VIT®

Vellore Institute of Technology

(Deemed to be University under section 3 of UGC Act, 1956)

DIGITAL ASSIGNMENT 1

ARTIFICIAL INTELLIGENCE

NAME: POLI VARDHINI REDDY

REGISTER NUMBER: 21BIT0382

1. Define the term “Artificial intelligence”.

Artificial Intelligence is the simulation and creation of human-intelligence in machines and computers that are programmed to mimic human activities such as learning, problem solving abilities, perception on data stored and decision making abilities. Tasks requiring human intelligence like recognizing patterns in data, making predictions is done by machines using AI. AI techniques includes various approaches and methods like Machine Learning, Deep Learning, NLP, computer vision and Robotics. Overall, the main objective of AI is to create intelligent machines that can perceive their environment uses agents, learn from experiences and interact with the humans in a manner that resembles/simulates the human intelligence with great accuracy and precision.

2. Provide a preferred example of AI – problem.

AI can be used for Anamoly Network Detection based on Self-Attention Mechanism.

3. Justify your AI problem with latest scientific journal.

According to a article by Wanting Hu, Lu Cao, Qunsheng Ruan and Qingfeng Wu (Submission received: 27 April 2023 / Revised: 15 May 2023 / Accepted: 23 May 2023 / Published: 25 May 2023) Network traffic anamoly detection is a key step in identifying and preventing network security threats. This study aims to construct a new deep-learning-based traffic anomaly detection model through in-depth research on new feature-engineering methods, significantly improving the efficiency and accuracy of network traffic anomaly detection. The following two elements are the primary focus of the particular research project: 1. Starting with the raw data of the classic traffic anomaly detection dataset UNSW-NB15, this article combines the feature extraction standards and feature calculation methods of other classic detection datasets to create a more comprehensive dataset. 1. The goal of this approach is to accurately and completely describe the network traffic status by re-extracting and designing a feature description set for the original traffic data. 2. For crucial time-series data found in the aberrant traffic datasets, this paper suggests a detection algorithm model based on LSTM and the recurrent neural network self-attention mechanism. With this model, the temporal dependence of traffic features can be learned via the LSTM's memory mechanism.

Secondly, with 108 elements in 5 categories, this article creates a rather comprehensive feature set for network traffic at various levels and protocol types that may precisely represent the session's status information. Feature selection was done on the feature set because of the abundance of these features and the existence of redundant or invalid features. This article uses feature recursive elimination and filtered feature selection techniques to choose a 19-dimensional feature subset. When using the same machine learning algorithm and raw traffic data, it is demonstrated through the validation of machine learning algorithms that the dataset construction method for network traffic in this paper can effectively reduce the algorithm training time and improve the algorithm detection ability. Subsequently, this article designs a deep learning network detection model based on the autonomous attention mechanism, which effectively improves the efficiency and accuracy of network traffic processing.

Only binary possibilities are supported by the current model. This article's technique is intended for the detection scenario, which merely requires the session to be identified as "normal" or "abnormal." However, it might also be applied to the identification situation, which would require the identification of particular kinds of exceptions. In fact, there are nine exception-type annotations of Fuzzers, Analysis, Backdoors, DoS, Exploits, Generic, Reconnaissance, Shellcode, and Worms available in the UNSW-NB15 dataset. Unfortunately, the various exception types' data amounts vary widely, which has a negative categorization effect. To create a better recognition method, it is therefore required to enhance both the data set and the classification algorithm.

Reference:

1. Aboaoja, F.A.; Zainal, A.; Ghaleb, F.A.; Al-rimy, B.A.S.; Eisa, T.A.E.; Elnour, A.A.H. Malware Detection Issues, Challenges, and Future Directions: A Survey. *Appl. Sci.* **2022**, *12*, 8482. [**Google Scholar**] [**CrossRef**]
2. Liaropoulos, A. Cyber-Security: A Human-Centric Approach. In *European Conference on Cyber Warfare and Security*; Academic Conferences International Limited: Oxford, UK, 2015; p. 189. [**Google Scholar**]
3. Juvonen, A.; Costin, A.; Turtiainen, H.; Hamalainen, T. On Apache Log4j2 Exploitation in Aeronautical, Maritime, and Aerospace Communication. *IEEE Access* **2022**, *10*, 86542–86557. [**Google Scholar**] [**CrossRef**]

4. **Research on Anomaly Network Detection Based on Self-Attention Mechanism by** by Wanting Hu, Lu Cao, Qunsheng Ruan and Qingfeng Wu

4. choose any algorithm for your problem

ALGORITHM—

Recursive feature elimination algorithm—

Input: classification data set *D* with *n* features; basic classification algorithm model (such as random forest, logistic regression, etc.); the number of features *k* ($1 \le k \le n$) for iteration stop; the number of features eliminated at each step.

1)Initial feature set $F=\{f_1,f_2,\ldots,f_n\}$

2) Training the basic algorithm model: use the *F* feature set of the data set *D* to train the basic algorithm model;

3) Calculate feature importance: for each feature in *F*, calculate its impact on model prediction results according to the training results of the model.

4) Recursively delete features: delete the least important step features in *F*;

5) Repeat steps 2 to 4 until the required number of features is reached, i.e., $|F| \le k$;

6) Preserve the selected features: use the feature set F to train the final model, and output the feature subset F and model.

Output: A feature subset composed of *k* features.

5. CONCISE OF 12 ARTICLES ON game playing

Article 1

Recent Research on AI in Games

Abstract—Games tend to have the properties of vast state space and high complexity, making them great bench marks for evaluating various techniques including AI ones. Broadly speaking, techniques utilized in games capable of making them more interesting, immersive, smarter etc. can all be considered to be certain forms of game AI. Considering there are few review son the more recent work in the game AI field from the perspective of important 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 AII.

INTRODUCTION

Game playing has always been a popular part of human life. Especially, ever since the 21st century, various sorts of videogames, 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 major breakthroughs [1]

IM PO RTANT AP PL IC ATION AREAS

In this section, we reviewed research work starting from2018 regarding each of the above-mentioned 3 application areas. We mainly uses Google Scholar as our data source and only reviewed the technical paper with evaluation results here. As shown in Fig.2, game AI applications mainly covers NPCs,PCG, search and planning, player modeling, AI-assisted game
Fig. 1. Game AI TimeLine design, and games as AI benchmarks [1].

DISCUSSION
With the fast development of emerging interaction and AI technologies, especially the emergence of concepts hybrid intelligence, AI techniques are taking steps further to wards 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

FUTURE WOR K AN D Conclusions
So far, three aspects concerning game AI have been dis-cussed. 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

REFERENCES

[1] G. N. Yannakakis and J. Togelius, “A panorama of artificial and com-putational intelligence in games,” IEEE Transactions on ComputationalIntelligence and AI in Games, vol. 7, no. 4, pp. 317–335, 2015.

