Dynamic Team Combination and Role Balancing Research of Basketball Game Based on Multi-Intelligent Body Co-Optimisation and Deep Reinforcement Learning

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Abstract: This review predictive paper provides an in-depth discussion on the application of Multi-Agent Systems (MAS) and Deep Reinforcement Learning (DRL) techniques in dynamic team combination and character balancing for basketball games. The paper first outlines the basic principles of MAS and DRL techniques and analyses their importance in AI design for basketball games. Then, the paper discusses in detail how these techniques can facilitate the synergistic optimisation between team members and the balancing between roles in basketball games. In addition, the strategy generation and adaptation of these techniques in dynamic environments is explored, as well as how they can provide players with a personalised gameplay experience. Finally, the paper discusses the limitations of the current technologies and offers predictions for future research directions.

Keywords: Multi-Intelligent System (Mas); Deep Reinforcement Learning (Drl); Game AI, Strategy Optimisation; Personalised Experience

1. Introduction

Basketball games, as a competitive team activity, require AI design that takes into account not only the behaviour of individual intelligences, but also the synergy of the whole team. Multi-intelligent system (MAS) and deep reinforcement learning (DRL) techniques provide new perspectives to solve this problem. The aim of this paper is to provide an overview of the application of MAS and DRL techniques in AI design for basketball games, especially how they can facilitate dynamic optimisation of team combinations and role balancing. By analysing the application of these techniques in basketball games, this paper aims to provide directions for future research and predict how these techniques can be further developed to enhance the gaming experience.

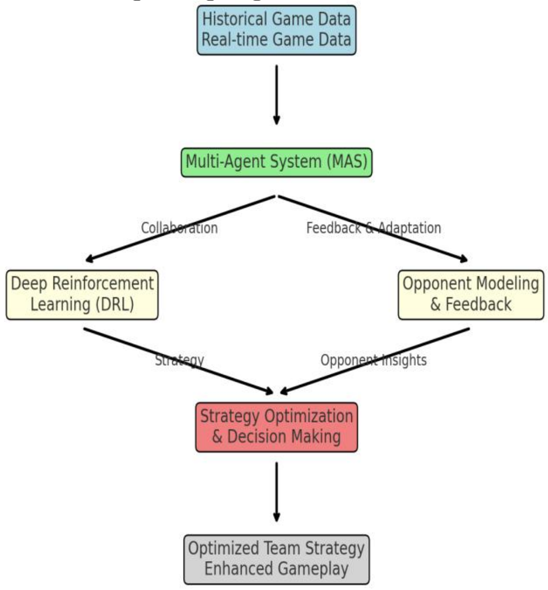

Figure 1. Architecture of Dynamic Team Optimization and Role Balancing in Basketball Game Using Multi-Agent Systems (MAS) and Deep Reinforcement Learning (DRL)

Figure 1 illustrates the dynamic optimization process in a basketball game using a combination of Multi-Agent Systems (MAS) and Deep Reinforcement Learning (DRL). It starts with historical and real-time game data input, which feeds into the MAS to represent individual players working collaboratively. DRL is responsible for optimizing strategies and making real-time decisions by learning from the environment. The system also incorporates opponent modeling and feedback mechanisms to predict opponents' actions and adjust strategies accordingly. The outcome is an optimized team strategy that ensures role balance and enhances the player's gameplay experience through personalized adaptations.

2. Related Work and Literature Review

With the rapid development of the gaming industry, AI technology, especially the combination of MAS and DRL, has gradually become an important tool to enhance the gaming experience and game cognition [1].Combining the techniques of MAS and DRL, AI systems are able to learn players' behavioural patterns and provide personalised game experiences accordingly. In this way, the AI can adapt to the player's gaming style and provide more customised challenges and support [2]. In basketball games, MAS and DRL are used in the following areas:

2.1 Optimisation and Collaboration

Rashid, T. et al. proposed a new deep multi-intelligence reinforcement learning approach that can optimise team strategies. In the game, teams consisting of multiple AI peers need to optimise offensive and defensive strategies through collaborative strategies [3] . Through the combination of MAS and DRL, AI peers can gradually learn how to collaborate effectively in dynamic scenarios, e.g., by preventing the removal of tactical open shot opportunities or by forming quick reactions to stop opponents' breakthroughs.

