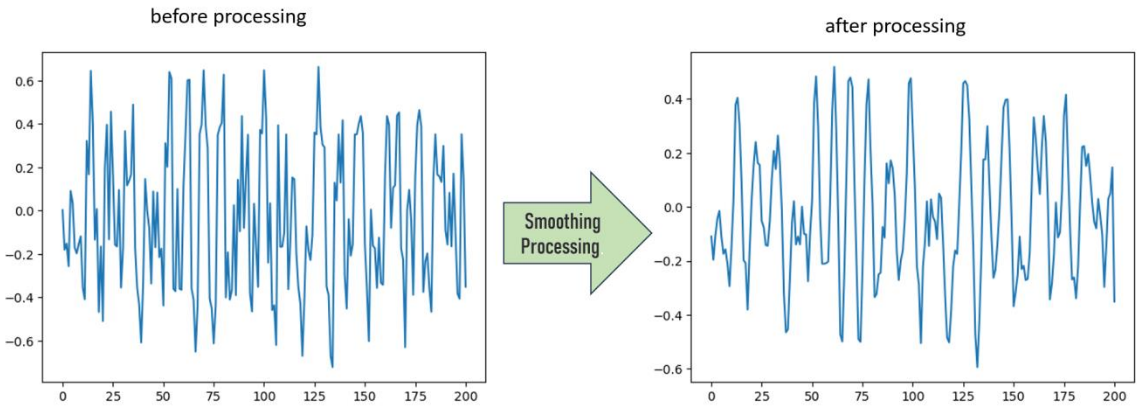

Figure 1. Handling of single point momentum

3.2.4 Momentum timing data visualization

Eventually we obtained the momentum expression based on the above inference as follows:

$$M_t = f(\alpha H_t + \beta Y_t + \lambda N_t + \mu S_t + \nu J_t) \tag{13}$$

Among them, t is the time point at which the score occurs, H_t representing the highlight index in the court, Y_t represents the suppression index, N_t represents whether to serve first, S_t represents the error index, J_t represents the moving distance index, $f(\ )$ is the smooth processing function, which is used for nonlinear mapping, where α, β, μ, ν, λ is the standardized weight of different indicators.

Player momentum in real games is not the change of a single time node, but the accumulation of a period of time, and the accumulated momentum value can better reflect the player's good performance and performance degree in the game and time. Based on the accumulated momentum time series data, this study can initially obtain the player's game performance situation graph, on top of which, highlighting the time points of hitting a good performance and hitting an error in the graph can more intuitively reflect the key time points of the player's performance changes.

As the left graph in Fig. 2 reflects the momentum change and the time point of hitting a good ball of player one, and the right graph shows the momentum change and the time point of generating errors of player two, the model has been able to better reflect the change of player's performance, and at the same time, it coincides with the eventual situation that player one gradually gained the advantage of winning, and player two gradually lost.

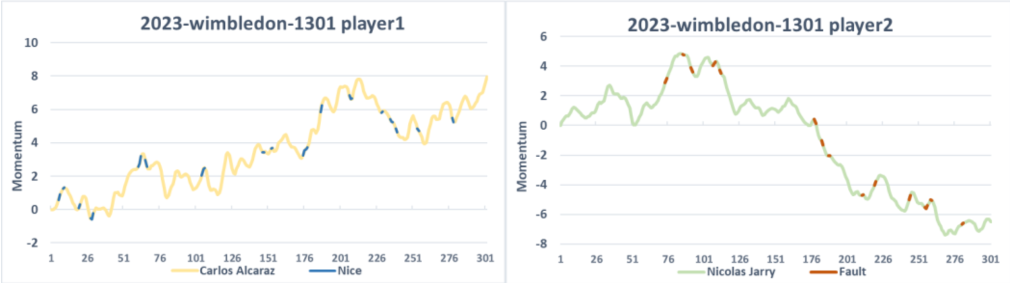

Figure 2. 2023-wimbledon-1301 Momentum changes

3.3. Wavelet Analysis

3.3.1 Wavelet analysis formula

After defining the momentum, the study determined that there were biases and errors caused by subjective judgment in the momentum visualization data of the visual analysis. In order to reduce the errors in the subjective analysis, we further used the wavelet analysis algorithm of the time series data to refine the trend and cycle of the momentum change.

