IEEE Access
Multidisciplinary ⋮ Rapid Review ⋮ Open Access Journal

Received June 25, 2018, accepted July 2, 2018, date of publication July 13, 2018, date of current version August 7, 2018.

Digital Object Identifier 10.1109/ACCESS.2018.2855970

Artificial Intelligence and Virtual Worlds – Toward Human-Level AI Agents

VLADIMIR M. PETROVIĆ
School of Electrical Engineering, University of Belgrade, 11000 Belgrade, Serbia
e-mail: vpetrovic@etf.bg.ac.rs

ABSTRACT Artificial Intelligence (AI) has a long tradition as a scientific field, with tremendous achievements accomplished in the decades behind us. At the same time, in the last few decades, we have witnessed a rising popularity of interactive computer games and multi-user virtual environments, resulting with millions of users inhabiting these virtual worlds. This paper deals with the intersection of AI and virtual worlds, focusing on AI agents and exploring the potential implications toward the human-level AI. It offers a unique multidisciplinary approach to the subject, in order to give a comprehensive view on the elaborated problems and the way they are interrelated. Benefits coming from this kind of broad study are twofold: on one hand, research on advanced AI agents in the virtual worlds is the necessary ingredient of their further evolution; and on the other hand, the virtual worlds represent an excellent platform for research on numerous problems related to the challenging field of AI.

INDEX TERMS Artificial intelligence, autonomous intelligent agents, human-level AI, machine learning, interactive computer games, MUVEs, virtual worlds.

I. INTRODUCTION

The idea of artificial or virtual reality (a simulated world where people can interact), has attracted a lot of attention several decades ago. At that time, virtual reality was defined as a HCI (human-computer interface) that includes simulations and interactions in real-time, using multiple sensors with the aim to provide a proper excitation of human senses (vision, hearing, touch, smell, and taste) [1]. Head-mounted displays, 3-D sound, sensing gloves, force-touch feedback, etc., were implemented in order to make a realistic illusion of presence at some virtual location and to provide users with the sense of immersion [2]–[5]. However, expectations and demands coming from the virtual reality concept were much higher than the technological capabilities at that time [6], [7].

Development of computer graphics in combination with internet technology heavily influenced evolution of one different sort of virtual interaction – computer games. Massively multiplayer online role playing games (MMORPGs) became especially widespread. One of the most illustrative examples is *WoW (World of Warcraft)* – with millions of open accounts, and more importantly millions of active subscribers as well. Some studies have shown that population of players belong to a broad age range, with demographic characteristics that widely vary [8]. Popularity of this sort of virtual interaction can also be recognized in the fact that students spend up to 20 hours a week playing various online computer games [9]. Population size and diversity of users involved in these gaming worlds represent a very valuable potential for different research studies. It is reported [10] that leading game developing companies (such as *Blizzard* and *EA Games*) collected and analyzed large data sets considering the player's behavior. Other companies also recognized the potential of gaming – e.g., *IBM* investigated the way successful playing of *WoW* leads to the improvement of strategic thinking techniques and leadership capabilities [11]. Further evolution of 3D computer games at one point led to something more socially complex – the development of MUVEs (multi-user virtual environments). These virtual environments, or "virtual worlds" as they are often called, attracted massive attention (e.g. – *There*, *Open Wonderland*, *ActiveWorlds*, *Second Life*, etc.). Hundreds of thousands of users, represented via avatars (animated human-like characters), found in them a place to simultaneously interact and socialize [12], [13]. It should be noticed that some researchers use a term 3D virtual worlds, as a broader classification when referring to both – interactive computer games and MUVEs [13]. Although they are very similar, it should not be forgotten that computer games and MUVEs have different objectives [12]. However, bearing in mind that virtual worlds can be defined [13] as a computer based simulated environments, in which users can interact

2169-3536 © 2018 IEEE. Translations and content mining are permitted for academic research only.
Personal use is also permitted, but republication/redistribution requires IEEE permission.
See http://www.ieee.org/publications_standards/publications/rights/index.html for more information.

between themselves or with artificial agents, this kind of terminology is rather justified and will be followed further in the paper. Computer games and MUVEs will also be simultaneously used as terms, depending on what should be pointed out in a particular sentence.

Popularity and continuous development of previously mentioned virtual interactive worlds, consequently enabled for new research directions to be opened in various scientific fields [7], including the field of Artificial Intelligence [14]. Among other, these virtual worlds are recognized as a fruitful ground for research in autonomous intelligent agents [15], which will be in the focus of this paper. Besides the field of AI itself, development of intelligent agents can be identified as a highly beneficial for virtual worlds as well. Therefore, this topic will be critically investigated from different perspectives, practical on the one side, and more abstract on the other – with the desire to elaborate and integrate valuable insights coming from both, academic community and commercially oriented industry.

The paper is organized in the following order. In Section 2, the role and significance of AI in virtual worlds will be discussed. Section 3 will provide an analysis of number of AI techniques aiming to provide an intelligent behavior of agents. In Section 4 virtual agents will be placed in a wider theoretical framework, aiming to provide a unique approach to the subject of potential implications and requirements leading toward human-level AI agents. Concluding remarks will be elaborated in Section 5. At the end, rich source of carefully chosen references used for this research study will be listed.

II. THE ROLE OF AI IN VIRTUAL WORLDS

It should be noticed that despite partial overlap, virtual worlds and earlier mentioned virtual reality represent very different concepts [7]. One of the crucial differences is reflected in the fact that MUVEs and modern computer games share a common property that differ them from old virtual reality ideas – most of the user sensation comes from the graphics displayed on the computer monitor. Advanced 3D graphics can be identified as the main ingredient of the tremendous success of virtual worlds in the past. However, despite the fact that state of the art 3D graphics acts very persuasive, it is questionable if it can fully provide two elements that are identified in [1] as a key issue – immersion & interaction. One should notice that these two elements are mutually dependable. As it was defined in [16], immersion represents a subjective impression that user participates in a realistic experience. In order to achieve higher level of immersion, graphical visualization is necessary but not sufficient requirement.

Therefore, it is not uncommon to read that the role of graphics in these virtual worlds came to the point where it can no longer represent a crucial enhancement of user's experience [15], [17]. Not to mention that in competitive game industry, high level of graphics long ago became quite expected [18], [19]. Consequently, stepping up to the next level of believable and realistic experience implies that research efforts must be more oriented toward the behavior of the game inhabitants, rather than on the visual appearance of the environment. It is even reported that with more complex visual appearance of the simulated world, the necessity for more complex NPCs (non player characters) is increasing [20]. Artificial intelligence is recognized as a key instrument which can largely contribute to virtual worlds [14], since AI can make NPC's behavior more appealing and natural. Higher level of life-like behavior certainly affects user's immersion in a large degree. Therefore, it is not surprising that the quality of the implemented AI is recognized as one of the main evaluation criteria of the successful games [14], [18], [21]–[23], with number of dedicated books dealing with the practical issues related to it (e.g., Steve Rabin's ''AI Game Programming Wisdom'' series).

In the early days of the field, range of AI techniques used in games was very limited, focusing mostly on a simple AI. Reasons were various: from the fact that some AI techniques are extremely complicated and require too much computational power, to the simple fact that sometime advanced AI in games is considered as unnecessary. Not to mention that graphics used the most of the CPU power, in that way leaving very small amount of processing resources for AI. This trend was changed to a great extent over the years, however some of the issues remained. Numerous efforts were made in the past, in order to reduce a strong gap between academic AI and game industry developers [14], [18], [24], since these two are often burdened with different natures of their goals. Still, despite the different approaches, computer gaming worlds probably represent the ''largest commercial application of artificial intelligence'' [25]. Great potential that lies in applying of academic AI research to virtual worlds is not beneficial only for their future development, but also for the field of AI itself. As it was observed [14], virtual worlds with its rich content represent a challenging platform for advanced AI research, especially in the domain of intelligent agents.

A. GAME AGENTS – NPCs

Observing the past, one could notice that the behavior of game agents, or NPCs as they are usually referred to, was among the main focuses of game AI. Although there are some variations on what exactly qualifies as the NPC, broadly accepted definition is that NPCs are all virtual world characters that are not controlled by a human user (no matter if they are acting as opponents, collaborators, or neutrally oriented supporting characters). As it was reported by some authors, an obvious distinction considering the commercial game AI on the one side and academic AI on the other could be noticed [17], [19], [21]. NPCs are maybe the best indicator of differences between the two, considering the nature of their goals.

