Game AI Revisited

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ABSTRACT

More than a decade after the early research efforts on the use of artificial intelligence (AI) in computer games and the establishment of a new AI domain the term "game AI" needs to be redefined. Traditionally, the tasks associated with game AI revolved around non player character (NPC) behavior at different levels of control, varying from navigation and pathfinding to decision making. Commercial-standard games developed over the last 15 years and current game productions, however, suggest that the traditional challenges of game AI have been well addressed via the use of sophisticated AI approaches, not necessarily following or inspired by advances in academic practices. The marginal penetration of traditional academic game AI methods in industrial productions has been mainly due to the lack of constructive communication between academia and industry in the early days of academic game AI, and the inability of academic game AI to propose methods that would significantly advance existing development processes or provide scalable solutions to real world problems. Recently, however, there has been a shift of research focus as the current plethora of AI uses in games is breaking the non-player character AI tradition. A number of those alternative AI uses have already shown a significant potential for the design of better games.

This paper presents four key game AI research areas that are currently reshaping the research roadmap in the game AI field and evidently put the game AI term under a new perspective. These game AI flagship research areas include the computational modeling of player experience, the procedural generation of content, the mining of player data on massive-scale and the alternative AI research foci for enhancing NPC capabilities.

Categories and Subject Descriptors

I.2.1 [**Artificial Intelligence**]: Applications and Expert Systems—*Games*; H.1.2 [**Models and Principles**]: User — Machine Systems—*Human factors*

Keywords

Game artificial intelligence, player experience modeling, procedural content generation, game data mining, game AI flagships

1. INTRODUCTION

Almost 30 years after the first reported video game conference at Harvard [33] and 12 years after Laird's and van Lent's seminal article [26] that, in part, established the foundations of game artificial intelligence (AI) and inspired early work in the field [34, 22, 25, 14, 3, 30, 58] the game AI term needs to be revisited and restructured.

Since those first days of academic game AI the term was mainly linked to non player character (NPC) behavior (i.e. NPC AI) and pathfinding [8] as most of the early work in that field was conducted by researchers with AI, optimization and control background and research experience in adaptive behavior, robotics and multi-agent systems[1]. AI academics used the best of their computational intelligence and AI tools to enhance NPC behavior in generally simple, research-focused, non-scalable projects of low commercial value and perspective. In almost every occasion the two (academic and industrial game AI), rather immature, communities would meet they would conclude about the gap existent between them and the need of bridging it for their mutual benefit [8]. The key message of academic AI has been that industry does not attempt to use sophisticated AI techniques with high potential (e.g. neural networks) in their games. On the other end, the central complaint of industrial game AI has been the lack of domain-knowledge and practical wisdom when it comes to realistic problems and challenges faced during game production.

While the vast majority of AI academics (including the author) would claim that games are fully scripted and still use 30-year old AI technology — such as A* and finite state machines — the game industry had been making small, yet important, steps towards integrating nouvelle (or modern) AI [8] in their games [55] during the early days of game AI. A non-inclusive list of games that advanced the game AI state-of-practice in industry [42] includes the advanced sensory system of guards in *Thief* (EIDOS, 1989); the advanced opponent tactics in *Half-Life* (Valve, 1998); the fusion of ma-

[1]Note that this paper deliberately excludes research in board game AI as — in contrast to the breadth and multifaced nature of AI research challenges met in game development — advances in that field can only be algorithmic with respect to a particular aim (i.e. learn to play a board game) in constrained board game spaces.

chine learning techniques such as perceptrons, decision trees and reinforcement learning coupled with the belief-desire-intention cognitive model in *Black and White* (EA, 2000); the dynamic difficulty adjustment (DDA) features in the *Halo* series (MS Game Studios); the imitation learning *Drivatar* system of *Forza Motorsport* (MS Game Studios, 2005); the AI director of *Left 4 Dead* (Valve, 2008)[2] and the neuroevolutionary training of platoons in *Supreme Commander 2* (Square Enix, 2010).

