Enhancing Badminton Player Performance via a Closed-Loop AI Approach: Imitation, Simulation, Optimization, and Execution

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ABSTRACT

In recent years, the sports industry has witnessed a significant rise in interest in leveraging artificial intelligence to enhance players' performance. However, the application of deep learning to improve badminton athletes' performance faces challenges related to identifying weaknesses, generating winning suggestions, and validating strategy effectiveness. These challenges arise due to the limited availability of realistic environments and agents. This paper aims to address these research gaps and make contributions to the badminton community. To achieve this goal, we propose a closed-loop approach consisting of six key components: Badminton Data Acquisition, Imitating Players' Styles, Simulating Matches, Optimizing Strategies, Training Execution, and Real-World Competitions. Specifically, we developed a novel model called RallyNet, which excels at imitating players' styles, allowing agents to accurately replicate real players' behavior. Secondly, we created a sophisticated badminton simulation environment that incorporates real-world physics, faithfully recreating game situations. Thirdly, we employed reinforcement learning techniques to improve players' strategies, enhancing their chances of winning while preserving their unique playing styles. By comparing strategy differences before and after improvement, we provide winning suggestions to players, which can be validated against diverse opponents within our carefully designed environment. Lastly, through collaborations with badminton venues and players, we apply the generated suggestions to the players' training and competitions, ensuring the effectiveness of our approach. Moreover, we continuously gather data from training and competitions, incorporating it into the closed-loop cycle to refine strategies and suggestions. This research presents an innovative approach for continuously improving players' performance, contributing to the field of AI-driven sports performance enhancement[1].

CCS CONCEPTS

• **Computing methodologies** → **Learning from demonstrations**; **Simulation environments**; *Multi-agent systems*; **Sequential decision making**.

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KEYWORDS

Imitation Learning; Reinforcement learning; Badminton simulation; Sports analytics

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1 INTRODUCTION

In recent years, the sports industry has witnessed a surge in interest regarding the utilization of artificial intelligence (AI) to boost performance. However, a research gap remains in applying deep learning techniques to enhance individual performance for badminton athletes in real-time scenarios. Challenges such as identifying weaknesses, generating effective suggestions, and validating strategy effectiveness have impeded progress in this area. A key factor contributing to these challenges is the limited availability of realistic environments and agents. The absence of realistic environments and agents hampers the accurate simulation of real-match dynamics, thereby reducing the applicability of subsequent analysis and generated winning suggestions to real athletes. This paper aims to bridge these gaps and make a valuable contribution to the badminton community by proposing a closed-loop AI approach.

Our closed-loop AI system, illustrated in Figure 1, comprises six key components: Badminton Data Acquisition, Imitating Players' Style, Simulating Matches, Optimizing Strategies, Training Execution, and Real-World Competitions. This paper focuses on three specific tasks within this system, namely **imitating players' styles (Task 1)**, **simulating matches (Task 2)**, and **optimizing strategies (Task 3)**. Together, these tasks and other components form an iterative and comprehensive approach that leverages AI and deep learning techniques to enhance badminton performance. The foundation of our closed-loop approach begins with the Badminton Data Acquisition phase. Through the utilization of a deep learning-based annotation system [5] and a vast collection of badminton videos [5, 14], we efficiently transform video data into offline behavioral data. We employ the BLSR representation [13], a unified language for describing badminton matches. This data acquisition process provides the groundwork for subsequent components.

Specifically, in the first task, we introduce a model called RallyNet, which aims to replicate players' decision-making processes. RallyNet utilizes contextual Markov Decision Processes (CMDP) [4] and geometric Brownian motion [10] to capture realistic strategies and player interactions, resulting in agents that mimic real players'

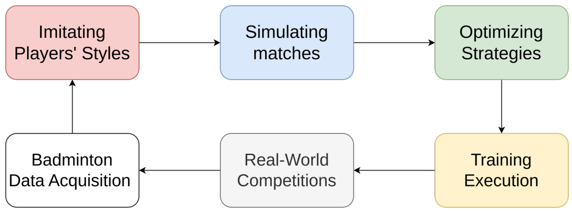

Figure 1: The closed-loop AI approach for enhancing badminton player performance.

behavior. Moving on to the second task, our focus shifts to creating a realistic badminton environment where agents can participate in matches that faithfully emulate real-game scenarios. This involves incorporating real-world physics and simulating authentic shuttlecock trajectories. By observing how agents execute strategies in these simulated matches, we gain valuable insights into their performance and strategic decision-making. The third task, known as optimizing strategies, aims to enhance win probability while preserving players' individual styles. Through the application of reinforcement learning algorithms, we compare the strategies of agents before and after reinforcement, and generate winning suggestions.