The purpose of AI in games is rather simple – to create a better, more realistic gaming experience for users. This does not necessary include making of an advanced AI system. In number of scenarios NPCs are not designed to actually be intelligent, but rather to give an illusion of intelligent behavior. One could consider it as a sort of ''smart'' cheating. From the developer's point of view, this approach is rather logical and even encouraged [19], because in very large percent simple illusion of intelligence can have the same effect as a more complex AI. Not to mention that in most cases, it is less cost effective and algorithmically simpler. So called ''suspension of disbelief'' [26], has its roots in the widely known ''Eliza effect'' [27]. Although the focus of this paper is not on the illusion of intelligence, some aspects must be discussed in order to provide a deeper understanding of the topic in general. One of the illustrative examples that are describing this phenomenon can be found in many different games where human user has computer controlled opponents. In a common scenario, group of hostile agents is acting is some environment and they are talking to each other: ''Watch for your back'', ''Set up a perimeter'', etc. Of course, they are randomly yelling these phrases, while at the same time act absolutely independent without any intelligent collaboration. However, if this communication between NPCs is carefully designed, it can often produce a sense of intelligent behavior for a human user participating in a game, in that way increasing his level of immersion into the virtual gaming environment. Other aspect of ''cheating'' is omniscience of the NPCs. It is especially noticeable when computer controlled enemy is playing against a human player in some game scenario – in majority of cases enemy agent possess unrealistic capabilities, especially when it comes to searching, or decision making speed. Related to the previous, one more aspect to be considered is the game difficulty. If the NPC is almost unbeatable, then the majority of players will lose their interest very fast. Same thing will happen if NPCs are too easy to beat. In order to prevent this kind of scenarios developers are trying to achieve a balance by designing opponents that are not stupid, but at the same time not too smart. In other words, aspects of cheating must be carefully implemented, in order to give an illusion of intelligent behavior. This challenging task is thoroughly analyzed by some authors (see [28]). Although this kind of approach is inspired by gaming needs, an analog example (with different motivation) can be found in academic AI. Alan Turing, one of the founding fathers of AI, described a sort of intelligence test (later well known as Turing test) and in his seminal work [29] he analyzed the situation where machines are not making any mistakes: ''It is claimed that the interrogator could distinguish the machine from the man simply by setting them a number of problems in arithmetic. The machine would be unmasked because of its deadly accuracy.'' In order to prevent this, simple solution is proposed – machines should make intentional mistakes in order to deceive human interrogator [29]. We will later return to the Turing test in the context of NPCs.

III. AI TECHNIQUES THAT SHAPE THE BEHAVIOR OF NPCs

As it was already mentioned, NPC's behavior is commonly shaped with some of the AI algorithms. It is noticed that academic AI and game AI have different views on what qualifies as artificial intelligence [30]. While game industry mostly observes NPC's AI in a broad sense, including even some problems that have different nature, academic community is often referring to NPC's AI in a more narrow sense, focusing only on the intelligent behavior [31]. In this section special emphasis will be on algorithms and techniques used for decision making and learning, as they represent essential topics regarding the underlining idea of the paper. I will briefly describe chosen techniques, provide examples (commercial and academic) of their implementation regarding the topic of intelligent agents, and discuss some of the benefits and drawbacks coming with their implementation.

A. APPROACHES BASED ON MORE TRADITIONAL METHODS

Number of successful AI programs was developed with **Rule-based Systems**, so it is not surprising that they are used for control of NPC's behavior at the very beginnings of the game AI. Their structure consists out of available knowledge (data) and a set of rules (if-then logic). Properly used, rule-based systems can provide a decently high degree of control and sufficient robustness. However they are rarely used as a dominant method, since in majority of cases there are simpler and more efficient techniques to achieve desired behavior [30].

Finite State Machines represent a well known computational model. Although not always the most optimal solution, it is probably the most widely used technique in a game AI development. Number of successful computer games, such as *Half-Life series* or *Quake series* used FSMs as a basis for the control of NPCs. The idea is rather simple: at any time, only one of a finite number of states is possible, and depending on the inputs that state could be changed. FSM is defined by its initial state, list of possible states, and transition conditions. FSMs use a Boolean logic, thus a state can be active or inactive (true or false). Switching between the states, changes the behavior of the NPC. FSMs are easy to implement, efficient (especially when it comes to simple NPC's behavior), compact, and very powerful algorithm, which makes them rather favorable in a game development [32], [33]. However, they are often criticized for being too inflexible, causing them to behave inaccurate in complex and unpredicted scenarios. Further on, one of the main disadvantages in this approach is that number of states can rapidly overgrow, if we exaggerate in complexity of the desired behavior. This could be partially avoided by introducing of sub-states into the systems, in that way creating a hierarchical finite state machines (HFSMs) [34].

Several variations of FSMs are possible, including **Fuzzy State Machines** where fuzzy logic is used as an alternative for the Boolean logic. As a consequence, unlike the FSMs, system could be in more than one state at a time. To be more precise, different levels of membership can be assigned to states. Introduction of multiple states, as well as fuzzy logic in general, gives a sense of more natural and realistic NPC's behavior. Although reasonably simple to implement, it must be taken into account that too many fuzzy states could lead to a rapid growth of the system complexity known as ''combinatorial explosion''. It should also be noted, that besides the fact that FuSMs have many advantages compared to standard FSMs (e.g., NPC's behavior is less predictable), the method is weaker in the terms of the problem generalization. There are numerous examples of FuSMs and fuzzy logic in virtual worlds reported in literature [17] and [18], especially when it comes to strategic and tactical games (e.g., *Civilization: Call to Power*).

Besides state machines, scripting is used in majority of virtual worlds, when it comes to building an AI system. It should be noted that scripts are considered to be static and often tend to be very complex, which implies their problem with predictability and difficulty scaling [35]. In order to solve this, dynamic scripting was described in [31]. This unsupervised online machine learning technique, which is based on reinforcement learning, aims to adapt AI to changing circumstances online, while the game is being played [31], [35], [36]. Algorithm is successfully tested on the *Neverwinter Nights* commercial game [31]. We will later return to the interesting topic of learning in computer games.

According to [30], **Decision Trees** are among the simplest decision making mechanisms used in game AI. In short terms, this hierarchical tree-like structure is organized in branch nodes and leaf nodes, where leaf nodes represent possible decisions. As it is described in [37], it implements divide-and-conquer strategy. Decision trees can be used alone, or in combination with other decision making techniques. This algorithm is reasonably fast, easy to modify, and simple to understand, as it was mentioned at the start. Besides decision making, Decision tree learning is one of the most common techniques for inductive inference [38]. One of the main advantages lies in the fact that this method is very robust considering the missing data. Number of Decision tree learning algorithms is described in [37] and [38]. Interesting example, considering computer games, is the *Black & White*. Creatures in this game use AI software architecture called *Belief-Desire-Intention*, derived from the theory of human practical reasoning [39]. It is based on several learning methods, such as widely known ID3 decision tree learning algorithm [40], as well as neural networks and reinforcement learning. Depending on weather the creature does something wrong or right, player can slap it (penalty, negative stimulus) or stroke it (positive stimulus). Creatures remember player's feedback and then according to it adapt their behavior.

Behavior Trees gained their popularity in game AI community, with *Halo 2*(see [41] for more implementation details). In the following years, BTs became dominant method in game AI with number of different implementations. Although not always the most efficient (traversal problem), this method represents a powerful tool for achieving of complex NPC's behavior and high level of control. In certain way, BTs synthesize several of exiting AI techniques and their strengths [30]. BTs are functioning in a modular manner, having tasks/behaviors instead of states that are used in state machines. Although having some similarities with the earlier mentioned HFSMs [30], approach is rather innovative. BTs solve many of the drawbacks found with state machines, such as maintenance issues. Removing or adding of the specific state entails changes in the conditions of other states related to it. Depending on number of states that are affected, this can be rather problematic as it increasingly opens possibility for errors. With BTs possibility for errors is reduced, as nodes are behaving independently and therefore are not affected by changes in other parts of the system. Easy to maintain, reusable, scalable, extensible, and customizable [42], it is not surprising that behavior trees became favorable tool for controlling of NPC's behavior.

Developers often use rather creative approaches in order to provide life-like behavior of the agents.*The Sims* is considered to be one of the games that heavily influenced the field of game AI. In this life simulation computer game, player can give orders and observe the life of number of autonomous NPCs, called *Sims*, while they interact with the environment. As it was observed in [19], Sims ''turned the concept of an AI inside out'', with its ''Smart Object'' approach. Uniqueness of this concept lies in the fact that large portion of intelligence, especially regarding the decision making, is not incorporated in the NPCs. Namely, NPCs are equipped with the needs, but all the information considering the interaction with some object are in the object itself.

B. MORE ADVANCED APPROACHES – IMPACT OF ACADEMIC RESEARCH

In complex virtual worlds, NPCs are faced with thousands of possible interactions. This makes implementing of advanced AI very difficult [31]. Therefore, it is not surprising that virtual worlds mostly rely on previously described standard approaches, which are well proven and thoroughly tested. For a long time, more advanced AI methods that were primary considered as academic, were avoided. These algorithms were often highly complicated, computationally expensive, and problematic for implementation, when compared to state machines. Earlier in the text, we sporadically mentioned learning on several occasions. Observations on wide range of possible machine learning applications to computer gaming worlds in general can be found in [43]. NPCs which can learn and adapt, represent one of the intriguing topics to academic community, since the ability to learn is one of the main characteristics of intelligent behavior. However, implementing of learning algorithms (especially in real-time) to NPCs is still not widely applied in commercial computer games, and represents a problematic endeavor for developers. The main reason lies in unpredictability. High level of autonomy and unpredictable behavior that often comes with advanced AI and machine learning is considered as undesirable in games [21], as it can spoil the playability. From all the previously said, it is clear why advanced AI algorithms were not considered as the best fit for the real-time constrained systems, such as interactive computer games. After all, goal of the game designers was to make AI only as complex as it was needed, so their reluctance toward the more complicated and often nondeterministic approaches was not surprising. Further on, programmers often did not know how to implement academic AI techniques in a practical manner [19]. However, neural networks, evolutionary algorithms, and other more advanced methods, gradually found their place in game AI. At this point, one should notice that utilization of advanced AI does not imply that standard algorithms such as state machines are unnecessary. As it was noticed in [44], advanced AI systems very often need to use some of these standard algorithms at different system levels.