The key criterion that distinguishes a successful AI in commercial-standard games had always been the level of integration and interweaving of AI in the design of the game [42]. While an unsuccessful coupling of game design and AI may lead to unjustifiable NPC behaviors, break the suspension of disbelief and immediately reduce player incorporation [6], the successful integration of AI in the design process in games such as *Façade* [31] or *Kinectimals* (MS Game Studios, 2010) may absorb potential "catastrophic" failures or limitations of the AI.

The level of AI sophistication in recent games such as *Left 4 Dead* (Valve, 2008) and *The Elder Scrolls V: Skyrim* (Bethesda Softworks, 2011) suggests that advances in NPC AI have converged to highly satisfactory solutions for most NPC control challenges faced during game production. Moreover, a number of game developers (and some game AI academics) have already taken sides arguing that NPC AI is almost solved [7, 35] for most production tasks while some claim that game AI research and development should focus on non-traditional uses of AI [35, 45]. Such indications suggest that further marginal enhancements of NPC AI may require significant effort and cost.

Due to the rise of robust and effective industrial game AI solutions, more frequent and constructive communication with the industry, the convergence to satisfying NPC performances, the support of the multidisciplinary nature of game AI and a more pragmatic and holistic view of the game AI problem, recent years have seen a shift of academic interests with respect to game AI. We have reached an era where the catholic focus of the application of AI in the domain of games is not on agents and NPC behaviors. The focus has, instead, started to shift towards interweaving game design and game technology by viewing the role of AI holistically: AI can help us to make better games but that does not *necessarily* imply better, more human-like or believable NPCs.

There are a number of key research areas, which I name *game AI flagships*, that have recently provided innovative, yet commercially-plausible solutions for a number of game development challenges. Those areas of common (academic and industrial) interest appear to both synthesize the framework of current and future academic research and already influence high-end commercial game technology. It is expected that a focus on these game AI areas (beyond NPC control) will most likely yield a larger impact on the making of better games via the use of AI. Player Experience Modeling (PEM), Procedural Content Generation (PCG), Large-Scale Game Data Mining and new perspectives in NPC AI are the four main game AI flagships considered in this paper. The list provided in this paper is, by no means, inclusive of all high-end potential game AI areas but it is representative of spotlight current research efforts and development advances.

[2]The success of the AI director and its positive impact to player experience has influenced game AI architectures in a number of other game productions including *Resistance 3* (Insomniac Games, 2011).

2. THE FLAGSHIPS OF GAME AI

In this section the emerging, non-traditional, flagship research areas of game AI are presented, corresponding successful examples are provided for each flagship, and arguments are listed for their inclusion as key game AI research and development areas.

2.1 Player Experience Modeling

Recent years have seen both a boost in the size of the gaming population and a demographic diversification of computer game players [23]. This, in turn, means that skills, preferences and experience differ widely among players of the same game. Therefore, the need for tailoring games to individual playing experiences is growing and the tasks of user modeling and experience-based adaptation within games become increasingly important and challenging. Game engines that are able to recognize and model the playing style and detect the current emotional and cognitive state of the user will be necessary milestones towards the personalization of the playing experience.

Player experience modeling (PEM) is the study and use of AI techniques for the construction of computational models of experience of players. PEM places an AI umbrella to the multidisciplinary intersection of the fields of user (player) modeling, affective computing, experimental psychology and human-computer interaction. Player experience, player satisfaction and their modeling have recently seen a growing number of dedicated workshops, special sessions and invited talks in top academic venues including the IEEE Conference on Computational Intelligence and Games (IEEE-CIG)[3], the Foundations of Digital Games (FDG)[4] and the Artificial Intelligence and Interactive Digital Entertainment (AIIDE) conference[5] and special issues to journals such as the IEEE Transactions of Computational Intelligence and AI in Games and IEEE Transactions on Affective Computing. In addition, top game developers (such as Valve) have recently started to experiment with multiple modalities of user input (e.g. physiology) for the personalization of experience in popular games such as *Left 4 Dead* (Valve, 2008) [1].