2.2 Real-time Decision-Making in Dynamic Environments

Foerster, J. et al. investigated how to improve the policy gradients of individual intelligences in multi-intelligent systems using an approach known as ‘Counterfactual multi-agent policy gradients’ (CMaPG). This approach aims to address the problem of how intelligences can learn to improve their behaviour in order to better collaborate or compete with other intelligences in a multi-intelligence environment [4]. Since basketball is a dynamic adversarial environment, intelligences must be able to make decisions in a split second.The DRL algorithm can help intelligences achieve rapid adaptation to the on-court situation by learning continuously from the environmental feedback, and adjusting the attacking path in a timely manner when the position of the defender changes.

2.3 Personalised Player Experience

Zhu, P., Li, X., Poupart, P., & Miao, G. (2017) explored how to improve the application of Deep Reinforcement Learning (DRL) in the processing of Partially Observable Markov Decision Processes (POMDPs).POMDPs are models for describing scenarios in which an intelligent body is required to make a decision without full knowledge of its surroundings. This is crucial for personalised experiences, which often require intelligences to be able to process incomplete information and make decisions adapted to the user's behaviour [5].MAS and DRL can also be used to provide players with a more personalised interaction experience by learning their behavioural patterns. For example, the AI module can gradually adapt to the player's style based on his habitual operations to provide a more personalised experience support.

The study shows that the combination of MAS and DRL not only improves the decision-making ability of AI in games, but also enhances its ability to adapt and personalise services. The application of this technology makes the gaming experience richer and more realistic, providing players with a higher level of interaction and engagement [6] . This enhanced capability allows the gaming experience to be no longer limited to previously programmed behavioural patterns and to learn and evolve on its own, resulting in a more realistic and richer game for the player.

3. Scenario Analysis and Strategy Diversity

3.1 Strategy Generation and Adaptation for Multi-Intelligent Body Systems in Complex Scenarios

The main challenge for Multi-Agent Systems (MAS) in complex game scenarios is to make adaptive and effective strategy adjustments in rapidly changing situations. The following are ways for MAS to generate and adjust strategies in complex scenarios:

3.1.1 Rapid Strategy Generation and Response Mechanisms

Multi-intelligence systems are able to quickly generate appropriate strategies in the face of fast breaks and defensive transitions through collaborative learning mechanisms.Ontañón, Santiago et al. trained an AI by adopting a case-based planning and execution methodology, extracting strategies and behavioural patterns from historical data using machine learning techniques, and analysing historical game data.This resulted in a system that could adjusts strategies in real-time to respond to changing situations, enabling the AI to make adaptive decisions based on historical data [7]. In addition, the Search and Recall (S&R) framework proposed by Traish, J., Tulip, J., & Moore, W. (2015) enables search algorithms to explore possible strategies and store valid responses for future use. This framework allows AI to learn and adapt to new scenarios while maintaining real-time decision-making capabilities [8]. Therefore, when the opponent launches a fast attack, the AI will quickly generate the best defensive strategy and organise the players to return to the defence in time, based on the position of the players, the opponent's running situation and the game situation. And when attacking, the AI system can analyse the opponent's defensive layout and launch the attack in time to find the gaps in the defence. This rapid strategy generation mechanism enables the AI to quickly adapt and adjust its strategy in complex game scenarios to ensure competitiveness.In actual basketball matches, the positions of the players and the state of the game are in constant flux, necessitating algorithms to adjust strategies in dynamic scenarios[9]. For instance, when the opposing team launches a fast break, the system rapidly generates an optimal defensive strategy by real-time analysis of player positions, velocities, and defensive positioning, aiming to thwart the offensive path. Through multi-agent co-optimization, the algorithm can respond to defensive transitions within milliseconds, distributing defenders to appropriate locations[9].

