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Article

Gaming Tree Based Evaluation Model for Badminton Tactic Benefit Analysis and Prediction

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Abstract: Badminton tactics refer to the techniques and strategies employed by players to win a match. Analyzing these tactics can help players improve their performance and outsmart their opponents. To study the tactics of top players, we use a gaming tree to analyze matches between two of the most powerful badminton players in history: Lin and Lee. By employing the Nash Equilibrium, we can discover the most beneficial strategies for both players, which reflect their most powerful techniques. Additionally, with the help of this gaming tree, we can precisely predict how players will implement their tactics. Empirical experimental results demonstrate that our proposed method not only evaluates and identifies each player's weaknesses and strengths but also has powerful capabilities to predict their tactics.

Keywords: tactic analysis; gaming tree; nash equilibrium; badminton analysis and prediction; computer-based analysis

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1. Introduction

Badminton is one of the most popular sports in the world [1,2], and is also the racquet sport with the highest speed in the world [3], with its competitive form being two single/pair athletes completing tactical implementation quickly and accurately [4,5] on an 80 square meter court. As a result, tactical strategies (strategical strokes) are one of the key factors for winning badminton matches [6].

With the rapid development of information technology, advanced statistical methods such as data mining and artificial intelligence are commonly used in tactical analysis. Such methods can mine implicit information from performance data of competitions to provide decision support for coaches and athletes, which is an important aspect of tactical strategy research for sports such as basketball [7,8], football [9,10], tennis [11,12], table tennis [13,14], badminton [15,16], and is also a promising direction for improvement and development of traditional performance diagnosis and evaluation methods [17,18]. In recent years, predicting match results (scores, wins/losses) using these methods has become a hot research topic [19,20]. Through prediction models, key tactical factors affecting match results can be analyzed. For example, Valero et al. [21] uses four data mining methods (including lazy learners, artificial neural networks, support vector machines, and decision trees) to evaluate classification-based and regression-based methods for predicting match results (home team win or lose) in Major League Baseball (MLB) regular season games over 10 years; Razali et al. [22] used Bayesian networks to predict home wins, away wins, and draws in the English Premier League; Karlis and Ntzoufras [23] constructed a bivariate Poisson model to analyze scores between two teams, etc. However, there has been no prediction research on badminton so far.

Game theory studies how rational actors make decisions and the equilibrium of such decisions under the assumption of mutual interaction and influence among relevant actors. The prediction

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ability, actual behavior selection and optimal selection between the two sides of the game are the research focuses of game theory. Consequently, game theory has been widely applied in the sports science, including sports teaching [24,25], tactical strategies [26–28], etc., while researches on its prediction in sports field has not yet been studied.

Badminton matches have strong confrontation and competition, and have obvious interactive and interdependent characteristics of tactics and strategies between opponents, which is consistent with the research object characteristics of game theory. Therefore, this study intends to use game tree method with game theory to explore the winning rate of badminton matches. By using important badminton match data in recent years, this study predicts the winning rate of the future matches through the tactics strategy of the history matches, so as to reflect the tactical winning factors in badminton matches.

2. Materials and Methods

2.1. Materials

In this paper, 29 matches of 2 most famous badminton players (i.e., Dan Lin and Chong Wei Lee) from 2006 to 2018 are selected. As men's single players, Lin has won nine major titles in the badminton world with 2 Olympic gold medals, while Lee was ranked first worldwide for 349 weeks including a 199-week streak. Thus, the selected matches between Lin and Lee present the highest-level badminton techniques and tactics, and are worth analyzing. All match videos were from television relay or the Internet Note that, the two players have announced retirement and the selected matches are only used for analysis, i.e., no technical guidance is provided.

2.2. Observation indices and tactical combination

Based on the studies by Butterworth and Turner [29], and Phomsoupha and Laffaye [30], we conclude the tactical observation indices including stroke technique, stroke placement, and rally results, as follows:

- Stroke technique: Serve, including short serve and long serve; Smash, an aggressive overhead shot with a downward trajectory; Clear, an overhead shot with a flat or rising trajectory towards the back of the opponent's court; Drop, is a smooth shot from above the head with a downward trajectory towards the front of the court; Net shot, denoting a precise shot from near the net, including the net drop, lob and kill; Drive, a powerful shot made at middle body height and in the middle of the court with a flat trajectory;
- Stroke placement: the start position and the target placement of each stroke. In this paper, the badminton court are evenly divided into 9 (3x3) grids, i.e., the combination of vertically three parts (front court, middle court, and back court) and horizontally three parts (left court, middle court, and right court);
- The rally results: scoring and losing.

