Physics Simulation Games

Jochen Renz and Xiaoyu Ge

Contents

Abstract

Building Artificial Intelligence (AI) that can successfully interact with the physical world in a comprehensive and human-like way is a big challenge. Physics simulation games, i.e., video games where the game world simulates real-world physics, offer a simplified and controlled environment for developing

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and testing Artificial Intelligence. It allows AI researchers to integrate different areas of AI, such as computer vision, machine learning, knowledge representation and reasoning, or automated planning in a realistic setting and to solve various problems that occur in the real world without having to consider all of its complexity at once. This chapter first outlines the main categories of physics simulation games, some of which have become increasingly popular in recent years with the widespread availability of handheld touchscreen devices. It then discusses the motivation and rationale for conducting Artificial Intelligence research on these games and highlights the main research goals. Some of the underlying AI problems and recent advances are discussed and exemplified using a popular physics simulation game. Finally, an overview of current research in related areas is given.

Keywords
Angry Birds game • General game playing (GGP) • Physics mixed reality games • Puzzle games • Research problems • Simulation games • Physics simulation games • Artificial intelligence • Procedure content generation (PCG) • Serious game

Introduction

Physics simulation games have been around since the beginning of video games. Even some of the very first games (e.g., breakout) (Weiss 2009) on commercial game consoles fall under this category. Such games consist of objects, liquids, or other entities that behave according to the laws of physics and they often use an underlying physics simulator that computes the correct physical behavior. These games look and feel very realistic as all actions a player performs have outcomes that are more or less consistent with what one would expect to happen in the real world. What this requires is that all physical properties of all game entities and the game world, such as mass, density, friction, gravity, metric, angles, or locations, are exactly known to the game. Then each action and each movement can be exactly and deterministically computed by the physics simulator.

Implementing the physics of these games is quite a standard task, and the biggest advance over the years has been the more and more realistic and sophisticated graphics. These games form a very popular game category, particularly through the rise of touchscreen devices that allow easy manipulation of the game world and easy execution of actions by the players. Interaction with the game via touching is particularly suitable for physics games as it feels like interacting with real objects.

Physics simulation games and Artificial Intelligence have always had a close and fruitful relationship. The goal of Artificial Intelligence is to develop systems or agents that act, think, and behave like humans, like intelligent beings. This is particularly useful for physics simulation games since other entities in the game world should behave intelligently; they should behave like they are controlled by other human players. This is part of the field of Game AI (McShaffry 2009;

Rabin 2013; Millington and Funge 2009) which tries to achieve a very realistic and smart behavior of other game characters.

What this chapter is about is a much more recent research trend in Artificial Intelligence. Its goal is to build systems or agents that can play physics simulation games as good as or better than human players. This is a very different problem from traditional Game AI and most probably a much harder one. The main difference is that for Game AI, all physical parameters and the complete information of the game world are known to the AI. What is unknown is the behavior of the human player who could be an opponent or a partner, or who could be ignored, depending on the game. In this chapter, the AI knows only as much about the game world as it can see, the physical parameters are unknown, the exact angles and locations of objects are unknown, it is even unknown what the objects are. That is, computer vision should be employed to detect objects and tell the AI where they are and what they are. While this gives us uncertainty about what and where the objects are, another major problem is that the outcome of actions is unknown. Simulating the effects of an action is easy when all physical parameters are known, but if they are not exactly known then a simulation does not produce accurate results and one has to find other ways of predicting the outcome of actions. Humans are very good at predicting physics thanks to a lot of practice and experience in interacting with the real world. For AI, this is still a very difficult problem that needs to be solved in order to build AI that can successfully interact with the real world.

Now why should this be an interesting and an important problem to solve and a research area worth considering? There are certainly enough human players to play these games, why to develop AI to play them too? The motivation for this is quite unexpected and has significant implications for the whole of AI. Much of AI research over the past decades has been divided into specific research areas devoted to specific sub-problems of AI, such as Machine Learning, Computer Vision, Knowledge Representation, etc. Most research in these AI areas is so focused on their particular sub-problems that the big vision of AI has been ignored. It is not possible to simply plug and play modules from these areas and to obtain a complete AI system. Also, much of the research is focused on solving toy problems that may have nothing to do with the real world or with real problems. This was necessary as the real world is simply too complex. There are too many distractions, such as reflections, other people, unexpected activities, etc., that make it very difficult to focus on the particular problem one tries to solve.