One of the illustrative examples when it comes to using of academic methods in commercial games is the *F.E.A.R.*, a blockbuster FPS (first person shooter) game. Among other, the game AI system exploits the STRIPS (STanford Research Institute Problem Solver) logic, a pioneering automated planner developed almost half century ago at Stanford University [45]. Detailed explanations of *F.E.A.R.'s* AI concept can be found in [46]. It is also important to mention SOAR cognitive architecture [47], which was used for extensive academic research on AI-based virtual characters. The *Soar Quakebot*, NPC tested in *Quake II* game, aimed to provide more reactive and flexible behavior [48]–[50]. Decision making of SOAR based intelligent agents, was rooted in a perceive-think-act cycle [48]. Further, prediction and anticipation capabilities were developed [49], [51], since anticipation is recognized as one of the key features of intelligent behavior. It is reported that *Soar Quakebot* successfully challenged even human opponents with intermediate level playing capacities [48].

It could be noted that **Bayesian theory** represents a cornerstone of today's machine learning. Therefore it is not surprising that its application to game AI attracted attention of academics. One of the early papers in the field [52] investigated Bayesian programming for learning of NPC behaviors in the *Unreal Tournament*. Developers took care of computational costs, which is very important issue for potential commercial applications. Several studies were carried out considering the *StarCraft*. This real-time strategy computer game, published by *Blizzard Entertainment*, gained massive popularity all around the world. Bayesian model is developed in [53], in order to predict the opening strategies in the game. Further on, same authors introduced a Bayesian probabilistic model for enabling NPCs to make tactical decision making and predict opponent's attacks [54]. Thorough analysis of game AI experimentation for NPCs in *StarCraft* is presented in [55].

Reinforcement Learning represents one of the major machine learning areas of research. As it was described in [56], RL aims to enable agent to learn by interacting with the world, without strong supervision and without the exact model of the world. Using of RL in game AI, is reported to be rather limited [30], [57], although this unique theory offers advantages which are highly important for the field (e.g., coping with unpredictable scenarios). There are, however, several interesting studies on the subject. Paper [58] describes using of RL concept in order to develop team of NPCs for playing the *Unreal Tournament* in domination scenario. Authors used modified Q-learning in order to enable NPCs to optimize decision making strategies. When it comes to FPS games, extensive research was also done in [57], concluding that RL can be successfully implemented in game AI. This paper also compared hierarchical, rule-based, and flat RL control. Work of Merrick and Maher [59]–[61] thoroughly analyzed Motivated RL for NPCs. Research was driven with desire to develop more adaptive characters for virtual worlds. Experimentation with MRL implemented in *Second Life* virtual world provided valuable results on the subject [59], [60]. Bearing in mind, that users of such virtual worlds can change the environment by adding or removing objects, NPCs which can learn and adapt represent a research topic of high interest. Some of the potential applications of RL to game AI in general, along with possible drawbacks are thoroughly analyzed in [30].

Neural Networks are more than successfully implemented in board games, such as *Backgammon*, and even highly complex *Go* [62]–[64]. When it comes to interactive computer games, using of neural networks in game AI was often considered as complicated and computationally expensive, and therefore for a long while it was not so common. However numerous successful examples of proper NN implementations during the years showed all the benefits coming from this method. One of the first and most significant examples of neural networks in games was seen in the late nineties. *Creatures*, a computer game recognized as one of the breakthroughs in artificial life science, used neural networks for sensory-motor coordination and behavior selection of synthetic agents [65], [66]. Strongly influenced by animal biology – biochemistry and genetic algorithm principles were also used for simulations [65], [66]. Neural networks are also implemented in several commercial racing games, such as *Forza Series* or *Colin McRae Rally*. *Forza Series* racing game published by *Microsoft Studios* developed AI system based on neural networks, called *Drivatar*. By analysis of collected data and Bayesian learning, *Drivatars* are trying to emulate real user's driving technique. The more some user plays the game, more data about his gaming behavior is available, thus enabling the *Drivatar* to have a larger degree of similarity with the user. The aim is to imitate specific features of individual's driving style (how you brake, or use gas, etc.), in that way creating AI agents that differ one from another. The *NERO (Neuroevolving Robotic Operatives)* game, developed at University of Texas, represents an interesting example of noncommercial machine learning based game. Human player has a role of an instructor to a team of agents (simulated robots). The goal is to prepare them for a combat, while agents start the training with no skills, just the ability to learn. In order to enable agents to learn, *NERO* use rtNEAT (real-time Neuroevolution of Augmenting Topologies) algorithm for evolving increasingly complex neural networks in real time [67]. Unlike the scripting where after a while weaknesses can be detected and exploited, this approach is aiming for NPCs to adapt and improve their behavior by learning. Neuroevolution, a combination of genetic algorithms and neural networks, is successfully implemented in real-time interactive environment [68]. Authors of the *NERO* even suggest that this concept could be used in the future for training people in sophisticated tasks [67]. Paper [69] provided detailed survey of neuroevolution applications in games, along with the detailed analysis of benefits and drawbacks coming with this approach.

Previously mentioned **Genetic Algorithms** rarely represent a method of choice in commercial games, as it is considered that this approach is often too slow, and requires too many CPU resources [18], [21]. However, since the appearance of the *Cloak*, *Dagger*, *and DNA* game (created by Don O' Brien), which implemented GAs in order to develop evolving NPCs, academics investigated possible applications of GAs in game AI. Besides already described neuroevolution, several studies were conducted based on applying GAs to popular games such as *Counter Strike* or *Quake III Arena* [70], [71]. It is believed by Lucas and Kendall [72] that properly used evolutionary algorithms could improve overall playability of the game, implying in that way that potential commercial applicability could eventually increase.

IV. HUMAN-LEVEL INTELLIGENCE & VIRTUAL WORLDS – PLACING NPCs IN A WIDER THEORETICAL FRAMEWORK

As it was sharply noticed in [73], ''Humans are humanity's favorite subject.'' This deep desire to understand the essence of our existence and behavior, led us to tremendous achievements in different aspects of science and art. Number of scientific fields revolved around the necessity to understand and generate human level capacities. Illustrative example is Robotics, where idea of making a fully functional humanoid robot has its roots grounded back in the history (e.g., see [74], [75]), long before the field itself was even established. When it comes to the closely related field of Artificial Intelligence, incredible results were accomplished in different domains during the last few decades. So called ''weak AI'' provided numerous specialized algorithms and solutions that are applied in order to enhance different aspects of technology and human life in general [76], [77]. However, developing of human-level AI (or ''strong AI'', as it is often referred) is still a dream, like it was on the very beginnings. Some of the AI pioneers, such as Marvin Minsky and Herbert Simon, were very optimistic in the early days of the field, predicting that human level AI will be achieved until the end of the 20th century, which will eventually enable machines to do everything that humans can [78], [79]. These predictions were not fulfilled, in that way opening numerous discussions that question why we still can not engineer human level machine intelligence, is human level intelligence necessary, and at the end is it even achievable. This is rather understandable considering the fact that not just that we did not achieved the human-level AI, but we are struggling to reach the capacities of organisms that we consider far simpler. An illustrative example given in [80] still applies today – despite the tremendous technological advancements we still do not have an autonomous mobile system that has an effectiveness and sophistication of a ''simple'' cockroach.

Computer games represent one of the most illustrative success stories of Artificial Intelligence systems which are comparable with humans [81]. If we take a look at computer systems that can play board or card games, remarkable results are accomplished in the last few decades, considering not just perfect-information but imperfect-information games (e.g., *Poker* [82]) as well. *Chess* was subject of research for decades, since the Shannon's seminal paper [83]. When IBM's *Deep Blue* system [84], [85] defeated Garry Kasparov in the epic chess battle rematch, public hype considering the AI was at the pick. Number of other examples can be listed too, such as *Checkers* [86], [87], or earlier mentioned *Backgammon* [62], [63] and *Go* [64], where computer systems reached the level of top-human performance. Further, *AlphaZero* algorithm was reported to have remarkable results playing *Chess*, *Shogi*, and *Go* [88]. Although superiority of some of these systems was not based solely on AI techniques [72], research in these games influenced the entire field of AI, strongly pushing new ideas and approaches. However, if we take *Checkers* as an example, despite the complexity of the game which is, among other things, reflected in a fact that this game has nearly 500 billion of possible positions [87], this is still a finite number of combinations. Besides that, classic board games are mostly perfect information, meaning that all participants of the game have insight in everything that has happened before they make a decision [72], [82]. Unlike these finite, deterministic, constrained gaming spaces, humans (as well as other living beings) live and make decisions in a world of uncertainness, with limited information available, where infinite number of interactions occurs every day. Therefore, in order to get closer to human-level intelligence we need more than a gaming board or a deck of cards. No matter how complicated and challenging these previously mentioned problems are, they represent only one fragment of human intelligence. In their seminal work [77], Laird and Van Lent recognized interactive 3D computer gaming worlds as a perfect testbed for research of the human-level AI. This view, latter supported by Schaeffer *et al.* [81], [89], opens up an interesting perspectives in different areas of AI research.

Namely, it is obvious from the previous sections of the paper that virtual worlds indeed provide us with a possibility to effectively research numerous problems related to intelligent agents, and consequently different segments of human-level AI problems. At the same time nature of mechanisms on which the virtual worlds are built, could impose a severe limitations for full utilization of their potential on this subject. Further in the text several aspects of Laird's suggestion will be analyzed, together with possible implications. In order to better understand the potential of virtual worlds on previous matters, the question of human-level AI from the perspective of selected theories must be briefly addressed first.