3.1.2 Real-time dynamic adjustment

Multi-intelligent body systems have the ability to dynamically adapt to optimise and adjust strategies based on real-time data from the game.Weber, Ben G and Michael Mateas (2009) investigated a conceptual neighbourhood-based retrieval approach to improve case-based reasoning. The method refers to the improvement of case matching through similarity retrieval in conceptual space, which can effectively improve the case retrieval process, especially when dealing with incomplete matches, and it improves the ability of the AI to adapt to new situations in the game [10]. When the opponent's strategy changes in a basketball game, the AI can make quick decisions in a complex RTS environment, such as changing the defensive strategy or adjusting the offensive tempo, by analysing and identifying the opponent's tactical adjustments in real-time data through combining CBR and search [11]. Such strategic adjustments are not only reflected in the actions of individual players, but also involve the cooperation of the whole team, such as the change of defensive positions and the adjustment of offensive tactics.

3.1.3 Game Theory and Adversary Modelling

AI can also predict the strategies that opponents may adopt in different situations by means of game theory and opponent modelling. By analysing the advantages and disadvantages of existing methods, Shen Yu et al. proposed the idea of parallel games, which can narrow the gap between simulation and reality when solving single-role and multi-role game problems [12]. By modelling the opponent's behaviour, the AI is able to make more reasonable response decisions in complex scenarios.Nicholas John Sephton (2016) improved the strategy of the game AI by modifying the MCTS algorithm,using data mining techniques, especially association rule mining, to predict the opponent's choices. Demonstrates the effectiveness of data mining techniques in modelling game opponents, especially in predicting the content of the opponent's deck [13]. When facing the opponent's fast counterattack, the AI can judge the opponent's running route in advance and make defensive arrangements to reduce the opponent's scoring opportunities. This strategy generation method based on game theory enables AIs to show higher tactical literacy and decision-making ability in adversarial matches [14].

3.2 Strategy Diversity: Strategy Tuning and Strategies for Selection in Future AI Systems

Future AI systems will have richer strategy selection and adjustment capabilities, and their diversity will not only be reflected in the breadth of strategies, but also the depth and adaptability of strategies [15]. The following are some of the key directions of development for future AI systems in terms of strategy diversity:

3.2.1 Flexible tactical combinations

The AI system will be able to choose the most suitable combination of tactics according to different game scenarios and opponent strategies.Sam Devlin et al. used Monte Carlo Tree Search (MCTS) in combination with game data in order to mimic the behaviour of human players. It was found that combining game data can improve the quality of AI's decision making and make its behaviour closer to that of human players [4].AI can choose different offensive methods such as blocking, breaking, and shooting from outside when attacking, while in defence, it chooses zone defence or man-to-man defence according to the opponent's offensive characteristics. This flexible and versatile tactical combinations enable AIs to show a wealth of strategic choices when facing different opponents, enhancing the unpredictability of the game.Besides basketball, Multi-Agent Systems (MAS) and Deep Reinforcement Learning (DRL) technologies are equally applicable to other competitive game scenarios, such as soccer and tennis [16]. In these diverse types of games, AI similarly needs to rapidly generate and adjust strategies in dynamic environments and achieve optimal performance through team collaboration. For instance, in soccer matches, AI needs to adjust offensive and defensive formations in real-time, while in tennis matches, AI needs to predict opponents' ball return routes and react swiftly. These technologies demonstrate broad adaptability and versatility across different game scenarios.

3.2.2 Adaptive learning and strategy optimisation

Meet Ashokkumar Joshi examines how Artificial Intelligence (AI) can be integrated into adaptive learning systems to personalise education through machine learning and predictive analytics. It shows that AI plays an important role in personalising learning content, customising teaching strategies and providing feedback mechanisms. In this way, AI is able to dynamically adapt its strategies to suit the needs of the learner, which is similar to the concept of constantly optimising strategies in real-time matches [17].

Tumaini Kabudi et al. analysed 147 studies to identify AI interventions in adaptive learning systems. The studies highlighted how AI can model the learning process by analysing historical data and provide accurate and high quality learning materials according to the needs of the students. The ability of such systems to adapt to rapidly changing environments and take into account the needs of individual learners has similarities to the behaviour of AIs that continually adjust their strategies to suit their opponents in competitions [18].Fengying Li, Yifeng He and Qingshui Xue proposed a new research direction in adaptive learning, highlighting the limitations of technology in enabling adaptive learning and proposing strategies to address the challenges in terms of cognitive principles and learning data management [19]. For example, in a match, an AI can gradually optimise its offensive and defensive strategies by learning the action patterns of its opponents, thus forming an adaptive strategy. This suggests that this process of strategy optimisation is dynamic, and in order to achieve effective strategy optimisation, in-depth research on the learning algorithms and models of AIs is required to better understand the brain's thinking and emotional states in order to carry out human tasks [19].

