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Quantitative Study of Tennis Match Momentum and Flow Based on Machine Learning

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Abstract. Momentum is a critical factor influencing the dynamics and outcomes of tennis matches. To enhance the predictive accuracy of these fluctuations, this study utilizes machine learning techniques and big data analytics to improve the prediction of these fluctuations. The study conducts a comprehensive analysis to identify the correlation between a player's momentum and 14 key features in a tennis match. An optimized BP neural network model, based on Levenberg-Marquardt theory, was developed to predict match flow and quantify the stalemate degree. The model is evaluated using a confusion matrix and ROC curve, affirming its predictive validity, where the results revealed an F1 Score and an AUC, both exceeding 0.5. With big data, this approach not only enhances the spectator experience by visualizing match dynamics but also aids in strategy development and training optimization for competitors. This research highlights the practical applications of quantitative modeling in understanding and forecasting the pivotal moments in tennis.

Keywords: Levenberg-Marquardt Back Propagation, Neural Network, Quantitative Model, Big Data.

1. Introduction

Tennis, which originated from lawn tennis in Birmingham, England in the late 19th century, has evolved into a globally popular competitive sport. Matches often feature dramatic swings in momentum, a concept long recognized in sports, where one player may suddenly gain an advantage [1]. Quantifying such momentum is challenging due to its intangible nature but is crucial for enhancing the spectator experience and aiding players in strategy development and training. Traditional analysis methods struggle to capture the dynamic changes and psychological states during matches, highlighting the need for advanced, data-driven approaches to study the effects of momentum in tennis effectively.

With the current development of big data, it has become possible to use models to predict momentum. This study uses the BP neural network, based on the Levenberg-Marquardt theory [2], to quantify tennis match momentum. The method has been applied in some fields like seismic responses [3] and power consumption of hydroelectric power stations [4]. Shuo Guan and Xiaochen Wang have applied BP neural network in predicting football matches [5], which shows great performance in sports events. Hence, machine learning should make sense in tennis matches [6].

This study aims to quantify the match momentum by using features associated with data from the 2023 Wimbledon Open. As the essence of the BP neural network algorithm is the gradient descent method, the LM algorithm can be used to increase the converging speed. this study uses an LM-BP neural network to predict the flow of a match and uses the confusion matrix and ROC [7] curve to verify the momentum of a pair of players can well represent the swings of the match.

2. Quantitative Analysis of Tennis Match Momentum

The data for the 2023 Wimbledon Open is selected from https://www.comap.com. In this case, the study uses the LM-BP neural network to learn the processed data through iteration, to quantitatively evaluate the momentum of the two contestants. After that, the results are to be compared and quantify the match flow.

2.1. Indicator Analysis

Assume that the other possible indicators not provided in the given dataset are controlled unchanged. It shows that numerous indicators affect the momentum of the two players. For the convenience of the idea sorting and the following discussion, after examining and cleaning the raw data, here firstly define three comprehensive influencing factors, namely, Serve Threat Level (STL), Mentality, and Stamina. Then, classify the sub-factors shown in Figure 1:

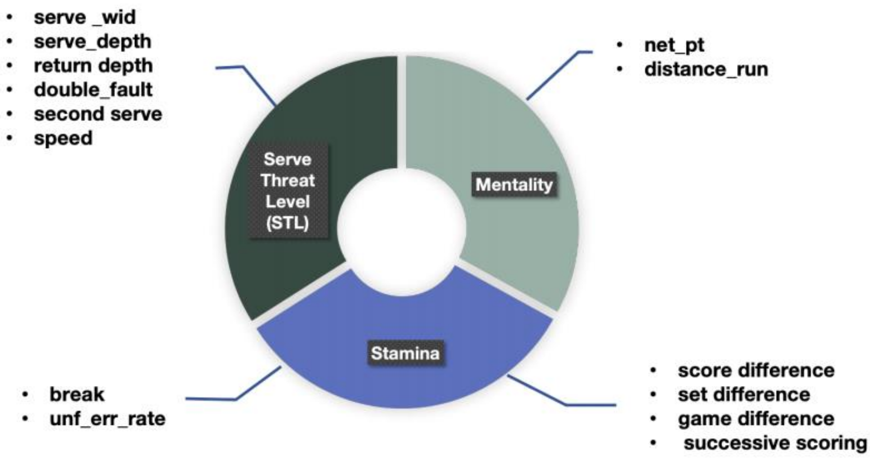

Figure 1. Indicator analysis

Since a return type [8] of "D" represents a high quality of return, i.e. a relatively low quality of serve, the depth of return is also used as a factor related to the threat level of the serve. To verify that the landing area of the serve is also related to the threat level of the serve, Figure 2 according to the probability that the return type is "D" on a certain area is developed, which shows that the landing area is highly correlated with the threat level of the serve.

