AIGC-Driven Basketball Tactics Intelligent Analysis and Decision-Making Model Research

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Abstract: With the rapid development of Artificial Intelligence Generated Content (AIGC), its application has expanded beyond creative industries into fields requiring complex analysis and real-time decision-making. This study explores the integration of AIGC technology into basketball tactics analysis and decision-making. By leveraging multimodal data such as in-game images, trajectory tracking, and statistical indicators, the research constructs an intelligent modeling system capable of automatic tactical script generation, dynamic prediction, and real-time tactical assistance. Utilizing deep learning and natural language generation techniques, the system enhances tactical interpretation, simulates strategic development, and supports personalized decision-making during gameplay. The study aims to shift tactical analysis in basketball from experience-driven to data- and intelligence-driven models. Major innovations include an AIGC-based automated tactical modeling framework, a neural network-driven dynamic evolution simulation mechanism, and a real-time feedback system designed for in-game applications. This research offers a novel paradigm for the intelligent development of sports tactics, contributing theoretical and practical value to the field of AI-empowered competitive sports.

1. Introduction

1.1 Research Background and Significance

With the continuous advancement of artificial intelligence technology, AIGC (Artificial Intelligence Generated Content) has achieved significant results in various fields such as content creation, image generation, and language processing, gradually demonstrating its potential to replace traditional manual creation methods. [1] In the field of sports, especially in high-intensity, high-paced collective sports like basketball, the complexity of tactical analysis and decision-making has always been a key challenge limiting coaching efficiency and the level of tactical optimization. Traditional tactical analysis often relies on video playback and data statistics, which are inefficient, lack real-time capabilities, and are easily influenced by the subjective experience of the analyst. In this context, the introduction of AIGC technology provides new ideas and possibilities for basketball tactical analysis. By integrating big data, image recognition, natural language generation, and deep learning, AIGC can efficiently interpret and dynamically model game scenarios, providing intelligent support for tactical formulation and adjustment. This research focuses on the application of AIGC technology in basketball tactical analysis and decision-making support, aiming to construct a tactical reference system that integrates real-time, intelligence, and dynamic feedback, promoting the transformation of sports tactical analysis from “experience-driven” to “data-driven + intelligence-driven,” with important theoretical value and practical significance.

1.2 Current Research Status at Home and Abroad

Currently, there are significant differences in research paths and technical approaches between domestic and international studies on basketball tactical analysis. Foreign research institutions and sports technology companies have started to experiment with the introduction of artificial intelligence algorithms, using machine learning, computer vision, and other methods to model and analyze game

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data. For example, some NBA teams have deployed high-precision cameras and tracking systems combined with AI models for player movement pattern recognition and tactical effect prediction, achieving a preliminary intelligent link from “data collection” to “tactical generation.” In contrast, domestic research in this area is still in its infancy. Although some studies focus on using AI to improve sports training and data analysis efficiency, systematic research applying AIGC to tactical evolution modeling and decision simulation is still relatively scarce. Especially in content generation and semantic understanding, there is currently a lack of mature model frameworks and case studies. Therefore, in-depth research on AIGC in basketball tactical analysis has the potential to fill the domestic gap and lead the development of intelligent sports.

1.3 Research Objectives and Innovations

This research aims to build a basketball tactical modeling system that integrates AIGC technology and multimodal data analysis, comprehensively enhancing the intelligence of tactical recognition, dynamic prediction, and decision-making support. By deeply exploring image information, trajectory data, and statistical indicators during the game, the study will achieve intelligent extraction and semantic construction of tactics, thereby forming a logically structured tactical script to assist coaching teams in fully understanding the game situation. Additionally, the research will use deep learning models to dynamically simulate and predict player behavior patterns and tactical development trends, improving the timeliness and foresight of tactical analysis. Ultimately, the research will design and implement an auxiliary decision-making system capable of providing intelligent, personalized, and dynamically adjustable tactical suggestions to the coaching team during the game, enhancing their ability to respond to changes and improve tactical deployment efficiency. The innovations of this research are mainly reflected in three aspects: First, breaking through the traditional tactical modeling method centered on statistical analysis, using AIGC to automatically generate tactical scripts from game data; Second, adopting deep neural networks to construct a dynamic prediction mechanism, strengthening the ability to simulate the tactical evolution process; Lastly, integrating real-time interaction and feedback generation mechanisms to create an auxiliary decision-making system for real-world scenarios. Through these approaches, the research will explore a new paradigm of AIGC technology in the intelligent development of sports tactics, providing a new theoretical foundation and practical solution for empowering competitive sports with artificial intelligence.

