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A Review of the Applications and Innovative Practices of Artificial Intelligence Algorithms in Gaming

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ABSTRACT

The rapid advancement of artificial intelligence technology is profoundly transforming the gaming industry, evolving from early rule-based opponent modeling to the integrated application of deep reinforcement learning, natural language processing, and generative agents. Existing research indicates that deep reinforcement learning demonstrates formidable decision-making capabilities in complex strategy and real-time strategy games, while natural language-driven human-machine interaction and content generation significantly enhance immersion and personalized experiences. In recent years, the emergence of large-scale model technology has propelled research toward Decision AI Models, driving a shift from AI-generated content (AIGC) to AI-driven decision-making (AIGA). This paper aims to review the application and innovative practices of artificial intelligence algorithms in gaming, focusing on breakthroughs in deep reinforcement learning for agent training, the potential of natural language processing in interaction and narrative generation, and the leading role of Decision AI Models in shaping the future gaming ecosystem. Research findings reveal that AI technology not only enhances the intelligence and entertainment value of games but also provides significant opportunities for interdisciplinary research and industrial upgrading.

KEYWORDS

Deep reinforcement learning; Natural language games; Adversarial machine learning; AIGC; AIGA; Large language models

1 Introduction

Within the gaming industry, the application of artificial intelligence algorithms has become a critical factor in enhancing player experiences and driving industrial innovation. While traditional rule-based game AI can accomplish predefined tasks, it exhibits significant limitations in open environments and complex decision-making scenarios. With advancements in deep learning and reinforcement learning, researchers have progressively integrated Deep Reinforcement Learning (DRL), Natural Language Processing (NLP), and AI-Generated Content (AIGC) into gaming scenarios to achieve smarter, more immersive interactive experiences.

Existing research indicates breakthroughs in DRL across board games, real-time strategy titles, and massively multiplayer online competitive games. Notable examples include DeepMind's AlphaGo and AlphaStar, alongside OpenAI Five's successful application in Dota 2, demonstrating DRL's robust decision-making capabilities in complex strategic environments. Concurrently, advancements in NLP and large language models have enabled free-form dialogue and narrative generation. For instance, AI Dungeon demonstrates language models' potential for open-ended narrative generation. However, current research faces limitations. First, deep reinforcement learning suffers from "black-box" opacity, where decision-making processes are difficult to interpret, hindering commercial game applications. Second, models exhibit insufficient generalization capabilities, leading to unstable performance in unfamiliar environments. Furthermore, while natural language-driven interactions enhance player experiences, challenges persist in contextual understanding and safety protocols. Furthermore, in the evolution from AIGC to AIGA (AI-Generated Agent, decision-making large models), balancing computational costs with diverse player demands remains an urgent issue.

Based on this, this paper provides a systematic review of AI algorithm applications and innovative practices in gaming. Research objectives include: mapping the application pathways of deep reinforcement learning in agent training and game decision-making; exploring the potential of natural language processing in human-machine interaction and reward modeling; and analyzing the evolution trend from content generation to decision-making large models and its industrial significance. By comparing and summarizing typical domestic and international research and practice cases, this paper aims to reveal the current state, existing problems, and future directions of game AI driven by artificial intelligence, providing reference for subsequent academic research and industrial applications.

2 Research Methodology

2.1 Theoretical Foundation and Methodological Framework

This study constructs a methodological framework encompassing Deep Reinforcement Learning (DRL), Large Language Models (LLMs), adversarial game theory, and Decision-Making Large Models (AIGA), based on the primary application pathways of AI in gaming.

(1) Deep reinforcement learning provides optimal strategy learning mechanisms in complex environments;

(2) Natural language processing and pre-trained models provide semantically driven support for human-machine interaction and reward modeling;

(3) The AIGA framework offers new theoretical foundations for future cross-task transfer and multimodal integration.

By integrating these theories, this paper explores research across three dimensions: "Decision Intelligence—Interaction Intelligence—Future Trends."