In fact, the speed of each stroke also contributes to the tactics. However, as the speed (including smash speed, clear shoot speed, e.t.c.) of high-level players are almost the same (especially for Lin and Lee), the influence of the stroke speed for the rally results is not considered in this paper.

Based on the above, the tactical combination is composed of the different stroke techniques and stroke placements of each strokes by two players, where each stroke has four attributes, i.e., the start position, the applied technique, the target placement and the final result for rally that this stroke belongs to.

2.3. Tactical frequency and scoring rate algorithm

In this study, the attributes of different strokes for each rally are computed first. Let P be a binary set that represent the stroking player, X be a set of stroke techniques, Y be a set of stroke placements, S be a set of strokes and D be a set of descriptive vectors of all rallies, a stroke $s_k^i \in S$ for the k^{th} stroke in the i^{th} rally can be denoted as $(p_k^i, x_k^i, y_k^i, x_{k+1}^i)$, where p_k^i is the player for this stroke, x_k^i

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is the applied technique, y_k^i is the start place for this stroke and the destination of this stroke is denoted as y_{k+1}^i. Based on the s_k^i, a descriptive vector $d_i \in D$ in a given rally can be denoted as $(s_1^i, s_2^i, \dots, s_n^i)$, where n is the length of strokes in this rally. For each rally, the sign of the end of the rally is that either side has lost a point, i.e., the loser has not returned the ball to the opponent's court, making that the stroke does not exist.

Consider all the strokes, rallies, and games in each match, the later ones are more important than the earlier ones, as the later strokes, rallies, and games decide the result of the general results of each rally, game and matches respectively. Thus, consider that each match has the total score of 1, the scores for each game $g_j \in G$, each rally $r_i \in R_j$, and each stroke $s_k^i \in S_i$ can be calculated as follows, where R_j denotes all the rallies in g_j, and S_i denotes all the strokes in r_i.

$$Score(g_j) = \frac{2j}{|G| \cdot (|G|-1)} \tag{1}$$

$$Score(r_i) = Score(g_j) \cdot \frac{2i}{|R_j| \cdot (|R_j|-1)} \tag{2}$$

$$Score(s_k^i) = Score(r_i) \cdot \frac{2k}{|S_i| \cdot (|S_i|-1)} \tag{3}$$

2.4. Evaluation model of tactical benefit

2.4.1. Tactical benefit

According to the feature of badminton match, i.e., each rally has only one result and each stroke has limited start placement and destination, the players have limited choices to conduct their techniques and tactics. Thus, if we consider each single rally is an individual game with different weights, we can count all the rallies together, and compute the benefit for each stroke. Given a number of rallies $R = \{r_1, r_2, \dots, r_m\}$, we construct a gaming tree T for all the strokes $S_i = \{s_1^i, s_2^i, \dots, s_n^i\}$ in each rally r_i. and compute the benefit for each node in the gaming tree. Specifically, each node of T represent a possible stroke, and all the nodes of T covers all the strokes in the selected rallies.

Figure 1 presents a simplified example (the specific technique and the destination for each stroke is not considered here) of building a gaming tree for three rallies r_1, r_2, r_3, where S denotes strokes, P denotes the player, the Y denotes the placement, and N denotes the gaming tree node. To illustrate, consider the strokes $\{s_1^1, s_1^2, s_1^3\}$, though they belong to different rally, they are the first stroke for each rally and share the same player and placement (player p_1 with the placement 1), leading to the same tree node position N_1. Note that, two strokes can be classified into the same tree node if and only if their player and placement are same and their previous strokes (if exist) all have the same player and placement. For this reason, s_2^1 and s_2^3 can be classified to be node N_2, as they succeed s_1^1 and s_1^3 separately (both can be regarded as N_1) and have the same player and placement. Meanwhile, though s_3^1 and s_3^3 also have the same player and placement, they belong to different tree nodes as their previous strokes are different, e.g., s_2^1 and s_2^3 have different placement.