[2] Wikipedia contributors, “Artificial intelligence in video games —Wikipedia, the free encyclopedia,” https://en.wikipedia.org/w/index.php?title=Artificial intelligence in video games\&oldid=915298805, 2019,[Online; accessed 12-October-2019].

[3] D. Silver, A. Huang, C. J. Maddison, A. Guez, L. Sifre, G. van denDriessche, J. Schrittwieser, I. Antonoglou, V. Panneershelvam, M. Lanc-tot, S. Dieleman, D. Grewe, J. Nham, N. Kalchbrenner, I. Sutskever,T. Lillicrap, M. Leach, K. Kavukcuoglu, T. Graepel, and D. Hassabis,“Mastering the game of go with deep neural networks and tree search,”Nature, vol. 529, no. 7587, pp. 484–+, 2016

Article 2

Evolutionary Algorithm in Game – A Systematic Review

Article Info Abstract Keywords: Evolutionary Algorithm, Game, Systematic Review Article history: Received: April 14, 2023 Accepted: May 30, 2023 Published: May 31, 2023 Cite: H. Armanto, H. A. . Rosyid, Muladi, and Gunawan, "Evolutionary Algorithm in Game – A Systematic Review", KINETIK, vol. 8, no. 2, May 2023. https://doi.org/10.22219/kinetik.v8i2.1714 *Corresponding author. Harits Ar Rosyid E-mail address: harits.ar.ft@um.ac.id

Abstract

Research in the game field is increasingly numerous and challenging. The high interest in research on games is influenced by public awareness of the importance of games in developing ways of thinking, although it is undeniable that many people only pursue pleasure in playing games. In the past, not much games research has influenced into topics such as artificial intelligence, education, or other computer topics. But now games are having a tremendous impact on these topics. In fact, not infrequently games are used in various areas of life. Right now, artificial intelligence is an integral part of the game. If before, it was only used for creating an enemy. Right now artificial intelligence can affect various things, starting from assets, game difficulty levels, nonplayer characters (NPC), and even bots (AI agents) to run player characters. The complexity of artificial intelligence which is getting higher and higher requires a good optimization algorithm.

1. Introduction
   Research in games has now become an interesting and hot topic among researchers. Not inferior to other research topics in computer science such as computer vision, data science, or other popular topics. Now Games have arised as one of the research topics that are felt to be useful. For example, according to bestcolleges1 , game-related research can be directed to its use to solve current world problems. In fact, not infrequently, these studies enter the area of computer science topics.
2. Evolutionary Algorithm Evolutionary algorithms2 [10], [11] are optimization algorithms obtained from the behavior of living organisms such as the behavior of birds in traveling [12], cats in searching for prey [13], or penguins in warming their bodies [14]. Apart from being based on the behavior of living things, the concept of evolutionary algorithms is also derived from natural phenomena such as the evolution of living things, water droplets, or symbiotic relationships between living things. Although the workings of these algorithms vary3 , the basic concepts used are similar. Which comes from its predecessor, namely genetic algorithm, and particle swarm optimization.
3. Evolutionary Algorithm in Games Research on games continues to grow and increase, including research using evolutionary algorithms. Currently, various types of evolutionary algorithms are studied to handle cases in games, where each type of case has its own complexity and target solution. The following sub-chapters will explain in more detail regarding each type of case that has been studied, the evolutionary algorithm used, to the results achieved by the research.

4. Conclusion

   Based on the studies from some relevant articles, some conclusions can be made. First, even though the development of the evolutionary algorithm is relatively rapid (minimum one algorithm per year), applications in games are lacking. Most researchers prefer genetic algorithms due to the easier implementation of genetic algorithms compared to newer evolutionary algorithms or lack of confidence when applying new algorithms in games. Second, if we talk about game problem representation, there are two types of representation in evolutionary algorithms for games: the parameters or properties of the problem and the inclusion of the machine learning algorithm's parameters. Third, in terms of research experiments, the existing studies used the preferences of the researcher or developer as the basis for their fitness function. In addition, the ability targets of AI Agents are also included, such as the impact on player health points, the number of wins, the number of losses, or something else. Fourth, there are four methods to measure experiments for this field of research: Measure success based on the fitness value where the higher the number the more human the AI; Questionnaires to players, concerning their knowledge of the game they played. However, this requires a vast number and types of participants to ensure the objectiveness of the responses; Analysis by an expert or a player who understands the problem being researched. However, subjectivity could hinder the expected result if not anticipated; Finally, an alternative approach via competition between NPCs. The NPC's winning rate will later be used as proof of success whether the NPC under study works well or not. Last, research on the NPC's behavior and AI agents for a game is extensive, deep, and growing research until recently. This is because both NPCs and AI Agents are highly dependent on the development of the game.

References

[1] Z. Hellman and M. Pintér, "Charges and bets: a general characterisation of common priors," Int. J. Game Theory, vol. 51, no. 3, pp. 567– 587, 2022. https://doi.org/10.1007/s00182-022-00805-4 [2] E. C. Ramón and E. Gutiérrez-López, "The equal collective gains value in cooperative games," Int. J. Game Theory, vol. 51, no. 1, pp. 249–278, 2022. https://doi.org/10.1007/s00182-021-00791-z [3] D. Christopher Opolot, "On the relationship between p-dominance and stochastic stability in network games," Int. J. Game Theory, vol. 51, no. 2, pp. 307–351, 2022. https://doi.org/10.1007/s00182-021-00794-w [4] M. S. O. Almeida and F. S. C. da Silva, "A Systematic Review of Game Design Methods and Tools BT - Entertainment Computing – ICEC 2013," 2013, pp. 17–29. https://doi.org/10.1007/978-3-642-41106-9_3

ARTICLE 3

Improved Belgian AI Algorithm for Dynamic Management inAction Role-Playing Games

Abstract:
Artificial intelligence in games is one of the most challenging tasks in academia and industry. In action role-playing games, how to manage combat effectively is a key issue related to game development and the player's experience. The Belgian artificial intelligence (BAI) algorithm is a classic but limited method that is widely used for combat management between the player and enemies

Keywords: action role-playing games; game artificial intelligence; dynamic difficulty adjustment; combat management

1. Introduction

Artificial intelligence is developing by leaps and bounds and has cut a figure in academia and industry. In general research, AI is highly technical and professional to lay the foundation of every walk of life [1–3]. In the field of games, artificial intelligence R and D is challenging work that requires game designers and developers to have creative thinking as well as solid insight [4,5]. Game AI aims mainly to maximize the fun of the player while enhancing the game challenge and supporting an extraordinary gaming experience [6–8]. The player experience refers to the total effect of feelings, thoughts, emotions, and behaviors exerted on the player during the gameplay, including immersive experience, game participation experience, demand satisfaction experience, etc. [9,10]. The player experience is not an attribute of the game, but the state in which the player interacts with the game, which directly determines the sales volume, praise, player retention rate, and other key indicators [11–13]. Dynamic difficulty adjustment (DDA) is a typical technology that can maintain the player's interest to ensure their gaming experience by modifying game parameters, behaviors, and scenes in real-time according to the player's skill level automatically [14–17].