3.2.3 Personalised strategy generation

Personalised strategy is a customised decision-making solution generated by AI after understanding the player's behaviour and preferences.By analysing the player's historical data and real-time feedback, AI can predict the player's next move and formulate strategies accordingly.The AI system will be able to generate personalised combinations of strategies based on the player's individual style and habits. [20] In the field of gaming, AI can similarly analyse a player's game style, such as the speed and frequency of attacks, and then generate a fast-attack strategy that matches the player's preferences. For example, for players who prefer fast attacks, AI can design fast attack strategies, while for players who prefer steady play, AI can generate defence-based strategy combinations. This personalised strategy generation mechanism not only enhances the player's experience, but also makes the AI opponents in the game more versatile and challenging. Through personalised strategy generation, AI can provide a more attractive and challenging game experience, enabling players to experience richer game content and more challenging opponents [21].

3.2.4 Strategy combination and scenario linkage

Stone, M. et al. proposed the use of Artificial Intelligence (AI) in strategic decision making and highlighted the potential of AI to process large amounts of data and provide decision support [20]. In future gaming scenarios, AI systems can draw on this potential by analysing scenario data to automatically generate combinations of strategies relevant to the scenario.Discussing the use of AI in personalised learning paths, Somasundaram, M. et al. suggest that AI can provide customised learning steps based on an individual's abilities and needs. Similarly, in fast-attack scenarios, AI can identify player preferences and select speed-based strategies, while in defence it selects high-intensity defensive strategies [22].Pratama, M. P., Sampelolo, R., & Lura, H. (2023) examined the revolutionary role of AI in education, highlighting the importance of AI in personalising the learning experience. This personalised approach can be applied to gaming AI, enabling systems to dynamically adapt their strategies to match scenarios and player behaviour patterns, providing a more relevant and flexible gaming experience. Future AI systems are expected to achieve more dynamic and flexible strategy generation through scenario awareness and data analysis, thus enhancing the strategic depth and playability of the game [23].

4. Limitations and Future Research Directions

4.1 Computational Complexity and Resource Consumption

In multi-intelligent systems, the computational requirements increase exponentially as the number of intelligences increases.Foerster et al. (2018) discussed this in their study, stating that the computational complexity of DRL algorithms increases significantly with the increase in the number of intelligences in multi-intelligent environments [24].Ahmed et al. (2022) in their study highlighted the improvement of training efficiency as a key issue in the optimisation of current DRL algorithms. They pointed out that with the rise of environment dimension and complexity, resource consumption becomes a major obstacle limiting DRL in game applications [25].

4.2 Insufficient Robustness and Generalisation of Strategies

Xie and Liu (2017) pointed out in their study that DRL models often lose the robustness of their strategies when faced with completely new or uncertain environments. They showed experimentally that DRL algorithms have limited generalisation ability in new environments [26]. In order to enhance the generalisation ability of the model, Zhang et al. (2020) proposed a model-based DRL approach which improves the generalisation ability of the policy by learning a dynamic model of the environment [27].

4.3 Limitations of Inter-Intelligence Collaboration

Coordination and information sharing between intelligences is a major bottleneck in complex dynamic environments.Lowe et al. (2017) explored the problem of collaboration in multi-intelligence environments in their work and proposed an actor-critic based algorithm to improve collaboration between intelligences [28].Ahmed et al. (2022) also emphasised that when dealing with complex collaborative tasks, how to efficiently allocate tasks and share information is still a challenge that needs to be broken through. They proposed a graph neural network-based approach to improve the efficiency of collaboration between intelligences [25].