2.1.1 General PEM Principles

A model of player experience predicts some aspect of the experience of a player in general, a type of player, or a particular player would have in some game situation. There are many ways this can be achieved, with approaches to PEM varying both regarding the inputs (from what the experience is predicted, e.g. physiology, level design parameters, playing style or game speed), outputs (what sort of experience is predicted, e.g. fun, frustration, attention or immersion) and the modeling methodology.

Computational models of player experience can be built on different types of data collected from the players which in turn define different approaches to player experience modeling (PEM). We can identify three main classes of approaches for modeling player experience in games which rely on (1) data expressed by players (*subjective* PEM); (2) player data

[3]www.ieee-cig.org/
[4]www.foundationsofdigitalgames.org/
[5]http://www.aiide.org/

obtained from alternative modalities of player response (*objective* PEM); and (3) contextual and behavioral data obtained through the interaction between the player and the game (*gameplay-based* PEM). Data from multiple modalities and types can be fused to better predict annotated player experience states.

If data recorded includes a scalar representation of experience, or classes and annotated labels of user (cognitive and affective) states any of a large number of machine learning (regression and classification) algorithms can be used to build models of experience. Available methods include neural networks, Bayesian networks, decision trees, support vector machines and standard linear regression. On the other hand, if experience is annotated in a ranking format (e.g. game version X is more frustrating than game version Y) standard supervised learning techniques are inapplicable, as the problem becomes one of *preference learning* [15, 57]. In particular, neuro-evolutionary preference learning has proven suitable for this task; in this method, the weights of neural networks are evolved to minimize the error between reported and predicted preferences [63, 57].

The following subsections provide further details about each of the three PEM approaches and corresponding successful examples of each approach. The section ends with a discussion on the potential of personalization of both the experience and the player experience model.

2.1.2 Subjective PEM

The most direct way to develop a model of experience is to ask the players themselves about their playing experience and build a model based on such data. Subjective PEM considers first person reports (self-reports). Reports expressed indirectly by experts or external observers can potentially provide reliable player experience annotations; however, third-person assessment is not covered in this paper. Subjective player experience modeling can be based on either players' *free-response* during play or on *forced* data retrieved through questionnaires. Forced self-reports can be further classified as *ratings*, in which the players are asked to answer questionnaire items given in a Likert scale or *rankings*, in which players are asked to compare their player experience in two or more sessions of the game [60, 57, 51]. A recent study has exposed the limitations of rating approaches over ranking questionnaire schemes (e.g. pairwise preference) including increased order of play and inconsistency effects [56].

While self-reports have inherent limitations including user self-deception, memory-dependencies and ordering effects numerous studies have shown that ranked self-reporting can successfully guide machine learning algorithms to capture aspects of player experience in prey/predator [59], physical interactive [61], platform [41, 40] and racing [51] games.

2.1.3 Objective PEM

Player experience can be linked to a stream of emotions, which may be active simultaneously, usually triggered by events occurring during gameplay. Games can elicit player emotional responses which in turn may affect changes in the player's physiology [64, 51], reflect on the player's facial expression [39, 24], posture and speech, and alter the player's attention and focus level [2]. Monitoring such bodily alterations may assist in recognizing and synthesizing the emotional responses of the player. The *objective* approach to player experience modeling incorporates access to multiple modalities of player input for the purpose of modeling the affective state of the player during play.

Models built via the objective PEM approach may be very accurate representations of player experience since player experience is approached in a holistic manner via the use of multiple input modalities. The key limitations of the objective PEM approach include its high intrusiveness and questionable feasibility. Most modalities are still nowadays not technically plausible within commercial computer games. For instance, existing hardware for physiology requires the placement of body parts (e.g. head, chest or fingertips) to the sensors making physiological signals such as EEG, respiration, blood volume pulse and skin conductance rather impractical and highly intrusive for most games. However, recent advances on biofeedback sensor technology have resulted in low-cost, unobtrusive biofeedback devices (bracelet sensors) appropriate for gaming applications[6].