2. Belgian Artificial Intelligence Algorithm

BAI is designed based on rectangular grids around the player. It divides the game scene into player-centric and uniformly aligned rectangular grids. The eight grids around the player are utilized to hold the attacking enemies; each grid can hold only one enemy. In action role-playing games, BAI sets four variables for the player, namely maximum grid capacity (MGC), current grid capacity (CGC), maximum attack capacity (MAC), and current attack capacity (CAC). MGC limits the number of enemies that can attack the player at the same time, while MAC determines the attack types. The initial CGC and CAC of the player are equal to the MGC and MAC, respectively. BAI sets grid weight (GW) and attack priority (AP) for each enemy, and attack weight (AW) for each attack type. GW represents the grid capacity value that the enemy occupies in the grid, while AW represents the attack capacity value of the enemy attack type. Each enemy has a normal attack, and its AW is zero.

Results and Discussion

In order to verify the improved effect of IBAI, two combat dynamic management systems were implemented in Unreal Engine 4 based on BAI and IBAI, respectively. The specific process and results of the design and implementation, testing, and comparison of the adaptability of the two systems are elaborated on in this section. Appl. Sci. 2022, 12, 11860 9 of 22 4.1. System Design and Implementation Each system contains one player, multiple enemies, a stage manager, and other required assets, which are tested by a series of combats between the player and enemies at different test levels. The specific implementation process according to the relationships between the core classes in the system is as follows: 1. Create the player class and set related variables, functions, events, and interfaces. 2. Create the enemy class and complete the creation of EnemyMelee, EnemyRanged, and other classes based on the inheritance relationships. The system has six types of enemies, including three that use melee attacks named EnemyMelee1, EnemyMelee2, and EnemyMelee3, as well as the rest named EnemyRanged1, EnemyRanged2, and EnemyRanged3 that attack from a range. Among them, Skill1 of EnemyMelee2 is the same as EnemyMelee3, Skill1 of EnemyRanged2, and EnemyRanged3 are equivalent as well. The related variables, functions, events, and interfaces are then set. 3. Create the stage manager class and set its and all other related variables, functions, events, and interfaces. 4. Create meshes, models, weapons, animations, skill effects, and sound effects for the player and enemies. 5. Build test levels. The settings of essential variables in the player class and each enemy class are shown in Table 3.

In order to ensure the clarity of the screenshots during gameplay, the test levels for BAI and IBAI are designed with different styles of terrain. Meanwhile, the player's head-up display information is hidden in the screenshots. The display of the player's current health value will not affect the process

Conclusions

This paper improves BAI, which is extensively used for managing combat, and proposes IBAI to enhance the adaptability of combat management systems for action role-playing games and provide players with a better game experience. IBAI accommodates the enemy in the MRBP ring model, whose parameters can be set adaptively according to the specific game mechanism. Both melee and ranged enemies can be managed efficiently, and the interaction area between enemies and the player in each sector of the same ring area is consistent. IBAI sets GP and strengthens the control of the stage manager through RID algorithm with a sound and more logical execution. Moreover, IBAI employs AWT and GCD to enhance combat diversity and game balance to ensure the best player experience. Various test and questionnaire results demonstrate that IBAI can provide an efficient and complete solution for action role-playing games. The algorithm is also helpful in shortening the development cycle and improving the player retention rate to a certain extent. The design and implementation of IBAI will play an active role in accelerating the widespread use of game AI technologies, especially DDA. It can also fill related research gaps and promote the common development of traditional artificial intelligence and games. Furthermore, this work provides a new insight for leading researchers in game AI, as well as extending the knowledge of nonprofessionals. Significant strengths notwithstanding, one concern about the algorithm is that it can only be used in action role-playing games at this stage. Particular technical expertise may be required for the users to apply the algorithm effectively during game R and D in different engines. Games realize the long-term goals of general intelligence the best. In future research, IBAI will be optimized for specific game engines and will be refactored to explore its applications for other game types. The generality of the algorithm and the extensibility of its roles within games will be enhanced at that time, so as to realize the frontier of game AI research.

Author Contributions:

Conceptualization, Q.M. and T.G.; methodology, Q.M.; software, Q.M.; validation, Q.M. and T.G.; formal analysis, Q.M.; investigation, Q.M. and T.G.; resources, Q.M. and T.G.; data curation, Q.M. and T.G.; writing—original draft preparation, Q.M.; writing—review and editing, Q.M. and T.G.; visualization, Q.M.; supervision, T.G. All authors have read and agreed to the published version of the manuscript. Funding: This research was funded by China Fundamental Research Funds for the Central Universities, grant number N2017003. Institutional Review Board Statement: Not applicable. The anonymous questionnaires in the study were used to survey player experience. All data collected is merely used for the experiment, and any personal details of the participants other than the information related to the results of the experiment shown in the paper will not be disclosed to avoid ethical issues. Ethics approval is not required for this research according to the cases above and relevant legislation. Any individual or organization cannot use the questionnaire data in the research without the authors' approval. Informed Consent Statement: Informed consent was obtained from all subjects involved in the study. Data Availability Statement: Not applicable. Acknowledgments: The authors gratefully acknowledge the efforts of the participants of their gameplay and questionnaire who invested their valuable time to contribute to this research. Conflicts of Interest: The authors declare no conflict of interest.

References

1. Heidari, A.; Navimipour, N.J.; Unal, M. Applications of ML/DL in the Management of Smart Cities and Societies Based on New Trends in Information Technologies: A Systematic Literature Review. Sustain. Cities Soc. 2022, 85, 104089. [CrossRef]
2. 2. Wen, B.J.; Chang, C.R.; Lan, C.W.; Zheng, Y.C. Magnus-Forces Analysis of Pitched-Baseball Trajectories Using YOLOv3-Tiny Deep Learning Algorithm. Appl. Sci. 2022, 12, 5540. [CrossRef]

3. Heidari, A.; Jabraeil Jamali, M.A.; Jafari Navimipour, N.; Akbarpour, S. Deep Q-Learning Technique for Offloading Offline/Online Computation in Blockchain-Enabled Green IoT-Edge Scenarios. Appl. Sci. 2022, 12, 8232. [CrossRef]

4. Liu, J.; Togelius, J.; Pérez-Liébana, D.; Lucas, S.M. Evolving Game Skill-Depth Using General Video Game AI Agents. In Proceedings of the 2017 IEEE Congress on Evolutionary Computation (CEC), Donostia, Spain, 5–8 June 2017; pp. 2299–2307. [CrossRef]

Article 4

Artificial Intelligence for Adaptive Computer Games.