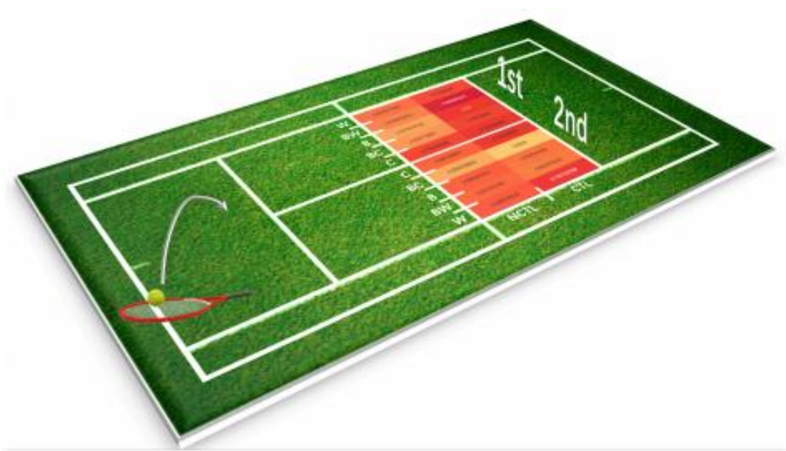

Figure 2. Serve position heat map

Considering the high variability [9] of the game state, the data used for analysis are all in units of one round. As the match progresses, both players' scores increase and their stamina decreases, so the score difference per point and running distance difference is more suitable to describe the difference in their momentum. As for the combined factor "Mentality", the level of the current point is influenced by the performances of players and their competitors. Similarly, it applies to the criterion "double_fault". Considering the above, the data processing methods are shown in Table 1:

Table 1: Data processing methods

Factors	Explanation	Input	
		Yes	No
successive scoring	if the player evaluated successively scored in point (i-1) and point (i-2)	1	0
break	if the player broke at the end of the game (i-1)	1	0
unf_err_rate	the rate of unforced error in the game (i-1)	N/A	N/A
serve	if the player evaluated is serving in the game i	1	0
double_fault	if there is a serve error in point (i-1)	1	0
second serve	if it is the second serve	1	0

At the same time, it is worth noticing that data in the column ‘speed’ of matches 1310 and 1311 are all denoted as “N/A”. This situation may be caused by some error in the recording system during the competition, which leads to data missing. Thus, the study chose to discard the data of the two matches in the following analysis.

Furthermore, according to the given note, the player serving has a much higher probability of winning the point. Hence, here assume the input value to be 1 if the player evaluated is serving. Otherwise, the input is defined to be 0.

Since different evaluation indexes have different scales and orders of magnitude, here standardized the data first so that each factor has the same level of influence in the neural network. At the same time, the neural network converges better using the standardized data.

2.2. Structure of LM-BP Neural Network.

Since this data is generated from actual matches, if directly fixing the scoring weights of each factor, the result may be perturbed by other random and unknown factors, thus leading to a decrease in the objectivity and accuracy of the evaluation. Moreover, the relationship between the input indicators and the target outputs is not easy to express by explicit rules. Considering the above, backpropagation is well-suited for such kind of supervised learning tasks where a labeled data set is available.

To avoid overfitting, the given data is randomly divided for training and testing with the approximate ratio of 10:3. The clarified process is shown in Figure 3:

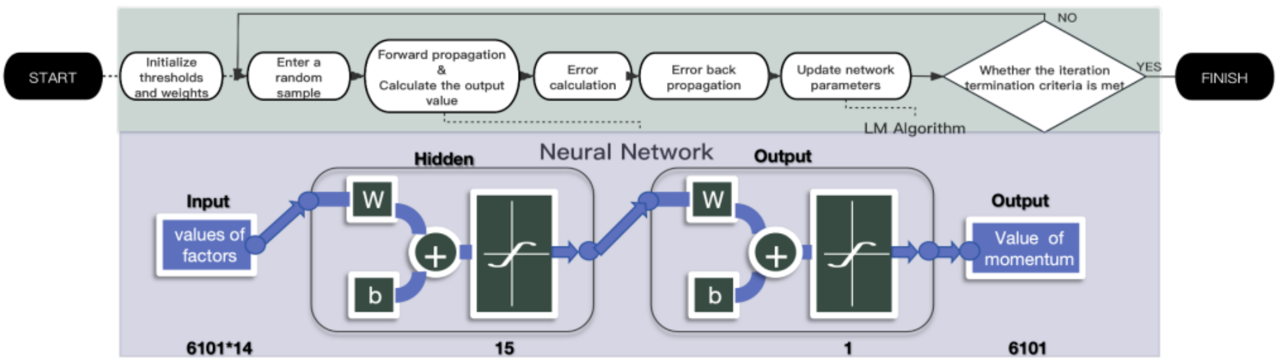

Figure 3. Flow chart of LM-BP Neural Network [10]

1. Determine the structure of the BP Neural Network. Set the number of input layers to 14, hidden layers to 15, and output layer to 1.

