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Designing A Popular Game Framework Using Neat A Genetic Algorithms

V Asha
Department of MCA
New Horizon College of Engineering
Bengaluru, India
asha.gurudath@gmail.com

Arpana Prasad
Department of MCA
New Horizon College of Engineering
Bengaluru, India
arpanaprasad2013@gmail.com

Vishwanath C. R.
Department of MCA
New Horizon College of Engineering
Bengaluru, India
vishwanathcr@gmail.com

Madava Raj K
Department of MCA
New Horizon College of Engineering
Bengaluru, India
madavaraj66@gmail.com

Manoj Kumar A R
Department of MCA
New Horizon College of Engineering
Bengaluru, India
manojmanu098123@gmail.com

Leelavathi N
Department of MCA
New Horizon College of Engineering
Bengaluru, India
leelavathi.reddy7@gmail.com

***Abstract*— The objective of conduct the current research is to understand the deep relationship between gaming along with how artificial intelligence (AI) is being incorporated into these fields. It is clear that gaming and AI have a natural connection, and the introduction of AI only strengthens this connection. This study aims to highlight the potential benefits of using AI in gaming and simulation, as well as the challenges that may arise in these contexts. The scope of the research includes exploring the various ways in which AI can be applied in gaming. In addition to optimizing programs and tasks, AI can be trained to work independently, reducing the need for human labour and potentially eliminating human error. Overall, this paper focuses on the diverse potential applications of combining AI with gaming and simulation. This research shows how AI can be learn to play independently with the help of Neuro Evolution of Augmenting Topologies (NEAT) a Genetic algorithm.**

Keywords: Artificial Intelligence, Gaming, Genetic Optimization, Flappy Bird Game, Machine Learning

I. INTRODUCTION

People have long enjoyed playing video games. The development of artificial and computational intelligence has led to rapid developments in a number of video game genres, whether they are played offline or online, particularly since the start of the twenty-first century.Since the establishment of game Artificial Intelligence(AI) as a separate academic field about 15 years back, significant progress is seen in the use of artificial intelligence in video games. AI has been a part of video games since its inception in the 1950s.

As a result, games are commonly utilized as a useful tool for tracking AI development. To help readers better understand the development of AI in games, we present a chronology of this process. The stages of AI development are depicted in the top line. This text discusses the history and progress of AI and game AI. It highlights notable software, programs, games, and events.

Developments in AI and Gaming is not congruent. To give a more holistic view of the gaming AI study field, researchers have concentrated more on the interactions and influences between various domains. Book on game AI that offers thorough knowledge of the sector was published in 2018. These examples serve as the basis for this study, which examines gaming AI and some of its key applications from 2018 to the present. In this article, we'll explore three aspects of gaming AI: This essay explores the use of artificial intelligence in various areas of gaming, including the creation of realistic non-player characters, the generation of game levels through procedural content generation, and the modelling of player experiences. In addition, the discussion section addresses the concept of general game AI as a frontier in game AI research and the potential use of hybrid intelligence in game development.

Following the introduction section the other sections in the paper are organized as follows; examination of some of the most significant research findings in application areas of AI in gaming is presented in section II, and then Section III discusses hybrid intelligence and its potential role in game development . Section IV gives a brief description of the methodology followed in the ongoing research presented in the paper. Usage of AI in a popular game flappy bird is given in Section V. Section VI summarizes the conclusion and future scope.

II. REVIEW OF LITERATURE

In the present work, a phase-by-phase literature review is carried out. AI and the game algorithm from the game developed for crossword game Japanese crossword game MyoGo were used in this study. The self-play game data from the Myogo AI was obtained in order to evaluate and enhance the game parameters. To make the game more balanced, we add blocks. The game will get more complex and require more skill for both new and seasoned players by lowering the minimum word length and introducing additional features. The board will make the game more unpredictable.We introduce ColorShapeLinks in this article, an AI board game competition framework created with accessibility and openness for game development instructors and students in mind[1].