Ashwin Ram, Santiago Onta˜n´on, and Manish MehtaCognitive Computing Lab (CCL)College of Computing, Georgia Institute of TechnologyAtlanta, Georgia, USA{ashwin, santi, mehtama1}@cc.gatech.edu

Abstract

Computer games are an increasingly popular applica-tion for Artificial Intelligence (AI) research, and con-versely AI is an increasingly popular selling point forcommercial games. Although games are typically asso-ciated with entertainment, there are many ”serious” ap-plications of gaming, including military, corporate, andadvertising applications. There are also so-called ”hu-mane” gaming applications for medical training, educa-tional games, and games that reflect social conscious-ness or advocate for a cause

Introduction

Computer games have been classified as the “Human-levelAI’s Killer Application” (Laird & van Lent 2000). State-of-the-art computer games recreate real-life environments witha surprising level of detail. These environments are usu-ally populated with many characters (allies or enemies) that require human-level intelligence and exhibit believable be-haviors. However, even though there have been enormous advances in computer graphics, animation and audio for games, most of the games contain very basic artificial in-telligence (AI) techniques.

Requirements for Game AI

In previous work, Laird and van Lent (2000) analysed differ-ent game genres, and the AI challenges that each presents. In their report, they considered the following types of games: action, role playing, adventure, strategy games, god games, individual and team sports games. In addition to those gen-res, we would like to consider two additional categories, namely, interactive drama (Mateas & Stern 2003) and ed-ucational games (Rieber 1996)

Challenges in Computer Game AI

Let us briefly describe some of the main issues that arise when developing artificial intelligence for computer games. This list is not exhaustive, but is intended to give a aver of the kind of problems that real computer games pose to the AI community

Conclusions

In this paper, we discussed a set of challenges that state-of-the-art computer games pose to the artificial intelligence community. Developing AI techniques that can deal with the complexity of computer games is a big challenge, but has the potential to have a big impact in several areas including entertainment, education and training. Our main goal is to develop AI techniques that can ease the effort of incorporating AI in computer games to make them more adaptive and appealing to the player. We call such games adaptive games. In this paper, we introduced three of our current research thrusts aimed at creating adap-tive games via the application of case-based reasoning tech-niques

References

Aamodt, A., and Plaza, E. 1994. Case-based reasoning:Foundational issues, methodological variations, and sys-tem approaches. Artificial Intelligence Communications7(1):39–59.Aha, D.; Molineaux, M.; and Ponsen, M. 2005. Learn-ing to win: Case-based plan selection in a real-time strat-egy game. In ICCBR’2005, number 3620 in LNCS, 5–20.Springer-Verlag.

Article 5

Review and analysis of research on Video Games and Artificial Intelligence: a look back and a step forward

Abstract

analysis based on a bibliometric survey carried out in the Scopus database. We first briefly reviewed the relation between video games and AI. Then, we introduced the methodology of literature collection, presented and discussed the query, as well the flow of data treatment in the applications and plugins used. Since the article is concerned with a historical point of view of the relationship between digital games and AI the results were many and, therefore, we focused on the top 10 of each ranking, and discussed these results separately. Finally, we discuss the limitations of our review, proposing future research directions for scholars.

Introduction

Despite the number of scientific papers related to this topic, and to the best of our knowledge, there is no bibliometric, scientometric, or informetric analysis of the existing scientific literature on the use of AI in video games. A search on Scopus and Web of Science (WoS) databases, with no proper results, seems to confirm that. Therefore, we intend to make a first contribution to filling this gap, by conducting a bibliometric study on the distribution and interest of publications relating to research between video games and AI, as well to identify the sources and authors with more scientific production. Thus, the research questions that this paper attempt to answer are the following: What are the most influential published articles? What are the main publication sources? Who are the most prolific authors from de search? What are the most frequently used keywords in articles published? To respond to these research questions, the major purpose of this study is to provide a holistic review of video games and AI research and to identify the challenges and gaps that are needed to be addressed by future research. The rest of the paper is structured as follows: first, the methodology used to obtain the dataset is described. Then, in Section 3, the results and quantitative analysis are presented, and finally, the discussion of the results and future work are addressed in Section 4.

Methodology

Before performing this search, topic keywords were applied to Scopus and WoS databases. As the Scopus took a significantly larger number than WoS, it was chosen. Our bibliometric analysis was carried out on publications published in peer-reviewed journals and conference proceedings; other documents such as books, reviews were excluded from this bibliometric analysis. Only publications written in English were considered, there were no time restrictions, and the search returned articles from 1971 to 2021. The resulting query is as follows: (TITLE-ABS-KEY("computer game" OR "video game" OR videogame) AND TITLE-ABS-KEY("artificial intelligence")) AND (LIMIT-TO (DOCTYPE,"cp") OR LIMIT-TO (DOCTYPE,"ar")) AND (LIMIT-TO (LANGUAGE,"English")) A set of 2604 publications was returned. This data was then downloaded in RIS format. Later, this dataset was imported to the Biblioshiny for Bibliometrix in R 4.1.1. R is an open-source environment for statistical computing and graphics, with a collection of several packages such as Bibliometrix, developed specifically for bibliometric and scientometric studies [7]. Biblioshiny is a user-friendly web interface for Bibliometrix, to perform comprehensive João Paulo Sousa et al. / Procedia Computer Science 204 (2022) 315–323 317 Author name / Procedia Computer Science 00 (2019) 000–000 3 science mapping analysis. Using those tools were carried out an analysis of a publication dataset and built matrices to perform network analysis for conceptual structure, intellectual structure, and social structure.