Finally, through collaboration with badminton venues and players, we apply our suggestions to real-world training and competitions, ensuring the practicality and effectiveness of our system. Data gathered from training execution and competitions is incorporated into the closed-loop cycle, refining the models, strategies, and winning suggestions. In summary, this research aims to leverage the power of AI to enhance the competitive performance of badminton players. By imitating player styles, simulating matches, optimizing strategies and collaborating with badminton players, we will advance the field of AI-driven sports performance enhancement[2]. We highlight our main contributions as follows:

- We propose a closed-loop AI approach to overcome the challenges of improving competitive performance for badminton athletes. Importantly, our approach can be readily extended to other turn-based sports like tennis.
- We propose an imitation learning model that replicates players' behavior in turn-based sports and a realistic badminton simulation environment, resulting in authentic simulated matches. The results show promising outcomes.

2 PRELIMINARIES

2.1 Badminton Tactical Analysis

AI has been widely utilized in the field of badminton sports analytics to address a range of challenges. For example, [13] proposed Badminton Language for Sequence Representation (BLSR), a unified language that efficiently converts match videos into analyzable datasets. BLSR is human-readable, universal, professional, facilitating easy interpretation of the entire match process without video footage. In strokes forecasting, [12] predict players' future strokes based on previous ones. Their novel framework, ShuttleNet, integrates position-aware fusion of rally progress and player styles, considering dependencies at each stroke. [1] presented the first movement forecasting task, encompassing stroke forecasting and player movements, employing DyMF, a novel dynamic graphs and hierarchical fusion model based on player movement graphs.

2.2 A Human-Annotated Badminton Dataset

AI has been instrumental in tackling challenges in sports analytics. Yet, capturing structured source data and stroke-level records has posed difficulties in existing studies of badminton sports analytics. To bridge this gap, [14] introduced ShuttleSet, the largest publicly available annotated badminton singles dataset with 36,492 annotated strokes from 104 rallies. It includes detailed annotations for 18 stroke categories, stroke positions, and player positions for each stroke. ShuttleSet's availability has paved the way for AI methods, including imitation learning and a realistic badminton simulation environment, to enhance player performance.

3 PROPOSED APPROACH

3.1 Task 1: Imitating player styles

In the first task, the objective is to replicate expert behavior through imitation learning using historical data. By creating an agent that mimics player behavior, coaches can gain valuable insights into player strategies and make well-informed decisions. Unlike previous models that rely on previous strokes, our approach allows the agent to generate actions based on any given state, making it more flexible and applicable.

In turn-based sports, where players take actions alternately, existing imitation learning methods face challenges due to the interdependence of player decisions. Mistakes by one player can cascade and impact other players' decisions, leading to significant errors. To overcome this, we propose RallyNet, a novel hierarchical offline network that models turn-based sports using a Contextual Markov Decision Process (CMDP) [4]. RallyNet captures player intentions through experiences, reduces errors by incorporating context, and leverages a latent geometric Brownian motion [10] to capture interactive relationships. To predict multiple outputs at each step, we employ a task-specific action projection layer that specializes in predicting shot types, landing positions, and moving positions.

3.2 Task 2: Simulating matches

Task 2 focuses on simulating realistic matches, considering the impact of real-world factors on tactics execution, such as the flight trajectories of the shuttlecock and the deviation of shuttlecock landing points. However, existing environments are ill-suited for developing new ideas in turn-based sports like badminton and tennis due to their unique characteristics. Task 2 faces two key challenges. First, accurately capturing 3-D trajectories is challenging due to limitations in detecting shuttlecock height in real-world settings. Second, describing various factors in a rally requires substantial effort, making it difficult to observe players' playing styles. To address these challenges, we propose an environment [6] based on the Multi-Agent Particle Environment (MAPE) [7] to recover the flight trajectories of shuttlecock. We achieve this by utilizing

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meta-parameters from the badminton dataset and integrating established methods from [2], which leverage realistic physics. This integration allows us to accurately simulate the flight trajectory of the shuttlecock. We expanded the environment[3] to incorporate previous stroke forecasting models such as ShuttleNet [12] and DyMF [1], providing quantitative and qualitative results. Integrated into a comprehensive system, it generates animations of matches, and visualizes statistical data (e.g., landing and movement distributions, automatic point loss analysis). This qualitative assessment empowers researchers to observe players' decision-making processes, facilitating the development of winning strategies.