2. Initialize thresholds and weights. Randomly assign a value between -1 and 1 to each connection weight and threshold. Also, initialize the learning rate between the output and hidden layers to be 0.01.

3. Start forward propagation. The formulas used for the hidden layers and output layer output are shown below:

$$\text{input layer– hidden layer: } Z^l = XW^l + B^l \tag{1}$$

$$\text{hidden layer– hidden layer: } Z^l = A^{l-1}W^l + B^l \tag{2}$$

$$\text{hidden layer–output layer: } z^L = a^{L-1}W^L + b^L \tag{3}$$

4. Mean square error calculation and backpropagation. The mean square error can be calculated using the formula below:

$$E(\hat{y}) = \frac{1}{2m}\left\|\hat{y} - y\right\|_2{}^2 \tag{4}$$

Set the acceptable error to 0.001, i.e., E_{accept} = 0.001. If $E \leqslant$ 0.001, then output the predicted value. If E > 0.001, then perform the backpropagation to update network parameters, to make adjustments to meet the acceptable error.

5. Network parameters updating. To accelerate the converging speed, here introduce the LM algorithm in network parameter updating. Based on the ordinary Gaussian Newton method, the Hessian matrix is as follows:

$$H \approx J^T J + \mu I \tag{5}$$

Based on the Gaussian Newton method, the LM algorithm corrects the problem that the algorithm may not converge due to the large step size in the Gaussian Newton method by defining the new step size Δx and enhancing the robustness.

6. Iteration termination. When the number of training time reaches 1000, the iteration will stop.

3. Visualization Analysis of Match Momentum and Flow

3.1. Performance comparison

Put the processed data from 2023-wimbledon-1701 into the LM-BP neural network for evaluation. This study gets the momentum ratings of the two players for each point in Figure 4.

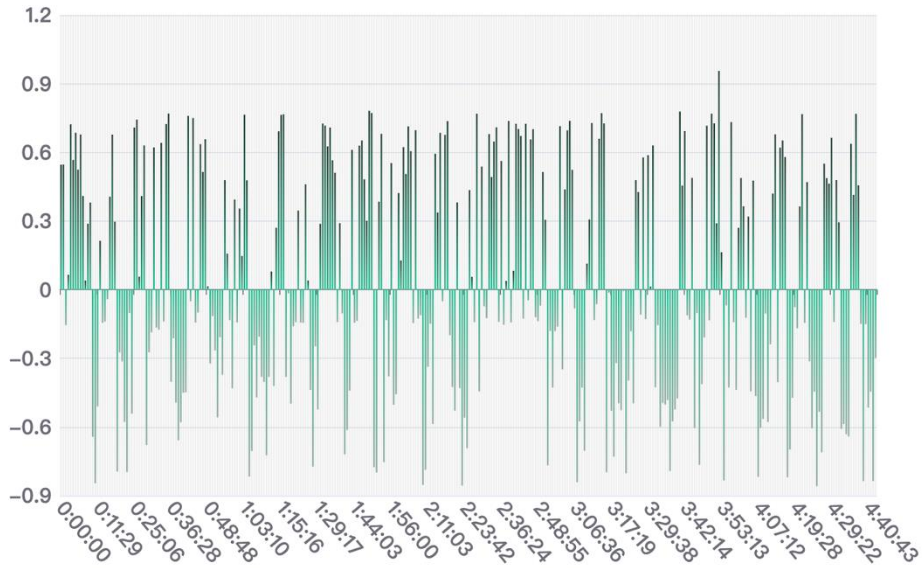

Figure 4: Visualization of momentum difference

Upon analyzing the graph, it becomes evident that the bars in the visualization consistently appear on the side of the player who performs better. This observation suggests a clear distinction between the two players in terms of their performance. The positioning of the bars on the better-performing side emphasizes the existence of a performance gap between the players.