2.2 Literature Collection and Data Processing Methods

To ensure comprehensiveness and scientific rigor, this paper adopts the **Systematic Literature Review (SLR)** methodology:

Data Sources: Web of Science, IEEE Xplore, Springer, and CNKI databases;

Search Keywords: "Game AI," "Deep Reinforcement Learning," "Natural Language Games," "Adversarial Machine Learning," "AIGC," "AIGA," "Large Language Models, "Machine Learning","Nature Language Processing", "Generative AI";

Time Range: 2010–2024;

2.3 Case Analysis and Comparison Methodology

The study employs a case comparison + technology induction approach:

Academic Cases: Examples like AlphaGo, AlphaStar, and OpenAI Five demonstrate breakthroughs in DRL for complex games;

Industrial Cases: AI Dungeon demonstrates natural language interaction and reinforcement learning in practical products;

Emerging Explorations: Including natural language reward models, human-agent collaborative learning games, stochastic prediction games, and the AIGA decision framework. Comparison dimensions encompass agent performance, interaction naturalness, generalization capability, computational cost, and safety robustness.

2.4 Analysis Steps and Improvement Methods

This study follows a systematic four-step analytical process to ensure the reliability and interpretability of results.First, relevant literature and case studies were collected and classified by algorithm type—Deep Reinforcement Learning (DRL), Natural Language Processing (NLP), and Decision-Making Large Models (AIGA).

Second, representative models such as AlphaGo, OpenAI Five, and AI Dungeon were evaluated using indicators like generalization, interpretability, and computational efficiency.

Third, a comparative synthesis was conducted to reveal the complementarities between DRL's decision-making strength and NLP's interactive flexibility.

Finally, improvement methods were proposed, including enhancing model transparency, applying transfer learning, reducing computational cost, and integrating multimodal information for future AIGA development.

2.5 Data Synthesis and Results Presentation

During data processing and result analysis, the following methods were employed:

(1) Table Comparisons: Summarizing the strengths and weaknesses of different research approaches, such as DRL's decision-making capability coexisting with its black-box nature, and the tension between LLMs' immersive experience and security concerns.

(2) Trend Analysis: Identifying key future research directions through combined qualitative and quantitative methods, such as enhancing interpretability, multimodal fusion, and developing large-scale decision-making models.

3 Research Findings

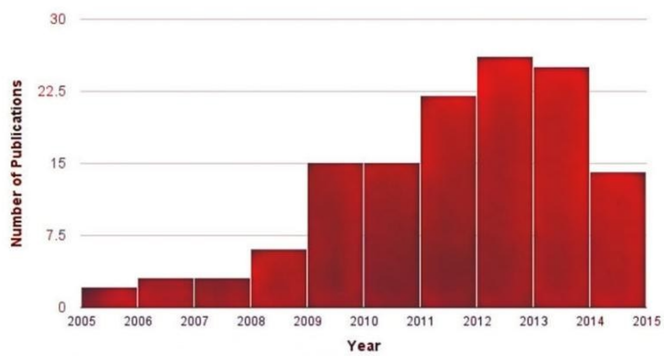
3.1 Evolutionary Path

In recent years, with continuous technological advancement, the video game market has matured into a thriving global industry. The flourishing electronic and computer gaming sector, coupled with diverse game genres and technologies, signifies that video game concepts and programming are being applied across numerous fields. Industry professionals have progressively integrated artificial intelligence into gaming, while AI's own evolution—driven by computational power and algorithmic improvements—has reciprocally influenced the gaming industry.

3.1.1 Early 21st Century (2005–2015)

AI applications in gaming (using serious games as an example)

In this paper, after thoroughly examining the listed research, the author cites the IEEE paper "Review of the Use of AI Techniques in Serious Games: Decision Making and Machine Learning" by Maite Frutos-Pascual and Begoñya García Zapirain to describe early 21st-century AI practices in gaming. After statistically analyzing and examining 170 papers published between 2005 and 2015 on the use of AI in serious games, the authors presented the following data:



(Image source: "Review of the Use of AI Techniques in Serious Games: Decision Making and Machine Learning" Authors: Maite Frutos-Pascual and Begoñya García Zapirain)

Regarding decision-making phases, the authors identified 27 papers describing research using decision trees, 16 papers employing fuzzy logic to evaluate user states during gameplay, 10 papers on Markov systems, and 19 papers utilizing finite state machines for level transitions or controlling in-game virtual characters (Frutos 135).

