Momentum in Tennis Echoes in each Bounce

Yifei Cheng [1, a], Linhui Zhao [2, b], and Jiexi Lian [1, c]

[1] School of Instrumentation and Optoelectronic Engineering, Beihang University, College Street, Haidian District, China;

[2] School of Software, Beihang University, College Street, Haidian District, China;

[a] 21373149@buaa.edu.cn, [b] 21373147@buaa.edu.cn, [c] 21371127@buaa.edu.cn

Abstract. The 2023 Wimbledon Gentlemen's final unfolded as a remarkable battle, characterized by momentum shifts. However, it is challenging to measure momentum and its effect on the events during the match. This article primarily focuses on how to quantify and evaluate momentum, predict the swings of the match, test the generality and provide useful advice to players and coaches. Firstly, we conduct data pre-processing by removing outliers on the given data according to the tennis rules. Next, in order to identify which player is performing better, we select 10 secondary indicators based on Spearman Correlation Coefficients, such as distance and rally_count from two aspects: technique and physiology. Then, we combine CRITIC method to calculate the weights of related indicators and TOPSIS method to evaluate the performance. The result indicates that the model can capture the flow of the match and Carlos Alcaraz performs better by a higher momentum of 0.06 in the given data with match_id of 2023-wimbledon-1301. Then, to assess the coach's claim regarding the role of momentum in the match, we establish a model for on-court situation changes using statistical methods and compare it with CRITICTOPSIS model. By comparison, we conclude that the change in momentum trend shows a 59% correlation with the outcome of the next point and there is a clear correlation between the changes in Momentum and on-court situation. That is to say, momentum do play a role in the match.

Keywords: CRITIC-TOPSIS, Momentum.

1. Introduction

Due to the enduring use of a unique scoring system of tennis, illustrated in Figure, predicting the match's flow becomes a challenging task. The 2023 Wimbledon Gentlemen's final showcased Alcaraz's triumph, marking a significant defeat for Djokovic. The match unfolded as an extraordinary battle, characterized by pronounced momentum shifts. The attribution of these play swings to the concept of "momentum" adds complexity to their measurement and understanding, occurring over individual points or entire matches.

Therefore, understanding and quantifying momentum in tennis carry significant implications for analyzing player performance and refining strategic approaches during matches, shedding light on the dynamics that contribute to the excitement and competitiveness of the sport.

To tackle the challenge of quantifying momentum in tennis is of great significance, providing effective strategies aimed at aiding coaches and players and predicting the flow of play. The following work needs to be done:

- Develop a model that tracks the in-game performance of tennis players, indicating their relative superiority and performance advantage, with consideration for the higher probability of winning points/games while serving.
- Utilize the model/metric to evaluate the claim that fluctuations in play and success runs by a player are random, challenging the notion of momentum's influence in tennis matches.
- Develop a predictive model and identify indicators for anticipating shifts in play. Subsequently, advise players entering new matches against different opponents.
- Evaluate the developed model on additional matches to assess its predictive accuracy for swings, identify potential factors for improvement in case of poor performance, and examine the model's generalizability across various conditions.

- Offer advice on preparing players to respond to events influencing the flow of play to coaches in the form of a memorandum.
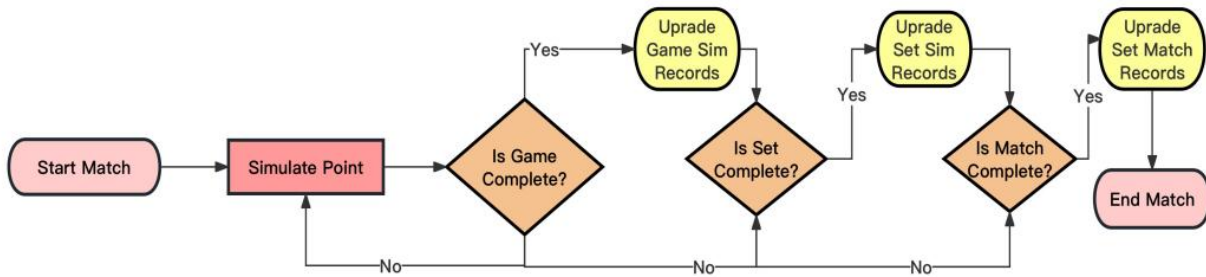

Fig. 1 Tennis Rules

2. Assumptions and Justifications

To simplify the considered problems, we make the following basic assumptions, which are appropriately justified. Other assumptions based on different models will be outlined in the subsequent sections related to the model.