Moreover, the length of the bars in this figure provides additional insights into the degrees of dominance exhibited by the players. Longer bars indicate a greater degree of dominance by the respective player, while shorter bars suggest less superiority. By incorporating this length-based representation, the visualization offers a more comprehensive understanding of the performance comparison.

Consequently, it effectively communicates the performance dynamics between the two players throughout the match and allows for a quick and intuitive grasp of the performance disparities, highlighting the dominant player and the varying degrees of dominance, ultimately contributing to a deeper analysis of the player's performance in the evaluated matches.

3.2. Visualization of the flow of the match

To gain a comprehensive understanding of the match dynamics, here employed a scatterplot visualization to explore the interplay between the match schedule, a player's quantitative momentum, and the stalemating level of the game situation in Figure 5.

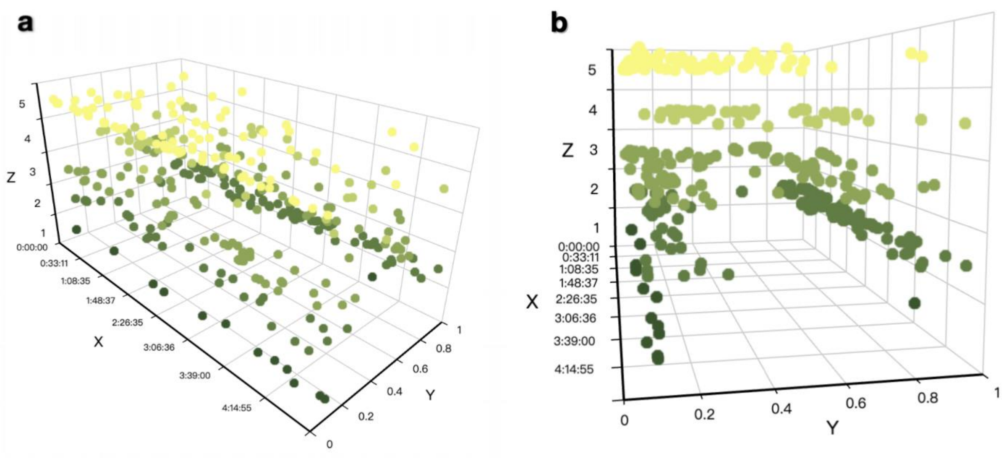

Figure 5: Visualization of the flow of match-1701 a. whole view b. z-y vision

In this visualization, the color and position of the scatter points provide insights into the stalemating level, with lighter colors and higher positions indicating a higher level of stalemating.

By analyzing the scatterplot image, meaningful conclusions about the match flow can be drawn. Specifically, when a player's momentum value deviates significantly from both 0 and 1, it suggests that the player is experiencing a similar momentum to their opponent, resulting in a tense and closely contested match. Consequently, here observe a concentration of dark-colored scatter points near the y-axis, around the value of 0.5, while the scatter points become sparser in this region. This observation aligns with the actual situation on the court, further validating the effectiveness of visualization.

3.3. Model Evaluation Analysis and Model Assessment

This study employed the regression model evaluation index to assess the performance of the model, yielding the following results as mean square error is 0.16616, and the mean absolute error is 0.33105.

These metrics serve as objective measures to evaluate the accuracy and effectiveness of the model. The obtained evaluation results, with low MSE and MAE values, suggest that this model performs well in predicting the flow of play.

While the constructed model appears to effectively capture the flow of play, it is important to address potential skepticism regarding the influence of "momentum" in the match. Some individuals question whether swings in play and runs of success by one player are truly driven by momentum or simply random occurrences.

To address this question, let’s start with a hypothesis that H_0: Swing in play and runs of success by one player are not random.

Take the match 2023-wimbledon-1701 as an example to visualize the changes in the player’s momentum differential and the changes in the actual score differential in Figure 6.