Pupillometry and gaze tracking are very sensitive to distance from screen and variations in light and screen luminance, which makes them rather impractical for use in a game application. Modalities such as facial expression and speech could be technically plausible in games even though the majority of the vision-based affect-detection systems currently available cannot operate in real-time [67]. At the positive end of the spectrum, Microsoft's XBox 360 Kinect[7] sensor device is pointing towards more natural game interaction and showcases a promising future of objective PEM.

2.1.4 Gameplay-based PEM

The main assumption that drives *gameplay-based* PEM is that player actions and real-time preferences are linked to player experience since games may affect the player's cognitive processing patterns and cognitive focus. On the same basis, cognitive processes may influence emotions as one may infer the player's emotional state by analyzing patterns of the interaction and associating user emotions with context variables. Any element derived from the interaction between the player and the game forms the basis for gameplay-based PEM. This includes parameters from the player's behavior derived from responses to system elements.

The inputs to a gameplay-based player experience model are statistical spatio-temporal features of game interaction. Those features are usually mapped to levels of cognitive states such as attention, challenge and engagement [11]. General measures such as performance and time spent on a task have been used in the literature, but also game-specific measures such as the weapons selected in a shooter game [18]. Moreover, several dissimilar difficulty and challenge measures (see [21, 37, 52] among many) have been proposed for different game genres. In all of these studies, difficulty adjustment is performed, based on a player experience model that implies a direct link between challenge and player satisfaction. Sometimes a player model [62, 20, 10] is embedded in the process of PEM. Data mining attempts to predict player actions and intentions as well as to identify different playing patterns within a game [12, 53] can also be viewed as gameplay-based PEM. Game data mining is covered in Section 2.3 in further detail as it is considered a game AI flagship on its own.

[6] http://www.emoticalab.com/

[7] http://www.xbox.com/kinect/

Gameplay-based PEM is arguably the most computationally efficient and least intrusive PEM approach but it usually results in a low-resolution model of playing experience.

2.1.5 Personalizing PEM

AI methodology can be used not only to construct a computational model of player experience but to also tailor the player experience model itself to the player's individual preferences during the interaction. An example of this promising direction within PEM research is the work of Liapis et al. [28] where computational models of player aesthetics are tailored to the player's selections and are further used for the design of personalized spaceships with respect to player aesthetics (see Fig. 2).

Figure 2: Example spaceship (rendered with three different methods) generated via an EDPCG algorithm. The algorithm both tailors computational user aesthetics models and generates personalized spaceships based on those tailored models.

2.2 Procedural Content Generation

Procedural content generation (PCG) can be viewed as the study and development of algorithms that generate content automatically. *Game content* refers to all adjustable game elements that may affect player experience (excluding NPC behavior) which may include elements such as terrains, maps, levels, stories, quests, rulesets, camera profiles and music. There are several benefits obtained from the automatic creation of content in games [50]: first, PCG can alleviate the enormous effort and cost of content creation and make it easier to tailor content to the player; second, content can automatically adapt the game to the needs and preferences of individual players and yield maximal game replayability; third, PCG can challenge human creativity and generate solutions beyond the designer's imagination in a stand-alone or mixed-initiative design [44, 4] fashion.

Even though PCG techniques have been incorporated in games since *Rogue* (1980) it is only very recently that an academic community is devoted to the study of PCG signaling the shift of interest towards this use of AI in games. That trend is reflected by an IEEE CIS Task Force[8] and a wiki[9] on the topic, a series of dedicated workshops at the FDG conference, an international PCG competition[10] and a special issue on PCG at the IEEE Transactions of Computational Intelligence and AI in Games. The use of PCG for the design of better games has reached a peak of interest in commercial game development which is showcased by successful (almost entirely procedurally generated) games such as *Minecraft* (Mojang, 2011) and *Love* (Eskil Steenberg, 2010) and the broad coverage of PCG topics in relevant conferences (such as the Paris Game AI conference series).