2. Technical Foundations and Model Construction Principles

2.1 Overview and Development of AIGC Technology

Artificial Intelligence Generated Content (AIGC) is an important development direction in the field of artificial intelligence in recent years, encompassing subfields such as text generation, image generation, audio generation, and video generation [2]. With the improvement of computing power and continuous optimization of algorithms, AIGC technology has made significant breakthroughs in the naturalness, personalization, and interactivity of generated content, gradually moving from laboratory experiments to practical applications. Among them, large language models (such as OpenAI's ChatGPT) exhibit high accuracy and contextual understanding in natural language understanding and generation, while diffusion models (such as Stable Diffusion) demonstrate strong detail control and creative expression in image and video content generation. AIGC is shifting from being an “auxiliary tool” to a “collaborative entity,” and its explainability, generative diversity, and real-time response capabilities provide new pathways for intelligent decision-making in complex systems, offering important technical support for modeling and real-time simulation of dynamic and complex tactical environments in sports.

2.2 Fundamentals of Basketball Tactical Modeling

Basketball, as a highly structured yet unpredictable competitive sport, has a multi-dimensional and complex tactical system. The fundamentals of basketball tactical modeling include the classification and coding of tactical types, the clear division of player roles and responsibilities, and the dynamic distribution of offensive and defensive spaces [3]. Traditional tactical analysis typically relies on video playback and statistical data, making it difficult to achieve abstract modeling and logical restoration of the tactical evolution process. Based on this, this research introduces spatio-temporal graphs and semantic label systems to structurally describe players' action trajectories, spatial distributions, and cooperative behaviors on the timeline, enabling traditional tactical information to have computable and learnable feature expressions that can be effectively recognized and reconstructed by training models. This modeling method provides a solid foundation for subsequent tactical recognition, prediction, and generation.

2.3 Decision Support System Architecture Design

In the process of achieving intelligent analysis and decision-making support for basketball tactics, constructing an efficient system architecture is crucial [4]. This research, based on deep neural networks, integrates the sequence modeling advantages of the Transformer structure and the strategy optimization capabilities of reinforcement learning, designing an intelligent system framework for tactical intent recognition and tactical generation. The architecture is divided into four modules: data preprocessing layer, feature extraction layer, strategy generation layer, and feedback optimization layer, realizing a complete closed-loop from multimodal raw data input to tactical recognition, dynamic prediction, and generation of suggestions and real-time feedback. Through continuous learning and parameter fine-tuning, the system can automatically adapt to different game scenarios and tactical needs, providing highly personalized, semantically clear, and real-time updated tactical output solutions. This architecture not only has theoretical universality but also excellent scalability and practical application potential.

3. Data Acquisition and Preprocessing

3.1 Data Sources and Collection Methods

The data used in this study primarily comes from high-level professional sports events such as the NBA (National Basketball Association) and CBA (Chinese Basketball Association). This data includes various formats such as video footage, optical tracking data, passing and shooting heat maps, player positions, and movement trajectories [5]. Among them, match videos are the core information carriers, providing a complete view of tactical execution and player behavior; optical tracking data from systems like Second Spectrum and SportVU capture real-time positions of all players and the ball with high frequency sampling, offering exceptional temporal precision and spatial resolution; heat map data reflects players' offensive preferences and area distribution, helping to analyze the effectiveness of tactical deployments. Data collection methods primarily include scraping from public databases, API calls, commercial collaboration platforms, and using automation tools for video frame extraction and object detection to ensure the diversity and usability of the data.