A. EVOLUTION, EMBODIMENT THEORY, AND SITUATEDNESS – FOLLOWING THE BIO-INSPIRED IDEAS

Classical AI, also called GOFAI (Good Old-Fashioned Artificial Intelligence) [90], showed a lot of shortcomings in pursuing of human-level AI. One of the main reasons lies in the fact that classical AI theories and expert systems are deeply grounded in information and symbol processing [91]. This approach proved itself as a powerful and very efficient, considering numerous problems and applications. However, it is often disputed when it comes to achieving of strong AI [91], [92], as the nature of human intelligence lies on different cornerstones.

Conclusion that there is a possibility, that we misinterpreted the very foundations of intelligence, was recognized by many scientists (e.g. [80]). To have a deeper understanding about this, we must seek into the some of the essential parts of the human evolution. How did humans become intelligent? Many possible theories and therefore many speculations are generated by the scientists in the relevant fields. Evolution theorists tried to recreate our past, and to discover key events and processes that influenced development of human intellectual capabilities, in that way deferring us from other known primates.

One could certainly notice that changes of physical characteristics caused the changes in intellectual capabilities, and vice versa. Early theories recognized bipedalism as a possible first change in evolution of humans [93], [94], dating a bipedal walking in the earliest known hominids [95], [96]. As a consequence of the adopted bipedalism, human body structure departs from apes in many ways [94], [97]. Bearing in mind the fact that bipedal walking is one of the key characteristics which are separating humans from other primates [98], [99], and that bipedalism is so unusual for mammalians in general [98], it is natural to question a reason for this kind of behavior. Number of different, and often opposite theories was made – e.g., some studies reported that bipedalism appeared as an energetically efficient solution comparing to quadrupedal locomotion [93], while others denied it [97], [100]. However, final answer to this complex problem is still remaining unsolved. What is certain is the fact that bipedalism preceded the brain expansion [94]. Therefore, one could conclude that bipedalism heavily influenced human behavior, and therefore affected the shaping of our intelligence. Upright walking changed the human perspective of the environment, and changed the way humans interact with it [94]. Free forelimbs enabled many useful activities such as manufacturing and using of tools, and manipulating the environment in general, in that way decisively influencing the human evolution.

Considering just a brief look at some of the evolution cornerstones mentioned in the previous text, it is obvious that human intelligence is inseparable from human body, and vice versa. As it was noticed in [80], ‘‘biological mind is, first and foremost, an organ for controlling the biological body.’’

This kind of approach is reflected in the *Embodiment Theory*, which appeared as a response to the classical AI. Number of scientists consider embodiment as a necessary condition for developing of any sort of true intelligent behavior [91], [101], analyzing this problem not just from the human perspective but with illustrative examples coming from different orders of animals as well. Regarding to that, Pfefier and Scheier described embodiment [92] as: “A term used to refer to the fact that intelligence cannot merely exist in the form of an abstract algorithm but requires a physical instantiation, a body.’’ Of course, this definition should not be understood in a simplified sense, bearing in mind the deeper meaning regarding the connections among neural and physical processes [91], [102].

The necessity to find an alternative to classical AI approaches was underlined in the pioneering research of Rodney Brooks (collection of the most important papers is given in [103]). His work in the field of autonomous robotics insisted on physical grounding hypothesis, instead of traditional symbol system hypothesis. Brooks thoroughly analyzed main characteristics of both approaches in his seminal work [104]. Unlike the traditional paradigm where AI system is based on a ‘‘system of symbols’’ and its manipulation, physical grounding hypothesis is based on the premise that representations of an intelligent system must be deeply grounded in its physical surrounding. In [104], Brooks elaborated why are physically grounded mobile robots superior to symbol based robots, supporting his ideas with number of developed prototypes. Among other, situatedness and embodiment [105] are enhancing robot’s adaptability to the changing environment, an attribute so characteristic for humans. It is further noticed that besides its morphology, behavior of some entity is also influenced by the environment in which it acts [106]. As it was elaborated in [107], ‘‘Intelligence is determined by the dynamics of interaction with the world.’’

B. POTENTIAL IMPLICATIONS TO VIRTUAL WORLDS AND NPCs

If we observe previously described paradigms (section IV.A) in the context of current computer games technology, we can easily notice the research potential behind these ideas, but also all the shortcomings which are constraining their full implementation into the interactive virtual worlds. Namely, NPCs appear in the form of human-like avatars or some creatures, and behave according to their capabilities within the virtual environment, at the same time affecting the environment in some way. However their embodiment and situatedness are simplified. As it was noticed in [108], NPCs are ‘‘virtually embodied’’, or more precisely graphically embodied. They are not built and therefore are not acting in the manner living beings are. Further, the virtual worlds themselves are focused on a visual resemblance, and they lack some of the crucial real-world characteristics. This is a very important issue, since evolution of human intelligence is strongly connected with recognizing and interacting with the dynamic 3-D world, its structures, and other living beings [109]. If we want to follow the earlier mentioned principles of embodiment and situatedness in a more real-world manner, then some adjustments of the virtual world mechanisms should be ensured. NPCs should probably be provided with a *virtual dynamical embodiment* and more strictly set *virtual situatedness*, all within interactive virtual environments modified to support such characteristics. This should not be understood in a simplified manner – as a mere introduction of some dynamical properties. More importantly, NPCs should be enabled (as much as it is possible) to sense the world around them and interact with other entities and the dynamical interactive surrounding in a way that resembles how living beings act in the real world. After all, situatedness is recognized as one of the key requirements in order to define something as an agent, meaning that it has to be capable to receive inputs from sensors, and accordingly in some way affect its environment [110]. Regarding this, so called "sensory honesty" [108], [111] represents one of the highly significant issues, since it is very rarely implemented in virtual worlds – NPCs are mostly built to be omniscient, without any real understanding of the world that is surrounding them.

Bearing in mind the briefly elaborated principles of subsumption architecture and embodiment theory, one should be careful – applying of these principles adjusted to virtual worlds should not lead toward just purely reactive AI agents, but rather enabling them to integrate and exploit different AI techniques and AI functionalities to a larger degree. It should also be noticed, that considering complexity of humans and following the ideas elaborated in [112], previously mentioned principles should be gradually applied by experimenting with artificial agents inspired with simpler organisms at first.

When it comes to already mentioned dynamical properties, thorough research studies on dynamically simulated graphical models were done in the past [113]–[115]. Dynamically simulated characters were presented in [116], as an alternative to motion caption and key-framing motion generation methods. In this research, two virtual environments were developed and populated with NPCs, simulating bicycle racing and a heard of ships. Animations of some chosen human movements based on dynamics, are also thoroughly researched in [117]–[119]. One should notice that majority of the studies dealing with dynamical models in virtual environments, primarily aimed to provide more realistic graphical sensation. An illustrative example of experimenting with physics based NPCs in a virtual world, under a different agenda, can be found in [120]. In this seminal work, virtual marine was filled with virtual 3D fish models, providing in that way some original insights in the field of artificial life. Simulated models were built according to simplified biomechanical and hydro-dynamical principles, together with emulated sensors and real fish behavior patterns.

Previously described academic studies provided important insights on dynamically modeled animations. When it comes to the commercial virtual worlds, most of them use some sort of physics engines rooted in the classical mechanics theory, whether they are based on rigid body physics or mass aggregate approach [121]. Illustrative examples are *Havok* engine (used by *Second life*, *Halo*, *Half-Life*, etc.), or *PhysX* engine (used by *Active Worlds*, *Mafia II*, etc.). Despite the fact that physics engines offer whole spectra of possibilities, virtual worlds tend to be rather statics [122] considering objects inside them, as well as the nature of interactions between players and NPCs with the environment. As it was noticed in [106], it is still problematic to precisely model and simulate real-world properties. Besides obvious complexity, bringing of some real-world properties through physics based models and advanced sensorial systems is also very computationally expensive. Introducing of physically complex objects is severely increasing number of interactions [24]. Further, with the increased number of simulated objects and interactions, CPU resources are dramatically running out [13]. Therefore, it is not surprising that the nature of the virtual worlds and interactions in them is still constrained, not modeled accurately enough, and not in the scale that is needed to fully apply principles behind the physical grounding hypothesis.

At this point, one should be careful in order to avoid possible misunderstanding of some of the previously exposed analyses. Namely, the goal is not to replicate the world in all of its diversity and complexity (not to mention that this is impossible to do), but rather to identify and emulate some of its essential characteristics, as well as they can be emulated. Human-level intelligence could be too dependable on various internal and external factors to be replicated in that way [123]. However, following the analogy from humanoid robotics example presented in [124] – exposing of NPCs to some of the essential real-world conditions and equipping them with some of the essential mechanisms and interaction patterns characteristic for living beings, could trigger evolutionary leap in their autonomy and intelligence. In other words, it could be one of the necessary "baby" steps toward developing of human-like intelligence and cognition mechanisms, or it could at least enable us to better understand foundations of human intelligence.