Rally r_1				*Rally r_2*				*Rally r_3*			
S	*P*	*Y*	*N*	*S*	*P*	*Y*	*N*	*S*	*P*	*Y*	*N*
S_1^1	p_1	1	N_1	S_1^2	p_1	1	N_1	S_1^3	p_1	1	N_1
S_2^1	p_2	3	N_2	S_2^2	p_2	9	N_3	S_2^3	p_2	3	N_2
S_3^1	p_1	2	N_4	S_3^2	p_1	5	N_6	S_3^3	p_1	4	N_5

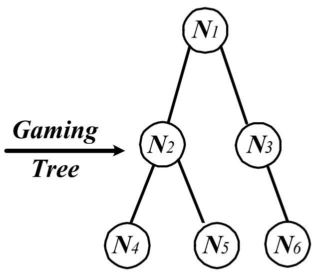

Figure 1. Illustration of the gaming tree for rallies.

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Based on the gaming tree constructed from each stroke $s_k^i = (p_k^i, x_k^i, y_k^i, x_{k+1}^i)$, each tree node represent a possible stroke and we can derive all the possible strokes for each single rally, as each rally starts from the root nodes (have no predecessors) of the gaming tree and ends at leaf nodes (have no successors). Meanwhile, the benefit of each possible stroke can be obtained by considering formula 3 and the gaming tree, i.e., we summarize the score of each stroke s_i that can be reduced to the same gaming tree node N (denoted as $s_i \in N$) and regard it as the benefit for that stroke. Generally, the benefit of each Node N can be computed as follows.

$$Score(N) = \sum_{s_i \in N} Score(s_i) \cdot \begin{cases} 1 & \textit{the server palyer win} \\ -1 & \textit{the server palyer loses} \end{cases} \tag{4}$$

For example, given two strokes s_k^i and s_k^j that can be reduced to the same gaming tree node N, and s_k^i leads to the server player wins while s_k^j is the opposite, we calculate the benefit of N as $Score(N) = Score(s_k^i) - Score(s_k^i)$. Note that, according to the formula 1-3, we can obtain that $\sum Score(s_k^i) = 1$. Thus, the benefit range of each node is [-1, 1].

2.4.2. Evaluation Model

The evaluation model for the badminton matches include two steps, i.e., (i) constructing the gaming tree for the history strokes and evaluating the techniques and tactics for two players, and (ii) analyzing the rallies and strokes using the constructed gaming tree.

Evaluating. Given a set of existing matches, we first formulize each rally as $r_i = \{s_1^i, s_2^i, \dots, s_n^i\}$ and each stroke as $s_k^i = (p_k^i, x_k^i, y_k^i, x_{k+1}^i)$. Then, we add s_k^i into the gaming tree. For example, consider the rally $r_i = \{s_1^i, s_2^i, \dots, s_n^i\}$, we first find if there exist a node N that has the same $(p_1^i, x_1^i, y_1^i, x_2^i)$ as s_1^i. If not, we create a new node N for s_1^i into the gaming tree. After that, we update the Score(N) with Score(s_1^i). Next, we check the leaves of N and check the following strokes $s_2^i, s_3^i, \dots, s_n^i$ as s_1^i. After all the rallies and strokes are evaluated and the gaming tree is constructed, we compute the net benefit for each tree node as follows.

$$Net(N) = Score(N) + Max_{N_i \textit{ is a leaf of } N}(Score(N_i)), \tag{5}$$

where $Max_{i \in m}(Score(N_i))$ denote the function that finds the maximal value among $\{Score(N_1), Score(N_2), \dots, Score(N_m)\}$.

Consider the example shown in Figure 2, where four rallies are given and the gaming tree is constructed with nine nodes. Specifically, in the first rally r_1, the server p_1 wins and continues to serve. In the second rally r_2, p_1 loses and alternates the service. However, the opponent player p_2 loses the rally r_3, and the service is alternated again. Finally, the player p_1 wins the fourth rally r_4 and the match ends. To model this match, we first build the gaming tree and compute the scores for each stroke, then the score of each tree node is obtained. Based on the above, we then compute the net benefit. Clearly, when it starts from N_2, the serve player always loses as the net benefit is negative.