This is where physics simulation games become very interesting: They allow AI researchers to develop methods and solve problems in a simplified and controlled environment where all these distractions can be removed, but that is still realistic enough and similar enough to the real world and to problems that need to be solved in the real world. In these controlled environments, it is then possible to integrate methods from the different AI areas to solve realistic problems. It is possible to see which existing methods work and which do not and what still needs to be developed in order to solve problems in the real world. Due to the difficulty of these problems, it is necessary to start simple, with games that only have a few features of the real world, and once these can be solved, to move to more realistic game worlds. Currently, the AI community aims to develop agents that can successfully play the game Angry Birds (Ge et al. 2014a; Renz et al. 2013), which is clearly at the lower end of this journey, but already requires us to solve some very realistic and very hard problems.

A further benefit of using games for developing AI is that it allows us to easily evaluate how well AI can already solve problems compared to human players. It also allows us to easily set up competitions, which is a very good way of achieving fast scientific progress in the area of the competition.

The remainder of this chapter is structured as follows. The next section introduces different kinds of physics simulation games. Section "Research Problems in PSG" then summarizes some of the important problems that need to be solved in order to build AI that can successfully play these games and also mentions some successful approaches to these problems. Section "Angry Birds: An Example" then explains some of the problems using the Angry Birds game, where a current AI competition has created some attraction. Section "Other Related Research" briefly summarizes some related research areas.

Physics Simulation Games

A physics simulation game (PSG) is a video game where the game world simulates real-world physics (Newtonian physics). In the following, different types of such games are discussed.

Puzzle Games

This genre has gained in popularity in recent years, especially on mobile devices. In the game, the player needs to solve a physical puzzle by obeying various laws of physics. These games have the following common features:

- Simple Physics. The game physics is simple in comparison to large commercial games. The laws of physics in these games are based on some basic principles of classical mechanics. Physical properties of the game objects are also simplified so that the entire game environment can be completely parameterized using a relatively small number of parameters. Besides, the game world in most of these games is two-dimensional, which further simplifies the underlying physics simulation in which the z-axis is ignored.
- Simple Actions. The player manipulates game objects via very simple actions such as finger gestures (tap, drag, swipe, etc.). Any chosen action can be simulated using an underlying physics simulator which makes the execution and the consequences of actions look very real. Despite a huge, and often infinite, action space (the number of ways to execute the action), it is common to have a small number of different actions in these games. For example, there are two actions in Angry Birds, namely, to drag and release a bird as well as to

tap to trigger a special ability of the bird. In Cut the Rope, the only action is to swipe to cut a rope. The actions are simple also in the sense that the outcome of these actions is deterministic.
- Simple (Commonsense) Knowledge to solve the puzzle. To be able to solve the puzzle, the player needs to predict the outcome of actions and plan a sequence of actions to achieve the desired result. Accurately predicting the outcome of each action is not hard for human players. In fact, most of these puzzles could be solved using knowledge of Naive Physics (Hayes et al. 1978).

These games can be further classified according to the types of puzzles.