Assumption 1: Assuming players are independent entities, their momentum is not influenced by each other.
Justification: During matches, players' technical performance indicators such as hitting winners or unforced errors influence the momentum of both themselves and their opponents. To simplify the analysis of the model, we only consider the momentum changes of the player.
Assumption 2: Assuming in all matches, aside from the metrics provided in the dataset, players share identical external conditions.
Justification: Given the complexity of external factors in reality, accurately estimating the impact of strategies on each player becomes challenging. Consequently, we adopt the assumption that players share identical external conditions, except for the provided metrics.
Assumption 3: Assuming the physiological indicators of both players are similar or close at each specific moment.
Justification: Due to the challenge in quantifying and analyzing exhaustion experienced by players, potentially influencing the quality of shots or strategic decisions, we disregard it in the analysis.

3. CRITIC-TOPSIS Evaluation Model of the Performance

This chapter evaluates the performance of the players by the metric called momentum, momentum is identified from two aspects: physiology and technique. Based on the given data, an CRITIC-TOPSIS model was established to calculate the weights of indicators, achieving a comprehensive evaluation of the performance of the players.

3.1 Indicator Selection

In order to establish the most suitable evaluation model for assessing the performance of the players, the metric called momentum was chosen and indicators were identified from two aspects, including physiological and technique indicators. 13 indicators in Table 2. were first chosen by referring to the tennis rules and then 10 indicators were further filtered by correlation analysis.

Table 1: Indicators

Indicator	Explanation
server	server of the point
serve_no	first or second serve
ace	an untouchable winning serve
winner	an untouchable winning shot
double_fault	missed both serves and lost the point
unf_err	an unforced error
net_pt	made it to the net
net_pt_won	won the point while at the net
break_pt	an opportunity to win a game another player is serving
break_pt_won	won the game another player is serving
break_pt_missed	missed an opportunity to win a game another player is serving
distance	player's distance ran during point (meters)
rally_count	number of shots during the point

3.1.1 Technique

In tennis matches, technical indicators refer to quantifiable metrics evaluating a player's performance, including parameters such as shot power, accuracy, speed, and more. Technical indicators can be divided into serving indicators (*Se*), scoring indicators (*Win*), and losing indicators (*Lose*). The scoring and losing indicators can be represented by the Venn diagram in Figure 2.
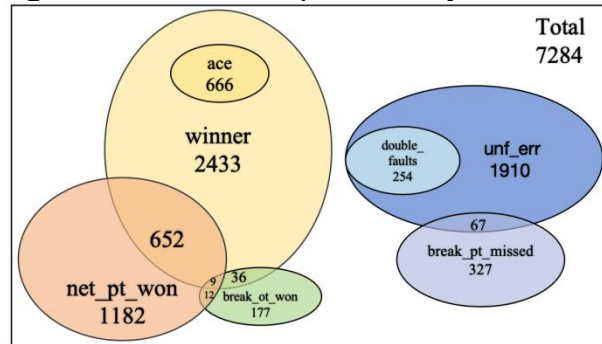

Fig. 2 Technical Indicators

The data for these is obtained from the provided database through statistical methods. The Venn diagram illustrates that certain technical indicators for players are correlated. For instance, a particular point can be both a *winner* and a *break_pt_won*.

3.1.2 Physiology

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Physiological indicators in tennis matches refer to metrics such as heart rate, respiratory rate, and lactate concentration, providing insights into players' physical endurance, fatigue levels, and recovery capacity. These indicators aid in training and strategic planning. Physiological indicators (*Ph*) encompass metrics such as running distance (*distance*) and rally count (*rally_count*), offering insights into a player's physical exertion and activity during a tennis match.