Besides previously described aspects, social behavior and therefore social interaction with other living beings is also recognized as the key element of the origin of human intelligence [125]. As it was observed in [94], humans are the only living beings that are using symbolic language, which among other enabled us to transfer our knowledge through generations. There will be no thorough analysis on these matters further in the text, as this topic deserves a survey of its own in order to be properly analyzed. However, in author's view, a brief discussion considering some aspects of the topic must be provided in the following lines. Namely, it is not surprising that agents, which can communicate in a human-like manner, represented subject of extensive research over the last few decades. Consequently, virtual worlds served as a perfect testbed for development of these chatterbots, as they are often called (e.g., "roboatars" tested in the *Second Life* [126], etc.). One of the benefits is reflected in the fact that virtual worlds provide NPCs with large number of human users to interact with. Another benefit comes from the fact that various challenging scenarios can be designed and tested in these virtual worlds. Annual Loebner Prize competition is organized, aiming for computer controlled characters to pass the Turing test through textual communication. Since it was introduced [29], Turing test caused a lot of different interpretations [127], [128], and a lot of opposite opinions considering its validity and efficiency (e.g., "Chinese room" discussion [129]). Argumentation about its relevance is not in the focus of this paper. However, what should be noted is that absence of the embodiment is recognized as one of the reasons which are disabling NPCs to pass the Turing test [130]. Bearing in mind that we use symbolic language to describe the world around us, the way we sense it and its phenomenon, a following logical question is imposing itself. Is it reasonable to expect that any disembodied computer system, which can not interact and sense the world in a human-like manner, could be capable to perform fully human-level intelligent conversation without any tricks?

At the end of this section, one should notice that there is no ultimate solution that guarantees progress toward achieving of human-level AI agents. In order to get close to the human-level intelligence, or at least achieve some segments of it, different theories, hybrid solutions, and techniques must be integrated in order to fully exploit their strengths and at the same time minimize their weaknesses. Besides that, virtual worlds themselves as well as NPCs acting in them should be carefully designed in order for these methods to be effective.

V. CONCLUDING REMARKS

This paper aimed to provide a unique perspective on the subject of AI agents in virtual worlds. The primary purpose was not to bridge the gap between AI academics and commercial based gaming industry, but rather to gather an important insights coming from both sides, critically evaluate them, interconnect them and point out the multidisciplinary richness and the research potential of the elaborated problems. Therefore, author is hoping that this research study will serve as a valuable source of information for a wide range of experts. Special emphasis of the paper was on human-level AI research in the context of intelligent agents in virtual worlds.

When it comes to AI agent problems that can be investigated in virtual worlds, number of possible applications is constrained only by imagination of research community [131], and current technical limitations. Therefore, it is important to mention, that implementation of techniques and theories presented in this paper is often constrained with CPU resources. This is especially regarding to some of the real-time related problems, that agents often meet [132]. Such technical issues were recognized, but not analyzed in details, as they are not in the main focus of the paper. After all, following the Moore's law, these constraints are significantly diminishing during the years, and therefore are not compromising the theoretical value of underlining research ideas.

In the earlier mentioned paper [77], Laird suggested that at one point in the future, computer games will have to evolve, inevitable concentrating on advanced AI agents with the need to even match human-level intelligence in order to provide next level of realistic experience for users. If one carefully observes previous sections of the paper, as well as the required properties of artificial systems defined in [133], in ideal scenario those agents should be among other enabled with several essential capabilities: appropriate reasoning about its environment and their role in it, learning and intelligently interacting with the dynamic environment including a successfully coping with uncertainties, and predicting the events and behavior of other dynamic entities in a dynamic environment. Practical justification of Laird's suggestion is reflected in several beneficial aspects to the further development of virtual worlds. As it is noticed in [134], human users are more engaged when competing with other humans, than with computer controlled opponents that often behave too predictable. Therefore, a need for intelligent agents that can provide more immersive and life-like virtual world experience seems rather obvious. Computer controlled AI opponents that can behave in a human-like manner are reported to be more challenging and enjoyable [135]. Another aspect is related to the fact that virtual worlds are becoming more dynamic and complex, with increased population of human users and NPCs as well. Therefore, there is a need for autonomous agents that can cope with unpredicted scenarios [134].

Laird's predictions are gradually progressing, as human-level characters are drawing an increased attention. Earlier mentioned real-time strategy game *StarCraft*, represents an illustrative example. Accordingly, *StarCraft* AI competitions are organized aiming to create agents with the ability to successfully play the game and compete with humans and other scripted NPCs [136], [137]. As Samuel sharply noticed [138], "Programming computer to play games is a stage in the understanding of the methods that must be employed for the machine simulation of intellectual behavior." Bearing in mind the massive popularity of this game, it is not surprising that it is recognized as a suitable testbed environment. The potential of *StarCraft* as a platform for research of human-like NPCs (see [139]) is recognized since the early days of the game. Although there is a long way until virtual characters reach top human performance in this complex virtual world, *StarCraft* represent a research topic of high interest. Supporting this, it should be noted that *DeepMind* and *Blizzard* research teams are actively working on the reinforcement learning environment developed on the basis of the *StartCraft II* [140]. With further advancements in deep learning [141], including human-level control [142], agents are getting close to some segments of human capabilities. It should also be mentioned that cognitive and behavioral modeling [133], [143]–[145], attracted a lot of attention in the last few years. Although this interesting, highly multidisciplinary topic was not a subject of analysis in this paper, one should recognize cognitive models as a potentially powerful method that can be used in a development (especially on a higher level) of future human-like agents. Cognitive models derived from available player's gaming data can enable exploration of various key properties listed in [144], such as ''adaptation to environmental constraints'' in that way increasing agent's autonomy.

Number of researchers noticed that very few of academics directly attacked the question of general intelligence (see [77], [146]). Regarding this, some authors rightfully claim that human-level AI is researched in the computer games domain with more effort than in any other, especially with general game playing [147]. Research in the human-level intelligent characters, can benefit the entire AI field. Therefore, this paper was dealing with crucial aspect of Laird's seminal work [77] – the fact that interactive virtual worlds could represent a powerful testbed for pursuing of human-level machine intelligence. These worlds are already characterized with a number of real-world elements and problems. More importantly, they are becoming more complex and dynamical, with real-time decision making and other human characteristics increasingly required. Further, computer characters in these worlds are exposed to numerous interactions with human users, between themselves, and with their surroundings. In author's opinion, this makes virtual worlds a rather unique testbed for different segments of AI research and their potential integration – e.g., state-of-the-art humanoid robots can not be safely exposed to such interactions, and in such scale within the real world (especially regarding the interaction with humans and other living beings).

There are different, often extremely opposite opinions regarding the possibility of achieving human-level artificial intelligence. After all, research in the human-level AI represents a tremendous endeavor. This is reflected in a fact that it is not problematic only to achieve all of the human main capabilities, but also to properly integrate them [148]. Many researchers are certain that human-level AI will eventually be achieved, but it requires for new approaches to be implemented and integrated together with the existing ones [149], [150]. Even if it should be proven in the future, that this tremendous endeavor is not possible, one could be certain that research in human-level AI is not only helping us to better understand principles of human intelligence, but is also producing numerous ''side-effects'' across almost all scientific fields. Regarding this, the aim of this paper was not to claim achievability of human-level AI, but rather to explore frontiers and to underlain benefits and shortcomings of current state-of-the-art virtual worlds and intelligent agents inhabiting them, in the context of human-level AI research.

At the end, author is fully aware that there is no analysis that could be attributed as thorough enough. Regarding this, there are several topics and theories that are not included and elaborated in this work. It should be clear that there was no intention to disregard or reduce importance of theories that are not analyzed in this research. Paper and its theoretical content are exposed and organized in the manner that in author's opinion best covers the underlining ideas behind this research study.

REFERENCES

[1] G. C. Burdea and P. Coiffet, *Virtual Reality Technology*. New York, NY, USA: Wiley, 1994.

[2] G. C. Burdea and P. Coiffet, *Force and Touch Feedback for Virtual Reality*. New York, NY, USA: Wiley, 1996.

[3] G. C. Burdea, ''Invited review: The synergy between virtual reality and robotics,'' *IEEE Trans. Robot. Autom.*, vol. 15, no. 3, pp. 400–410, Jun. 1999.

[4] J. E. Lloyd, J. S. Beis, D. K. Pai, and D. G. Lowe, ''Programming contact tasks using a reality-based virtual environment integrated with vision,'' *IEEE Trans. Robot. Autom.*, vol. 15, no. 3, pp. 423–434, Jun. 1999.

[5] R. J. Adams and B. Hannaford, ''Stable haptic interaction with virtual environments,'' *IEEE Trans. Robot. Autom.*, vol. 15, no. 3, pp. 465–474, Jun. 1999.

[6] S. R. Ellis, ''What are virtual environments?'' *IEEE Comput. Graph. Appl.*, vol. 14, no. 1, pp. 17–22, Jan. 1994.

[7] W. S. Bainbridge, ''The scientific research potential of virtual worlds,'' *Science*, vol. 317, no. 5837, pp. 472–476, 2007.

[8] N. Yee, ''The demographics, motivations, and derived experiences of users of massively multi-user online graphical environments,'' *Presence, Teleoperators Virtual Environ.*, vol. 15, no. 3, pp. 309–329, 2006.

[9] C. W. Thompson, ''Next-generation virtual worlds: Architecture, status, and directions,'' *IEEE Internet Comput.*, vol. 15, no. 1, pp. 60–65, Jan./Feb. 2011.

[10] G. N. Yannakakis, ''Game AI revisited,'' in *Proc. 9th Conf. Comput. Frontiers (CF)*, Cagliari, Italy, May 2012, pp. 285–292.