Rally r₁			*Rally r₂*			*Rally r₃*			*Rally r₄*	
N	*Score*		*N*	*Score*		*N*	*Score*		*N*	*Score*
N_1	0.0167		N_1	-0.02		N_2	-0.1		N_1	0.0667
N_3	0.0333		N_3	-0.04		N_4	-0.2		N_4	0.133
N_6	0.05		N_7	-0.06					N_8	0.2
			N_9	-0.08						

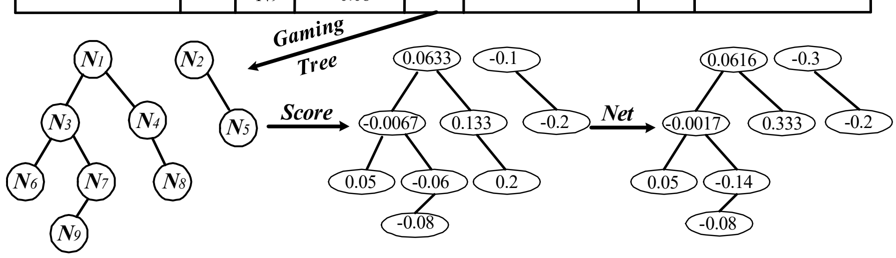

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Figure 2. Illustration of the gaming tree evaluation.

However, when it comes to start from N_1, the tactics becomes complicated, as the opponent has two choices to play, i.e., move to N_3 with the benefit of -0.0067 or move to N_4 with the benefit of 0.333. According to the Nash Equilibrium, the opponent should move to N_3 and will win this rally. Thus, though in this example the player that serve at r_1, r_2, and r_4 seems to have more possibility to win the match, the opponent also has the chance to change the result. This makes our proposed gaming tree not only have the ability to evaluate how the player have performed in the existing matches by leveraging the net benefit, but also can analyze how the players use their techniques with tactics by finding Nash Equilibriums in the gaming tree.

Analysis. Based on the above, we find that the score of each stroke illustrate how much important that stroke is to the whole match. Thus, we propose the following rating strategy to find Nash Equilibriums in the gaming tree, which helps analyzing the existing strokes, rallies, games and matches.

$$Score'(N) = \sum_{s_i \in N} Score(s_i) \tag{6}$$

Based on equation 6, we compute the importance weight $Score'(N)$ of each node N. Next, we propose the win-loss flag table to determine whether the node N leads to the server win or lose. Note that, the win-loss table is obtained by following the strategy that the player will choose the best strategy to win the game, and the opponent will make the player lose the game. To illustrate, consider a node N that is an odd stroke, there are two situations: (i) N is a leaf, the server must win when $Score(N)$ is positive, while the server lose if $Score(N)$ is negative, and the result is draw if $Score(N)$ =0, and (ii) N is non-leaf node, the server win when it holds that $Max_{N_i \in successors\ of\ N}(Score'(N_i) \cdot \text{Flg}(N_i))$ is positive, and the result is lose or draw if the value is negative or equal respectively. Based on the above, we can also analyze the result when N is an even stroke. The summarized table is shown below.

Table 1. Win-loss flag table.

Node N: Odd/Even	Node N: Situation	Win/ Lose	Flg(N)
Odd Stroke	Leaf node, and the $Score(N)$ is positive	Win	1
	Leaf node, and the $Score(N)$ is negative	Lose	-1
	Leaf node, and the $Score(N)$ is 0	---	0
	Non-leaf, $Max_{N_i \in successors\ of\ N}(Score'(N_i) \cdot \text{Flg}(N_i))$>0	Win	1
	Non-leaf, $Max_{N_i \in successors\ of\ N}(Score'(N_i) \cdot \text{Flg}(N_i))$<0	Lose	-1
	Non-leaf, $Max_{N_i \in successors\ of\ N}(Score'(N_i) \cdot \text{Flg}(N_i))$ =0	---	0
Even Stroke	Leaf node, and the $Score(N)$ is positive	Win	1
	Leaf node, and the $Score(N)$ is negative	Lose	-1
	Leaf node, and the $Score(N)$ is 0	---	0
	Non-leaf, $Min_{N_i \in successors\ of\ N}(Score'(N_i) \cdot \text{Flg}(N_i))$>0	Win	1
	Non-leaf, $Min_{N_i \in successors\ of\ N}(Score'(N_i) \cdot \text{Flg}(N_i))$ <0	Lose	-1
	Non-leaf, $Min_{N_i \in successors\ of\ N}(Score'(N_i) \cdot \text{Flg}(N_i))$ =0	---	0

Generally, based on the Win-loss flag table, the Nash Equilibrium for each tree node N can be obtained, and the $Flg(N)$ correspond to rally result (win, lose, or draw). Especially, we can decide whether the server will win or lose by directly checking the $Flg(\cdot)$ function for the root node (i.e., the initial stroke).