3.3 Task 3: Optimizing Strategies

In Task 3, our focus is on enhancing the strategies of agents using reinforcement learning techniques and comparing them with their original strategies. This enables us to provide valuable training and competition winning suggestions to players. While reinforcement learning has achieved notable success in various domains, such as games and robotics, its application often overlooks the feasibility of the improved strategies for humans. Task 3 emphasizes applying these learned strategies in real competitions, generating practical and acceptable solutions for badminton players. There is growing interest in applying reinforcement learning strategies to real-world scenarios, particularly in *Safe Reinforcement Learning*. This field presents unique challenges, including safety concerns in domains like robotics [15] and autonomous driving [11].

Our goal incorporates the player's original strategy as a constraint. While maximizing long-term rewards, we also consider the discrepancy between the improved strategy and the strategy learned through imitation learning. This ensures that the improved strategy remains manageable for players, avoiding situations where they struggle to execute new strategies during official matches. This aspect has not been addressed in previous sports analytics studies. Although existing methods can be directly applied in badminton, potential issues remain. For instance, each player possesses a unique style, physical abilities and preferences. Considering this information is vital when learning new strategies to identify the most suitable winning approach among numerous possibilities. Neglecting these individual differences may hinder players from effectively executing the provided winning strategies. Therefore, our future reinforcement learning model design will consider player differences. This ensures that the improved strategy and winning suggestions can be effectively applied by players in real competitions.

4 PRELIMINARIES RESULTS

4.1 Imitating Turn-Based Players' Styles

We follow [12], the model for the task of imitating players' styles is trained on the first 80% of the rallies in each match to ensure it incorporates past information from all players. For evaluating the shot type prediction, we employ the Connectionist Temporal Classification loss [3], which quantifies the negative log-likelihood of the labels given input sequences. For evaluating the predicted landing and moving positions, we utilize Dynamic Time Warping [8] to compute the distance between the generated sequence and the correct sequence. In our previous work[4], RallyNet was compared against several imitation learning baselines and ShuttleNet. We present two tasks: Task 1 involves predicting from the initial state only, while Task 2 requires predicting from the states of the first two steps for comparison with ShuttleNet. Results of different models are presented in Table 1. Significantly, RallyNet outperforms all baselines across all metrics, whether given only the initial state, or the state of the first two steps. These results provide evidence that RallyNet effectively captures the decision-making nature of turn-based sports. Figure 2 illustrates the simulated distributions of player landing positions under different conditions. We present three distinct scenarios: (i) player in the front-right court, opponent on the left side of the net, (ii) player using a smash, and (iii) player in the front-right court, opponent in the front-left court. This characterization offers insights for coaches to understand player behavior better and develop tactical plans.

Table 1: Quantitative results. The best is in boldface and the second best is underlined. Since ShuttleNet predicts based on past strokes, the symbol – denotes unavailable results.

	Task 1			Task 2		
Model	Land	Shot	Move	Land	Shot	Move
BC [9]	0.86	55.90	0.44	1.03	54.87	0.57
Option-BC [16]	0.74	35.53	0.40	0.96	35.00	0.55
ShuttleNet [12]	-	-	-	0.90	34.04	0.50
RallyNet (Ours)	**0.59**	**18.86**	**0.34**	**0.79**	**19.51**	**0.49**

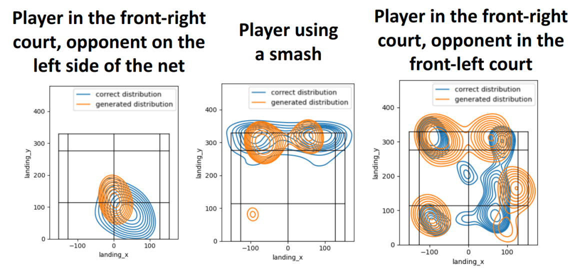


Figure 2: A player's landing distributions in different conditions.

