Recent Research on AI in Games

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***Abstract*—Games tend to have the properties of vast state space and high complexity, making them excellent benchmarks for evaluating various techniques, including AI ones. Techniques utilized in games capable of making them more attractive, immersive, smarter etc. can all be considered to be certain forms of game AI. Considering there are few reviews on the more recent work in the game AI field from the perspective of essential applications, in this paper, we make a systematic review of typical research from 2018 on three application fields of game AI: believable agents in non-player characters research, game level generation in procedural content generation, and player profiling in player modeling. We also provide a timeline of game AI history to give the readers a clearer picture of the game AI field. Moreover, general game AI and hybrid intelligence for games are discussed.**

***Index Terms*—Game, Artificial Intelligence (AI), Game AI**

I. Introduction

Game playing has always been a popular part of human life. Notably, ever since the 21st century, various sorts of video games, online or offline, have undergone rapid changes with the development of artificial and computational intelligence. The research field of artificial intelligence in games, namely game AI, has existed as an individual one in roughly the past 15 years and has gone through quite a lot of breakthroughs [1].

Ever since its emergence in the 1950s, AI has been introduced to video game playing, and in turn, games have widely served as a useful measurement of the signs of progress in AI [2]. In order to provide readers with a clearer understanding of the game AI history, we present a timeline of the development of AI and game AI (see Fig.2). The upper line represents the development stages of AI. The under lines show the history of game AI corresponding to the development of AI. Some essential software, programs, games and events are marked as milestones of game AI in this line. For example, recently in 2017, Google DeepMind's AlphaGo [3] defeated Ke Jie, the world's number one ranking Go player. Be noted that the progress of AI and game AI are not necessarily consistent. For example, game AI had been still making notable progress even during the AI winters (periods of reduced funding and interest in AI research [4]). Moreover, some research work takes the period of 1971 to 1983 to be the golden age of arcade video games, which overlaps a lot with the first AI winter [5].

This work is funded by Civil Aviation Joint Funds of the National Natural Science Foundation of China (Grant No. U1633121).

Yannakakis and Togelius [1] identified ten major research areas standing out within the game AI field. Their work aimed to offer aa higher-level overview of the game AI research field and was more about the interactions among these areas as well as the influences they had on each other. Furthermore, a textbook on Game AI was published in 2018, which offers comprehensive knowledge of the game AI field [6]. Motivated by them, this paper presents an insight into game AI as well as its important applications from 2018 to the present. Based on [1], we intend to summarize the more recent technical studies on three aspects of game AI: believable non-player characters (NPCs), procedural level generation (PLG) in procedural content generation (PCG), player experience modeling in player modeling. And general game AI (GGAI), as a frontier of game AI research, along with hybrid intelligence for games, are discussed in the discussion section. The main contributions of this paper are that it makes up for the lack of a review on more recent studies on the Game AI field from the applicational perspective, and that some emerging techniques are discussed, pointing out a possible direction for future research.

The remainder of this paper is organized as follows: In section 2, we respectively review some of the representative research work regarding each of the three application areas mentioned above. Then in section 3, we discuss hybrid intelligence as well as its potential to be applied to the game field and GGAI. Finally, an overall conclusion is drawn.

II. Important Application Areas

In this section, we reviewed research work starting from 2018 regarding each of the above-mentioned three application areas. We mainly use *Google Scholar* as our data source and only reviewed the technical papers with evaluation results here.