3. Analysis

   Table 1 shows key information about data and document types retrieved from the Scopus database query on November 12, 2021. A total of 2604 publications from 1971 to 2022 were retrieved, of which 456 were journal articles, and 2148 articles from conference proceedings. A total of 5865 authors were identified, the average of authors per publication was 2.25 and 88% of the documents were written by more than one author. Table 1. Main information about the search. Description Results Total publications 2604 Articles 456 Proceedings papers 2148 Period 1971-2022

Discussion

Through the analysis of articles returned by the query, it was possible to identify two relationships between AI and video games: video games can use AI algorithms to incorporate into their gameplay. For example, the case of using an AI algorithm to create certain behaviors in an NPC, controlling the real-time strategy (RTS) game AI, or the procedural level generation. The use of video games to test and assess the ability of the algorithm to solve problems. Video games are usually designed to challenge humans and allow you to recreate more or less complex virtual environments. This makes video games excellent tools to test various cognitive problems, including reasoning, planning, strategy, coordination, perception, behavior, kinesthetics, among others. One example is the use of video games in learning algorithms ([6], [16], [19]). In the top 10 of the most cited articles, and through co-occurrence, it is 322

João Paulo Sousa et al. / Procedia Computer Science 204 (2022) 315–323 8 Author name / Procedia Computer Science 00 (2019) 000–000 possible to observe that researchers around the world are using video games to create environments to be used in learning algorithms. The doubling of the number of articles published in 2016, can be due to the convergence of some factors that promoted the rapid growth of deep learning, including the availability of a great amount of data and more processing power given by GPUs evolution, new algorithms like convolutional neural networks, in 2012, Generative Adversarial Networks, in 2014, and the availability of more user-friendly machine learning frameworks, like Tensorflow, introduced by Google in 2015.

Acknowledgments
This work has been supported by FCT---Fundação para a Ciência e Tecnologia within the Project Scope: UIDB/05757/2020.

References [1] C. E. Shannon, 'Programming a Computer for Playing Chess', in Computer Chess Compendium, D. Levy, Ed. New York, NY: Springer New York, 1988, pp. 2–13. doi: 10.1007/978-1-4757-1968-0_1. [2] F. Domınguez-Estevez, A. A. Sanchez-Ruiz, and P. Pablo, 'Training Pac-Man bots using Reinforcement Learning and Case-based Reasoning', p. 12, 2017. [3] G. N. Yannakakis, 'Game AI revisited', in Proceedings of the 9th conference on Computing Frontiers - CF '12, Cagliari, Italy, 2012, p. 285. doi: 10.1145/2212908.2212954.

Article 6

Games, AI and Systems

Authors

- **Michael Straeubig**University of Plymouthhttp://orcid.org/0000-0001-9822-6849

DOI:

https://doi.org/10.7557/23.6176

Abstract

In recent years, we have observed impressive advancements at the intersection of games and artificial intelligence. Often these developments are described in terms of technological progress, while public discourses on their cultural, social and political impact are largely decoupled. I present an alternative rhetoric by speculating about the emergence of AI within social systems. In a radical departure from the dominant discourse, I describe seven roles - Mechanic, Alter/Ego, Observer, Protector, Player, Creator and God - that an AI may assume in the environment of videogames. I reflect on the ramifications of these roles for the idea of an artificial general intelligence (AGI), mainly hoping to irritate the prevailing discussion.

2002: A Revolution Brewing

“A revolution has been brewing”, writes Paul Tozour, then an AI developer at Ion Storm, in his essay “The evolution of game AI” (Tozour 2002). The revolution he is alluding to is the rapidly growing role of artificial intelligence and machine learning in the video game industry.Tozour sees progress through advancements in hardware, a better understanding of AI in games, and dedicated AI programmers. He argues for AI-centric game design and predicts a closer relationship between academic AI and video game AI. If this sounds familiar from today’s perspective, one may ask if the current situation finally marks the revolution[1]Tozour wished for. 2002 is the year that sees games like Metroid Primeon the Game Cube, Grand Theft Auto: Vice Cityon the Playstation 2, and Neverwinter Nights, America’s Armyand Battlefield 1942on the PC platform. Notable high-end game engines include id Tech 3 and Unreal Engine 2. Early versions of the beginner-friendly GameMaker are published as freeware, whereas the Unity game engine is not around yet—the company will be established two years later

Cultural Impact vs. Public Discourse

In terms of cultural impact and public discourse, games and AI have evolved separately and at a different pace. The growing influence of experimental and independent creators has brought video games to a larger and more diverse audience outside of the AAA mainstream. A still growing independent games scene and an artistic fringe have differentiated themselves from each other. Yet Zimmerman’s (2002) essay outlining the soul-seeking cultural self-reflection of indie game creators is surprisingly up-to-date

The Seven Roles of Game AI

In this section, I discuss seven roles—Mechanic, Alter/Ego, Observer, Protector, Player, Creator, and God—that AI inhabits or is about to assume in video games (Yannakakis and Togelius 2015; Yannakakis and Togelius 2018, pp.279-291). The final role (God) remains speculative, yetI will attempt to sketch out how it could emerge from the other six.
nited States Army (2002) America’s Army.United States Army (PC).Digital Illusions CE (2002) Battlefield 1942.Electronic Arts (PC).Lionhead Studios (2001) Black and White.Electronic Arts (PC).Rockstar North (2002) Grand Theft Auto: Vice City.Rockstar Games (Playstation 2).Retro Studios and Nintendo (2002) Metroid Prime.Nintendo (Game Cube).BioWare (2002) Neverwinter Nights.Infogrames (PC).Hello Games (2016) No Man’s Sky. Hello Games (PC).Blizzard Entertainment (2010) StarCraft II: Wings of Liberty.Blizzard Entertainment (PC).

References

Alexander, L. (2014) ‘Gamers ’don’t have to be your audience. ‘Gamers ’are over. [Online]. Available from: https://www.gamasutra.com/view/news/224400/ Gamers_dont_have_to_be_your_audience_Gamers_are_over.php[Accessed: 5 March 2019].Anderson, C. A., and Dill, K. E. (2000) Video games and aggressive thoughts, feelings, and behavior in the laboratory and in life. Journal of Personality and Social Psychology, 78 (4), pp.772–790.

Article 7

Call for AI Research in RTS Games

Abstract

This position paper discusses AI challenges in the area of real–time strategy games and presents a research agenda aimed at improving AI performance in these popular multi– player computer games. RTS Games and AI Research Real–time strategy (RTS) games such as Blizzard Entertainment's Starcraft(tm) and Warcraft(tm) series form a large and growing part of the multi–billion dollar computer games industry. In these games several players fight over resources, which are scattered over a terrain, by first setting up economies, building armies, and ultimately trying to eliminate all enemy units and buildings

Research Agenda

The main goal behind the AI research being proposed here is not to increase the entertainment value of RTS games, but rather to create the strongest RTS game AI possible. The former goal is pursued by the commercial games industry, whereas the latter tries to push the cognitive abilities of machines to new levels. Note, however, that increased playing strength can be converted into higher entertainment value by adapting to the player's performance level to keep games challenging. Also, we acknowledge that commercial RTS game AI often cheats to compensate for its lack of sophistication. Tricks of the trade include map revealing and faster resource gathering. The resulting AI systems may outperform human players and may even create challenging encounters, but they do not advance our understanding of how to create intelligent entities.