Implementing the board game of arbitrarily large Simplexity within the framework strikes a good balance between simplicity and complexity, making it approachable for undergraduates while posing a difficult problem for academics and more experienced students. A theoretical model and self-play AI data were used to evaluate the game instead of actual player input. Potential future directions that gather feedback from actual players (novice and experienced players) on the gaming experience and assess the game's effects on other perspectives of the game through long-term observation may be worthwhile endeavours. One such perspective is the educational potential of playing Myogo[2].

The AI agents processed velocity and distance as inputs, rather than relying on learning from high-dimensional image data (screenshots from the game) as was done in previous attempts. Additionally, the neural network's ability to generalize well in the game's continuous state space contributed to the unexpectedly good performance of the NE agent. Although it was defeated by the NE agent, the RL agent still performed at a level that would have earned it a platinum medal[3].

This work may be further enhanced by paying more attention to the parameter modifications that were performed in order to raise the complexity and by giving a more thorough analysis of the more challenging gameplay by looking at more than thirty (30) generations. [4].

This paper provides some early evidence that, when it comes to videogame avatars, a person's ideal self may incorporate fantastical features that are present in gaming worlds but not available in the actual world. This might possibly provide theories on self-concept a new angle. [5].

III. AI IN GAMING

AI, or artificial intelligence, is a term used to describe programs that can perform tasks that were previously only possible for humans, such as playing chess or interacting with customers online. AI is often used interchangeably with its subfields, such as deep learning and machine learning, but there are some distinctions between these concepts. While all AI relies on machine learning, it is important not to confuse the two.

Data science is a multidisciplinary field that combines knowledge of business with expertise from fields such as computer science and statistics to analyze data from various sources. Data scientists use various methods, including scientific ones, to extract insights and value from data[6].

IV. METHODOLOGY

Use of Artificial Intelligence in gaming is applied on Flappy Bird game. This investigation used the game program and artificial intelligence (AI) of the Flappy Bird video game. Self-Play random data is used to evaluate and improve the various parameters of the Flappy Game. In other words, even if it is only for a specific game genre, there is still much work to be done before game AI is generalized. Techniques like hybrid intelligence and control of agents is becoming advanced when applied to gaming.

Game AI is expected to have a promising future as techniques like hybrid intelligence and cerebral control become more advanced and are applied in gaming. These approaches are currently receiving increasing attention and will likely play a significant role in the future of game AI[10].

AI continues to be a valuable and relevant field, particularly in the current climate where machine learning is a popular topic and many people are interested in it. AI has the potential to offer innovative and unique ideas, as well as benefiting other technology disciplines, particularly simulation and gaming. The findings suggest that learning from raw pixels is a promising development in AI due to the adaptability and dynamism of settings like VizDoom. In future research, we plan to expand on these strategies in various ways to enhance the range of learning-related behaviors.[11].

A. AI Algorithms Used In Gaming

1) *Mini-Max Algorithm:*

Decision making is achieved through recursive backtracking using min-max algorithm. If both players' opponents play optimally, players are given optimum moves. The Min-Max algorithm is frequently used by artificial intelligence to play games. Games for two players, such as chess, checkers, go, and tic tac toe[12]. This method finds the decision of minimax for the current state. One player is referred to as MAX and the other as MIN in this system. Players compete against one another by selecting the maximum value and least value. MAX finds the highest value, whereas MIN finds the lowest value. The minimax approach explores the whole game tree using depth-first search. Prior to recursively climbing the tree back up, the minimax approach falls all the way to the tree's terminal node[13].The minimax algorithm's operation may be explained with the aid of an illustration. Here is an illustration of a game-tree for a two-player game. Maximizer and Minimizer are the two participants in this case. We must travel through the full game tree to get to the terminal nodes because this approach uses DFS. [14].

