

# Application of AI in Video Games

Ashish Bhutkuri<sup>1</sup>, Abdul Azeez<sup>2</sup>, Dheeraj Shetty<sup>3</sup>, Mohammed Saad<sup>4</sup>,  
Vikram<sup>5</sup>, Mr. Ramachandra H Y<sup>6</sup>

Students, Department of Computer Science and Design<sup>1,2,3,4,5</sup>

Assistant Professor, Department of Computer Science and Design<sup>6</sup>

Alvas Institute of Engineering and Technology, Mijar, Moodbirde, India

ashishbhutkuri02@gmail.com, abdulazezcsd@gmail.com, dheerajshetty162@gmail.com

mohammedsaad2478@gmail.com, 4a121cg060vikram@gmail.com, ramachandrahya@aiet.org.in

**Abstract:** *AI brings up a new revolution for transforming the gaming business by improving gameplay, streamlining the process of creating new games, and opening up new avenues for user involvement. In order to better understand the many uses of AI in gaming, this review paper we will concentrate on three main areas: Automated testing, AI based NPC's and Ethic of AI in practice. AI tools simplify the process of creating realistic settings, NPC behaviors, and dynamic storylines in game design and production. AI enhances player experience by offering tailored game experiences through intelligent teaching systems, variable difficulty, and improved NPC interactions that respond to player actions instantly. AI-driven procedural content generation makes it possible to create huge, varied gameenvironments and objectives that provide players with one-of-a-kind, immersive experiences*

**Keywords:** Artificial Intelligence, Algorithm, Non-Playable-character(NPC), Ethics, Automated testing, Artificial Neural Link, Active learning.

## I. INTRODUCTION

The video game industry has experienced significant growth in recent years, with the number of games being produced rising rapidly and the global market value reaching \$134.9 billion in 2018. Artificial intelligence (AI) in computer games encompasses the behaviour and decision-making processes of game-playing opponents, known as non-player characters (NPCs). Modern computers and videogames provide an exceptionally intriguing platform for AI research and innovation. These games feature rich, complex environments paired with expertly developed, stable, physics-based simulations [1].

In response to growing demand from game development companies, many video games employ procedural generation techniques to create content, ensuring both quality and quantity, and thereby enhancing replay value.

An example of procedural generation is the automatic creation of game levels using specially designed algorithms. This means that players can encounter new levels each time they start the game. These game levels include elements such as level geometry, interactive entities, player characters, and non-player characters [2][3]. Today's video games often lack sufficient interactivity, and the goal is to address this issue. The gaming industry is expanding rapidly, and the quality of games has improved significantly, featuring graphically stunning environments and emotionally engaging stories. However, as major companies focus on maximizing profits, the emphasis has shifted towards quickly selling games rather than developing them for greater immersion. Implementing advanced AI that can react, adapt, and make decisions based on player actions, environmental cues, and interactions with other AI characters could enhance this aspect [4].

## II. AUTOMATED TESTING USING AI

The video game industry has seen a substantial surge in popularity, with ever-growing fanbases and an increasing demand for high-quality gaming experiences. In response to this, game development companies are turning to automated game testing to streamline their workflows and enhance the creative aspects of game development. This shift allows designers and developers to focus on innovative and engaging game experiences, rather than being bogged down by the tedious and time-consuming process of manual testing [5].

Numerous approaches have been proposed in the literature for testing video games. There are a significant number of video game testing techniques that do not depend on traditional software testing methods.[2]

### **Human playing style imitation**

This is particularly beneficial in search-based procedural content generation, where a simulation-based evaluation function utilizes AI to play through the candidate game content, assigning a numerical fitness value based on the playability of the content. The fitness of a level may depend on whether the AI can successfully navigate and complete it. This method can be used to evaluate content, test game levels for bugs, and determine if they can be completed by a human player [2],[6]. There are many methods defined for imitating human player behavior.

### **Heuristic**

A very simple approach involves using hand-coded rules without any learning capability and ignoring the game environment. For instance, an NPC following this approach might continuously move in one direction and jump whenever possible [2].

### **Artificial Neural Network**

An artificial neural network (ANN) [2] can be employed to simulate human behaviour. A supervised learning ANN approach utilizes direct representation by using game environment data obtained from human gameplay as its training set [2],[7].

### **Dynamic Scripting**

Dynamic scripting (DS) [2] is an online competitive machine-learning technique for game AI, characterized by stochastic optimization [8]. DS includes a rule base with potential rules that can be applied to a game, with each rule assigned a weight reflecting its effectiveness based on the agent's performance in previous games [2].

### **REALM**

Realm [2] is a rule-based evolutionary computation agent designed to play a modified version of Super Mario Bros [9]. It operates on the principle of learning classifier systems, where rules are evolved based on their fitness value [2].

#### **Grammatically evolved behavior trees**

Behaviour trees offer a top-down structure, starting from the root and extending to the leaves [10]. Control nodes determine which branches of the tree will be executed next, while leaf nodes contain the specific actions to be performed [2].

### **Playtesting with procedural personas**

Archetypal player models, known as procedural personas, can be utilized for generative player modelling and automatic game content testing [11]. This approach employs a variant of Monte Carlo tree search combined with genetic programming applied to trees, rather than using Upper Confidence Bound

1. This method evolves persona-specific evaluation formulas, enabling the discovery of mappings between persona utility functions and state evaluation algorithms [2].