Conclusion

In this paper we have motivated AI research in RTS games and outlined a research agenda whose goal it is to produce AI systems that reason, learn, and plan in this popular and challenging domain. We invite AI researchers to participate in creating and improving RTS game AI systems, to contribute to the ORTS project, and to compete on-line. Competition is a powerful driving force for AI innovation which has been witnessed in the areas of classic board games, planning, and auctions. We hope that it will also lead to strong RTS game AI and elevate our understanding of real–time decision making under uncertainty.

Acknowledgments

Thanks go to Tim Furtak and Keith Yerex for their important contributions to the ORTS project. This research is supported in part by grants from NSERC, Canada.

References

Buro, M. 2002. ORTS: A hack-free RTS game environment. In Proceedings of the Third International Conference on Computers and Games, 156–161. Buro, M. 2003. Real-time strategy games: A new AI research challenge. In Proceedings of the International Joint Conference on AI, 485–486.

Article 8

Research Directions for AI in Computer Games

Chris Fairclough, Michael Fagan, Brian Mac Namee, Pádraig Cunningham Department of Computer Science, Trinity College, Dublin 2, Ireland.

Abstract

The computer games industry is now bigger than the film industry. Until recently, technology in games was driven by a desire to achieve real-time, photo-realistic graphics. To a large extent, this has now been achieved. As game developers look for new and innovative technologies to drive games development, AI is coming to the fore. This paper will examine how sophisticated AI techniques, such as those being used

in mainstream academic research, can be applied to computer games and introduce three projects doing just that.

1. Introduction
    The computer games industry is now bigger than the film industry [7]. Until recently, technology in games was driven by a desire to achieve real time photo realistic graphics. To a large extent, this has now been achieved. At least, it will no longer be huge leaps in graphics technology that make one game stand out in the manner that Doom (www.idsoftware.com) stood out when it was first released in 1993.

2. The role of AI in different game genres Before embarking on a discussion of the different game genres on the market today, a glaring contradiction needs to be resolved. A large, and ever growing, body of research work into computer implementations of classic games, such as chess, Go and Othello, already exists. When we refer to computer games, we are not referring to games such as these. Rather, we refer to what might be more familiarly termed video games - games made specifically to be played on computers. Further, little of the research into classic games is applicable to the games considered by this project. The main reason for this is that the number of degrees of freedom in modern video games is far beyond that of classic games.

    Role Playing Games

    Often seen as an extension of the adventure game style, role playing games (RPGs) stem from the popular Dungeons & Dragons (www.playdnd.com) paper based games that originated in the 1970's. Over the past two decades the computer versions of these games have metamorphosed from being mostly text based to the beautifully rendered, hugely involved games available today. Baldur's Gate (www.interplay.com/bgate) was a turning point for the genre. The level of detail in the Baldur's Gate world involves complexity far beyond anything seen before, with completion of the game involving over 100 hours of gameplay. RPGs see the player taking on the role of an adventurer in an exotic, mythical world, where gameplay consists of questing across the land, engaging in a mixture of puzzle solving and combat. Interactions with NPCs and an intricate plot are also important in the genre

Academic Research in Game AI

Academic research into AI for games has been rare over the past number of years, however the level of interest is growing. A number of research efforts are currently underway and courses are being offered in some US universities. Much of the research being undertaken has emerged from work conducted with military institutions. Many of the goals are similar and so there is a large crossover of techniques. One such effort is the Soarbot project [17] in which agents have been created to play the 3D action game Quake (www.idsoftware.com) using the rule based SOAR architecture. Forbus et al. [4] describe another interesting research project in which a military system designed to analyse terrain in order to plan attacks [3] is being adapted for use in strategy games.

An Interactive Story Engine
The field of interactive stories has its roots in the arts of oral storytelling and theatre, and ideas from these fields have been incorporated into new forms of storytelling using the computer as a medium. Amongst the earliest projects based on the use of a computer storyteller was 'Tale Spin' by James 3 This is an interesting version of the old philosophical question "Does a tree falling in the forest make a sound if there is no-one there to hear it?" In reality most people would believe it would, whereas in current

computer games it most definitely would not! Meehan4 [9], which composes stories based on giving each character some goals to achieve and forming plans for each of the characters. A very simple example output: One day Wilma was very thirsty. Wilma wanted to get near some water. Wilma flew from her nest across the meadow through a valley to the river. Wilma drank the water. Wilma wasn't thirsty anymore. . . etc . . . Since an early interest in the topic was quashed in the 70's, research in computer storytelling was non existent until relatively recently. Carnegie Mellon University in Pittsburgh was a hotspot of interest in the field in the early 90's, spearheaded by Joseph Bates [13], [14]. The OZ project5 at CMU consists of a group of researchers interested in diverse aspects of the field, and has spawned some companies that are developing some very interesting products, for example www.ottoandiris.com. This part of the TCD project will consist mainly of developing a 3D game engine which is populated by believable characters, and which has a story director agent (SD) that has some control over these characters. This agent pushes the characters into following a dynamic, coherent plotline which changes according to the player(s)' actions in the game world.

References

[1] Bates, J., The Nature of Character in Interactive Worlds and The Oz Project, Technical Report CMU-CS-92-200, School of Computer Science, Carnegie Mellon University, Pittsburgh, PA. October 1992. [2] Coco, D., Creating Intelligent Creatures, Computer Graphics World, July 1997. [3] Forbus, K., Nielsen, P. and Faltings, B., Qualitve Spatial Reasoning: The CLOCK Project, Artificial Intelligence, 51 (1 – 3), October 1991.

Article 9

AI in Human-computer Gaming: Techniques, Challenges and Opportunities

Abstract: With the breakthrough of AlphaGo, human-computer gaming AI has ushered in a big explosion, attracting more and more researchers all over the world. As a recognized standard for testing artificial intelligence, various human-computer gaming AI systems (AIs) have been developed, such as Libratus, OpenAI Five, and AlphaStar, which beat professional human players. The rapid development of human-computer gaming AIs indicates a big step for decision-making intelligence, and it seems that current techniques can handle very complex human-computer games. So, one natural question arises: What are the possible challenges of current techniques in human-computer gaming and what are the future trends? To answer the above question, in this paper, we survey recent successful game AIs, covering board game AIs, card game AIs, first-person shooting game AIs, and real-time strategy game AIs. Through this survey, we 1) compare the main difficulties among different kinds of games and the corresponding techniques utilized for achieving professional human-level AIs; 2) summarize the mainstream frameworks and techniques that can be properly relied on for developing AIs for complex human-computer games; 3) raise the challenges or drawbacks of current techniques in the successful AIs; and 4) try to point out future trends in human-computer gaming AIs. Finally, we hope that this brief review can provide an introduction for beginners and inspire insight for researchers in the field of AI in human-computer gaming.