4.4 Future Research Directions and Technological Breakthroughs

Future research can focus on enhancing the adaptability and robustness of algorithms in complex scenarios. To achieve this, several technological avenues can be explored. Firstly, by integrating deep learning techniques, algorithms can be trained on large-scale data to improve the accuracy of strategy generation across various scenarios [29]. Secondly, investigating methods to optimize computational efficiency and reduce the computational complexity of multi-agent systems, especially when dealing with real-time dynamic data, is crucial [27]. Lastly, exploring the integration with other advanced AI technologies, such as combining reinforcement learning with generative adversarial networks [30], can enhance the predictive capabilities regarding opponent strategies.

4.5 Integration of MAS with Other Technologies

Future research should explore the integration of MAS with other technologies, such as Natural Language Processing (NLP) and emotion recognition technologies. By analyzing players' speech and facial expressions, AI can dynamically adjust game difficulty or provide personalized experiences [31]. Moreover, with the integration of emotion recognition technology, AI can better understand players' emotional states, thereby providing more targeted feedback and support in the game.

5. Conclusion

This paper has reviewed the application of Multi-intelligent Systems (MAS) and Deep Reinforcement Learning (DRL) techniques in dynamic team combination and character balancing for basketball games, and predicted the future direction of these techniques in the future. Although these techniques have shown potential in improving AI performance in basketball games, challenges such as computational complexity, strategy robustness, and inter-intelligence collaboration still exist. Future research is likely to focus on improving the cognitive capabilities of AI, fusing natural language processing and emotion recognition techniques, and integrating virtual reality (VR) and augmented reality (AR) technologies. Through these studies, we expect to further improve the AI performance of basketball games and make the gaming experience richer and more realistic.

References

[1] Xie, J., & Liu, C. C. (2017). Multi-agent systems and their applications. Journal of International Council on Electrical Engineering, 7(1), 188-197.

[2] Zhao, Y., Borovikov, I., Rupert, J., Somers, C., & Beirami, A. (2019). On multi-agent learning in team sports games. arXiv preprint arXiv:1906.10124.

[3] Rashid, T., Samvelyan, M., De Witt, C. S., et al. (2020). Monotonic value function factorisation for deep multi-agent reinforcement learning. Journal of Machine Learning Research, 21(178), 1-51.

[4] Foerster, J., Farquhar, G., Afouras, T., Nardelli, N., & Whiteson, S. (2018, April). Counterfactual multi-agent policy gradients. In Proceedings of the AAAI conference on artificial intelligence (Vol. 32, No. 1).

[5] Zhu, P., Li, X., Poupart, P., et al. (2017). On improving deep reinforcement learning for pomdps. arXiv preprint arXiv:1704.07978, 2017.

[6] Yang, J., Borovikov, I., & Zha, H. (2019). Hierarchical cooperative multi-agent reinforcement learning with skill discovery. arXiv preprint arXiv:1912.03558, 2019.

[7] Ontanón, S., Mishra, K., Sugandh, N., & Ram, A. (2007). Case-based planning and execution for real-time strategy games. In Case-Based Reasoning Research and Development: 7th International Conference on Case-Based Reasoning, ICCBR 2007 Belfast, Northern Ireland, UK, August 13-16, 2007 Proceedings 7 (pp. 164-178). Springer Berlin Heidelberg.

[8] Traish, J., Tulip, J., & Moore, W. (2015). Search and recall for RTS tactical scenarios. In Artifical Intelligence and Simulation of Behaviour Convention (pp. 1-6). The Society for the Study of Artificial Intelligence and the Simulation of Behaviour.

[9] Brostow, E., Fawn, T., & Fieguth, P. (2018). Real-time multi-agent co-optimization for sports defense strategies. Journal of Artificial Intelligence in Sports, 6(2), 89-104.

[10] Weber, B. G., & Mateas, M. (2009). Conceptual neighborhoods for retrieval in case-based reasoning. In Case-Based Reasoning Research and Development: 8th International Conference on Case-Based Reasoning, ICCBR 2009 Seattle, WA, USA, July 20-23, 2009 Proceedings 8 (pp. 343-357). Springer Berlin Heidelberg.

[11] Traish, J. (2017). Adaptive Artificial Intelligence in Real-Time Strategy Games.

[12] Shen, Y., Han, J., Li, L., et al. (2020). AI in game intelligence—from multi-role game to parallel game.