The study uses wavelet analysis to analyze the relationship between momentum and time. Compared with ARIMA model of time series, wavelet analysis has good time-frequency localization, that is, it can provide both time and frequency information of signal. Wavelet function has finite duration, so it is localized in both time and frequency domain.

The study uses Molet wavelet basis function for wavelet analysis. Morlet wavelet is a highly localized wavelet basis function with good time-frequency localization characteristics [4]. In data analysis, Morlet wavelet can be used for the analysis, prediction and classification of time series data.

First, the data is transformed by wavelet:

$$WT(a,\tau)=\frac{1}{\sqrt{a}}\int_{-\infty}^{\infty}f(t)*\psi\left(\frac{t-\tau}{a}\right)\mathrm{d}t \tag{14}$$

The Morlet wavelet basis function is:

$$\psi(t)=\exp(iwt)\exp\left(-\frac{t^2}{2}\right) \tag{15}$$

Perform the morlet transform:

$$\psi f(a,b)=\int_{-\infty}^{\infty}f(t)\exp\left(-iw\frac{(t-b)}{a}\right)\exp\left(-\frac{(t-b)^2}{2a^2}\right)\mathrm{d}t \tag{16}$$

3.3.2 Visual analysis

Continue to use 2023-wimbledon-1301 data analysis to obtain the results, through the formula to calculate the momentum of players in the process of the game into the game data for calculation, plot the momentum of players in the process of the game to achieve the quantification and visualization of momentum. Figure 3 below shows a plot of the momentum time series data for the two players.