4.2 Simulating by Badminton Environment

Our environment[5] enables the evaluation of agents, generating match results between them. We also provide default realistic opponents for comparison, currently employing a combination of ShuttleNet [12] and DyMF [1]. In the future, RallyNet will be introduced to offer more realistic opponents. To facilitate a clear understanding of the model's performance, the implemented functions are described as follows and are shown in Figure 3: **Animated Simulation.** We simulate realistic shuttlecock flight trajectory using real-world physics. The animation is presented on the left side.

[3]The extended version of the environment was accepted at the KDD 2023 Workshop on Data Science and AI for Sports (DSAI4Sports).

[4]This work was accepted by the ICML 2023 Workshop on Structured Probabilistic Inference & Generative Modeling (SPIGM)

[5]The visualization of player matchups and the simulation of shuttlecock trajectories can be observed at https://youtu.be/9S2RNVno84g

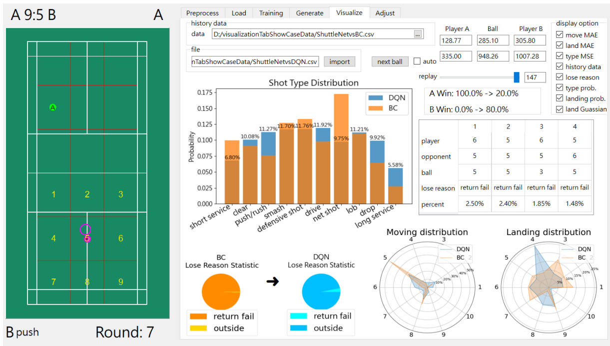
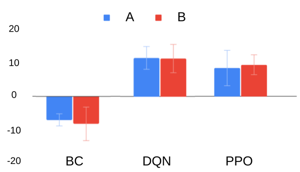
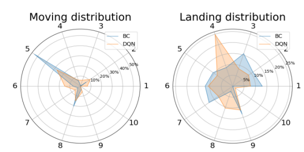


Figure 3: Visualization tabs. Users can compare the result with the specified match data to obtain useful information.



(a) Average goal difference.



(b) Variations in both landing and moving distributions.

Figure 4: Quantitative and qualitative results of agents.

Strategic Difference. We provide a comprehensive analysis of variations in positions (illustrated using radar charts) and shot types (represented in a bar chart), to present a comparison between simulated and desired matches. **Scoring Reasons.** We analyze losing actions, including out-of-bounds shots and hitting the net, and represent their proportions in a pie chart. We also analyze the reasons behind point drops, presenting the top five states where losing actions are most likely to occur in tabular format.

4.3 Optimizing Strategy in Badminton

While we continue to work on developing a reinforcement learning algorithm that considers individual differences and preserves players' original playing styles, we can still leverage existing reinforcement learning algorithms when we have realistic agents and a simulation environment to gain insights of winning strategies. Figure 4a presents experimental results with two opponents: Tien-Chen Chou (opponent A) and Tzu-Ying Tai (opponent B). The DQN and PPO algorithms, trained for 1,000 steps, achieve victories against opponents A and B, while the Behavior Cloning (BC) agent falls short. Through analysis using visualization tabs in Figure 4b, we identify factors for overcoming opponent A, including optimization of landing positions and enhancing defensive positioning diversity across different court regions. These findings highlight the potential of our environment in improving strategies for players.

5 CONCLUSION AND FUTURE WORKS

With the increasing interest in sports analytics and the potential of AI to enhance player performance in sports, this paper aims to tackle the challenges faced by AI technologies in this domain, particularly the lack of realistic environments and agents. To address this, we propose a closed-loop AI approach. Specifically, leveraging a developed annotation system, we collected a dataset from game videos. This dataset serves as the foundation for our research and enables the creation of RallyNet, a model that emulates players' styles and produces agents that demonstrate behavior akin to real athletes. Furthermore, we developed a realistic environment that incorporates real-world physics, allowing agents to compete in a setting that accurately reflects the dynamics of real matches. This environment provides visualization interfaces that facilitate the identification of players' weaknesses and the observation of overall strategies. Subsequently, using reinforcement learning algorithms, we enhance players' strategies and offer winning suggestions for players. For future research, we will explore reinforcement learning methods that consider players' physical conditions and preferences. This will result in more applicable suggestions for players. Finally, through collaborations with badminton venues and players, and the application of suggestions to player training and competitions, we will ensure the practicality of our system. We will continuously collect data from training and competitions to refine the model, update strategies, and provide new winning suggestions.