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3. Results

3.1. Basic Data

The detailed information of selected matches is shown in Table 2, with Lin winning 19 times while Lee winning 10 times in total. In Table 2, during the early period (2006 to 2009), the two players have roughly the same winning times. However, during the middle period (10-15), Lin shows a higher-level performance, and beats Lee at most of matches. In the last three year (2016-2018), the two players come back to a stalemate.

Table 2. Match statics.

No.	Year	Tournament	Match	Round	Winner
1	2006	Hong Kong Open	Super Series	Final	Lin
2	2007	Sudirman Cup	BWF tournaments	Group stage	Lee
3	2007	China Masters	Super Series	Semi-finals	Lin
4	2007	Japan Open	Super Series	Semi-finals	Lee
5	2007	Hong Kong Open	Super Series	Final	Lin
6	2008	Swiss Open	Super Series	Final	Lin
7	2008	Thomas Cup	BWF tournaments	Semi-finals	Lee
8	2008	Olympic Games	Multi-sport events	Final	Lin
9	2008	China Open	Super Series	Final	Lin
10	2009	All England Open	Super Series	Final	Lin
11	2009	Swiss Open	Super Series	Final	Lee
12	2009	Sudirman Cup	BWF tournaments	Semi-finals	Lin
13	2010	Thomas Cup	BWF tournaments	Semi-finals	Lin
14	2010	Japan Open	Super Series	Final	Lee
15	2010	Asian Games	Multi-sport events	Final	Lin
16	2011	All England Open	Super Series Premier	Final	Lee
17	2011	BWF World Championships	BWF tournaments	Final	Lin
18	2011	China Open	Super Series Premier	Semi-finals	Lin
19	2012	Korea Open	Super Series Premier	Final	Lee
20	2012	Olympic Games	Multi-sport events	Final	Lin
21	2013	BWF World Championships	BWF tournaments	Final	Lin
22	2014	Asian Games	Multi-sport events	Semi-finals	Lin
23	2015	Japan Open	Super Series	Last 16	Lin
24	2015	China Open	Super Series Premier	Semi-finals	Lee
25	2016	Badminton Asia Championships	BAC tournaments	Semi-finals	Lee
26	2016	Olympic Games	Multi-sport events	Semi-finals	Lee
27	2017	Malaysia Open	Super Series Premier	Final	Lin
28	2017	Badminton Asia Championships	BAC tournaments	Semi-finals	Lin
29	2018	All England Open	Super 1000	Quarter-finals	Lin

3.2. General Analysis

In this paper, we analyze the matches based of the gaming tree, while leveraging the benefit and net benefit (formulas 4 and 5) to evaluate the strokes of each player and use the Nash Equilibrium derived by gaming tree and win-loss flags to analyze the general win-loss situation.

Firstly, according to the definition of the benefit, the higher benefit value implies that the stroke leads to higher contribution for winning the game. Thus, we compute the gaming tree for all the