2) *Alpha-Beta Pruning:*

The minimax technique has been extended to include alpha-beta pruning. Since the exponent cannot be removed, we can only reduce it by 50%.Pruning is a technique that enables us to determine the optimal minimax decision without examining every node in the game tree. It is called alpha-beta pruning because it involves the two expansion threshold values, Alpha and Beta. It is also known as the Alpha-Beta Algorithm. Alpha-beta pruning can be applied to any depth of a tree and may sometimes eliminate entire sub-trees in addition to individual leaves. The two parameters fit into the following definitions. Alpha represents the most advantageous (highest-value) choice that has been discovered at each point of the Maximum search. The initial value of Alpha is -∞.

At each stage of the Minimizer's search, Beta indicates the best (lowest-value) alternative that has been identified. Beta's initial value is +. Alpha-beta pruning criteria The following are the specifications for alpha-beta pruning: Knowledge essential to understanding alpha-beta pruning Only the Max player will modify the value of alpha. Only the Min player will have the ability to alter the beta value. Node values rather than alpha and beta values will be given throughout the retracing of the tree. To the child nodes will only be given the alpha and beta values.

V. FLAPPY BIRD GAME

The player controls a bird in the side-scrolling game Flappy Bird. Avoiding pipe columns is the objective. The game stops and a new episode starts whenever the bird lands on the pipes. The height of the bird is controlled by a controller , which causes the bird to fall and jump when the control key is depressed. On the same horizontal level, the distance between the present pipe and the following pipe is consistently the same, despite the fact that the pipe heights were arbitrarily selected. In the game's Python code, we can access the bird and pipe locations.The bird's coordinates, vertical velocity, and direction, as well as the X and Y coordinates of the closest lower pipe, are displayed in the histogram as scattered data; and the vertical position of the nearest upper pipe. These statistics were recorded when the player scored 64 points in a game (The number of pipes the birds successfully passed was pretty high.). Note that the X coordinates for the nearest upper and lower pipes are the same shown in Fig 1.

A). AI Algorithms For Flappy Bird Game

A genetic optimization algorithm is used by the unsupervised machine learning technique known as neuro evolution (NE) to fit a neural network model. It entails giving an agent feedback in the form of rewards to let it know whether it is doing effectively or poorly. The reward function determines the utility of the agent, and the objective is for the agent to learn to operate in a way that maximises the anticipated benefits.

1). Genetic Optimization:

The basic principles of natural selection in a genetic algorithm are as follows: Inheritance: Children receive traits from their parents through heredity. Variation: The population must have a range of traits. The likelihood that certain population members will live and transmit on their genetic makeup to their progeny. Algorithm 1 describes the NE algorithm's stages as they relate to the NE Flappy Bird player.

We start by generating a population of N neural network models, each of which is represented in the game by a bird avatar. The initial properties of these models, such as the number of hidden layers or the weights of the neural network, are chosen at random since they are formed at random Fig 2. To enhance the performance of the models, our solution entails changing these basic attributes. We specifically change the neural network's weights and the quantity of hidden layer units. The next phase is to choose two parents from the population, with parents with greater fitness having a greater chance of being picked Fig 3. Crossover is the process by which the qualities of the parents are blended to produce a kid. The following generation may then be produced by the child's attributes being randomly modified by a predetermined probability known as the mutation probability Fig 4. Until a model is created, for instance, when a neural network agent achieves a certain score, this procedure is repeated Fig 5.

2). *NEAT Algorithm*

Set up the game environment, including the bird, the obstacles, and the screen.

Use a machine learning algorithm, such as a neural network, to train an AI to play the game.

Define the inputs for the neural network, such as the position of the bird, the position of the obstacle, and the velocity of the bird.

Define the outputs for the neural network, such as whether the AI should jump or not.

Train the neural network using a dataset of input-output pairs, where each input corresponds to a certain game state and the corresponding output is the action the AI should take in that state.

Use the trained neural network to play the game by inputting the current game state into the neural network and getting the output action.