- Build a Stable Structure. These games often require the player to remove or add objects to form a stable structure. Typical games: Super Stacker (http://www.thegamehomepage.com/play/super-stacker-2/), Moonlights (http://www.bonuslevel.org/moonlights/), World of Goo (http://worldofgoo.com/).
- Dismantle a Stable Structure. The player needs to remove or destroy objects to dismantle a structure while achieving specific goals. For example, the goal of Angry Birds is to kill all the pigs which are usually protected by a sheltering structure. In Jungle Bloxx, the goal is to collect all the diamonds within a structure. Typical Games: Angry Birds (http://www.angrybirds.com/), Jungle Bloxx (http://www.gamespot.com/jungle-bloxx/).
- Build a Rube Goldberg Machine. The player needs to create or use existing game objects to build a Rube Goldberg device that performs a certain task by triggering a chain of interactions. Typical games: The Incredible Machine (http://www.mobygames.com/game-group/incredible-machine-series), Bad Piggies (http://www.badpiggies.com/), Amazing Alex (http://www.amazingalex.com/), Crayon Physics Deluxe (http://www.crayonphysics.com/).
- Modifying a Physical System. In the game, the player needs to make some changes to the existing physical system to achieve a particular goal. Typical games: Cut the Rope (http://www.cuttherope.net/), Feed me Oil (http://holywatergames.com/), God of light (http://www.playmous.com/).

Simulation Games

This category contains all the video games wherein a physics engine is used to simulate the game world. Compared with the puzzle games, these games typically use extensive physics engines (e.g., Bullet (http://www.bulletphysics.org/)) to create more realistic game play. Unlike a puzzle game of which the actions and goals are strictly defined, a simulation game usually allows the player to freely control a game character to perform various "real-world" tasks in a simulated environment. The tasks include playing sports (e.g., playing tennis, snooker, bowling), racing, and combating. The simulated physical system sometimes can be extremely realistic and extremely complicated (e.g., Microsoft's Flight Simulator (http://www.microsoft.com/games/fsinsider/)).

Physics Mixed Reality Games

A mixed reality game is a game played in both reality and simulated environment simultaneously. It is typically played on a mobile device equipped with a camera that captures the real-world images. The game uses techniques from computer vision and augmented reality to allow real and visual objects interact physically on the device's screen. For example, in the mixed reality driving game (Oda et al. 2008), the player needs to drive a simulated car around on the player's physical desk using real and virtual obstacles. One challenge in implementing a mixed reality game lies in modeling the physical interactions between virtual and physical objects. Recent years also have seen a rapid advancement in haptic technology (e.g., Kinect (Zhang 2012)) that enables players to physically interact (moving their bodies) with the game world.

Research Problems in PSG

PSG is a new benchmark for Artificial Intelligence. The following features make PSGs an excellent test bed for research in physical reasoning.

- The research problems identified in PSGs domain are the same problems that need to be solved by AI systems that can successfully interact with the physical world. Just like the real-world physics, the physics simulator of a PSG works as a black box that hides all the equations and parameters from the player. To be able to play these games well, the player does not need to understand how the black box functions and neither does the player need to perform numerical calculations. In fact, what the player does in the game is essentially the same as what the player does in performing daily tasks – solve problems by intuition and qualitative reasoning (aka naive physics).
- Video games have the advantage that all images are generated and rendered using computer graphics where objects typically do not have the complexity and diversity that can be found in real world images. Therefore, working in the game domain allows researchers to focus on the problems independent of the computer vision problems.
- Intelligent agents can be tested by comparing their performance against the human performance in these games.
- Human computation in computer games has received considerable attention for the past decade. Many research efforts (Kuo et al. 2009; Von Ahn et al. 2006; Lieberman et al. 2007; Speer et al. 2009) have been devoted to extracting commonsense knowledge from computer games. In PSGs games, one can easily record player-generated behavioral data and use it as an excellent source for learning and reasoning algorithms. PSGs have another big advantage over the existing research-directed or serious games (Zyda 2005). Most of the existing research-directed games were developed with a particular research task in mind, which usually sacrifices fun in the game; therefore the game can hardly attract

the public. In fact, most players are from the research area, and the number of players is on average far less than a normal popular video game. In contrast, PSGs are games that are truly popular among the general public of various educational background, which may generate meaningful and more general behavioral data.

The ultimate goal is to develop an intelligent agent that can play the physics simulation games as well as or better than human players. Unlike the traditional in-game AI that has complete knowledge about the game world, the agent is only allowed to access the same information the human player can obtain from the game. The following is a selection of research problems that need to be solved in order to achieve the goal of AI playing PSG better than human players and ultimately for AI to be successful in interacting with the physical world.