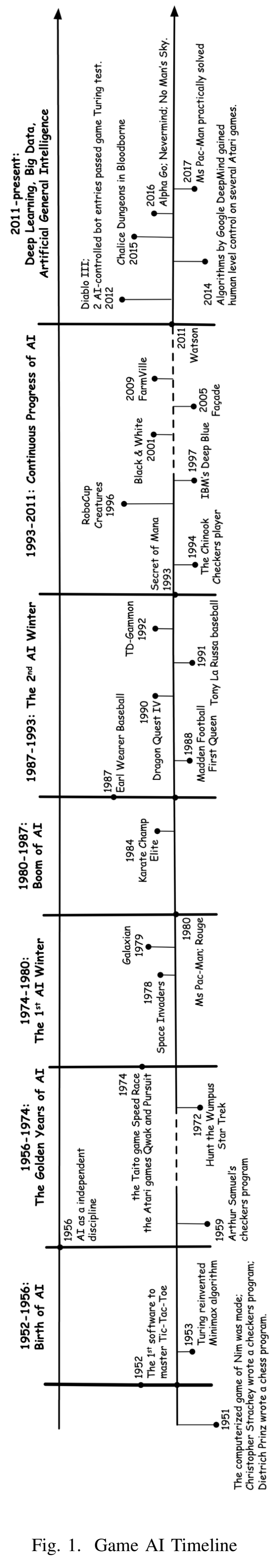

Fig. 1. Game AI Timeline

As shown in Fig.2, game AI applications mainly cover NPCs, PCG, search and planning, player modeling, AI-assisted game design, and games as AI benchmarks [1]. In this paper, we only cover a small part of the applications, which are painted in a darker color. As for GGAI, since we only mention it in the discussion considering its importance and we do not go through it in detail due to space limit, it is painted in a lighter color than those three subjects.

A. Game AI for Believable NPCs

With advanced graphic fidelity of modern video games and the application of technologies like Virtual Reality and Augmented Reality in games, game players now more than ever enjoy the immersion and playability of games. As a result, it brings game designers the challenge of creating more intelligent NPCs to build more engaging and challenging games [7]. In the following part of this section, we will present the readers with some recent work concerning intelligent and believable NPC agents.

Reinforcement learning (RL) has been commonly used in the design of game NPCs. Arzate et al. [8] introduced their framework for evolving believable agents using RL. According to the authors, the framework could handle two major challenges on creating human-like NPC agents, respectively exploring huge state space while still being human-like, and exhibiting behavior diversity while being able to adapt to different users. An evaluation was done in a 2D fighting game *Street Fighter IV*, and their method acquired more than 0.6 human-likeness ratios for the third-person Turing test, which is quite promising. Also, Zhao et al. [9] presented their preliminary work on training human-like agents with high skills in team sports games based on hierarchical learning, which utilized both imitation learning and RL. Their goal was to design believable agents in terms of both strategies and tactics, and the proposed approach achieved good performance though the complete work was still in progress. Borovikov et al. [10] proposed using imitation learning with a human in the loop to interactively create NPCs of higher quality. Notably, Razzaq [11] used augmented reality and RL together to derive more wise NPCs, and Nadiger et al. [12] firstly used federated RL for the personalization of NPCs. Other work like [13], [14] also based their methods on RL for smarter NPCs.

On the other hand, natural language processing (NLP) has been of increasing importance in the design of narrative human-like game NPCs. Ontanon [15] introduced their prototype game where the NPC was based on Winograd's NLP framework [16] in order to offer more intelligent performance. Similar work utilizing NLP to build more interactive and smart NPCs includes [17], [18] etc.

Apart from training intelligent agents to play games or interact with human players in a more human-like way, work has been done to construct believable agents to help playtest and design games as well [19]. And there are some other studies done on creating human-like agents (e.g. [20], [21]), but the authors did not specifically apply their method in game environments. So we will not discuss them here.