Repeat steps 5 and 6, adjusting the neural network's parameters and/or the dataset as necessary to improve the AI's performance.

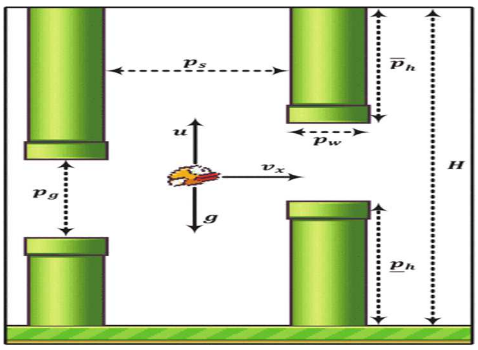

Fig.1. Snapshot of flappy bird game.

B). Performance Evalution

The neural network model uses the same inputs as the reinforcement learning technique: the distance between the bird and the next lower pipe (dx,dy) and the bird's velocity on the y-axis. These variables are used to forecast the bird's future move and indicate the status of the game. The neural network contains three layers in total, with the output layer being made up of one sigmoid node. Four sigmoid nodes are originally put in the hidden layer. Three units and a bias unit are present in the input layer. A grid search was done over several discrete values to find the optimal population size and mutation probability, two crucial hyperparameters of the model the population size was set at 300 birds each generation, and the mutation probability was set at 1%. Different numbers were used to test the learning rate (0.3, 0.5, 0.7, 0.9).

The evolutionary method used to train the neural network includes the mutation probability as a key hyperparameter. It gauges how likely it is that during the genetic process, the NN weights or the total number of hidden layer units will change. It should be noted that the mutation probability has a significant impact on the score, with a mutation probability of 0.3 producing the best results. The odds of discovering the best neural network agent increase with population size in principle, but in fact, the cost of computing may restrict this option. The population size varies between 50, 100, 200, 300, and 500, and the learning curves put the mutation probability at 0.3. The graphs show that a population size of between 100 and 200 is enough for steady progress. Figure 6's curves, which depict the general structure of the learning process, show the moving average scores over five-episode sequences. Figure 6 displays the outcomes of training the NE model with the ideal hyperparameters (mutation probability = 0.3, population size = 200). (c).

The neural network agent was able to attain high scores, ranging about 105, after 280 iterations of the genetic algorithm, which is a considerable improvement in its capacity to perform effectively in the game. The results for the last 10 episodes are shown in Table 1, with the highest score being 149652 points and the average being 28694 points. The agent had performed at a high level, and the game was interrupted because the episodes were taking too long to finish. Although some sources state that the highest score ever recorded for the game is 1940 points, there are no official records for human-player Flappy Bird competitions

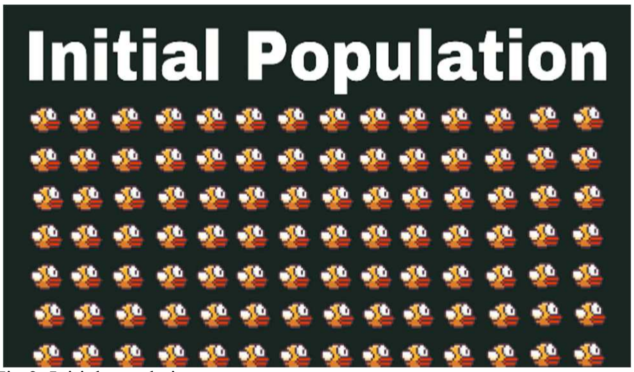

Fig.2. Initial population.

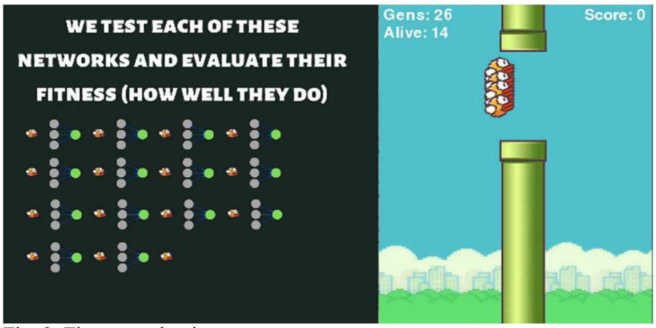

Fig. 3. Fitness evaluation.