Visual Detection of Objects

Object detection (Papageorgiou et al. 1998) and recognition (Grauman and Leibe 2011) are two major research problems in the field of computer vision (see Forsyth and Ponce (2002) for a survey) which has been extensively studied in the last two decades. A lot of efforts have been devoted to solving these two problems on real-world images. Given an image, object detection concerns the question: where a particular object is in the image? The detection focuses on a certain class of objects, such as human faces (Zhang and Zhang 2010) and pedestrians (Dollar et al. 2012), and the algorithm is usually trained on the annotated images containing objects of the same class.

Instead of detecting objects from a previously known class, object recognition targets on identifying and classifying both known and unknown objects in an image, which finds applications in various areas such as robotics and scene understanding. The recognition techniques can be appearance (Belongie et al. 2002) and/or features (Lowe 1999), supervised (Branson et al. 2010) and/or unsupervised (Niebles et al. 2008). One challenging problem in object recognition is to reliably detect and classify unknown objects while assuming minimal prior information, which is also known as category learning (Lee and Grauman 2012).

Most of the vision research has been done within the real-world context. In contrast, vision problems in the game domain have been largely ignored. The nature of the illumination, texture, and perceptual noise in a real scene is completely different from the artificial setting of the game world which is rendered by a graphics engine. It is not surprising that vision researchers are rarely interested in solving problems in such artificial domain because of its “simplicity.” What is surprising is that one can hardly find a suitable solution within the state-of-the-art that can reliably detect and categorize unknown objects in different games without human intervention (annotation and feature selection). One reason is a lack of generality of those techniques which are specialized for handling real-world images rather than game images. Another reason is that most of the state-of-the-art computer vision methods are purely statistical methods that operate at pixel level. What they miss are mechanisms to model rich spatial information and reasoning mechanisms to figure out what and where an object should be. It turns out that video games is a suitable test bed for developing and testing computer vision algorithms that focus on a high level understanding of the scene (which is more close to the way humans "see" the world) by modeling and reasoning about spatial information (Christensen and Nagel 2006; Cohn et al. 2003).

Physical Reasoning

Physical reasoning is an essential capability for AI agents seeking to interact with physical systems. In PSG games, there is a diverse set of tasks that require physical reasoning and planning for solving them while physical reasoning in the PSG domain remains an open problem. There are two main research paradigms in physical reasoning, namely, qualitative physics and simulation-based reasoning.

Qualitative physics has been extensively studied in the area of knowledge representation and reasoning (see Davis (2008a) for a survey). Much of the research in qualitative physics focuses on the development of qualitative representations and reasoning mechanisms that enable AI to make commonsense inferences about physical systems. For example, Forbus (1984) developed the qualitative process theory that allows one to specify dynamic processes in formal languages. This theory has been successfully applied to various applications, such as Cogsketch (a sketch understanding system) (Forbus et al. 2008), PEARS (Eckstein et al. 2015) (a physics engine that simulates complex physical phenomena), and analogical reasoning (Friedman and Forbus 2009). Davis (2008b, 2011) proposed a framework based on first order logic for reasoning about the physical properties of solid objects and liquids. Davis et al. (2013) invented a mechanism for qualitative reasoning about containers. The major advantage of the qualitative methods is that they are able to draw some useful conclusions or inferences rapidly from incomplete and noisy data. However, most methods are based on domain specific theories and cannot be easily generalized.

On the other hand, simulation-based reasoning methods can offer precise predictions when the environment is fully observable. This family of methods make physical inferences based on probabilistic simulations of Newtonian mechanics. Simulation-based reasoning methods have been mainly used for solving prediction problems. For example Battaglia et al. (2013) applied probabilistic simulations based on "intuitive physics engine" to verify the stability of a tower of blocks. Johnston and Williams (2007) applied quantitative simulation to solve the egg-cracking problem (a benchmark problem in commonsense reasoning). Similarly, in robotics, Nyga and Beetz (2012) and Kunze et al. (2011) used simulation physical reasoning to perform daily tasks such as housework. Davis and Marcus (2013) offers a detailed discussion on the role of simulation-based reasoning in solving physical reasoning problems.