3.1.3 Indicator Correlation Analysis based on Spearman Correlation Coefficients

To further refine the selection of indicators, we conducted Spearman correlation analysis on the initially chosen 13 indicators, ultimately confirming 10 key metrics.

Firstly, we compiled the scoring situations corresponding to all technical indicators of players in each match, applying them to the correlation analysis. By conducting Spearman correlation co-efficient analysis, we obtained the correlation coefficients between each indicator and *point_victor*, the result is showed in Figure 3(a).

Upon observation, it is evident that all technical indicators are significantly correlated with *point_victor*, indicating that these technical indicators influence a player's scoring situation.

Specifically, scoring indicators such as server and *p1_points_won* are positively correlated with *point_victor* (at this point, representing player 1), while miss indicators like *double_fault* and *unf_err* are negatively correlated with *point_victor*. Therefore, all technical indicators can be considered as measures of momentum. It is noteworthy that the correlation coefficient between serving indicators and *point_victor* is remarkably high, indicating a more pronounced impact of serving on scoring. After calculation, the serving success rate of all players in the dataset reached 67.3119%, validating our conclusion.

Next, we conducted Spearman correlation coefficient analysis on individual match indicators, taking match1301 as an example. The correlation coefficients between each indicator and *point_victor* are in Figure 3(b).
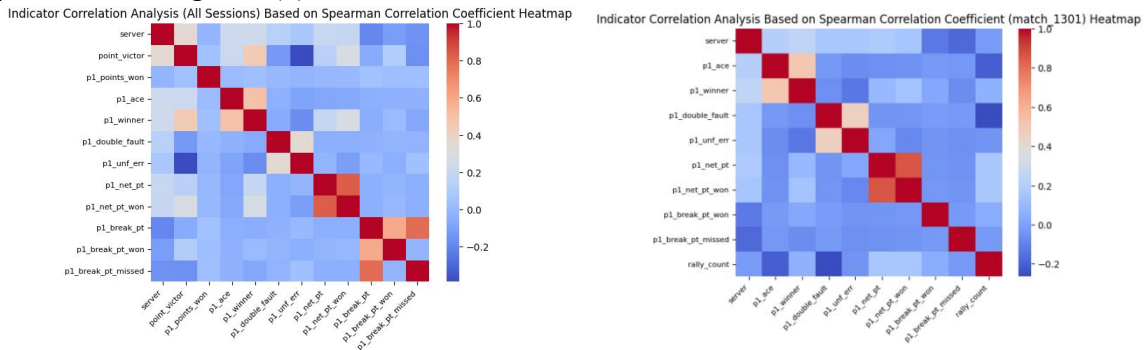

Fig. 3 (a) Indicator Correlation Analysis (All Sessions) Heatmap
(b) Indicator Correlation Analysis (match 1301) Heatmap

By observing, we found that some indicators significantly correlated in the overall correlation analysis did not exhibit significant correlations in individual matches. For instance, *break_point* did not show significant correlation in this match, possibly because the changes brought by indicators like *break_point* affect both players, making it less relevant for the specific match analysis. Therefore, we choose not to include *break_point* as our indicator in this match analysis. Additionally, *rally_count* shows a significant positive correlation with *point_victor*, indicating that p1 possesses strong multi-rally capabilities and can gain an advantage in extended rallies.

Therefore, the final set of 10 selected indicators includes: **server, ace, winner, double_fault, unf_err, net_point, net_point_won, break_point_won, break_point_missed, rally_count**.

3.2 Data Pre-processing

As we need to utilize the COMAP official dataset "Wimbledon_featured_matches.csv," which includes data for over 7000 shots, there is a possibility of data anomalies. Therefore, we conducted preprocessing on this data by Removal of Outliers before constructing the model.

• **Processing of Score Situations and Basic Technical Statistics Comparison**

This system can be used for many types of airplanes, and it also solves the interference during the procedure of the boarding airplane, as described above we can get to the optimization boarding time. We also know that all the service is automate.

• **Processing of Running Distance, Rally Count, and Serving Speed per Point**

In tennis matches, as long as the server does not commit a double fault, the running distance is not zero, the number of rallies per point is greater than or equal to 1, and the serving speed is not "NA." We observed outliers in these three indicators in the dataset. Therefore, we removed these data points during data processing.