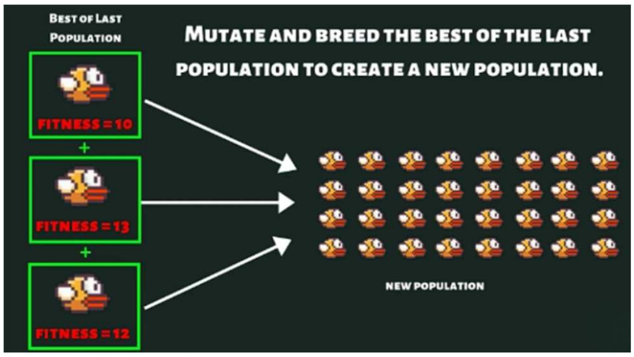

Fig.4. Mutation operation.

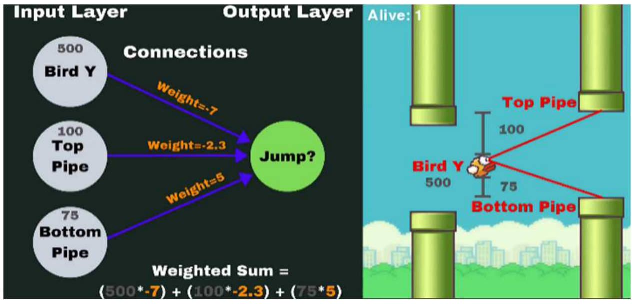

Fig 5. Input and output layers.

a).Results and Data

Table 1. Results.

#	RL Score	NE Score
1	120	4112
2	120	1639
3	245	2200
4	68	1812
5	70	18
6	105	21
7	100	1301
8	120	46321
9	90	79844
10	75	149652

Model	Average	SD (σ)	Best	Worst
RL	111.3	51.23	245	68
NE	28694	50235.52	149652	18

Fig 6. Results.

VI. Conclusion And Future Work

By concentrating on the interactions between users and avatars in virtual world environments, this systematic review of the literature has helped to advance our knowledge of issues like avatar identification and self-concept domains and processes in the context of game design. The literature review omitted a number of crucial elements of this interpersonal interaction. This contains proof that persons with GD commonly produce an avatar that looks like their idealised self.AI approaches can be used to test and compare games by measuring their performance. In this study, we evaluate the ability of the Flappy Bird game to be played using settings for Reinforcement Learning and Neuro evolution Learning. It took about 8 generations for our AI to fully train for the simple Flappy Bird game. The birds in the game frequently hit the ground during the early phases of training. The NEAT (Neuro Evolution of Augmenting Topologies) algorithm was able to learn how to avoid collisions by the fifth or sixth generation, though. The birds had perfected the ability to avoid pipes by the seventh generation. NEAT proved its usefulness as a strategy by winning the game in only 8 generations despite having a small population. NEAT excels because it looks for the most straightforward answer. This technology can be used in future games to quickly find the optimal solution after only a few generations. The experiments' findings show that including extra elements produces much better results. Benefits of allowing the model to produce a wider range of predictions are comparable to those that auxiliary tasks have on a deep learning visual classifier's performance. Because the DFP is not constrained by objectives, it can simultaneously pursue numerous complicated goals. The research has shown how well different machine learning algorithms and techniques work in a challenging 3D multi-agent environment where the agents are engaged in competitive games. Without the use of per-programmed instructions or scripts, these techniques may be utilized to produce experienced opponents in commercial games Additionally, the study demonstrates that reformulating the reinforcement learning issue as supervised learning can result in better performance and quicker training provided the environment offers rich and temporally dense measurement data.

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