[11] IBM, ''Virtual worlds, real leaders: Online games put the future of business leadership on display,'' A Global Innovation Outlook 2.0 Report, 2007.

[12] P. R. Messinger *et al.*, ''Virtual worlds—Past, present, and future: New directions in social computing,'' *Decis. Support Syst.*, vol. 47, no. 3, pp. 204–228, 2009.

[13] S. Kumar *et al.*, ''Second life and the new generation of virtual worlds,'' *Computer*, vol. 41, no. 9, pp. 46–53, Sep. 2008.

[14] K. D. Forbus and J. Laird, ''AI and the entertainment industry,'' *IEEE Intell. Syst.*, vol. 17, no. 4, pp. 15–16, Jul. 2002.

[15] J. E. Laird, ''Using a computer game to develop advanced AI,'' *Computer*, vol. 34, no. 7, pp. 70–75, Jul. 2001.

[16] C. Dede, ''Immersive interfaces for engagement and learning,'' *Science*, vol. 323, no. 5910, pp. 66–69, 2009.

[17] E. F. Anderson, ''Playing smart—Artificial intelligence in computer games,'' in *Proc. zfxCON Conf. Game Develop.*, Hankensbüttel, Germany, Oct. 2003.

[18] D. Johnson and J. Wiles, ''Computer games with intelligence,'' in *Proc. 10th IEEE Int. Conf. Fuzzy Syst.*, Melbourne, VIC, Australia, vol. 3, Dec. 2001, pp. 1355–1358.

[19] S. Cass, ''Mind games,'' *IEEE Spectr.*, vol. 39, no. 12, pp. 40–44, Dec. 2002.

[20] M. Zyda, ''From visual simulation to virtual reality to games,'' *Computer*, vol. 38, no. 9, pp. 25–32, Sep. 2005.

[21] A. Nareyek, ''AI in computer games,'' *Queue ACM*, vol. 1, no. 10, pp. 59–65, 2004.

[22] S. Laukkanen, I. Karanta, V. Kotovirta, J. Markkanen, and J. Rönkkö, ''Adding intelligence to virtual reality,'' in *Proc. 16th Eur. Conf. Artif. Intell. (ECAI)*, Valencia, Spain, Aug. 2004, pp. 1136–1141.

[23] M. Y. Lim, J. Dias, R. Aylett, and A. Paiva, ''Creating adaptive affective autonomous NPCs,'' *Auton. Agents Multi-Agent Syst.*, vol. 24, no. 2, pp. 287–311, 2012.

[24] M. Luck and R. Aylett, ''Applying artificial intelligence to virtual reality: Intelligent virtual environments,'' *Appl. Artif. Intell.*, vol. 14, no. 1, pp. 3–32, 2000.

[25] M. van Lent, W. Fisher, and M. Mancuso, ''An explainable artificial intelligence system for small-unit tactical behavior,'' in *Proc. 19th Nat. Conf. Artif. Intell. (AAAI), 16th Conf. Innov. Appl. Artif. Intell. (IAAI)*, San Jose, CA, USA, Jul. 2004, pp. 900–907.

[26] J. Bates, ''Virtual reality, art, and entertainment,'' *Presence, Teleoperators Virtual Environ.*, vol. 1, no. 1, pp. 133–138, 1992.

[27] J. Weizenbaum, ''ELIZA—A computer program for the study of natural language communication between man and machine,'' *Commun. ACM*, vol. 9, no. 1, pp. 36–45, 1966.

[28] L. Lidén, ''Artificial stupidity: The art of intentional mistakes,'' in *AI Programming Wisdom 2*, S. Rabin, Ed. Hingham, MA, USA: Charles River Media Inc., 2004, pp. 41–48.

[29] A. M. Turing, "Computing machinery and intelligence," *Mind*, vol. 59, no. 236, pp. 433–460, Oct. 1950.
[30] I. Millington and J. Funge, *Artificial Intelligence for Games*, 2nd ed. San Mateo, CA, USA: Morgan Kaufmann, 2009.
[31] P. Spronck, M. Ponsen, I. Sprinkhuizen-Kuyper, and E. Postma, "Adaptive game AI with dynamic scripting," *Mach. Learn.*, vol. 63, no. 3, pp. 217–248, 2006.
[32] M. Cavazza, "Al in computer games: Survey and perspectives," *Virtual Reality*, vol. 5, no. 4, pp. 223–235, 2000.
[33] D. Fu and R. Houlette, "Putting AI in entertainment: An AI authoring tool for simulation and games," *IEEE Intell. Syst.*, vol. 17, no. 4, pp. 81–84, Jul. 2002.
[34] D. Harel, "StateCharts: A visual formalism for complex systems," *Sci. Comput. Program.*, vol. 8, no. 3, pp. 231–274, 1987.
[35] P. Spronck, I. Sprinkhuizen-Kuyper, and E. Postma, "Difficulty scaling of game AI," in *Proc. 5th Int. Conf. Intell. Games Simulation (GAME-ON)*, 2004, pp. 33–37.
[36] M. Ponsen, H. Munoz-Avila, P. Spronck, and D. W. Aha, "Automatically generating game tactics through evolutionary learning," *AI Mag.*, vol. 27, no. 3, pp. 75–84, 2006.
[37] E. Alpaydin, *Introduction to Machine Learning*, 2nd ed. Cambridge, MA, USA: MIT Press, 2010.
[38] T. M. Mitchell, *Machine Learning*. New York, NY, USA: McGraw-Hill, 1997.
[39] M. E. Bratman, *Intention, Plans, and Practical Reason*. Cambridge, MA, USA: Harvard Univ. Press, 1987.
[40] J. R. Quinlan, "Induction of decision trees," *Mach. Learn.*, vol. 1, no. 1, pp. 81–106, 1986.
[41] D. Isla, "Handling complexity in the halo 2 AI," in *Proc. Game Developers Conf.*, vol. 12, 2005.
[42] R. Marcotte and H. J. Hamilton, "Behavior trees for modelling artificial intelligence in games: A tutorial," *Comput. Games J.*, vol. 6, no. 3, pp. 171–184, 2017.
[43] L. Galway, D. Charles, and M. Black, "Machine learning in digital games: A survey," *Artif. Intell. Rev.*, vol. 29, no. 2, pp. 123–161, 2008.
[44] A. Nareyek, "Game AI is dead. Long live game AI!" *IEEE Intell. Syst.*, vol. 22, no. 1, pp. 9–11, Jan. 2007.
[45] R. E. Fikes and N. J. Nilsson, "STRIPS: A new approach to the application of theorem proving to problem solving," *Artif. Intell.*, vol. 2, nos. 3–4, pp. 189–208, 1971.
[46] J. Orkin, "Three states and a plan: The AI of FEAR," in *Proc. Game Developers Conf.*, 2006.
[47] J.-E. Laird, A. Newell, and P.-S. Rosenbloom, "SOAR: An architecture for general intelligence," *Artif. Intell.*, vol. 33, no. 1, pp. 1–64, 1987.
[48] M. van Lent and J. E. Laird, "Developing an artificial intelligence engine," in *Proc. Game Developers Conf.*, San Jose, CA, USA, Mar. 1999, pp. 577–588.
[49] J. E. Laird, "It knows what you're going to do: Adding anticipation to a Quakebot," in *Proc. 5th Int. Conf. Auton. Agents (AGENTS)*, Montreal, QC, Canada, May/Jun. 2001, pp. 385–392.
[50] J. E. Laird and J. C. Duchi, "Creating human-like synthetic characters with multiple skill levels: A case study using the soar Quakebot," in *Proc. AAAI Spring Symp. AI Interact. Entertainment*, Palo Alto, CA, USA, 2001, pp. 54–58.
[51] J. E. Laird, "Research in human-level AI using computer games," *Commun. ACM*, vol. 45, no. 1, pp. 32–35, 2002.
[52] R. Le Hy, A. Arrigoni, P. Bessière, and O. Lebeltel, "Teaching Bayesian behaviours to video game characters," *Robot. Auton. Syst.*, vol. 47, nos. 2–3, pp. 177–185, 2004.
[53] G. Synnaeve and P. Bessière, "A Bayesian model for opening prediction in RTS games with application to StarCraft," in *Proc. IEEE Conf. Comput. Intell. Games (CIG)*, Seoul, South Korea, Aug./Sep. 2011, pp. 281–288.
[54] G. Synnaeve and P. Bessière, "Special tactics: A Bayesian approach to tactical decision-making," in *Proc. IEEE Conf. Comput. Intell. Games (CIG)*, Sep. 2012, pp. 409–416.
[55] S. Ontanon, G. Synnaeve, A. Uriarte, F. Richoux, D. Churchill, and M. Preuss, "A survey of real-time strategy game AI research and competition in StarCraft," *IEEE Trans. Comput. Intell. AI in Games*, vol. 5, no. 4, pp. 293–311, Dec. 2013.
[56] R. S. Sutton and A. G. Barto, *Reinforcement Learning: An Introduction*. Cambridge, MA, USA: MIT Press, 1998.
[57] M. McPartland and M. Gallagher, "Reinforcement learning in first person shooter games," *IEEE Trans. Comput. Intell. AI in Games*, vol. 3, no. 1, pp. 43–56, Mar. 2011.
[58] H. Wang, Y. Gao, and X. Chen, "RL-DOT: A reinforcement learning NPC team for playing domination games," *IEEE Trans. Comput. Intell. AI Games*, vol. 2, no. 1, pp. 17–26, Mar. 2010.
[59] K. Merrick and M. L. Maher, "Motivated reinforcement learning for non-player characters in persistent computer game worlds," in *Proc. ACM SIGCHI Int. Conf. Adv. Comput. Entertainment Technol. (ACE)*, Hollywood, CA, USA, Jun. 2006, Art. no. 3.
[60] K. Merrick and M. L. Maher, "Motivated reinforcement learning for adaptive characters in open-ended simulation games," in *Proc. Int. Conf. Adv. Comput. Entertainment Technol. (ACE)*, Salzburg, Austria, Jun. 2007, pp. 127–134.
[61] K. E. Merrick and M. L. Maher, *Motivated Reinforcement Learning: Curious Characters for Multiuser Games*. Berlin, Germany: Springer-Verlag, 2009.
[62] G. Tesauro, "Temporal difference learning and TD-gammon," *Commun. ACM*, vol. 38, no. 3, pp. 58–68, 1995.
[63] G. Tesauro, "Programming backgammon using self-teaching neural nets," *Artif. Intell.*, vol. 134, nos. 1–2, pp. 181–199, 2002.
[64] D. Silver *et al.*, "Mastering the game of Go with deep neural networks and tree search," *Nature*, vol. 529, no. 7587, pp. 484–489, 2016.
[65] S. Grand, D. Cliff, and A. Malhotra, "Creatures: Artificial life autonomous software agents for home entertainment," in *Proc. 1st Int. Conf. Auton. Agents (AGENTS)*, Marina del Ray, CA, USA, 1997, pp. 22–29.
[66] S. Grand and D. Cliff, "Creatures: Entertainment software agents with artificial life," *Auton. Agents Multi-Agent Syst.*, vol. 1, no. 1, pp. 39–57, 1998.
[67] K. O. Stanley, B. D. Bryant, and R. Miikkulainen, "Real-time neuroevolution in the NERO video game," *IEEE Trans. Evol. Comput.*, vol. 9, no. 6, pp. 653–668, Dec. 2005.
[68] A. K. Agogino, K. O. Stanley, and R. Miikkulainen, "Online interactive neuro-evolution," *Neural Process. Lett.*, vol. 11, no. 1, pp. 29–37, 2000.
[69] S. Risi and J. Togelius, "Neuroevolution in games: State of the art and open challenges," *IEEE Trans. Comput. Intell. AI in Games*, vol. 9, no. 1, pp. 25–41, Mar. 2017.
[70] N. Cole, S. J. Louis, and C. Miles, "Using a genetic algorithm to tune first-person shooter bots," in *Proc. IEEE Congr. Evol. Comput. (CEC)*, Portland, OR, USA, vol. 1, Jun. 2004, pp. 139–145.
[71] C. Liaw, W.-H. Wang, C.-T. Tsai, C.-H. Ko, and G. Hao, "Evolving a team in a first-person shooter game by using a genetic algorithm," *Appl. Artif. Intell.*, vol. 27, no. 3, pp. 199–212, 2013.
[72] S. M. Lucas and G. Kendall, "Evolutionary computation and games," *IEEE Comput. Intell. Mag.*, vol. 1, no. 1, pp. 10–18, Feb. 2006.
[73] C. C. Kemp, P. Fitzpatrick, H. Hirukawa, K. Yokoi, K. Harada, and Y. Matsumoto, "Humanoids," in *Handbook of Robotics*, B. Siciliano and O. Khatib, Eds. Springer-Verlag, 2008, ch. 56.
[74] M. J. Mataric, *The Robotics Primer*. Cambridge, MA, USA: MIT Press, 2007.
[75] B. Siciliano and O. Khatib, Eds., *Springer Handbook of Robotics*. Berlin, Germany: Springer-Verlag, 2008.
[76] N. J. Nilsson, "Human-level artificial intelligence? Be serious!" *AI Mag.*, vol. 26, no. 4, pp. 68–75, 2005.
[77] J. E. Laird and M. vanLent, "Human-level AI's killer application: Interactive computer games," *AI Mag.*, vol. 22, no. 2, pp. 15–25, 2001.
[78] H. A. Simon, *The Shape of Automation for Men and Management*. New York, NY, USA: Harper & Row, 1965.
[79] M. Minsky, *Computation: Finite and Infinite Machines*. Englewood Cliffs, NJ, USA: Prentice-Hall, 1967
[80] A. Clark, *Being There: Putting Brain, Body, and World Together Again*. Cambridge, MA, USA: MIT Press, 1996.
[81] J. Schaeffer, "A gamut of games," *AI Mag.*, vol. 22, no. 3, pp. 29–46, 2001.
[82] M. Bowling, N. Burch, M. Johanson, and O. Tammelin, "Heads-up limit hold'em poker is solved," *Science*, vol. 347, no. 6218, pp. 145–149, 2015.
[83] C. E. Shannon, "Programming a computer for playing chess," *London, Edinburgh, Dublin Philos. Mag. J. Sci.*, vol. 41, no. 314, pp. 256–275, 1950.
[84] M. Campbell, "Knowledge discovery in deep blue," *Commun. ACM*, vol. 42, no. 11, pp. 65–67, 1999.
[85] M. Campbell, A. J. Hoane, Jr., and F.-H. Hsu, "Deep blue," *Artif. Intell.*, vol. 134, nos. 1–2, pp. 57–83, 2002.