• **Processing of Serving Width, Serving Depth, and Return Depth**

When the server does not commit a double fault, if the serve width and serve depth appear as "NA", we attribute it to technical reasons and can delete such data. It's worth noting that there are many "NA" values in the return depth, which may not be data anomalies but rather due to the fast and angled serves of male players, making it difficult to return, hence resulting in many "NA" values.

3.3 Combination of CRITIC and TOPSIS

We integrated the CRITIC and TOPSIS methodologies, leveraging the CRITIC approach to derive weights for the TOPSIS method. This combined approach enhances the objectivity of our evaluation, resulting in more robust and comprehensive assessment outcomes. The relation is showed in Figure 4.
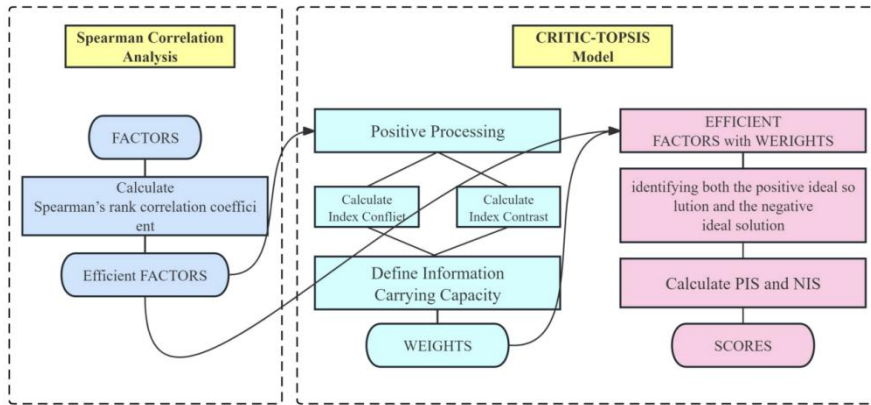

Fig.4 Combination of CRITIC and TOPSIS

3.3.1 Calculation of Indicator Weights

Weighting models is essential to evaluate the different contribution of the indicators.Conse-quently, CRITIC model is adopted to calculate the weight vector in this section.

After the forward processing of the data, the following matrix is obtained, where X_{mn} represents the value of the nth evaluation index in the mth sample.

$$X = \begin{pmatrix} x_{11} & \cdots & x_{1n} \\ \vdots & \ddots & \vdots \\ x_{m1} & \cdots & x_{mn} \end{pmatrix} \#(1)$$

To eliminate the influence of dimensions, it is necessary to standardize the data. For positive indicators, the formula is as follows:

$$x'_{ij} = \frac{x_{ij} - \min(x_j)}{\max(x_j) - \min(x_j)} \#(2)$$

For reverse indicators, the formula is as follows:

$$x'_{ij} = \frac{\max(x_j) - x_{ij}}{\max(x_j) - \min(x_j)} \#(3)$$

Step 1 Calculate the contrast of the indicator: the variability of the indicator is expressed by the standard deviation of the data in each column. The formula is as follows:

$$S_j = \sqrt{\frac{\sum_{i=1}^{m} (x_{ij} - \bar{x}_j)^2}{n-1}} \#(4)$$

Step 2 Calculate the conflict of indicators: the conflict of indicators is expressed by the correlation coefficient. The formula is as follows:

$$A_j = \sum_{i=1}^{n} (1 - r_{ij}) \#(5)$$

Step 3 Define the information carrying capacity: conflicting usage is represented using the correlation coefficient. The formula for calculating the correlation matrix of the indicators is:

$$R = \frac{\sum_{j,k=1}^{n} (x_{ij} - \bar{x}_j)(x_{ik} - \bar{x}_k)}{\sqrt{\sum_{j=1}^{n} (x_{ij} - \bar{x}_j)^2 \sum_{k=1}^{n} (x_{ik} - \bar{x}_k)^2}} \#(6)$$