The physical reasoning problems in the PSG domain are challenging: When playing a PSG game, the agent can only receive visual inputs from the game environment. While the physical properties of the game environment and the game objects are initially unknown, the tasks in these games are complicated and usually require multiple actions to complete, and it is difficult to formalize the knowledge about the PSG domain. Therefore, one possible direction to tackle the physical reasoning problems is to integrate the qualitative methods and simulation-based methods, which is known as hybrid reasoning. For instance, Johnston and Williams (2008) combined simulation with tableaux reasoning to solve some commonsense reasoning problems. Abdo et al. (2015) developed a hybrid reasoning approach that guides robots to clean up shelves according to users' preferences.

Predict the Outcome of Actions

The ability of reasoning about action and change (RAC) (Prendinger and Schurz 1996) is essential for an intelligent agent to adapt to a dynamic environment. RAC has been addressed as a knowledge representation and reasoning problem, which is a central topic in Artificial Intelligence. There have been various formalisms proposed for the representation and reasoning (Brachman and Levesque 2004) about a dynamic environment, of which the important ones are situation calculus (McCarthy 1963; Levy and Quantz 1998), fluent calculus (Thielscher 1998), event calculus (Kowalski and Sergot 1989), and action languages (Giunchiglia and Lifschitz 1998). Another related research stream is qualitative spatial and temporal reasoning (QSTR) (Cohn and Renz 2008) that aims to mimic the human commonsense knowledge about space and time. There have been quite a few calculi and reasoning mechanisms developed and applied in various areas ranging from GIS to computer-aided design (see Wolter and Wallgrün (2012) for a recent survey on QSTR applications). One way to predict the outcome of an action is to know which object before the action corresponds to which object after the action. To be able to establish a correct correspondence, an agent can track the objects on its continuous observations, which can be treated as a tracking problem (see Yilmaz et al. (2006) for a survey). When observations are not continuous, a proper reasoning mechanism becomes necessary (Ge and Renz 2014).

Automated Planning

Equally important is automated planning (see Ghallab et al. (2004) for a survey) which is about the derivation of sequence of actions that lead to an optimal result. Planning has been widely applied to video games since the last decade for various tasks such as controlling intelligent nonplayer characters (NPCs) and generating stories. The commonly used techniques include STRIPS planning (Fikes and Nilsson 1972), hierarchical planning (Kelly et al. 2008; Li and Riedl 2010), and behavior trees (Lim et al. 2010). There are two planning paradigms, namely, online planning and offline planning. Online planning assumes minimal prior knowledge of the game environment and computes an optimal plan in real time. In contrast, offline planning has complete knowledge of the game environment and generates plans offline ahead of time. Therefore, online planning algorithms surpasses their offline counterparts in handling unforeseen situations and works better in dynamic environments while offline planning algorithms use much less computational resources during the game play.

Planning in PSG remains a big challenge due to the fact that the action and state space in these games are huge, possibly infinite while the outcome of actions is unknown, which renders a brute-force search or simulation implausible. Over the past 10 years, a wide range of techniques have been developed for planning in huge, uncertain, and partially observable environments (see Vaccaro (2010) for a survey). Learning strategies from human experts is also a well-established topic (Khardon 1996). PSGs are great learning platforms where human players' strategies can be digitized and made available for learning algorithms.

Learning Properties of the Game World

Learning properties of game objects and the game environment is another fundamental problem in implementing AI in PSG. The properties of game objects consist of two types: (1) physical properties such as density, friction, elasticity, and strength; (2) object affordances (Gibson et al. 1990) and functional features. While the visual detection of objects answers what the object is, object properties learning answers how this object can be used. There has been a significant amount of work within the robotics community in learning object affordances. Some approaches identify object affordances by observing visual clues (Sun et al. 2010), a combination of visual and physical attributes (Hermans et al. 2011), or geometrical properties (Aldoma et al. 2012) of objects, which are usually applied to static images. Some methods learn object functions through robots' exploratory actions (Moldovan et al. 2012; Montesano et al. 2008) in real-world scenarios or simulated environments. There are also some learning techniques that focus on learning object functionalities and learning to perform actions from human demonstrations Koppula et al. (2013); Saxena et al. (2008); Li et al. (2010).