3.2 Data Labeling and Standardization

High-quality data labeling is the foundation for building an effective tactical model. To improve the accuracy and training efficiency of the dataset, this study adopts a hybrid strategy combining semi-automated labeling tools with manual expert review, ensuring that the labeling process is scalable while maintaining the precision of tactical semantics [6]. Specifically, key action nodes and player interactions are first identified through pre-trained models, with potential tactical segments extracted. These segments are then manually corrected and categorized by labeling personnel with basketball expertise, creating a label system covering typical tactical actions such as Pick and Roll, Hand-off, and Corner 3 Screen. The labels include tactical types, executing players, coordination rhythm, and spatial layout of the tactics, among other dimensions. Finally, all data is converted into a standardized format (e.g., JSON or Tensor format) for model input, and normalized to eliminate heterogeneity, improving the model's adaptability to multi-source data.

3.3 Multimodal Data Fusion Method

Basketball tactics have high spatiotemporal dynamics and multimodal features, making it difficult to fully capture tactical intent and evolution paths relying solely on a single data dimension. Therefore, this study introduces a multimodal data fusion mechanism that integrates visual, semantic, and spatiotemporal trajectory information to create more comprehensive tactical models. The specific method is as follows: first, a Graph Neural Network (GNN) is used to model player positional relationships and construct a dynamic interaction graph to capture tactical coordination structures; then, multimodal embedding techniques map keyframe features, commentary, and coach instructions from the game video into a unified semantic space, integrating them with positional and movement trajectory information. The fusion model uses an attention mechanism to dynamically weight the importance of different modalities, improving tactical recognition accuracy and contextual understanding. This approach not only helps to understand complex tactical coordination patterns but also provides a richer informational foundation for tactical generation and feedback.

4. Model Implementation and Experimental Analysis

4.1 Tactical Recognition Model Design

In the tactical recognition phase, this study constructs a hybrid model combining Convolutional Neural Networks (CNN) and Transformer architecture to fully extract spatiotemporal features from videos and enhance the accuracy and robustness of tactical pattern recognition. The CNN part mainly extracts local spatial features from video frames, such as player positions, body posture, and court layout; the Transformer structure, on the other hand, incorporates a multi-head attention mechanism to model dynamic player coordination, tactical rhythm, and event sequences, capturing global temporal relationships. The model input consists of processed optical tracking data and video frame sequences, and the output is the corresponding tactical labels and tactical type confidence scores. This model can effectively recognize complex tactics such as Pick and Roll, Hand-off, and Pick and Roll pop, laying the foundation for subsequent tactical generation.

4.2 Tactical Generation and Adversarial Simulation

In the tactical generation phase, this study adopts the AIGC (Artificial Intelligence Generated Content) core framework to generate multiple paths for the identified tactics, including offensive development path prediction, defensive strategy adaptation simulation, and in-game adjustment suggestions. The approach is based on a hybrid Transformer and RNN architecture, which extends the tactical sequence along the timeline, predicting possible subsequent actions and collaborative changes. The model can generate multiple branching paths for offensive or defensive strategies based on different scenarios (e.g., remaining time, score margin, player status), and output tactical scripts and visualization simulation results.

Additionally, to enhance the realism and strategic competitiveness of the generated content, a Generative Adversarial Network (GAN) is introduced as a simulation optimization module. The generator is responsible for producing new tactical segments, while the discriminator evaluates the authenticity and feasibility of the generated tactics based on actual match data, driving the generator to iteratively optimize. This adversarial training mechanism ensures that the generated tactics are not only logically consistent but also remain executable and adaptable under high-intensity game conditions, greatly improving the practical value of the system.

4.3 Model Training and Performance Evaluation

In model training, this study deploys a parallel training environment based on GPU clusters and uses a large-scale labeled dataset for end-to-end training to ensure the model's generalization ability in diverse tactical environments [7]. The training process is divided into two stages: the first stage focuses on pre-training the feature extraction and recognition modules using supervised learning for tactical classification; the second stage involves the generation module and adversarial training, using reinforcement learning and adversarial optimization mechanisms for strategy generation and feedback cycle training.

Model performance is evaluated using multiple quantitative indicators, including accuracy, recall, and F1-score, to assess tactical recognition effectiveness. In the generation module, a tactical feasibility scoring system is used, where a professional coaching team rates the generated tactics based on their executable nature, logical consistency, and innovativeness.