Research efforts that couple the PEM and the PCG flagships has resulted to research projects of high commercial potential under the *experience-driven procedural content generation* (EDPCG) framework [65]. According to the EDPCG framework, content is viewed as a building block of player experience which can be adjusted to optimize the experience of the player (predicted via player experience models). Examples of EDPCG work include the adaptive content creation framework of Shaker et al. [43] where personalized Super Mario Levels are generated for maximizing models of player experience states, such as *fun*, which are built via crowdsourced *fun* reports about mini Super Mario Bros levels (see Fig. 1 for two example levels).

[8]http://game.itu.dk/pcg/
[9]http://pcg.wikidot.com
[10]http://www.marioai.org

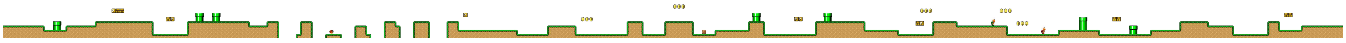
In addition to Super Mario Bros levels, racing tracks [47], strategy maps [48], game rule sets [5], buildings [29] and weapons [17] (among other types of content) have been generated based on models of player experience. The work of Liapis et al. [27, 28] is indicative of the power of EDPCG for game design as personalized spaceships can rapidly be generated based on player aesthetics models via interactive evolution. Both the models of user aesthetics and the aesthetic attributes of the spaceships are adapted to the preferences of the user/designer yielding personalized spaceship designs such as those presented in Fig. 2.

2.3 Massive-Scale Game Data Mining

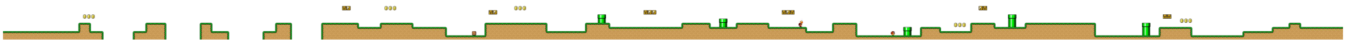
Game data mining may be loosely defined as the use of AI (data mining algorithms) for addressing questions such as: *how do people play a game?*; *is the game played as intended?*; *why do people stop playing a game?*; *why do we play a game this way?*; *can we predict what a player will do?*; *does the game offer the right experience?*; *what is the personality of a player?*. All these are critical questions that are tied to user-oriented testing procedures used in the game industry. In iterative-phased game development, representative samples of the target audience as well as internal professional testers spend time and put effort on testing the games and evaluating the quality of the gaming experience.

During the last five years — as an alternative to traditional testing — key game developers (including Zynga, Blizzard, Bioware, Square Enix Europe and EA Games) have been collecting and analyzing detailed and massive-scale player behavioral and contextual data (i.e. game metrics) via specialized monitoring software. As argued by big data analysts we have now reached a point were existing data mining algorithms cannot follow the growth of data availability and the massive size of datasets available and, thereby, cannot fully support the analysis of such data. This poses new exciting challenges and avenues of research for AI in games since the use of AI for inferring playing patterns from data can provide a quantitative approach to and supplement of traditional qualitative approaches of user and playability testing [13].

Even though directly linked to context-based PEM (see Section 2.1), the mining of gameplay data deserves its own game AI flagship as game metrics and game metric analysis is currently a spotlight research and development area within the games industry supported by a growing number of game data analytics companies. Game data mining has seen extensive coverage in game developer meetings such as



(a) Human



(b) World-Champion AI

Figure 1: Example levels generated for two different Super Mario players. The levels generated maximize the modeled *fun* value for each player. The level on top depicts the level generated for a human player while the level below is the level generated for the world champion agent of the Mario AI competition.

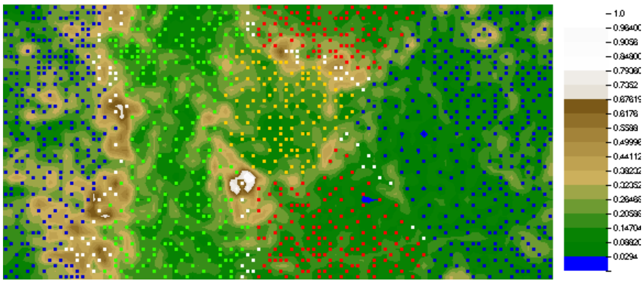


Figure 3: U-matrix visualization of a self-organizing map depicting the 4 player clusters identified in a population of 1365 Tomb Raider: Underworld players (shown as small colored squares). Different square colors depict different player clusters. Valleys represent clusters whereas mountains represent cluster borders.

the game AI summit at GDC[11] and the Paris Game AI Conference[12] as well as dedicated panels, tutorials and special sessions in top game AI academic conferences such as IEEE-CIG and AIIDE.