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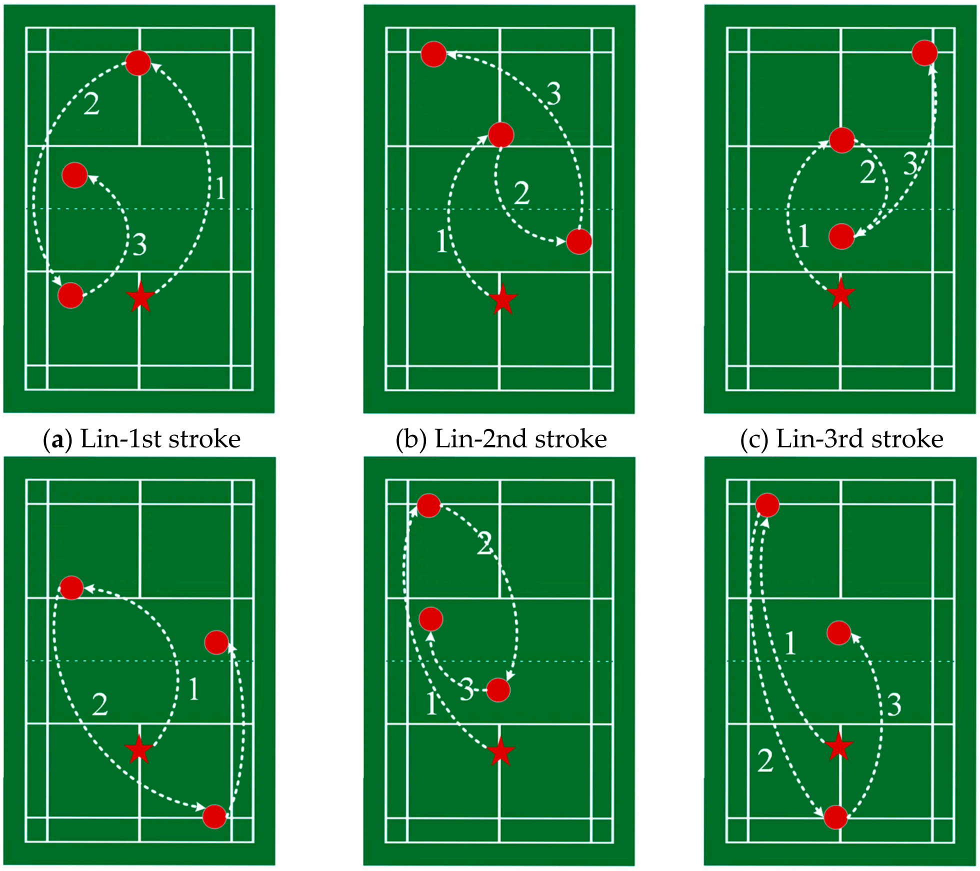
matches, and find the strokes with the top-3 benefits during the first three beats as shown in Figure 3, aiming at illustrating the tactics of two players for the first three beat. From the figures, we find that the best choices for Lin is to hit the shuttle to the backcourt while that for Lee is to control the forecourt.



(**a**) Lin-1st stroke (b) Lin-2nd stroke (c) Lin-3rd stroke

(d) Lee-1st stroke (e) Lee-2nd stroke (f) Lee-3rd stroke

Figure 3. The top-3 benefits strokes.

Next, we find the Nash Equilibrium based on the gaming tree, and derive the results as shown in Table 3. As can be seen from the table, with the growing beats, Lin and Lee have more choices to win or lose the match, while mostly the number of the strokes that result in losing is larger than the strokes that lead to wining the rally. This also implies that Lin and Lee have many tactics and techniques to win each other, and will lose the game with high possibility. However, during the matches, they defend the with great skills and seize the opportunity to win the match. Besides, according to the win-loss ratios, Lin has higher value than Lee, which is consistence with the results that Lin wins more matches than Lee.

Table 3. Win-Loss comparison for all matches.

	First 3 Beats		First 5 Beats		First 7 Beats		First 9 Beats		All Beats	
	Win	**Lose**	**Win**	**Lose**	**Win**	**Lose**	**Win**	**Lose**	**Win**	**Lose**
Lin	122	114	487	550	830	984	906	1066	910	1071
Lee	102	119	433	539	769	925	841	999	846	1005
					Win-Loss Ratio					
Lin	0.517		0.47		0.458		0.459		0.459	
Lee	0.462		0.445		0.454		0.457		0.457	

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3.3. Analysis for Different Periods

In different career period, the results are different. Thus, we compute the Nash Equilibrium for different period and present the result in Figure 4. Specifically, we divide all the matches into four groups, i.e., matches 1-7, 8-14, 15-21, and 22-28. For each group, we construct an individual gaming tree and compute there Nash Equilibrium results. The results are consistent with the analysis in Sec 3.2, while there also exists a new observation that as the two players play more match, they find more ways to beat each other. However, when it comes to the last period (matches 22-28), there is a significant drop for both players. This is because they are too familiar with each other that their tactics are not efficient, and their bodies cannot support their all tactics and techniques. As a result, they try to use the most effective way to win the game, making the number of gaming strategies descend.

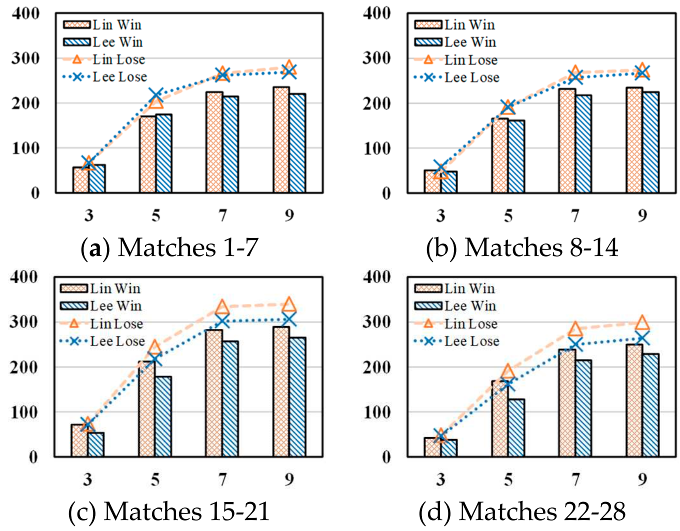

Figure 4. The Win-Loss results for different career period.