Experimental results show that the AIGC-driven tactical generation model significantly outperforms traditional rule-based engines or template-based methods in terms of generation accuracy and diversity, especially in complex defensive simulations and fast-break transitions, demonstrating the effectiveness and cutting-edge nature of this research solution.

5. Application Scenarios and Future Prospects

5.1 Tactical Decision Support System Development

Based on the model framework built in this study, a comprehensive tactical decision support system platform can be further developed to serve coaching teams and analysts in real-time match scenarios. This platform can integrate live match data streams, including video signals, sensor trajectory data, and textual commentary, and quickly identify tactical trends on the court using pre-trained models, providing high-confidence tactical assessments. On this basis, the system can generate several predictive tactical development paths, recommend dynamic roster adjustments and counter-strategy suggestions based on the current game situation (e.g., score, remaining time, fouls). The platform also supports coaches in "simulation battles" based on different opponent styles, allowing for advanced preparation of offensive and defensive strategies in possible scenarios, thus enhancing the scientific and proactive nature of in-game decision-making and contributing to the establishment of a "data-driven" intelligent coaching decision system.

5.2 Player-Specific Training Guidance

In terms of training, the tactical modeling system can also be used to construct virtual tactical scenarios for personalized player training [8]. By analyzing behavioral patterns under different tactical types, the system can optimize individual player weaknesses, such as movement trajectories, decision delays, and coordination, and output personalized training suggestions. Players can use the diverse tactical scene videos, maps, and audio prompts generated by the system to engage in repetitive learning and simulated confrontations, strengthening their understanding of complex tactical systems and improving on-the-spot reaction skills. This training mode, especially for young players, accelerates the tactical learning curve and enhances their ability to read the game and adapt to tactics.

5.3 Expansion to Other Competitive Sports

Although this study focuses on basketball, its modeling ideas, data fusion mechanisms, and generation strategies are highly adaptable and have the potential to be applied to other team-based sports. In the future, this system can be expanded to applications in soccer, volleyball, ice hockey, rugby, and other high-intensity team sports, serving the needs of tactical recognition, formation evolution, individual role modeling, and virtual confrontation simulation in different sports. In particular, in sports like soccer, where player distribution is wider and passing routes are more complex, the value of multimodal modeling capabilities and generation algorithms will be more evident. Furthermore, the system framework can also be combined with wearable devices and physiological sensor data to create an integrated intelligent training and management system that spans tactical-level decision-making to physical performance management, promoting the deep integration of artificial intelligence and sports science.

6. Summary

This study focuses on the development of an "AIGC-driven basketball tactical intelligence analysis and decision-making model," systematically outlining the technical foundation and data processing workflows. It designed an intelligent model with capabilities for recognition, prediction, and generation of basketball tactics. Through experimental validation, the study demonstrated the feasibility and advantages of AIGC (Artificial Intelligence Generated Content) in basketball tactical analysis, especially in the areas of tactical recognition, real-time decision-making, and simulation generation. The research also explored the broad prospects of AIGC technology in coach decision support, personalized player training optimization, and cross-domain applications. The study's findings revealed that AIGC holds significant potential in transforming basketball tactics by enhancing decision-making and offering novel insights for both coaches and players [9]. It showcased how AIGC-driven models could support coaches by providing real-time tactical suggestions, optimizing training regimens for individual players, and simulating various game scenarios for strategy testing. Moreover, it highlighted the value of the integration of different data modalities and AI-driven simulations to generate tactical patterns that are dynamic and adaptable to the fast-paced nature of basketball. Looking forward, future research could further focus on improving the real-time response performance of the model, optimizing its ability to adapt to multiple contextual scenarios, and exploring collaborative mechanisms with human expert systems. Such advancements would contribute to the creation of an even more intelligent "AI tactical coach" system, which would provide invaluable support to professional teams and coaches in real-world applications. Additionally, future developments could integrate more advanced AI techniques, such as reinforcement learning and unsupervised learning, to continuously improve the model's ability to evolve with new data and emerging trends in basketball tactics.

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