### **ICARUS**

Intelligent Completion of Adventure Riddles via Unsupervised Solving [12] is a framework designed for autonomous video game playing, testing, and bug reporting. It operates on discrete reinforcement learning in a dualistic manner, incorporating volatile short-term memory alongside persistent long-term memory that extends across different game iterations. This framework can iterate through entire game cycles, facilitating the detection of all major bug categories or assisting in their detection [2].

### Hyper-heuristics

The hyper-heuristics approach [13] involves developing a hyper-agent for general video game playing, leveraging the strengths of various individual controllers to outperform them individually when encountering unfamiliar games. This hyper-agent adopts an offline learning strategy, gathering insights into controller performance from a set of trained instances and constructing a selection model that effectively generalizes to new games. Rather than directly controlling the main character, the hyper-agent selects the optimal controller to fulfill this role [2].

### Rolling horizon evolution

Rolling Horizon Evolutionary Algorithms (RHEA) [14] provide an alternative to Tree Search for making action decisions in real-time games. These algorithms utilize Evolutionary Algorithms along with a simulator to train a controller offline. The pre-evolved controller is then utilized for gameplay. RHEA methods implement evolution in a manner akin to tree search, employing a forward model to assess sequences of actions [2].

### Active Learning

Active learning involves choosing from a range of potential inputs to achieve the optimal output while reducing the number of inputs tested [2]. In [15], the authors define the optimal output as a parameter tuning design objective and consider a set of game design parameters as inputs. The aim of minimizing the number of inputs tested is to reduce the number of playtests conducted [2].

### Genetic Algorithm

In [16], the utilization of Genetic Algorithms for learning levels from the Mario AI simulator, based on the Infinite Mario Bros game, is investigated. Agents learn a sequence of actions by employing a genetic algorithm with integer encoding, aiming to maximize the score achieved upon completing the level. This approach involves two distinct stages: initially, domain-independent genetic operators are applied, followed by the incorporation of domain-specific knowledge into these operations to enhance outcomes [2].

## III. AI BASED NPC'S

Artificial Intelligence (AI) in computer games encompasses the behavior and decision-making processes of in-game opponents, also known as non-player characters (NPCs) [17]. Artificial Intelligence (AI) in game development enables NPCs to exhibit intelligent behavior, offering a great alternative for player interaction without requiring another human player. Traditional games operate on a fixed set of rules and states, lacking the ability to learn from their environment. Moreover, many AI game movements remain imperfect, often appearing unsmooth and unnatural. In contrast, in-game AI should be designed to be dynamic and adaptable to changing environments, thereby creating additional challenges and enhancing the fun for human players [18].

Neuro-Evolution of Augmenting Topologies (NEAT) is an unsupervised learning technique for evolving artificial neural networks using a genetic algorithm. Introduced by Ken Stanley from the University of Texas at Austin [19], NEAT is based on the principle that beginning with small, simple networks and progressively increasing their complexity over successive generations is the most effective approach to evolution [18].

To evolve the network, training sets are generated using forward kinematics, geometric relationships, and muscle mechanics equations. By employing two neurocontrollers, Position-Angle and Angle-Activation, the control model can simultaneously address redundancy and nonlinear problems in distinct neurocontrollers [18][20].

AI perception is a crucial factor in the success of any game AI. In a stealth-based game like The Last of Us, knowing the positions of other characters is particularly important. The developers initially opted to use a Vision Cone, a common method for visualizing an enemy's field of view, which has been employed in games like Uncharted [22] and Alien: Isolation [21].

The Vision Cone is very effective at detecting players from a distance but fails to register players who are in close proximity to or standing right next to the NPC. This results in the NPC appearing unaware of its surroundings, making it easy to fool and causing players to lose interest in the game. One solution is to implement multiple Vision Cones, similar to those used in the Xenomorph AI in Alien: Isolation [23][22].

#### IV. ETHICS OF AI IN PRACTICE

Although values like transparency, trustworthiness, and responsibility are fundamental to ethical systems in other domains, video games present unique ethical challenges. Issues such as dark patterns in game design [24], predatory monetization strategies [25], and the black-box nature of games hinder transparency [26] and raise significant ethical concerns. These challenges affect not only game design and development [27],[28] but also have broader societal impacts and implications for research ethics [29][30]. Although ethical frameworks have been developed to provide guidance, their lack of specificity often results in limited adoption [30]. Examining the core issue of transparency, which is essential for assessing other components of AI trustworthiness, reveals that both affective computing and game applications are falling behind [31][30]. In the European Union, the General Data Protection Regulation (GDPR) [32] provides a legal framework and ensures transparency in data handling.

A review of serious games—developed for purposes like healthcare, education, and hiring—revealed that two years after GDPR's implementation, it has had minimal impact on the research community [33]. Similarly, in a recent analysis of affective computing in relation to GDPR laws, Hauselmann identified significant issues concerning transparency, responsibility, and predictability in the field [34]. Hauselmann underscores the sensitive nature of emotional data, which, despite being deeply personal to users, isn't adequately protected under current legal frameworks. Additionally, while user behaviours can be easily observed and recorded, emotional data is often inferred through peripheral signals and machine learning, rather than directly observed [35]. Consequently, most affective computing applications are inherently opaque. Since there should be a right to an accurate representation of personal data, the use of inaccurate predictors could infringe on users' personal rights [30].

#### V. CONCLUSION

In conclusion, the application of AI in video games offers significant advancements in creating immersive and engaging experiences. However, it also brings unique ethical challenges, particularly regarding transparency, trustworthiness, and the handling of personal data. As AI continues to evolve within the gaming industry and foster a sustainable future for AI in video games.

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