Besides, we compute the win-loss ratio for two players in four career periods based on the win-loss results presented in Figure 4, and the results are shown in Figure 5. For example, Lin#1 with parameter 3 denotes the win-loss ratio between the winning strokes and lose strokes for player Lin among the first three beats in the career period #1 (i.e., the matches 1-7). We find that the results are consistence with the real matches, i.e., in the first three period the win-loss ratio of Lin is larger than Lee, thus Lin has more possibility to win the game. In the last period, the ratio of Lin is larger than Lee when the beats are not larger than 5, while it becomes the opposite when the beats are 7 or more. Thus, Lin and Lee have the equal possibility to win the match.

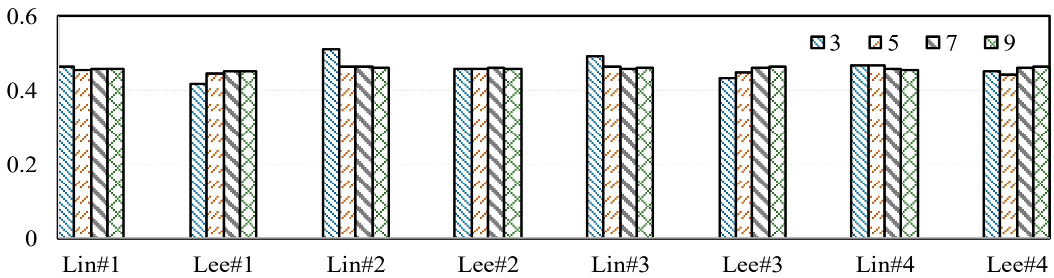

Figure 5. The Win-Loss ratio for different career period.

3.4. Prediction using Top-k Benefits

This section may be divided by subheadings. It should provide a concise and precise description of the experimental results, their interpretation, as well as the experimental conclusions that can be drawn.

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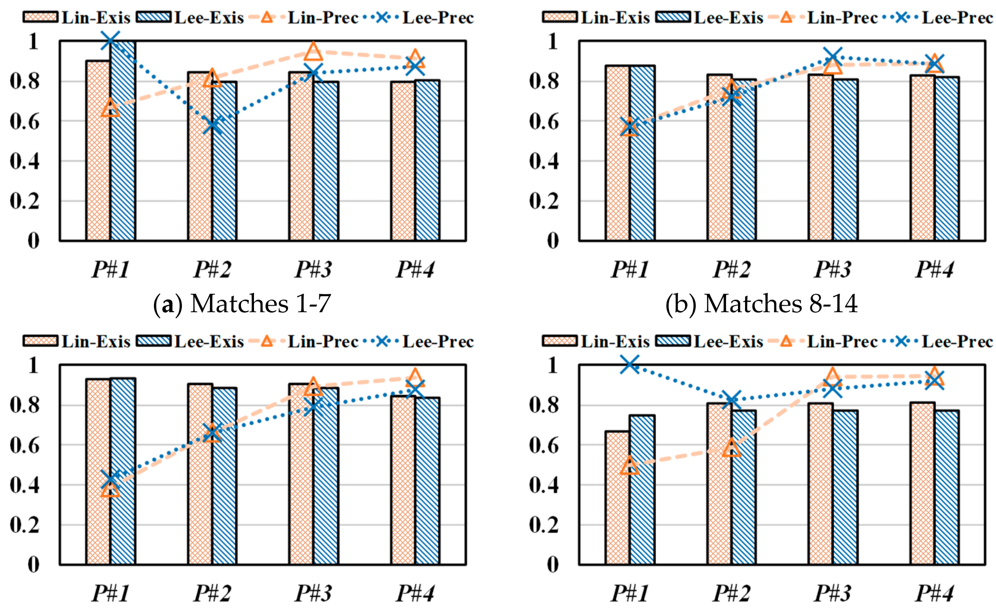
As stated in Sec 2.4.1, the score and benefits imply how each stroke contribute to the match result. Thus, when the player comes to a specific node in the gaming tree, we can predict the next stroke by considering the top-k strokes with the highest benefits in the predecessors (children) of that node. For this reason, we construct the gaming tree for four different career period and use the strokes with top-k to predict the first m beats in the next match. Note that, we use four parameters group of (k, m) to demonstrate the effectiveness of gaming tree prediction capability, i.e., P#1(3, 3), P#2(5, 3), P#3(5, 5), and P#4(5, 10). For example, for predicting the first period career of (matches 1-7) with parameters P#1(3, 3), we use matches 1-6 to construct the gaming tree, and use the strokes with top-3 benefits to predict all the first 3 beats.