3.1.2 The rise of Large Language Models (LLMs) and Their Application in Gaming

In recent years, large language models (LLMs) have experienced explosive growth. Since the 2019 releases of GPT-2 , it has been discovered that transformer models trained on large text corpora can not only generate high-quality, coherent text but also be controlled through carefully designed prompts. Roberto Gallotta published a 2024 review article titled "Large Language Models and Games: A Survey and Roadmap." It evaluates the current strengths and weaknesses of LLM applications in gaming while outlining future evolution paths. Presently, LLMs serve diverse roles across games: NPCs, player assistants, commentators, game hosts, game mechanics, automated designers, and design aids. These applications not only enhance world immersion and credibility to enrich player experiences (as NPCs), but also serve as player assistants in management-based games to reduce decision-making burdens. Furthermore, they can function as commentators generating engaging, relevant, and real-time commentary based on gameplay. More significantly, LLMs can even be employed to create game plots, characters, and narratives, or provide players with novel insights as game mechanics.

However, LLMs currently exhibit certain limitations. Firstly, as NPCs, they are prone to "hallucinations"—text generated that deviates from the original context or contradicts established facts. This primarily occurs when NPCs accumulate excessive repetitive information during gameplay, causing biased knowledge retention within the model. Research on their role as commentators remains limited, and they tend to generate repetitive "secondary content." As game masters, taking AI Dungeon as an example, research by Hu Zhipeng in his paper "Research and Application of Artificial Intelligence in the Interactive Entertainment Industry" indicates significant issues persist: without incentive mechanisms, player enthusiasm may rapidly decline; the boundless nature of generated content necessitates extensive adaptation work; and the lack of necessary guidance and constraints often leads to misuse.

3.1.3 Deep reinforcement Learning

Against the backdrop of advancing Deep Learning and Reinforcement Learning, Deep Reinforcement Learning (DRL) has garnered extensive attention by leveraging deep learning's representational capabilities and reinforcement learning's self-supervised learning capacity. The integration of deep neural networks from deep learning into reinforcement learning gave rise to DRL, which combines feature representation capabilities with the ability to adjust strategies through rewards.

DRL algorithms can be categorized into two types: offline and online. Offline learning involves training using existing data without requiring real-time interaction to acquire new data, while online learning enables training through real-time interaction with the environment and utilizing acquired real-time data. Taking the offline DQN algorithm as an example, as described in Sadredini and Elaheh's paper "Impala: Algorithm/Architecture Co-Design for In-Memory Multi-Stride Pattern Matching," its performance in Atari games has progressively surpassed human capabilities (Sadredini). The Double-DQN algorithm decouples action selection from value function estimation, enhancing robustness. However, Double-DQN remains susceptible to noise interference (Hado). When reward functions are scarce or ambiguous, Hierarchical Reinforcement Learning (HRL) employs a dual-layer network architecture, with both layers utilizing DQN networks. This approach achieved significantly superior results to DQN in Atari games and Montezuma's Revenge (Tejas D. Kulkarni). However, due to its excessive parameters, the algorithm remains unsuitable for other environments (Yang Siming).

3.1.4 Evolution Toward Artificial Intelligence Generated Action (AIGA)

According to Xie Zheng's paper From AIGC to AIGA: A New Frontier in Intelligence—Decision-Making Large Models, AIGA involves multiple rounds of cycles comprising observation, adjustment, decision-making, and action. Specifically, it "employs reasoning and optimization algorithms to evaluate the effectiveness of different decision schemes and select the optimal decision path." AIGA constitutes an entire class of algorithms, encompassing Decision Generative Intelligence (GenAI) and domain-specific decision-making large models exemplified by AlphaGo and AlphaZero. Among these, Decision Generative Intelligence excels in open scenarios, namely open-world games. Through its generative technology, GenAI can produce synthetic data to enhance model training volume and improve accuracy, providing theoretical insights for refining NPC behavior patterns in open worlds. Domain-specific decision-making models like AlphaGo excel in strategy and board games, such as Go. Utilizing neural networks to evaluate value and action probability distributions, and through extensive reinforcement learning, they have surpassed world-class players in Go and chess, while reaching or exceeding the average human player level in most strategy game domains. Today, exemplified by the improved AlphaGo—now known as AlphaZero—some domain-specific decision-making models no longer rely on expert data. Instead, they enhance decision capabilities through self-iteration, demonstrating formidable learning capacity and developmental potential. General-purpose models like DeepMind's Gato excel across diverse domains. Beyond natural language processing, Gato can execute strategic game decisions and has surpassed average human player performance in certain games. Their training process resembles that of language models: tasks are converted into tokens, which are then processed through Transformer models to learn occurrence distributions, ultimately yielding trained models. However, since AIGA represents a collection of decision-making models and currently requires balancing training costs against model accuracy, related research papers remain relatively scarce.