Introduction

Human-computer gaming has a long history and has been a main tool for verifying key artificial intelligence technologies[1, 2] . The Turing test[3] , proposed in 1950, was the first human-computer game to judge whether a machine has human intelligence. This has inspired researchers to develop AI systems (AIs) that can challenge professional human players. A typical example is a draughts AI called Chinook, which was developed in 1989 to defeat the world champion, and such a target is achieved by beating Marion Tinsley in 1994[4] . Afterward, Deep Blue from IBM beat the chess grandmaster Garry Kasparov in 1997, setting a new era in the history of human-computer gaming[5]

Typical games and AIs

Based on the recent progress of human-computer gaming AIs, this paper reviews four types of games and their corresponding AIs, i.e., board games, card games, FPS games, and RTS games. To measure how hard a game is to develop professional human-level AI, we extract several key factors that challenge intelligent decision-making[22

Learning difference

Nowadays, deep reinforcement learning accelerated by distributed learning has become a general method to train high-performance AIs. Apart from this, the four typical AIs, i.e., AlphaStar, OpenAI Five, JueWu, and Com mander, share several differences. Firstly, to train each generation of agents, those AIs utilize self-play (or revised self-play) or population-play mechanisms. In JueWu and OpenAI Five, a relatively simple self-play is performed to train each generation of agents. To avoid strategy collapse and ensure that the learned agent is robust to a wide range of opponents, a certain percentage of past versions are usually selected as opponents. This selection can be specially designed instead of using fictitious self-play, i.e., uniformly selecting past versions. For example, OpenAI Five selects past versions with 20% of rollout games. AlphaStar utilizes a prioritized fictitious self-play mechanism to select opponents, based on which relatively hard agents and agents with similar levels are more likely to be chosen. What's more, AlphaStar and Commander adopt league training, which is a powerful population-play compared with selfplay for more diverse agent learning

Discussions

Based on the current breakthrough of human-computer gaming AIs, currently utilized techniques can be roughly divided into two categories, i.e., tree search (TS) with self-play (SP) and distributed deep reinforcement space. Fictitious self-play[48] provides an evolutionary strategy for agent learning, which can approach the Nash equilibrium in certain types of games, such as two players zero-sum games and potential games, and exceptions, such as multiple players zero-sum games can not guarantee convergence. However, the computation of fictitious self-play for a complex game is high due to the best response calculation and average strategies updating, so researchers develop various self-play or population-play strategies and use distributed reinforcement learning to learn each generation of agents.

Conclusions

In this paper, we have summarized and compared techniques of current breakthroughs of AIs in humancomputer gaming, covering board games, card games, FPS games, and RTS games. The main difficulties among different kinds of games are illustrated, and learning frameworks of representative human-computer gaming AIs are elaborated with detailed comparisons. Based on the comparison, we illustrate two mainstream frameworks used for developing professional-level AIs and how to use one of them to be a general technology for developing AIs. More importantly, we summarize the main limitations of current AIs, trying to propose future directions along with the challenges faced in the field. Through this survey, we hope that beginners can quickly become familiar with the techniques, challenges, and opportunities in this exciting field, and researchers on the way can be inspired for deeper study.

Acknowledgements

This work was supported by National Natural Science Foundation of China (No. 61906197).

References

N. E. Cagiltay. Teaching software engineering by means of computer-game development: Challenges and opportunities. British Journal of Educational Technology, vol.38, no.3, pp.405–415, 2007. DOI: 10.1111/j.1467-8535.2007. 00705.x. [1] R. J. Crouser, R. Chang. An affordance-based framework for human computation and human-computer collaboration. IEEE Transactions on Visualization and Computer Graphics, vol.18, no.12, pp.2859–2868, 2012. DOI: 10. 1109/TVCG.2012.195

Article 10

Artificial Intelligence for Game Playing

Abstract

This paper discusses the history of AI systems in artificial intelligence for playing games. The part learning and self-play in AI cover how self-play can be applied in various games which may be deterministic such as Chess, Go and Checkers or games with hidden randomness like Poker, Bridge, and Backgammon. This has led to several questions, including: "how has deep learning been successfully applied to self-play?" and "to what extent have these learning and self-play issues changed through the history of AI?" To answer these questions, research and experiments of self-play will be discussed. This will be followed by addressing to what extent machine learning is important and the techniques of machine learning for developing high quality AI programs to play games. Finally, how these advancements changed the history of AI will be addressed as well.

1. Introduction

The requirement for satisfying computing artificial intelligence (AI) is perceived as necessary by game players these days as the virtual environments have become increasingly realistic. Even today, the AI of virtually all games is predicated on a finite set of actions whose sequence may be simply expected by knowledgeable players (Fabio Aiolli, 2008). Instead, behaviour of the players in a game can be classified by using the machine learning techniques to the present aim. When a game is taken into consideration its machine can process/play in two ways.

2. Learning and Self-play in AI

This section concentrates on machine learning and its techniques in AI. Self-paly in AI and some examples of self-play and their outcomes. Addressing the questions related to learning and self-play. How the new techniques improved the self-play in AI.

2.1 Machine Learning

"Machine learning usually refers to the changes in systems that perform tasks associated with artificial intelligence (AI). Such tasks involve recognition, diagnosis, planning, robot control, prediction, etc" (Nilsson, 1998).

Machine learning techniques are classified into two main categories:

1. Supervised Learning
2. Unsupervised Learning

3. Conclusion

The advancements in machine learning techniques created a great impact on gameplay in AI. Gaming in AI started with the techniques of machine learning and there are newer techniques emerging day by day. As there are some limitations with the existing machine learning techniques (limited progress, optimised playing strategies, etc.) self-play depended more on advanced machine learning techniques such as neural networks, reinforcement learning, and more. There are some breakthrough depending on machine learning techniques such as invention of first digital version of tic-tac-toe by Douglas in 1952 and absolute fitness function.

AI is often depicted to alter or complement human abilities, but rarely as a full team member, performing tasks similar to humans. As these game experiments involve machine human collaboration, they offer a glimpse of the future. In the case study of DOTA2 capturing the flag's human players considered bots to be more collaborative than other humans, but DOTA 2 players responded mixed to their AI teammates. Some people were quite excited, saying that they felt supported and learned to play with him. A professional DOTA 2 player, teamed up with Bots about his experience (Lavanchy, 2019).