Angry Birds: An Example

This section explains the aforementioned problems using the Angry Birds game and reviews the techniques that have been proposed to tackle these problems. The AI Birds competition was founded in 2012 as an initiative to encompass a variety of AI areas to achieve its long-term goal – "build an intelligent Angry Birds playing agent that can play new levels better than the human players" (Renz 2015). Angry Birds is a typical physics simulation game wherein the game world is completely parameterized, which is simulated by the Box2D (http://www.box2d.org) physics engine.

Visual Detection of Objects

To solve new levels, the agent has to be able to detect and classify both known and unknown objects as well as localize foreground objects amid an intricate background. There are no existing off-the-shelf computer vision solutions for solving this problem; Ge et al. (2014b) took this challenge and developed a novel method based on qualitative stability analysis. The method infers the existence of yet undetected objects by observing that other objects that have already been detected are physically unsupported and therefore must be supported by some object still to be detected. The method was tested on 444 available Angry Birds levels (http:\chrome.angrybirds.com); Initially, only the green pig is known to the algorithm. After a few iterations for all the levels, all the game objects are detected.

Physical Reasoning

In the past three competitions, almost all the angry birds playing agents have been endowed with a certain degree of capability for physical reasoning. For instance, Brovicka et al. (2014) performs spatial reasoning to find a connected block structure (distinguished between Pyramid, Rectangle, and Skyscraper) near pigs and selects the most suitable block (often the weak point of the structure) by considering the supporters, reachability, and the shape of the block. Calimeri et al. (2013) uses a declarative, logic-programming based module to model the domain knowledge and compute optimal shots based on spatial configurations of the current game scene. Narayan-Chen et al. (2013; Tziortziotis et al. (2014) are machine learning agents that preserve essential structural and spatial information in the feature space, and "learn" to solve the puzzle by analyzing the structures. Walega et al. (2014) proposed a qualitative physics approach to evaluate a shot regarding its reachability and the scale of the damage to the target. Zhang and Renz (2014) developed a spatial calculus to represent the game objects and used it to identify the weak points to hit. Similarly, Ge and Renz (2013) devised a qualitative spatial representation for general solid rectangles (GSR), i.e., rectangles that can have an arbitrary angle, and cannot be penetrated, which can be used to analyze the stability of structures.

Polceanu and Buche (2014) tackle the problem by advanced simulation. The agent first detects all the objects in the game by the provided software and then uses these objects to construct an "Imaginary World" in which mental simulations can be performed. The objects' motion in the world is governed by Newtonian physics.

Predict the Outcome of Actions

The core action in Angry Birds is firing a bird. Some agents use simulation to estimate the consequence of a shot. For instance, Polceanu and Buche (2014) proposed an agent that performs multiple parallel simulations to test different courses of actions and chooses the best action. A good simulation relies on an accurate knowledge of the underlying physical system. However, the parameters of the physical system are invisible to the agent, which adversely affects the simulation result.

Another approach is to identify how objects are affected by a shot, specifically, is to determine which objects before a shot correspond to which objects after a shot. To be able to identify the correct correspondences, the agent can track objects through the before-and-after observations. The problem becomes challenging when the observations are not continuous (the time gap between the observations is greater than 50 ms), and when those objects are perceptually indistinguishable (i.e., have the same appearance). Ge and Renz (2014) developed a spatial reasoning based tracking method that can accurately track perceptually indistinguishable objects in discrete observations with large time gaps.