The information quantity is given by:

$$C_j = S_j \times A_j \#(7)$$

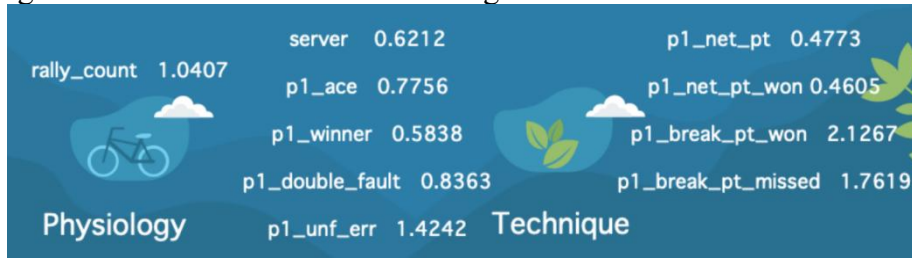Average weights are calculated and showed in Figure 5.

Fig.5 Average weights

3.3.2 Reflect the Differences between Players

Step 1 Positive normalization of the original data matrix: the common types of data evaluation indicators include large-type, small-type, medium-type, and interval-type indicators, and they need to be transformed into large-type indicators. The function used for transformation is not unique.

Step 2 Positive matrix standardization: assuming there are n evaluation objects and m positive evaluation indicators, the positive evaluation matrix formed by them is as follows:

$$X = \begin{pmatrix} x_{11} & \cdots & x_{1n} \\ \vdots & \ddots & \vdots \\ x_{m1} & \cdots & x_{mn} \end{pmatrix} \#(8)$$

So for the standardized matrix Z, each element in Z can be denoted as:

$$z_{ij} = \left. x_{ij} \middle/ \sqrt{\sum_{i=1}^{n} x_{ij}^2} \right. \#(9)$$

Step 3 Calculate the score and normalize: Defining the maximum value Z^+, the minimum value Z^-, and the distances D_i^+ and D_i^- for the i-th $(i = 1, 2, \ldots, n)$ evaluation object:

$$Z^+ = \max_{j=1} Z_j \quad Z^- = \max_{j=1} Z_j \#(10)$$

$$D_i^+ = \sum_{j=1}^{m} (Z_{ij} - Z_j^+)^2 \quad D_i^- = \sum_{j=1}^{m} (Z_{ij} - Z_j^-)^2 \#(11)$$

This can be used to calculate the non-normalized score for the i-th evaluation object.

$$S_i = \frac{D_i^+}{D_i^+ + D_i^-} \#(12)$$

Clearly, $0 \le S_i \le 1$, and as S_i increases, D_i^+ decreases, meaning it gets closer to the maximum value. Therefore, the normalized score is:

$$\widetilde{S}_i = \frac{S_i}{\sum_{i=1}^{n} S_i} \#(13)$$

3.4 Analysis of Results

Based on the evaluation model established above, We measure the current player's momentum based on the performance of both players in the past 15 shots and obtain good processing results in Figure 6.

It can be observed that the momentum of both players is continuously changing as the game progresses. By comparing the situation of each point in the dataset with the curves , we found that

- **The potential energy curve in each set generally corresponds to the overall score trend of that set.**

    Our model can identify when a player performs better at a specific time

- **The player's superior performance is associated with a larger momentum advantage over the opponent.**

    When a player's momentum is larger during a specific time interval, the difference in momentum between the player and the opponent is also larger, and the player's performance during that period is better.

In a nutshell, the average momentum of Carlos Alcaraz is 0.53 while the average momentum of Nicolas Jarry is 0.47. So, Carlos Alcaraz performs better by a higher momentum of 0.06 in the given data with match_id of 2023-wimbledon-1301.
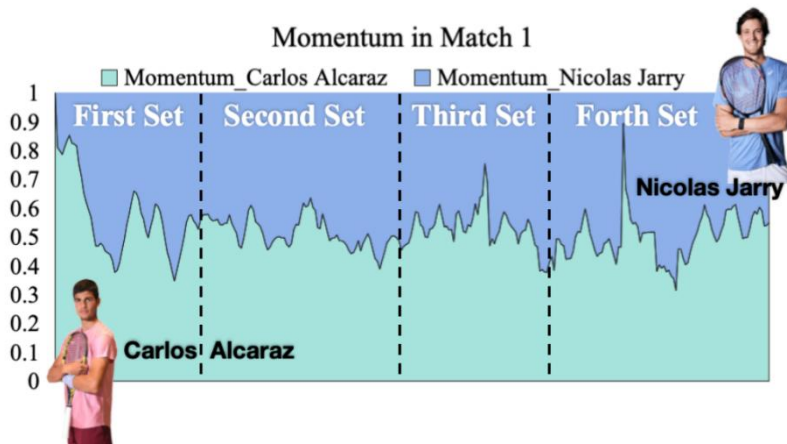