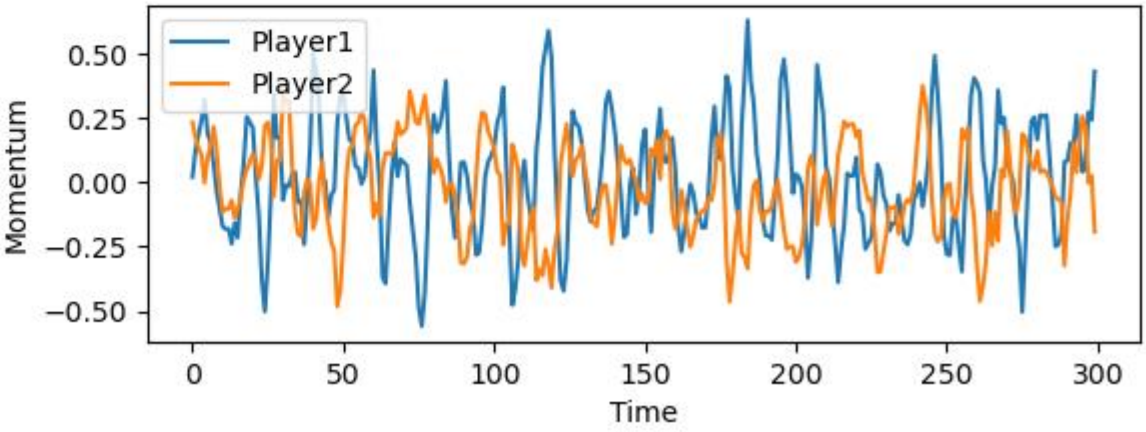

Figure 3. Line chart of momentum change of player 1 and 2 in the game

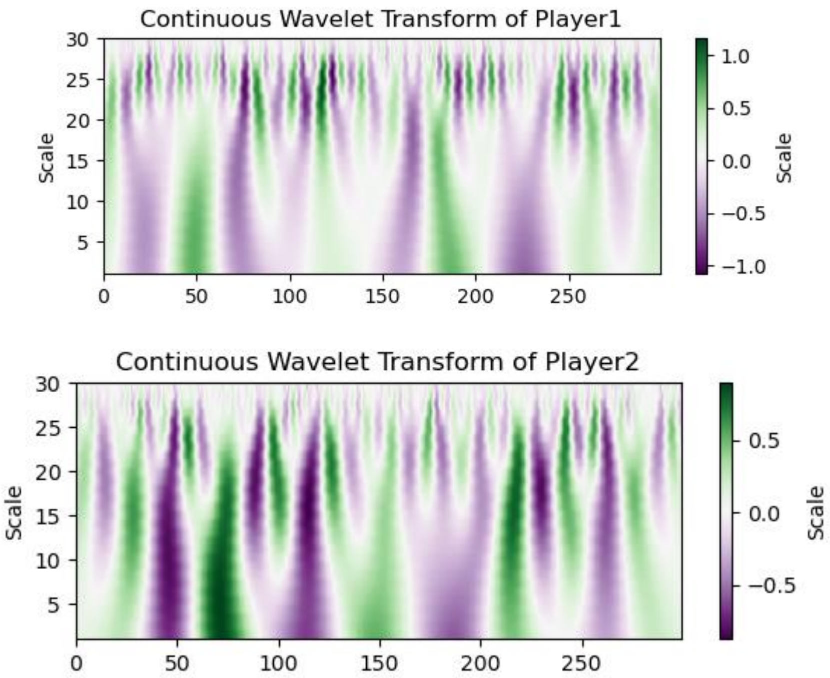

Figure 4. Fractional sequence of wavelet analysis

The score sequence of wavelet analysis is further obtained, and the genealogical chart is finally drawn in Fig. 4. By analyzing its color and depth, the momentum of players can be in-creased or decreased in a small period of time, in which green represents the rise, purple rep-resents the decline, and the darker the color, the greater the fluctuation. It can be concluded that the momentum change itself is relatively stable, the color is lighter, corresponding to a relatively long momentum increase and decrease potential, less twists and turns, the wave amplitude is large[5,6]; However, the momentum of player two has large changes, deep color, frequent fluctuations, more twists and turns, and does not maintain a long-term increase or decrease in potential, and the wave amplitude is small.

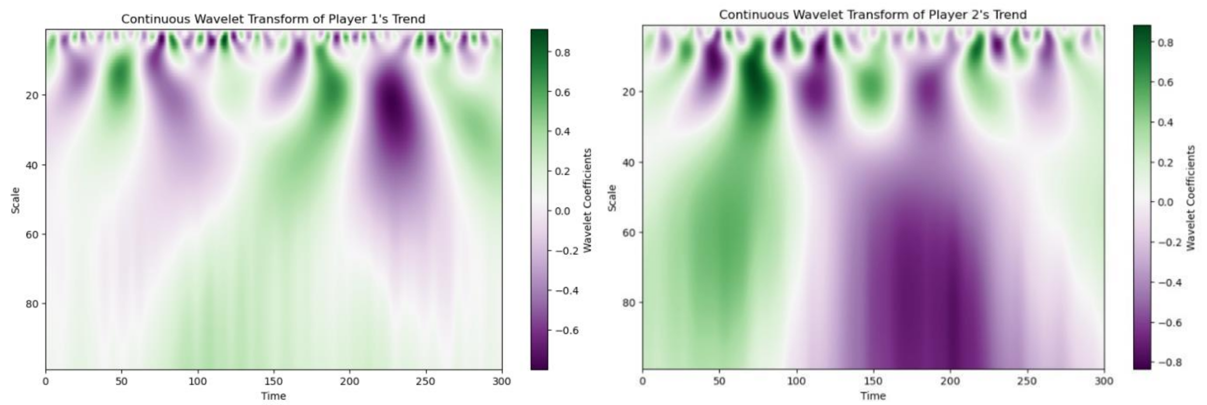

Figure 5. Wavelet coefficient plot

However, the too-dense wavelet fraction sequence still increases the difficulty in visualizing the momentum change, namely the change of players' performance. We further obtain the wavelet coefficient graph. This kind of graph can analyze the change of players' momentum in a longer time dimension relatively simply and clearly [7]. For example, in the figure, the momentum single point data of the players in the early stage of the second round shows an increasing trend over time, while the momentum single point data in the middle and late stage shows a decreasing trend over time.

3.4. Model significance

This quantitative momentum scoring model has a wide range of applications in tennis. It is not only able to predict the change of player's performance in the whole match and provide instant analysis data for coaches, but also provide decision support for the formulation of match strategy.

Through the model's real-time analysis of their own players' game data, coaches can clearly understand the players' momentum changes during the game. This change may be reflected in the player's batting quality, running ability, reaction speed and many other aspects. When the player is in the stage of rising momentum, coaches can encourage the player to maintain the state and continue to play advantageously; while when the player's momentum drops, coaches can make timely adjustments, such as changing tactics and adjusting the player's mentality to cope with the unfavorable situation in the game.