Other Related Research

Physics Simulation in Serious Game

A serious game, as defined in Zyda (2005), is "a mental contest, played with a computer in accordance with specific rules, that uses entertainment to further government or corporate training, education, health, public policy, and strategic communication objectives." Serious games have been used for physics education since the early 1980s (White 1984; Lee et al. 1993). Compared to commercial physics puzzle games, these serious games feature a more accurate simulation of Newtonian physics. The game Newton's Playground (Ventura et al. 2013) has been used to help secondary school students understand qualitative physics (naive physics). In the game, the instructor can create a simple physical machine to illustrate certain physical concepts to students in a qualitative way. Similar games are Coller and Scott (2009; Squire et al. (2004). There are also 3D platform games that emphasize realistic simulations for training purpose (Davis 2004). Some researchers (Erignac 2001; Cavazza et al. 2004) proposed the use of qualitative simulation to simulate the way objects behave according to naive physics. Limited research has been done in those games to qualitatively simulate (Zhou and Ting 2006; Lugrin and Cavazza 2007) the physical behavior of game objects.

General Game Playing

General game playing (GGP) (Genesereth et al. 2005) aims at developing intelligent agents that can play a class of previously unknown games effectively. Given an arbitrary game, the agent can access a formal description (written in logic) file of the game and it needs to figure out the legal actions, winning strategy, and winning goals by itself. Considerable research (Finnsson and Björnsson 2008; Banerjee and Stone 2007; Cerexhe et al. 2014) has been done in this area, and a number of successful playing agents (Kuhlmann and Stone 2006; Geier et al. 2014; Kirci et al. 2011) have been developed and evaluated in the GGP competition at the annual AAAI conference (Genesereth and Bjrnsson 2013). The competition tests the performance of GGP agents in abstract strategy games such as chess-like games and card games.

Atari-GGP (Bellemare et al. 2013) shifts the focus from abstract strategy games to video games. An Atari game is a video game that has simple graphics and game settings. There is a finite set of discrete actions (e.g., move the game character in different directions) available to the player. Recently, Mnih et al. (2013) developed an agent that can play a range of Atari games with minimal domain specific knowledge. The technique is based on the integration of reinforcement learning and deep learning. During playing, the agent only receives the screenshot from the current game screen and the agent is able to figure out the game dynamics over time. There are few Atari games that involve some physics while they do not require sophisticated physical reasoning. For example, the task in Breakout is to destroy all bricks by bouncing a ball on them. In this scenario, bouncing is one of the few physical phenomenon an agent should "understand" in order to complete the task. However, PSG games usually have more physical elements and the tasks are much more complicated. There is no existing technique for developing general game playing agents in the PSG domain.

Procedure Content Generation

Procedure content generation (PCG) (see Hendrikx et al. (2013) for a survey) refers to the development of an automated or semiautomated procedure for game content generation. The game content refers to various aspects of a game ranging from game levels to game stories. Nowadays, it is not uncommon that a physics puzzle game such as Angry Birds has hundreds of different levels. Therefore, PCG becomes one of the major efforts in the game industry in part due to the need for reducing time consumption as well as budget for content generation and in part due to the need for increasing game content variations. In the meantime, PCG has received increasing attention from the AI community, and a variety of AI techniques have been developed for solving PCG problems such as modeling behavior of game objects (Hastings et al. 2009; Hidalgo et al. 2008), generating levels (Shaker et al. 2010; Dormans 2010), and creating puzzles (Iosup 2011; Ashlock 2010). Generating levels for physics puzzle games have attracted a growing interest in recent years. This genre provides an interesting test bed for level generation techniques as it imposes certain physics constraints that are essential for evaluating the quality of the generated levels. The state-of-the-art is dominated by evolutionary algorithms (Cardamone et al. 2011; Cook and Colton 2011; Mourato et al. 2011). For example, Shaker et al. (2013) combined an evolution algorithm with a grammatical representation to generate levels in Cut the Rope; Ferreira and Toledo (2014) viewed level generation in Angry Birds as an optimization problem and developed a search approach (known as Search Based Procedural Content Generation, for a survey see Togelius et al. (2011)) built on an evolution algorithm. All these techniques are entirely application specific and therefore not reusable. Another issue to overcome when developing level generators in these games is playability evaluation (Shaker et al. 2013) which has to be done through physics simulation. As there is no source code available for most commercial games, game researchers have to develop their own simulators that "clone" the physical behaviors of the simulator of the original game.

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