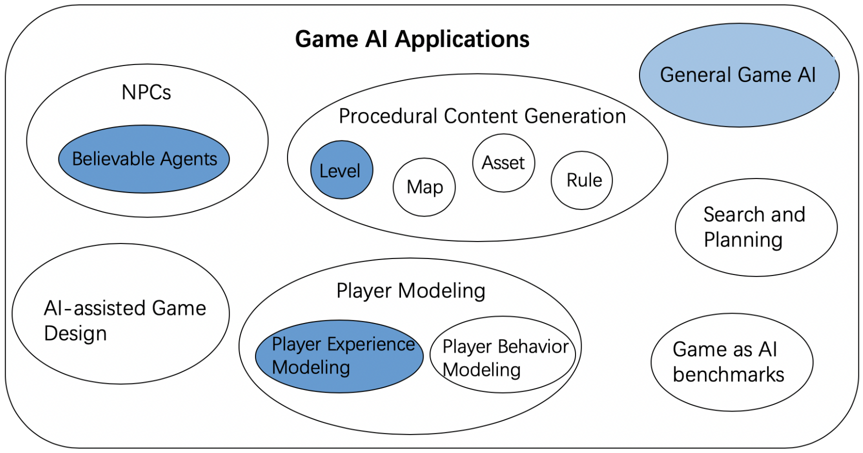

Fig. 2. Game AI Applications

B. *Game AI for Procedural Level Generation*

Although many other studies focus on the generation of other aspects like game rules, mechanics, assets and so on, it is hardly possible for us to review all the aspects of procedural content generation (PCG) here. So, in this paper our emphasis is with level generation only. Procedural Level Generation (PLG) means programmatically generating game levels randomly or pseudo-randomly, which leads to a series of unpredictable possible game levels [22].

Super Mario Bros. has been a popular benchmark game for game PCG, especially PLG. Guzdial et al. [23] proposed using two groups of inputs to create new outputs through machine learning methods without needing extra training data. Their approach, as well as three existing ones, was evaluated by generating levels of *Super Mario Bros.*, proving the effectiveness of the proposed method. Khalifa et al. [24] used constrained evolutionary algorithms and quality-diversity algorithms for the generation of part of *Super Mario Bros.* levels that were solvable and were targeted at certain game mechanics. Guzdial et al. [25] explored co-creative level design in games and presented a framework. Co-creation is a new domain of PLG via machine learning (i.e., PLGML) where human and AI agents work together. Their framework was used to generate *Super Mario Bros.* levels. The evaluation results proved that current PLGML approaches could handle co-creation well. Other work focusing on PLG for *Super Mario Bros.* includes [26]–[28] etc.

Games of *Angry Birds* style are another type of commonly seen games in the research of PLG. Abdullah et al. introduced their level generator for an Angry Birds-like game, which was based on Rube Goldberg Machine (RGM) mechanisms. The proposed method could generate stable levels by selecting pre-defined segments. Experiment results showed their level generator was competitive against two existing ones, including the winner of the 2018 AIBIRDS Level Generation Competition [29]. Stephenson et al. [30] built their work on an existing level generator and added a new feature of dynamic difficulty adjustment. Calle et al. [31], [32] presented an approach for PCG in *Science Birds*, an open-source version of the original game. Their method, built on a search-based PLG using evolutionary algorithms, could generate stable free-from game structures, which were essential for the generation of game levels.

Karavolos et al. [33] presented a surrogate model of various game content for PLG. This model, trained via deep learning, could allow game designers to adjust game levels towards specific directions, which assembles the core idea of the above-mentioned co-creation. The proposed model was evaluated in a Shooter game, and the results revealed several possible future directions. Similarly for shooter games, Giacomello et al. [34] proposed using Generative Adversarial Networks (GANs) for PLG of a first-person shooter (FPS) game. The authors concluded that their preliminary evaluation results were promising, and GANs had the potential to generate FPS levels. Also, work like [35], [36] demonstrated methods to generate levels for shooter games.

For other types of games like dungeon games, Sheffield et al. [37] demonstrated their preliminary work to generate dungeon levels; Smith et al. [38] proposed to generate dungeons with correct lock-and-key structures via declarative constraint solving to cope with several hard gameplay and design constraints. Other work has been done to study PLG in bullet hell games [39], educational games [40] and other games [41]–[43].

Apart from the PLG for traditional video games, PLG for virtual or augmented reality games is a relatively new research direction. Xie et al. [44] presented a novel approach to optimize level designs of such motion-based games. They took into consideration the actual challenges the player might encounter during game playing. The authors thought of a game level to be comprised of chunks featured by the exercise intensity they had on players, and further considered the level generation task as an optimization problem where these assembled chunks needed to realize the optimized intensity level. And the effectiveness of their method for motion-based virtual reality games was validated via user study.

C. Game AI for Player Experience Modeling

Player experience modeling, as a major branch in player modeling, aims to model how the player feels during game-playing. As is mentioned earlier, the main motivation of game AI is to provide players with more immersive and interesting game experience, so the model of player experience is also of importance.