3.2 Results Overview

This study aims to systematically review the current applications and innovative practices of AI algorithms in gaming, focusing on deep reinforcement learning (DRL), natural language-driven human-computer interaction, and the evolution from AIGC to AIGA. Through comparative analysis of 14 core papers and 5 representative industry cases spanning 2010–2024, this study summarizes the performance of different methods in terms of agent capabilities, interaction naturalness, generalization ability, and computational cost.

3.3 Data Presentation and Comparison

Table 1 summarizes the strengths and limitations of different research approaches

Method Category	Representative Study	Advantages	Limitations
Deep Reinforcement Learning (DRL)	DQN, Double-DQN (Atari games), Q-DQN (Montezuma's Revenge)	High-level game capabilities; adapts to complex state spaces	Susceptible to noise interference; insufficient generalization
Natural Language Processing (NLP/LLM)	AI Dungeon	Enhances immersion and interactive freedom	Limited contextual understanding; security risks
Early 21st Century AI Applications in Gaming: Decision trees, Markov systems, fuzzy logic, finite state machines	Maite Frutos-Pascual and Begoñya García Zapirain Serious games in the example	Strong decision-making capabilities in specific scenarios	Lacks sufficient anthropomorphism and universality
Decision-Making Large Models (AIGA)	From AIGC to AIGA: A New Frontier in Intelligence—Decision-Making Large Models	Cross-task transfer; potential for general intelligence	High cost; still in exploratory phase

3.4 Results Description

Analysis reveals:

(1) Early 21st-century AI applications in gaming predominantly utilized decision trees, Markov systems, fuzzy systems, finite state machines, etc., aiming to enhance AI's dynamic decision-making capabilities without emphasizing

anthropomorphism. In layman's terms, the AI you play against demonstrates strong decision-making abilities but exhibits pronounced AI characteristics.

(2) Comparative analysis of results from various review and experimental papers indicates that deep reinforcement learning, due to its high-level game-playing capabilities, has become the most mature method for complex strategy games. It has achieved win rates surpassing professional human players in Go and real-time strategy games, and reached human-level performance in most Atari games. However, its susceptibility to noise interference and reliance on heavily customized game settings in existing experiments result in poor adaptability, rendering it ineffective across diverse open-world environments.

(3) Large Language Models (LLMs) have significantly enhanced game immersion and player freedom, particularly in narrative generation and NPC dialogue. However, they often fail to provide sufficient player incentives, leading to diminished engagement. Persistent challenges include context inconsistencies caused by "hallucinations" resulting from processing massive information volumes, alongside security risks stemming from the boundless nature of generated content—which can be exploited by players to inject harmful information.

(4) Decision-making large models (AIGA), as an emerging direction, demonstrate potential for cross-task transfer and integrated reasoning, positioning them as a future development trend. However, they remain in the early exploratory phase for commercial applications.

3.5 Group Comparison

To further illustrate differences between approaches, this paper compares "academic cases" and "industrial cases":

(1) Academic Cases (AlphaGo, AlphaStar, OpenAI Five): Focus on agent performance in high-complexity tasks, emphasizing win rates and game-playing capabilities.

(2) Industrial Cases (Montezuma's Revenge, AI Dungeon): Prioritize player experience and immersion, emphasizing natural interaction and entertainment value.

Results indicate a distinct division of labor between academic research and industrial practice: the former drives breakthroughs in algorithmic frontiers, while the latter emphasizes technology implementation and user experience.

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