Fig.6 Momentum in Match 1

4. Assessment of Momentum's Role

To assess the coach's claim regarding the role of momentum in the match, we establish a model for on-court situation changes using statistical methods and compare it with the model of performance. If the trends of both models remain consistent over a relatively long period, then we believe that Momentum does play a role in the match, and the fluctuations in player performance are not random.

4.1 Establishment of Situation-changing Model

To capture the on-court situation changes in tennis matches, we have chosen the most intuitive indicator: the evolution of the score. If a player wins significantly more points than the opponent during a certain period, they are considered to be in control of the game at that time. We believe that the Momentum of the player winning more points will increase during this period.

We define the on-court situation (Δ) as the ratio of the points won by both players in the last 15 points (including the current score) to the total points won by both players before the current score (including the current score). Formally, this is expressed as:

$$\Delta S = \frac{point\_15}{point\_total} \#(14)$$

For 1, the perceived on-court situation change (ΔS_{p1}) is defined as:

$$\Delta S_{p1} = \frac{\dfrac{\Delta point\_p_1}{\Delta point\_p_1 + \Delta point\_p_2}}{\dfrac{point\_p_1\_total}{point\_p_1\_total + point\_p_2\_total}} \#(15)$$

By plotting the above formula, we can visualize:

4.2 Contrast of Models and Analysis

Comparing Figure 6 with Figure 7, the direct result is showed in Figure 8 and the trend is showed in Figure 9 . We observe that in the majority of the game situations, the flow of Momentum is related to the flow of Δ .
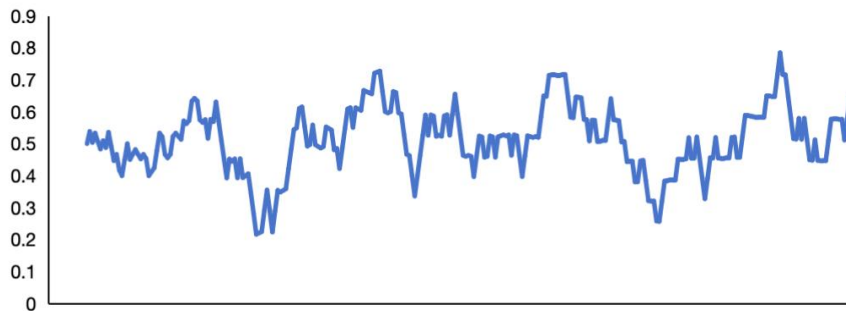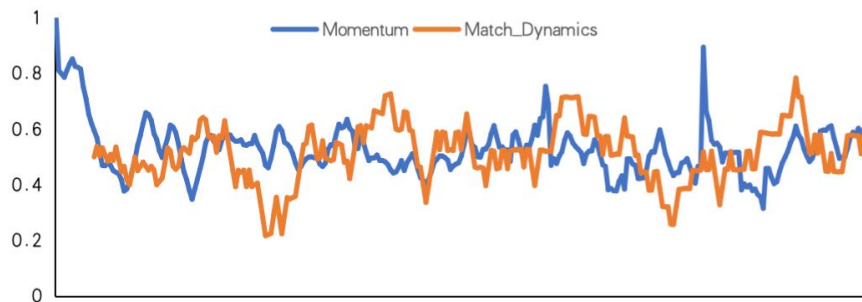