Lavanchy (2019), arises the question, should AI learn from us or continue to teach itself? Selflearning can teach AI greater efficiency and creativity without mimicking humans, but it can also make algorithms more suitable for tasks that do not involve human collaboration, such as warehousing robots. On the other hand, one could argue that it would be more intuitive to have a machine trained than humans- humans using such AI can understand why a machine did this.

As AI gets smarter, we humans get more surprised.

4. References

Abshire, C. (2018, April 6). *Self-Supervised Learning: A Key to Unlocking Self-Driving Cars?* Retrieved from medium.com: https://medium.com/toyota-ai-ventures/selfsupervisedlearning-a-key-to-unlocking-self-driving-cars-408b7a6fd3bd

Brownlee, J. (2019, August 16). *What is Deep Learning?* Retrieved from machinelearningmastery.com: https://machinelearningmastery.com/what-isdeeplearning/

Article 11

Artificial Intelligence in Games

Faking Human Behavior
Mattias Edlund

Abstract
This paper examines the possibilities of faking human behavior with artificial intelligence in computer games, by using efficient methods that save valuable development time and also creates a more rich experience for the players of a game. The specific implementation of artificial intelligence created and discussed is a neural network controlling a finite-state machine. The objective was to mimic human behavior rather than simulating true intelligence. A 2D shooter game is developed and used for experiments performed with human and artificial intelligence controlled players. The game sessions played were recorded in order for other humans to replay. Both players and spectators of the game sessions left feedbacks and reports that could later be analyzed.

Introduction
Technology has developed greatly during the years, with ever increasing amount of operations that can be executed per second. The development within games, shooter games in particular, has been mostly about graphics rendering, and realistic visual representations of game worlds. The Artificial Intelligence in such games rarely feel alive, and computer controlled units will in almost every case run to its death in stupidity. This has led to an Artificial Intelligence which does not pose a challenge for human players, as it can be easily exploited once the player understands the design of the AI.

Based on Expert Players
The AI was based on how an expert player would play the game, to optimize the levels of the challenges for the players, since every AI had the same neural network, and thus reacted the same way. Every AI was essentially an expert player with added timers for limited reaction time. In every game session played, there were at least one human player significantly less skilled. These players did not have a

matching AI for their level. Even though some AIs were really slow at making decisions, they still used the same tactics as an expert player. A tactic could be to wait for the other players to use their abilities and then strike to prevent the other players to dodge.

Conclusion

The conclusion from this research project is that faking the human behavior is very much possible without having to create a virtual human brain. But much more research is necessary in this field in order to find the perfect solution for this. The answer to the first research question, "How do we design AI in shooting games to seem more human?", is hard to answer as it depends on the specific game in question. However, one thing learned from this research project was that players expect AI players to be perfect and never make mistakes. While human players, expert or novice, makes mistakes. Different games has different goals with the AI. Speaking in context of this thesis, with believable human-like movement behaviors, personalities and simulated emotions can be assumed to make an AI even more believable. The key here would be to design AI players as they were humans, define their play style and preferable choices. Items to consider on their personality might be how self-secure they are, their tendency to search out other opponents and their standpoints on risks. Since humans are very driven by emotions like for example anger, jealousy and fright, implementing emotions to your bots will also be assumed to increase the realism in faking their human behaviors. Even in a game as small as the one implemented as a part of this research project, emotion like fear of dying from an opponent that the AI knows has been dangerous before, will change the way it is playing. This can make the AI seem more dynamic, even though it can be as simple as adding one more input into the neural network.

References

Literature Adams, E. (2009). Fundamentals of Game Design. 2nd ed. New Riders, p. 3. Köse, U. (2012). Developing a fuzzy logic based game system. Computer Technology and Application, 3(7), p. 510.

Article 12

The Impact of Artificial Intelligence on the Gaming Industry

The gaming industry has come a long way since the days of Pong and Tetris.Today, video games are sophisticated, immersive, and incredibly realistic, thanks in no small part to the integration of Artificial Intelligence (AI) technology.

AI has revolutionized every aspect of gaming, from the behavior of Non-Player Characters (NPCs) to dynamic storytelling and procedural content generation.

Evolution of AI Algorithms

AI in gaming has evolved from simplistic rule-based systems to complex algorithms. Early NPCs followed pre-defined patterns, but modern AI enables them to exhibit lifelike behaviors.

AI in NPC Behavior

One of the most noticeable impacts of AI in gaming is on the behavior of NPCs. These virtual characters are no longer bound by rigid scripts.

AI algorithms breathe life into NPCs, allowing them to react dynamically to the player's choices and the game's environment.

Creating Dynamic Game Worlds

AI plays a crucial role in creating dynamic and immersive game worlds. NPCs populate these worlds, and their AI-controlled behavior makes the game environment feel alive and responsive.

Enemy AI

Enemy AI, often referred to as Enemy AI (EAI), is a pivotal component in many games, especially in action and strategy titles.

impact on Game Difficulty and Realism

The quality of EAI directly affects game difficulty and realism. Well-designed EAI ensures that players are consistently challenged, leading to a more satisfying gaming experience.

Dynamic Storytelling

AI has revolutionized storytelling in games by enabling dynamic narratives that evolve based on player choices.

Natural Language Processing (NLP)

Natural Language Processing (NLP) is making its way into gaming through AI-driven chatbots and voice-controlled gaming.

Voice-Controlled Gaming

Voice-controlled gaming is gaining popularity, particularly in virtual reality (VR) and augmented reality (AR) experiences.

Dynamic Music

In music composition, AI creates soundtracks that adapt to the pace and mood of gameplay. This dynamic music generation adds to the atmosphere and emotional impact of the game.

Popular Games Utilizing AI

Several popular games have made headlines for their extensive use of AI technologies. These games showcase the capabilities of AI and how it can elevate the gaming experience.

- **The Witcher 3: Wild Hunt**
- **No Man's Sky**
- **"Halo" Series**
- **Red Dead Redemption 2**
- **The Elder Scrolls V: Skyrim**

Enhanced Graphics and Realism

AI-driven graphics will continue to improve, making game worlds more realistic and visually stunning.

Procedural Generation Advancements

Procedural content generation will become even more sophisticated, offering players procedurally generated worlds of unparalleled complexity and detail.

Conclusion

Artificial Intelligence has transformed the gaming industry, pushing the boundaries of what is possible in interactive entertainment.

From lifelike NPC behavior to dynamic storytelling and procedural content generation, AI has elevated the gaming experience to new heights. As AI technology continues to evolve, gamers can look forward to even more immersive, challenging, and personalized experiences.

The fusion of AI and gaming is not just leveling up gameplay; it’s taking it to a whole new dimension, where the possibilities are limited only by our imaginations.