REFERENCES

[1] Kai-Shiang Chang, Wei-Yao Wang, and Wen-Chih Peng. 2023. Where Will Players Move Next? Dynamic Graphs and Hierarchical Fusion for Movement Forecasting in Badminton. In *AAAI*. AAAI Press, 6998–7005.

[2] Lung-Ming Chen, Yi-Hsiang Pan, and Yung-Jen Chen. 2009. A study of shuttlecock's trajectory in badminton. *Journal of sports science & medicine* 8, 4 (2009), 657.

[3] Alex Graves. 2012. *Connectionist Temporal Classification.* Springer Berlin Heidelberg, Berlin, Heidelberg, 61–93. https://doi.org/10.1007/978-3-642-24797-2_7

[4] Assaf Hallak, Dotan Di Castro, and Shie Mannor. 2015. Contextual Markov Decision Processes. *CoRR* abs/1502.02259 (2015).

[5] Tzu-Han Hsu, Chih-Chuan Wang, Yuan-Hsiang Lin, Ching-Hsuan Chen, Nyan Ping Ju, Tsì-Uí Ik, Wen-Chih Peng, Yu-Shuen Wang, Yu-Chee Tseng, Jiun-Long Huang, and Yu-Tai Ching. 2019. CoachAI: A Project for Microscopic Badminton Match Data Collection and Tactical Analysis. In *APNOMS*. IEEE, 1–4.

[6] Li-Chun Huang, Nai-Zen Hseuh, Yen-Che Chien, Wei-Yao Wang, Kuang-Da Wang, and Wen-Chih Peng. 2023. A Reinforcement Learning Badminton Environment for Simulating Player Tactics (Student Abstract). In *AAAI*. AAAI Press, 16232–16233.

[7] Ryan Lowe, Yi I Wu, Aviv Tamar, Jean Harb, OpenAI Pieter Abbeel, and Igor Mordatch. 2017. Multi-agent actor-critic for mixed cooperative-competitive environments. *Advances in neural information processing systems* 30 (2017).

[8] Meinard Müller. 2007. *Dynamic Time Warping*. Springer Berlin Heidelberg, Berlin, Heidelberg, 69–84. https://doi.org/10.1007/978-3-540-74048-3_4

[9] Dean A Pomerleau. 1988. Alvinn: An autonomous land vehicle in a neural network. *Advances in neural information processing systems* 1 (1988).

[10] Daniel Revuz and Marc Yor. 2013. *Continuous martingales and Brownian motion.* Vol. 293. Springer Science & Business Media.

[11] Garrett Thomas, Yuping Luo, and Tengyu Ma. 2021. Safe Reinforcement Learning by Imagining the Near Future. In *Advances in Neural Information Processing Systems*, A. Beygelzimer, Y. Dauphin, P. Liang, and J. Wortman Vaughan (Eds.). https://openreview.net/forum?id=vIDBSGl3vzl

[12] Wei-Yao Wang, Hong-Han Shuai, Kai-Shiang Chang, and Wen-Chih Peng. 2022. ShuttleNet: Position-Aware Fusion of Rally Progress and Player Styles for Stroke Forecasting in Badminton. In *AAAI*. AAAI Press, 4219–4227.

[13] Wei-Yao Wang, Teng-Fong Chan, Hui-Kuo Yang, Chih-Chuan Wang, Yao-Chung Fan, and Wen-Chih Peng. 2021. Exploring the Long Short-Term Dependencies to Infer Shot Influence in Badminton Matches. In *2021 IEEE International Conference on Data Mining (ICDM)*. 1397–1402.

[14] Wei-Yao Wang, Yung-Chang Huang, Tsi-Ui Ik, and Wen-Chih Peng. 2023. ShuttleSet: A Human-Annotated Stroke-Level Singles Dataset for Badminton Tactical Analysis. arXiv:2306.04948 [cs.LG]

[15] Haonan Yu, Wei Xu, and Haichao Zhang. 2022. Towards safe reinforcement learning with a safety editor policy. *Advances in Neural Information Processing Systems* 35 (2022), 2608–2621.

[16] Zhiyu Zhang and Ioannis Paschalidis. 2021. Provable hierarchical imitation learning via em. In *International Conference on Artificial Intelligence and Statistics*. PMLR, 883–891.