[86] J. Schaeffer, R. Lake, P. Lu, and M. Bryant, "CHINOOK: The world man-machine checkers champion," *AI Mag.*, vol. 17, no. 1, pp. 21–29, 1996.
[87] J. Schaeffer *et al.*, "Checkers is solved," *Science*, vol. 317, no. 5844, pp. 1518–1522, 2007.
[88] D. Silver *et al.* (2017). "Mastering chess and shogi by self-play with a general reinforcement learning algorithm." [Online]. Available: https://arxiv.org/abs/1712.01815
[89] J. Schaeffer and H. J. van den Herik, "Games, computers and artificial intelligence," *Artif. Intell.*, vol. 134, nos. 1–2, pp. 1–8, 2002.
[90] J. Haugeland, *Artificial Intelligence: The Very Idea*. Cambridge, MA, USA: MIT Press, 1985.
[91] R. Pfeifer and J. Bongard, *How the Body Shapes the Way we Think: A New View of Intelligence*. Cambridge, MA, USA: MIT Press, 2007.
[92] R. Pfeifer and C. Scheier, *Understanding Intelligence*. Cambridge, MA, USA: MIT Press, 1999.
[93] P. S. Rodman and H. M. McHenry, "Bioenergetics and the origin of hominid bipedalism," *Amer. J. Phys. Anthropol.*, vol. 52, no. 1, pp. 103–106, 1980.
[94] P. H. Raven and G. B. Johnson, *Biology*, 6th ed. Boston, MA, USA: McGraw-Hill, 2002, ch. 23, pp. 477–492.
[95] C. P. E. Zollikofer *et al.*, "Virtual cranial reconstruction of *sahelanthropus tchadensis*," *Nature*, vol. 434, no. 7034, pp. 755–759, 2005.
[96] C. O. Lovejoy, "Reexamining human origins in light of *ardipithecus ramidus*," *Science*, vol. 326, no. 5949, pp. 74e-1–74e1-8, 2009.
[97] C. O. Lovejoy, "Evolution of human walking," *Sci. Amer.*, vol. 259, no. 5, pp. 118–125, Nov. 1988.
[98] C. O. Lovejoy, "The origin of man," *Science*, vol. 211, no. 4480, pp. 341–350, 1981.
[99] B. G. Richmond and D. S. Strait, "Evidence that humans evolved from a knuckle-walking ancestor," *Nature*, vol. 404, no. 6776, pp. 382–385, 2000.
[100] C. R. Taylor and V. J. Rowntree, "Running on two or on four legs: Which consumes more energy?" *Science*, vol. 179, no. 4069, pp. 186–187, 1973.
[101] T. Ziemke, "What's that thing called embodiment," in *Proc. 25th Annu. Cogn. Sci. Soc.*, Boston, MA, USA, Jul./Aug. 2003, pp. 1305–1310.
[102] R. Pfeifer, F. Iida, and G. Gomez, "Designing intelligent robots—On the implications of embodiment," *Adv. Robot.*, vol. 24, no. 7, pp. 783–790, 2006.
[103] R. A. Brooks, *Cambrian Intelligence: The Early History of the New AI*. Cambridge, MA, USA: MIT Press, 1999.
[104] R. A. Brooks, "Elephants don't play chess," *Robot. Auton. Syst.*, vol. 6, nos. 1–2, pp. 3–15, 1990.
[105] R. A. Brooks, "New approaches to robotics," *Science*, vol. 253, no. 5025, pp. 1227–1232, 1991.
[106] R. Pfeifer, M. Lungarella, and F. Iida, "Self-organization, embodiment, and biologically inspired robotics," *Science*, vol. 318, no. 5853, pp. 1088–1093, 2007.
[107] R. A. Brooks, "Intelligence without reason," in *Proc. 12th Int. Joint Conf. Artif. Intell. (IJCAI)*, Sydney, NSW, Australia, vol. 1, Aug. 1991, pp. 569–595.
[108] D. Isla and B. Blumberg, "New challenges for character-based AI for games," in *Proc. AAAI Spring Symp. AI Interact. Entertainment*, Palo Alto, CA, USA, Mar. 2002, pp. 41–45.
[109] J. McCarthy, "The well-designed child," *Artif. Intell.*, vol. 172, no. 18, pp. 2003–2014, 2008.
[110] N. R. Jennings, K. Sycara, and M. Wooldridge, "A roadmap of agent research and development," *Auto. Agents Multi-Agent Syst.*, vol. 1, pp. 7–38, Jan. 1998.
[111] D. Isla, R. Burke, M. Downie, and B. Blumberg, "A layered brain architecture for synthetic creatures," in *Proc. 17th Int. Joint Conf. Artif. Intell. (IJCAI)*, Seattle, WA, USA, vol. 2, 2001, pp. 1051–1058.
[112] R. A. Brooks, "Intelligence without representation," *Artif. Intell.*, vol. 47, nos. 1–3, pp. 139–159, 1991.
[113] D. Terzopoulos and K. Fleischer, "Deformable models," *Vis. Comput.*, vol. 4, no. 6, pp. 306–331, 1988.
[114] J. Wilhelms, "Using dynamic analysis for realistic animation of articulated bodies," *IEEE Comput. Graph. Appl.*, vol. 7, no. 6, pp. 12–27, Jun. 1987.
[115] A. Nealen, M. Müller, R. Keiser, E. Boxerman, and M. Carlson, "Physically based deformable models in computer graphics," *Comput. Graph. Forum*, vol. 25, no. 4, pp. 809–836, 2006.
[116] D. C. Brogan, R. A. Metoyer, and J. K. Hodgins, "Dynamically simulated characters in virtual environments," *IEEE Comput. Graph. Appl.*, vol. 18, no. 5, pp. 58–69, Sep. 1998.
[117] J. K. Hodgins, W. L. Wooten, D. C. Brogan, and J. F. O'Brien, "Animating human athletics," in *Proc. 22nd Annu. Conf. Comput. Graph. Interact. Techn. (SIGGRAPH)*, Los Angeles, CA, USA, Aug. 1995, pp. 71–78.
[118] W. L. Wooten and J. K. Hodgins, "Animation of human diving," *Comput. Graph. Forum*, vol. 15, no. 1, pp. 3–13, 1996.
[119] P. Faloutsos, M. van de Panne, and D. Terzopoulos, "The virtual stuntman: Dynamic characters with a repertoire of autonomous motor skills," *Comput. Graph.*, vol. 25, no. 6, pp. 933–953, 2001.
[120] D. Terzopoulos, X. Tu, and R. Grzeszczuk, "Artificial fishes: Autonomous locomotion, perception, behavior, and learning in a simulated physical world," *Artif. Life*, vol. 1, no. 4, pp. 327–351, 1994.
[121] I. Millington, *Game Physics Engine Development*. San Francisco, CA, USA: Morgan Kaufmann, 2007.
[122] R. Lopes and R. Bidarra, "Adaptivity challenges in games and simulations: A survey," *IEEE Trans. Comput. Intell. AI in Games*, vol. 3, no. 2, pp. 85–99, Jun. 2011.
[123] N. J. Nilsson, *Artificial Intelligence: A New Synthesis*. San Francisco, CA, USA: Morgan Kaufmann, 1998.
[124] J. Zlatev, "The epigenesis of meaning in human beings, and possibly in robots," *Minds Mach.*, vol. 11, no. 2, pp. 155–195, 2001.
[125] V. Reynolds, *The Biology of Human Action*. San Francisco, CA, USA: Freeman, 1976.
[126] D. J. H. Burden, "Deploying embodied AI into virtual worlds," *Knowl.-Based Syst.*, vol. 22, no. 7, pp. 540–544, 2009.
[127] R. M. French, "The turing test: The first 50 years," *Trends Cogn. Sci.*, vol. 4, no. 3, pp. 115–122, 2000.
[128] D. Proudfoot, "Anthropomorphism and AI: Turing's much misunderstood imitation game," *Artif. Intell.*, vol. 175, nos. 5–6, pp. 950–957, 2011.
[129] J. R. Searle, "Minds, brains, and programs," *Behav. Brain Sci.*, vol. 3, no. 3, pp. 417–424, 1980.
[130] D. Gamez, Z. Fountas, and A. K. Fidjeland, "A neurally controlled computer game avatar with humanlike behavior," *IEEE Trans. Comput. Intell. AI in Games*, vol. 5, no. 1, pp. 1–14, Mar. 2013.
[131] M. Bowling, J. Fürnkranz, T. Graepel, and R. Musick, "Machine learning and games," *Mach. Learn.*, vol. 63, no. 3, pp. 211–215, 2006.
[132] F. Dignum, "Agents for games and simulations," *Auton. Agents Multi-Agent Syst.*, vol. 24, no. 2, pp. 217–220, 2012.
[133] L. Castillo, C. López, M. Bedia, and F. López, "Collective strategies for virtual environments: modelling ways to deal with the uncertainty," in *Proc. 12th Int. Conf. Distrib. Comput. Artif. Intell. (DCAI)*, Salamanca, Spain, in Advances in Intelligent Systems and Computing, Jun. 2015, pp. 183–191.
[134] A. Khoo and R. Zubek, "Applying inexpensive AI techniques to computer games," *IEEE Intell. Syst.*, vol. 17, no. 4, pp. 48–53, Jul. 2002.
[135] B. Soni and P. Hingston, "Bots trained to play like a human are more fun," in *Proc. IEEE Int. Joint Conf. Neural Netw. (IJCNN)*, Jun. 2008, pp. 363–369.
[136] G. Robertson and I. Watson, "A review of real-time strategy game AI," *AI Mag.*, vol. 35, no. 4, pp. 75–104, 2014.
[137] S. S. Farooq, I.-S. Oh, M.-J. Kim, and K. J. Kim, "StarCraft AI competition: A step toward human-level Ai for real-time strategy games," *AI Mag.*, vol. 37, no. 2, pp. 102–106, 2016.
[138] A. L. Samuel, "Programming computers to play games," *Adv. Comput.*, vol. 1, pp. 165–192, 1960.
[139] M. Freed, T. Bear, H. Goldman, G. Hyatt, P. Reber, and J. Tauber, "Towards more human-like computer opponents," in *Proc. AAAI Spring Symp. Artif. Intell. Interact. Entertainment*, Palo Alto, CA, USA, vol. 1, Mar. 2000, pp. 22–26.
[140] O. Vinyals *et al.* (2017). "StarCraft II: A new challenge for reinforcement learning," pp. 1–20. [Online]. Available: https://arxiv.org/abs/1708.04782
[141] Y. LeCun, Y. Bengio, and G. Hinton, "Deep learning," *Nature*, vol. 521, pp. 436–444, May 2015.
[142] V. Mnih *et al.*, "Human-level control through deep reinforcement learning," *Nature*, vol. 518, pp. 529–533, 2015.
[143] C. J. Bohil and F. A. Biocca, "Cognitive modeling of video game players," Dept. Telecommun., Inf. Media, Michigan State Univ., East Lansing, MI, USA, Tech. Rep., 2007.