Typically, access to game engine or log information is required to get the player's game data (e.g. [45], [46]), which is a major drawback for researchers since this kind of data is usually hard to access. To cope with the problem, Luo et al. [47] proposed to model player experience using gameplay videos. Their method, based on convolutional neural networks (CNN) and transfer learning, could derive game logs from a game video. Evaluation in a *Super Mario Bros.* style game showed their method was superior to several existing ones. In [48], the authors also explored three different deep CNN to learn the player's interest in a game through gameplay videos. They evaluated these methods in an annotated gameplay video dataset and gained an overall accuracy of 75%. Similarly, studies like [49] also investigated into player experience modeling using gameplay videos.

Also, the research on using psychophysiological indicators to model player experience is getting more attention. Čertickỳ et al. proposed to use such measurements to handle player experience modeling since involuntary physiological responses are more objective. The authors used heart rate data to help capture a player's state while playing *HeartStone* or *Dota 2*. Preliminary as the experiment was, it showcased the correlation between these psychophysiological indicators and a player's in-game activities. Also, the users suggested combining more psychophysiological indicators such as electrodermal activity or respiratory activity to achieve better performance and this improvement was done in another work of them [50]. And the work of Siqueira et al. [51] also proposed using facial expressions and electrodermal activity together to assess the player experience.

III. Discussion

With the fast development of emerging interaction and AI technologies, especially the emergence of concepts hybrid intelligence, AI techniques are taking steps further towards a more prosperous future. In this section, we intend to mainly talk about a) general game AI, and b) hybrid intelligence and its potential to be applied to games in the future.

A. General Game AI

General game AI (GGAI) is the use of game AI techniques to handle various problems in more than one game, which covers the content of general game playing (GGP) [52]–[55], general PCG [56]–[58] and so on. GGAI is currently a frontier in game AI research since the problem is only partly solved and requires further study. So far, most studies on GGAI are focused on a certain game type, or games of similar features, which results in less value since the application of these studies are severely limited, lacking generality and extensibility. This is why GGAI is the frontier of the field, thus needing more attention. Detailed knowledge on GGAI can be found in [6], and we are not going to discuss the problem in length here.

B. Hybrid Intelligence

According to the definition given by Dellermann et al. [59], hybrid intelligence refers to the ability or technology to accomplish difficult and complex tasks by merging human intelligence and AI. In this combined way, the results could be better achieved than those human and AI could have done independently, and human and AI systems could co-evolve by continuously learning from each other.

Games, as popular benchmarks and testbeds for AI techniques, have an equally important role to play for the evaluation of hybrid intelligence techniques. AI-assisted game design is a perfect example of hybrid intelligence since it is a process where human expert knowledge and AI techniques together serve the purpose of game design. More specifically, PCG is usually a semi-automatic process, in which human designers collaborate with AI agents to generate game content. That is, by combining human intelligence and game AI, game content of better quality could be generated within less time, costing less money. The core idea of the concept co-creation mention in section 2.B can be considered a good example of hybrid intelligence for games. The above examples of hybrid intelligence for games all showcase the value and potential of this technique. And once hybrid intelligence is more developed, games are bound to benefit more from it.

IV. Future Work and Conclusion

So far, three aspects of game AI have been discussed. It is undeniable that this review is by no means comprehensive since Game AI covers various aspects, some of which are bound to be beyond the scope of this paper. For example, game AI has been used for other application purposes such as assisting game design and production, game testing etc., which are not discussed in this paper. In the future, we plan to make a more detailed review covering more aspects of game AI.

As a frontier of game AI research, current studies on GGAI tend to be limited to only a small number of games, which are usually of the same type. That is, we still have a long journey ahead in order to realize the generalization of game AI, even if it is just for a certain game genre. In the meanwhile, with techniques like hybrid intelligence and cerebral control gaining more attention, game AI is bound to have a promising future once these techniques are developed enough to be applied to game fields.

With this paper, we hope the readers could get to know the development history of game AI and could develop a clear understanding of current research topics and trends of the game AI field.

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