The model can also instantly analyze the performance of opponent players. By comparing the momentum changes of both players, coaches can determine the strengths and weaknesses of their opponents, so as to formulate more targeted game strategies. For example, when it is found that the opponent's player's momentum drops significantly at a certain stage, coaches can seize this opportunity to strengthen the offense or change the game tempo in order to strive for more scoring opportunities.

The analytical results of the model can also provide guidance for athletes' training. Through long-term tracking and analysis of players' game data, coaches can discover players' shortcomings in technology, physical fitness, psychology, etc., so as to formulate a more personalized training plan to help players improve their comprehensive strength.

4. Analyze momentum and the nature of the game

4.1. Correlation analysis between momentum and competition

This study will investigate the randomness of the momentum and the correlation between the momentum and the results of the game in order to verify the validity of the momentum model. The next step will investigate the correlation between the momentum data and the race scorer data in terms of single point data and the overall trend.

First, we calculate that the accumulated momentum of a total of 31 matches between 1301 and 17011 will calculate that there are four mismatches, with an efficiency of 87.1%.

4.1.1 Unit time data analysis

Considering that tennis game data records data by scoring time node, this study firstly conducts correlation analysis for momentum data and its indicator data and scoring results from the time perspective, as the data of each unit time node is the entry point and the data are all discrete data, this study will use Spearman correlation coefficient analysis method.

Given that Spearman's coefficient is suitable for rank correlation analysis, it can be used to evaluate the correlation between two or more ordered variables, and it is insensitive to outliers, suitable for discrete data The paper chooses Spearman coefficient correlation analysis.

Spearman correlation coefficient indicates the direction of correlation between X(independent variable) and Y(dependent variable)[8]. If Y tends to increase as X increases, Spearman's correlation coefficient is positive. If Y tends to decrease as X increases, Spearman's correlation coefficient is negative.

$$\rho=\frac{\sum_{i=1}^{n}\left(R_i-\bar{R}\right)\left(S_i-\bar{S}\right)}{\sqrt{\sum_{i=1}^{n}\left(R_i-\bar{R}\right)^2\sum_{i=1}^{n}\left(R_i-\bar{R}\right)^2}} \tag{17}$$

In the formula, R_i, S_i represent the values of the observed values i respectively. $\bar{R},\bar{S}$ represent variables' average value.

This study constructs a specific formula for calculating momentum. At the same time, this study deeply analyzes the correlation between momentum and match scores at a single time point and conducts a correlation analysis between momentum data and its indicators and match scores.

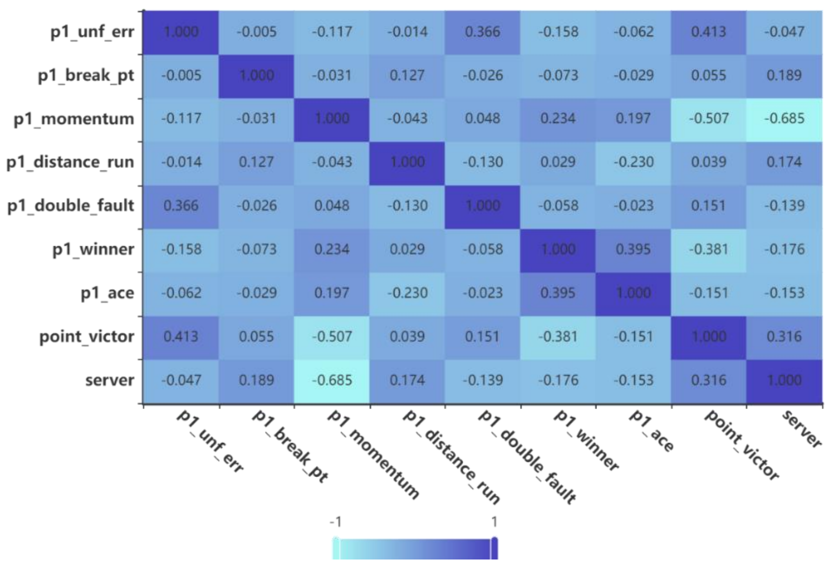

Figure 6. Heatmap of correlation coefficients of various indicators

As shown in Figure 6 Heat map of Spearman's correlation coefficient between multiple indicators. The Spearman correlation coefficient between momentum and score is 0.507, and there is a good correlation between the two, so momentum has an impact on the game [9].