[144] Z. Kasap and N. Magnenat-Thalmann, "Intelligent virtual humans with autonomy and personality: State-of-the-art," in *New Advances in Virtual Humans: Artificial Intelligence Environment*, N. Magnenat-Thalmann, L. C. Jain, N. Ichalkaranje, Eds. Springer-Verlag, 2008, ch. 2.
[145] S. C. J. Bakkes, P. H. M. Spronck, and G. van Lankveld, "Player behavioural modelling for video games," *Entertainment Comput.*, vol. 3, no. 3, pp. 71–79, 2012.
[146] M. L. Minsky, P. Singh, and A. Sloman, "The St. Thomas common sense symposium: Designing architectures for human-level intelligence," *AI Mag.*, vol. 25, no. 2, pp. 113–124, 2004.
[147] J. Togelius and G. N. Yannakakis, "General general game AI," in *Proc. IEEE Conf. Comput. Intell. Games (CIG)*, Santorini, Greece, Sep. 2016, pp. 1–8.
[148] W. Swartout *et al.*, "Toward virtual humans," *AI Mag.*, vol. 27, no. 2, pp. 96–108, 2006.
[149] J. McCarthy, "From here to human-level AI," *Artif. Intell.*, vol. 171, no. 18, pp. 1174–1182, 2007.
[150] L. A. Zadeh, "Toward human level machine intelligence—Is it achievable? The need for a paradigm shift," *IEEE Comput. Intell. Mag.*, vol. 3, no. 3, pp. 11–22, Aug. 2008.

VLADIMIR M. PETROVIĆ was born in Belgrade, Serbia. After he graduated from the prestigious Mathematical Grammar School in Belgrade, he enrolled the studies in electrical engineering at the School of Electrical Engineering, University of Belgrade, where he received the B.S. and M.Sc. degrees in electrical engineering from the Signals & Systems Department, in 2011 and 2012, respectively. He is currently pursuing the Ph.D. degree with the School of Electrical Engineering, University of Belgrade.

Since 2012, he has been a Research Assistant with the School of Electrical Engineering, University of Belgrade. He participated in several research projects, including the projects belonging to the Horizon2020 Research and Innovation Program. His research interests include a number of topics related to artificial intelligence, robotics, and virtual worlds. He is a reviewer of several respectful international journals.

Mr. Petrović was a recipient of the Best Young Researcher's Paper Award by the ETRAN Society (Serbian National Society for Electronics, Telecommunications, Computers, Automation and Nuclear Engineering).