Fig.7 Match Dynamics

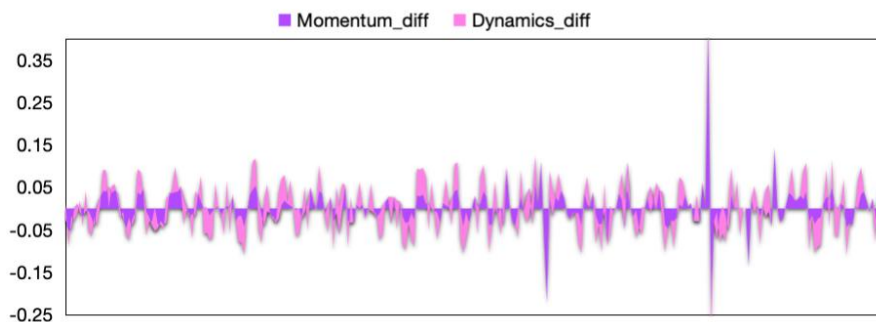Fig.8 Momentum vs Match Dynamics

Fig.9 the trend of Momentum and Match Dynamics

In other words, the trend of Momentum is generally consistent with the trend of on-court situation changes, indicating that Momentum does play a role in the game. This reflects that players indeed experience Momentum during the match, and the increase or decrease in Momentum corresponds to the respective increase or decrease in scores during the current time period. Through the analysis of the 1301 match, we observe that :

- **There is a clear correlation between the changes in Momentum and on-court situation dynamics:** the trends of change for the two variables follow similar paths.
- **The change in momentum trend shows a 59% correlation with the outcome of the next point:** a decrease in momentum corresponds to losing the point, while an increase in momentum correlates with winning the point, demonstrating a reasonably good fit.

5. Sensitivity Analysis

To assess the sensitivity of model outputs to input parameters, providing a better understanding of the model's behavior, stability, and reliability, we made Sensitivity Analysis.

(a) point 15   (b) point 16

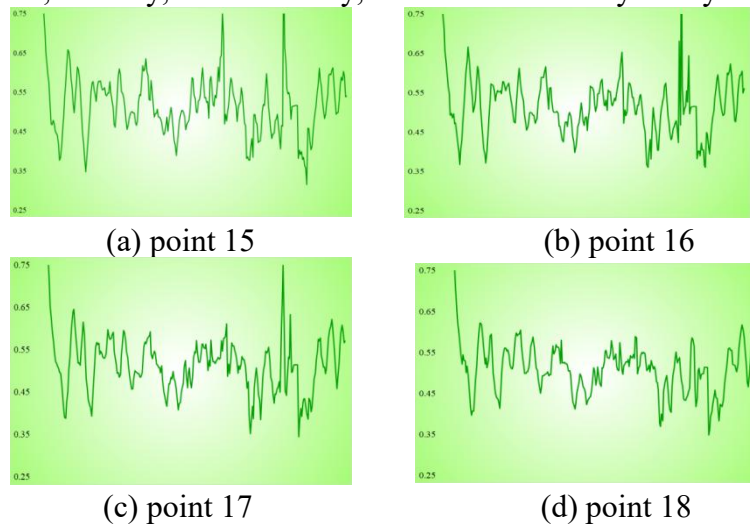(c) point 17   (d) point 18

Fig. 10 on-court situation changes

- In question one, we measured Momentum based on various player indicators, assuming each 15 points form a stage. Now, we conduct sensitivity analysis by varying the score interval (x) from 15 to 18 in increments of 1. The results show that the player's indicators' influence on Momentum remains stable, indicating they are minimally affected by changes in the set score intervals.
- In question two, we assessed on-court situation changes based on the score as an interval. Assuming each 15 points form a stage yielded positive results. Sensitivity analysis, varying the score interval (x) from 15 to 18 in increments of 1, showed a stable match dynamics trend. This indicates that measuring on-court situations through changing score trends is robust and minimally affected by variations in set score intervals.