4.1.2 Trend correlation

In order to verify our conclusion and increase the rigor of the paper, we used Kendall for secondary correlation analysis. Kendall correlation analysis is a non-parametric statistical method used to measure the correlation between two variables. It is used to study the hierarchical relationship between two variables, that is, the relative size of the variable rather than the specific value. Let X and Y be momentum and score.

To two elements of X and Y (X_i, Y_i)和(X_j, Y_j),if

$$X_i > X_j \ and \ Y_i > Y_j \ or \ X_i < X_j \ and \ Y_i < Y_j \tag{18}$$

Then X and Y are consistent.

if

$$X_i > X_j \ and \ Y_i < Y_j \ or \ X_i < X_j \ and \ Y_i > Y_j \tag{19}$$

Then X and Y are inconsistent.

When calculating the relationship between the point-won indicator and the momentum, the influence of the same element on the final statistical value is not considered, and the formula Tau-c is used.

$$\eta = \frac{C - D}{0.5N^2 \frac{M-1}{M}} \tag{20}$$

C means that the two indicators have the same number of elements (two elements are a pair), D means that there is an inconsistent number of elements in the two indicators, M means the smaller number of rows and columns, and N means the number of elements.

The analysis steps are as follows:

Step 1:

First, the significance relationship of the statistic is tested to determine whether the P-value is significant ($P<0.05$). If it is significant, it indicates that the data is consistent.

Step 2:

Then, the positive and negative direction and correlation degree of Kendall coefficient are analyzed.

Step 3:

The analysis results are summarized, and the conclusion is concluded: the momentum and the competition have strong correlation. Table 3 below will show the numerical results of the Kendall's W analysis.

Table 3. Kendall's W analysis results

name	Rank average	median	Kendall's W coefficient	X^2	P
momentum_p1	1.002	3.477	0.997	299	0.000***
p1_points_won	1.998	76.5			

Kendall's coefficient of concordance test is to analyze the overall (all data) correlation: the overall data significance P-value is 0.000***(***, **, and * represent the significance levels of 1%, 5%, and 10%, respectively), the level of extremely significant, reject the null hypothesis, so the data is consistent, the model's Kendall's coefficient of concordance W-value of 0.997, the correlation is basically the same degree.

4.2. Examine randomness of momentum and the games

In order to test whether the obtained kinetic data results are random data and to further determine the validity of the kinetic model, this paper will conduct a randomness test for the kinetic data and race results

This paper begins to explore game volatility and score randomness by testing the two variables for randomness using run analysis [10, 11], a statistical method used to test sequence randomness.

$$z=\frac{R-\left(\frac{2n_1n_2}{n_1+n_2}+1\right)}{\sqrt{\frac{2n_1n_2\left(2n_1n_2-n_1-n_2\right)}{\left(n_1+n_2\right)^2\left(n_1+n_2-1\right)}}} \tag{21}$$

Table 4. Runs test

name	Sample size	z	P
momentum_p1	301	-16.57	0.000***
p1_points_won	300	-17.234	0.000***

As Table 4 above shows the data results of the Runs test.

Based on the variable momentum_p1, the significance P value is 0.000***(***, **, and * represent the significance levels of 1%, 5%, and 10%, respectively), There is significance in the level, rejec

ting the null hypothesis; Based on variable p1_points_won, the P value is 0.000***(***, **, and * represent the significance levels of 1%, 5%, and 10%, respectively), The null hypothesis is rejected.

To sum up, it can be shown that the change of momentum is not random but has a high correlation with the score of the player.

5. Conclusion

Through an in-depth study of momentum, this paper successfully constructs a specific formula for momentum calculation and analyzes in detail the close relationship between momentum and match score at a single time point. Further, we conducted a comprehensive correlation analysis of momentum data and its related indexes with match scores, which helps to understand more deeply the important role of momentum in the process of the match and provides valuable references for research and practice in related fields.

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