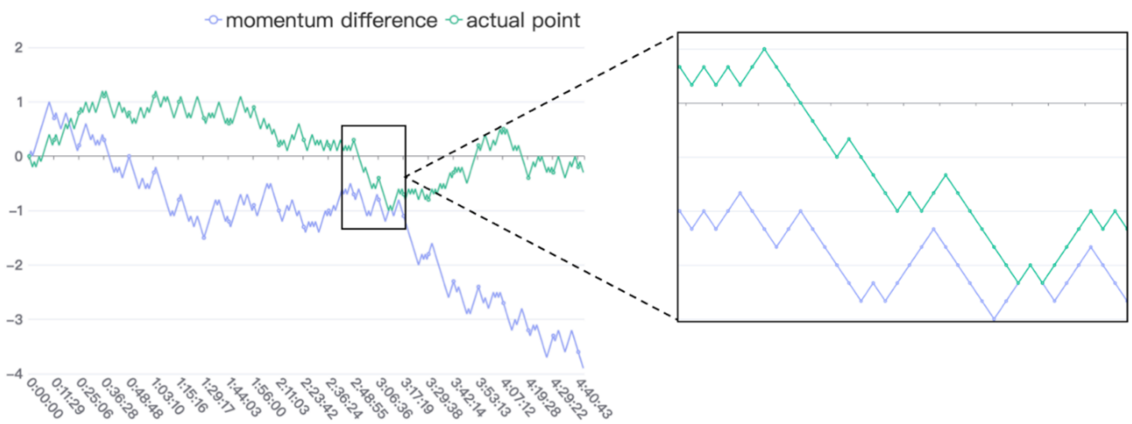

Figure 6: change of momentum vs. change in the flow of the game

The findings revealed a noteworthy observation: inflection points in the player's momentum differential coincided with inflection points in the actual score differential. In other words, significant changes in the momentum of a player were closely aligned with notable shifts in the score difference between the players.

This observation leads us to hypothesize that the alteration in the flow of the game can be attributed to corresponding changes in the player's momentum. When a player experiences a significant shift in their momentum, it appears to have a direct impact on the overall dynamics of the match, ultimately influencing the score differential between the players.

These findings provide valuable empirical evidence supporting the notion that a player's momentum plays a crucial role in shaping the course of a match. The close alignment between inflection points in momentum and score differentials strengthens the argument that changes in a player's momentum are closely linked to shifts in the flow and outcome of the game.

Next, since defining the input value of the score as 1 and otherwise 0 for the quantitative analysis of the flow of matches, here transform the problem into one of evaluating the classification effectiveness of a binary classification model.

This study introduces a confusion matrix to get a more advanced classification metric. Two statistically significant measures, ROC and AUC[11], are also used to evaluate the classification effect. The results are shown in Figure 7, Table 2, and Table 3.

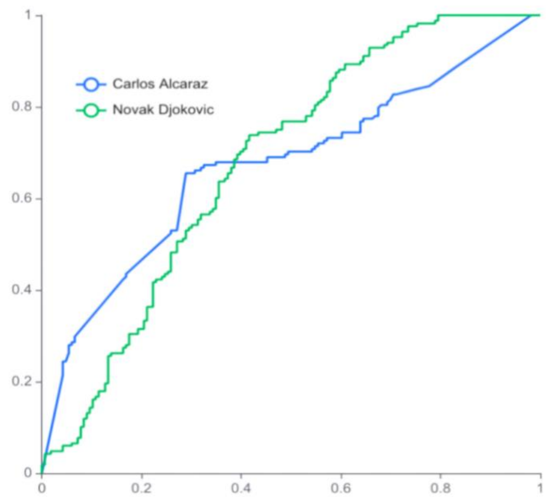

Figure 7: Model assessment

Table 2: Assessment calculation results

Accuracy	Precision	Recall	Specificity	F1 Score
0.670658683	0.689189	0.61445783	0.72619048	0.649681528

Table 3: AUC values with 95% confidence level

players	AUC	95% confidence interval upper bound	95% confidence interval lower bound
Carlos Alcaraz	0.672	0.614	0.729
Novak Djokovic	0.68	0.623	0.737

As shown in Table 3 by the calculations, the AUC values of both players are greater than 0.5 with a 95% confidence level. Therefore, the original hypothesis that the swings in plays and runs of success by one player are not random can be accepted.

4. Conclusion

In summary, this paper reveals the impact of “momentum”, an invisible factor that always has a subtle effect on the swing of a tennis match and a player’s performance based on machine learning, through which one can efficiently supervise and predict the flow of a tennis match. The research found that a player’s momentum is correlated with 14 factors, listed as serve width, serve depth, return depth, double default, second serve, speed, whether a player is at net, running distance, break, unforced error rate, successive scoring and the difference of score, set, and game respectively. Then by introducing the concept “degree of the stalemate in the match”, an optimized prediction model based on LM-BP neural networks is built to predict the flow of the match, visualized with a 3D scatter plot. From the assessment of the confusion matrix and ROC curve, with an F1 score of 0.650 and an AUC of 0.672, it is drawn that the momentum of a pair of players can well represent the swings of the match.

This paper reveals an idea and research framework for extracting effective learning inputs and performing back-propagation machine learning based on players' past performances and observable features to accomplish their complex mapping with movement patterns, which can help solve problems in related areas of movement pattern analysis.

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