(a) point 15   (b) point 16
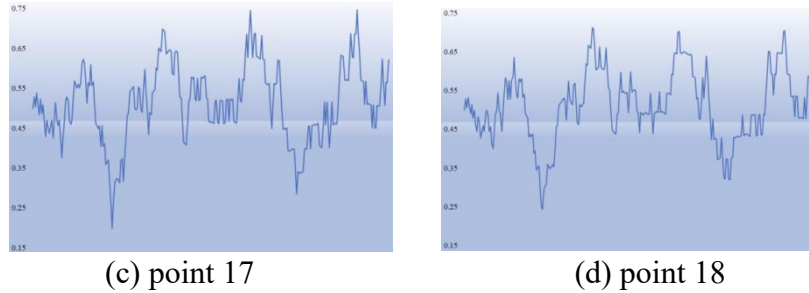
(c) point 17   (d) point 18
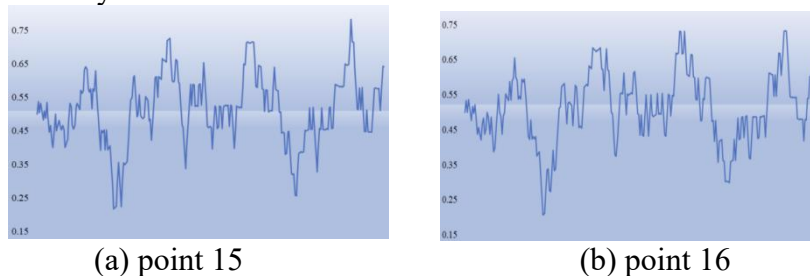
Fig. 11 on-court situation changes

In summary, the models for measuring Momentum and on-court situation changes appear to be stable. They show minimal variation with changes in set score intervals, indicating that our assumptions have simplified the models, ensuring their robustness.

6. Literature Review

Tennis is an enduring sport known for its unique scoring rules, providing an entertaining spectacle. Players may sense momentum during prolonged matches, influenced by factors[1] like break points and crucial service games. Therefore, gaining momentum is crucial in tennis, offering players a sense of control and exerting pressure on opponents to regain control [2] and strive for victory.

There is a divergence of opinions among academics and sports professionals regarding the existence of momentum in tennis. Peter O'Donoghue & Emily Brown (2009) [3] argue that momentum in tennis is a misconception, asserting that it does not impact player performance. Conversely, Ben Moss & Peter O'Donoghue (2015) [4] posit that momentum affects players' offense and psychological support. Over time, expert perspectives on momentum may evolve. A deeper analysis by Philippe Meier (2020) [5] suggests that psychological and strategic momentum may coexist, especially after converting break points.

Tennis coaches also hold diverse views on momentum. British tennis coach Alistair Higham asserts that momentum is a hidden force in tennis, progressing through five distinct stages, requiring players to identify their current stage. Chuck Kriese believes that tennis is more akin to a dynamic game than any other sport. [6]

After analyzing momentum, Kselz(2013) [7] proposes techniques to control momentum on the tennis court. However, their approach lacks a definitive measure of momentum, relying on match experience to assess its existence and how to manage it. We integrate their work, considering various indicators in tennis matches, and propose creative strategies.

7 Model Evaluation and Further Discussion

7.1 Strengths

- The selected evaluation metric system in this article is scientific and accurate. We strictly adhere to the metrics provided in the dataset for analysis, ensuring the accuracy of our results.
- The article adopts the CRITIC method to determine metric weights. Furthermore, it assesses Momentum and situational changes in stages, defining each stage as every 15 points scored by a player. This approach not only acknowledges the significance of subjective factors but also demonstrates the inherent correlations among metrics, contributing to a more comprehensive and scientific establishment of the evaluation model.
- The weights assigned to the indicators in the selected predictive model in this article are largely consistent with the weight values used in our established evaluation model. This provides evidence that the evaluation model we employed is accurate, reasonable, and capable of providing a relatively precise assessment for multiple matches.

- During the data preprocessing in this article, missing values in certain indicators were directly handled through deletion based on the technical metrics of tennis matches.This approach enhances the accuracy and simplicity of the model.

7.2 Weakness

- The model constructed in this article does not take into account the impact of unforeseen factors. While the impact may be minimal, incorporating the influence of emergency situations would contribute to a more accurate model.
- This article solely examines the factors influencing Momentum in the context of tennis and its changing trends. It provides evidence for the rationality of various indicators and the universality of the predictive model. However, there might be other sports events, such as badminton or table tennis, that have not been considered.

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