Among the relatively few studies in the young field of game data mining [13], Yee has analyzed the relationship between player motivations, demographic variables and in-game behaviors of 3000 MMORPG players [66]. Drachen et al. [12] have identified four potential player types in *Tomb Raider: Underworld* using self-organization (see Fig. 3) in direct collaboration with the developer of the game (i.e. Crystal Dynamics). Thurau et al. [46] have applied non-negative-matrix factorization to mine 1.6 million images on World of Warcraft guilds while Mateas and Weber [54] have mined game metrical data for the prediction of player strategies in StarCraft. In addition to empirical player data, alternative analytical apporaches have been proposed for evaluating games and their playability [36].

2.4 NPC AI: Different Perspectives

As AI has already provided satisfactory solutions to most NPC tasks (including navigation and lower levels of NPC control) the focus of research on NPC AI may shift towards under-researched, yet very promising, directions that will enhance NPC capabilities. A different perspective to NPC AI is to view NPC control as a mapping of the NPC's context (environment) and attempt to alter the latter to observe changes in the perception of the first. So far, the question of whether empirical research efforts should be put more on the agent or its environment (or both) in order for the agent to appear more believable, human-like, or intelligent remains largely unanswered. The ability of the environment — instead of, or in addition to NPC attributes — to absorb non-believable agent behaviors can define new variables for optimization. This raises new research questions such as *how can the design of a game be altered to allow for maximal absorption of AI weaknesses with minimal effort* and *how can constructive or search-based* [50] *content creation processes be coupled with NPC AI control for achieving such a goal.* The issue of assessing NPC believability through contextual content creation and adaptation has already been addressed by a recent study on the believability of Super Mario Bros players [49]. In addition, game Turing test competitions such as those in Super Mario Bros[13] and in *Unreal Tournament* (Epic Games, 1999) [19] define attempts on further exploring the unknown mapping between NPC agent behavior, game context and NPC believability.

Beyond standard single NPC control, a promising trend on NPC AI research — which already has an impact on recent game productions — appears to be the generation and detection of patterns of complex social behavior and interaction among NPCs and humans [68, 38] with a focus on cognitive/affective agent architectures for social games such as the *Prom Week* game [32]. In addition, data-driven modeling of groups of NPCs and players via group structure identification [16] can offer a complementary perspective towards well-grounded human behavior models [9] that can guide personalization in social games.

3. CONCLUSIONS

More than ten years after the establishment of the game AI field the term needs to be revisited and enhanced with non-traditional research and development areas beyond NPC control. The plethora of ways AI is currently used in games, beyond traditional areas such as NPC AI, showcases the potential and impact of a broader conception of the research field, and can enlarge the boundaries of design within these creative industries.

This paper listed a number of flagship areas that are currently at the spotlight of game AI state-of-the-art research and commercial-standard development. Methods for modeling player experience, algorithms and processes for generating content of high value automatically, approaches for mining massive-scale data of players and alternate perspec-

[11]http://www.gdconf.com/

[12]http://gameaiconf.com/

[13]http://www.marioai.org/turing-test-track

tives on NPC AI research define the framework of the four key game AI areas presented.

The list of flagships is not inclusive of all potential core uses of AI in the years to follow. In addition to the game AI flagships discussed in this paper the current trends of pervasiveness, embedded systems and natural interaction in design have already seen their integration in gaming contexts (e.g. the Primesense camera-based sensor). Thus, natural and multimodal interaction for player behavioral and movement pattern analysis arguably define core AI domains in the near future at the crossroad of the game data mining and the player experience modeling flagships. Finally, at the crossroads of procedural content generation and player experience modeling, substantial effort is expected on the development of sophisticated AI techniques for meaningful story generation and the design of personalized authoring tools.

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