The results are shown in Figure 6, where the Exist. denotes that the number of real strokes that can be found in the gaming tree, and the Prec. denotes precision for correctly predicted strokes that exist in the gaming tree. As can be observed, the Exist. drops as the beats increase, while the precision generally keeps ascending, and the precision is above 90% when we use top-5 benefit strokes to predict more than 5 beats, demonstrating the effectiveness of our strategy. Meanwhile, there is also an interesting observation that during the first period and the last period, when Lin and Lee have similar win-loss result, our model performs well for the first 3 beats on Lee. However, during the middle period (matches 8-21), when Lin wins more, the precision of our method for the first 3 beats on Lee is low. Thus, we can conclude that the first 3 beats of Lin are always hard to predict, while Lee can be predicted with high accuracy at the early and late career stage.



(a) Matches 1-7 (b) Matches 8-14

(a) Matches 1-7 (b) Matches 8-14

Figure 6. The prediction results for different career period.

4. Discussion

Authors should discuss the results and how they can be interpreted from the perspective of previous studies and of the working hypotheses. The findings and their implications should be discussed in the broadest context possible. Future research directions may also be highlighted. In this paper, we use gaming tree to analyze the technical and tactical strategies of Lin and Lee. Based on the analysis results, we make precise predictions for some of their matches. In addition, we analyze the different stages of their professional careers and find that they have made some adjustments to their technical and tactical strategies with their increasing ages, thus revealing some hidden factors that determine the outcome of the match. However, with the recent adjustment of competition rules and the wide application of Hawk-Eye system, badminton matches are undergoing tremendous changes. The technical and tactical analysis revealed in this paper is only for top men's singles matches in the past decade. There are still two aspects of technical and tactical analysis to be explored.

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- Tactics combinations. Unlike male players, female players do not have such strong offensive ability, resulting in a difference in the technical and tactical skills of female singles matches. In addition, double matches require higher cooperation ability from the players, so the technical and tactical skills in doubles matches are completely different from those in singles matches, e.g., Cao et al. [31] find special tactics in mixed double table tennis matches, and Abián-Vicén et al. [32] analyze the different performance between men's and women's double matches. In addition, tactic length and tactic frequency are also important for players to control the match, as illustrated by Liu [33] and Zhou [34]. For instance, when a match reaches its final stage, both players face increased pressure. Therefore, using an efficient tactic combination (i.e., utilizing a smaller number of tactics) can significantly increase the chances of winning the match. Thus, the tactic combinations are worth studying;
- Factors that are outside the tactics. In a match, the match length and the point difference also contribute to the final result. For example, based on the analysis of recent math lengths, Iizuka et al. [35] suggest badminton players to strengthen their physical capabilities to win the match; Barreira et al. [36] find that a small point difference not necessarily implies the winning of the match, while a more than 4 points lead to great possibility for winning the match; O'donoghue [37] observe the grand slam singles tennis matches and conclude that some key points determine the match results. Besides, Chu et al. [38] demonstrated the significant influence of spatial information on tactics and techniques by visualizing badminton strokes, thus helping badminton players to win the match.

5. Conclusions

In this paper, we study the problem of tactical benefit in badminton matches. To tackle this problem, we propose to a gaming tree that consider the contribution of each stroke to the result of the match, and develop an evaluation model with prediction techniques to analyze the strokes of each player. To further analyze the tactics and techniques of the two world's top players, we leverage the Nash Equilibrium derived by the gaming tree to help analyze their tactics behind the strokes. The experiment results demonstrate that our evaluations for the strokes of two players are consistence with the real match result, and our prediction model are with high accuracy. Thus, our proposed methods are effectiveness and have the potential to help players find their strengths and weaknesses, and further improve their tactics.

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