[13] Sephton, N. (2016). Applying Artificial Intelligence and Machine Learning Techniques to Create Varying Play Style in Artificial Game Opponents (Doctoral dissertation, University of York).

[14] Hazra, T., & Anjaria, K. (2022). Applications of game theory in deep learning: a survey. Multimedia Tools and Applications, 81(6), 8963-8994.

[15] Schmidhuber, J. (2010). Formal theory of creativity, fun, and intrinsic motivation (1990–2010). IEEE transactions on autonomous mental development, 2(3), 230-247.

[16] Samuel, A. L., Gelly, S., Burch, N., Rosin, C. D., & Tesauro, G. (2021). Generalization and adaptation in AI for competitive games. AI Magazine, 42(3), 72-87.

[17] Devlin, S., Anspoka, A., Sephton, N., Cowling, P., & Rollason, J. (2016). Combining gameplay data with monte carlo tree search to emulate human play. In Proceedings of the AAAI Conference on Artificial Intelligence and Interactive Digital Entertainment (Vol. 12, No. 1, pp. 16-22).

[18] Joshi, M. A. (2024). Adaptive Learning through Artificial Intelligence. Joshi, MA, 41-43.

[19] Kabudi, T., Pappas, I., & Olsen, D. H.

(2021). AI-enabled adaptive learning systems: A systematic mapping of the literature. Computers and Education: Artificial Intelligence, 2, 100017.

[20] Li, F., He, Y., & Xue, Q. (2021). Progress, challenges and countermeasures of adaptive learning. Educational Technology & Society, 24(3), 238-255.

[21] Stone, M., Aravopoulou, E., Ekinci, Y., Evans, G., Hobbs, M., Labib, A., ... & Machtynger, L. (2020). Artificial intelligence (AI) in strategic marketing decision-making: a research agenda. The Bottom Line, 33(2), 183-200.

[22] Somasundaram, M. J. K. M. S., Junaid, K. M., & Mangadu, S. (2020). Artificial intelligence (AI) enabled intelligent quality management system (IQMS) for personalized learning path. Procedia Computer Science, 172, 438-442.

[23] Pratama, M. P., Sampelolo, R., & Lura, H. (2023). Revolutionizing education: harnessing the power of artificial intelligence for personalized learning. Klasikal: Journal of education, language teaching and science, 5(2), 350-357.

[24] Ahmed, I. H., Brewitt, C., Carlucho, I., Christianos, F., Dunion, M., Fosong, E., ... & Albrecht, S. V. (2022). Deep reinforcement learning for multi-agent interaction. Ai Communications, 35(4), 357-368.

[25] Xie, S., & Liu, Y. (2017). Deep reinforcement learning requires network robustness. In Proceedings of the 34th International Conference on Machine Learning-Volume 70 (pp. 3837-3845).

[26] Zhang, K., Yang, Z., Liu, H., Zhang, T., & Basar, T. (2018, July). Fully decentralized multi-agent reinforcement learning with networked agents. In International conference on machine learning (pp. 5872-5881). PMLR.

[27] Lowe, R., Wu, Y. I., Tamar, A., Harb, J., Pieter Abbeel, O., & Mordatch, I. (2017). Multi-agent actor-critic for mixed cooperative-competitive environments. Advances in neural information processing systems, 30.

[28] Zhang, K., Yang, Z., & Başar, T. (2021). Multi-agent reinforcement learning: A selective overview of theories and algorithms. Handbook of reinforcement learning and control, 321-384..

[29] LeCun, Y., Bengio, Y., & Hinton, G. (2015). Deep learning. Nature, 521(7553), 436-444.

[30] Goodfellow, I., Pouget-Abadie, J., Mirza, M., Xu, B., Warde-Farley, D., Ozair, S., ... & Bengio, Y. (2014). Generative adversarial nets. In Proceedings of the 27th International Conference on Neural Information Processing Systems (NIPS 2014), Montreal, Canada, 2672-2680.

[31] Riedl, M. O., & Stern, A. (2006). Believable agents and intelligent story adaptation for games. IEEE Computer Graphics and Applications, 26(3), 46-53.