Evolving Entertaining NPCs

Automated Synthesis of NPC AI with ADA

Project Report

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Abstract

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An abstract is a brief summarizing statement, usually between 75 and 150 words long. It gives the reader a synopsis of the problem, method, results, and conclusions of your document. The abstract takes the form of a paragraph, usually with 5-10 sentences. Abstracts are often collected into volumes and must be able to stand alone. They are read by parties who are trying to decide whether or not to read the main document. Sometimes they are read by people who want to get the big picture before reading the main document. Abstracts can save readers an immense amount of time.

Acknowledgements

Prerequisites (OPTIONAL)

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Chapter 1

Introduction

Computer games are a major part of the entertainment industry these days, with major titles having budgets matching Hollywood movies. Even so, there is a lot of potential for improvement on their appeal. Artificial Intelligence is an area where games can improve substantially as limitations of the past are disappearing, creating games that seem more realistic and interesting. Increases in the computing power of the average computer has made it possible to take into use techniques previously thought too computationally expensive. Machine Learning has the power to create NPC characters that seem intelligent and can add more realism to games, and as such make the game more satisfying to the player.

1.1 Motivation

Video games are a massive industry with budgets comparing to the ones of Hollywood movies, with Rockstar's GTA 4 having an estimated production budget of $100 million. It follows that video games are a big part of people's regular entertainment, with young people spending on average two hours per day on video games. (Norwegian Ministry of Culture, 2008)

Since the inception of the game industry, game producers have been heavily focused on creating more and more audio-visually impressive games, and this development has reached a point where the improvements made can only be minor. During this process, the development of the AI for game characters has been only as necessary, to meet the demand of players for characters that are as sophisticated as the graphics. (Champandard, 2003)

Until the late 90s there had not been much focus on improving the AI utilized by the characters in gamesTozour (2002), but this is shifting rapidly, as games focus more on intelligent characters, using it as their latest and greatest selling point. There have even been entire game series that focus entirely on AI, such as *Creatures* (Grand et al., 1997), *Black & White* (Lionhead Studios, 2001) and *The Sims* (Maxis, 2000).

Despite this, the majority of game AI still uses simple techniques that have been the cornerstone of game AI since its early days. Simple scripted rules and Finite State Machines still dominate the implementation methods due to their simplicity, performance and ability to function "well enough" to implement simple AIs. (Woodcock, 2001) This creates AI that, while entertaining and believable in most situations, is ultimately limited by the forethought of the AI programmers, and is easily outmatched by most experienced players.

In recent times Massively Multiplayer Online Games have emerged and become immensely popular, through titles such as *World of Warcraft*, and games have grown to have a high focus on Player versus Player multiplayer, with popular shooter game series having either no single player campaign, or an extremely short one. This trend gives a strong indication that players are looking for more intelligent opponents and more varied game play, and that this cannot be provided through the single player opponents in the games.

To alleviate the limitations of simple, static AI opponents, machine learning could be utilized. ML could create more engaging and interesting computer opponents, and enables the system to scale up to more complex worlds and situations. (Funge, 2004) In the same vein, it is believed that utilizing evolutionary computing can enable the creating of computer opponents that are interesting and interactive, and as such entertaining. (Yannakakis, 2005)

This thesis will explore if ADATE (Olsson, 1994), a system for inductive programming (an offshoot of evolutionary computing), can be employed to generate entertaining AI opponents. Additional challenges consist of finding a way to quantify the entertainment value of the generated agents, and the creation of a game framework to support the research. Towards this end, there are a set of objectives and questions (shown in the following section) that need to be addressed to reach our goal.

1.2 Objectives and Research Questions

Given the motivation for this thesis, there are a selection of questions to be addressed to further our objectives. The questions that will be answered in this thesis are as follows.

1. How can a player's satisfaction in a game (entertainment) be measured quantitatively?

2. Can the use of evolutionary computing increase a game's interest and ultimately create a more interesting game than static AI?

1. Establish a metric for measuring a game opponent's interest level to the player.

2. Adapt this metric to the ADATE platform and decide upon a test bed suited to the platform and metric.

3. Use the platform to enhance the entertainment level of the computer opponents in the test bed.

maybe change this when a test bed is located?

1.3 Summary

1.4 Thesis layout

Chapter 2

Background

2.1 AI techniques

There is constant work on new AI techniques, both to make AI more efficient, and to make AI seem smarter or more human. Familiarizing oneself with some of these will allow better ability to choose an implementation technique that fits with the goal of using inductive programming.

There is some differences between the techniques employed in "traditional" AI and game AI, primarily based on the performance of the various methods and their focus on the AI's ability to solve problems and be entertaining, respectively. The two areas seem to be converging, however, as traditional AI is starting to shift from the goal of being "really smart" and solving hard problems, to making computers that seem more human, have an ability to learn and adapt, and maybe act like assistants, as detailed in Ramos et al. (2008) and evidenced by the AI-controlled assistant feature, named Siri, in the Apple iPhone 4S (Apple Software, 2011).

When it comes to games (both video games and traditional games), the biggest deciding factor in how to implement the AI stems from whether or not the agents have perfect information and whether there is chance involved. A perfect-information game will require a completely different approach to AI than a hidden-information or stochastic game, and this will heavily influence what type of AI is utilized, as mentioned in Schaeffer and Van den Herik (2002, pg. 4-5).

2.2   Traditional AI techniques

As noted in Munakata (2008, chap. 1), AI techniques can be divided into six areas, although these divisions can be debated and should not be considered a rigorous division, namely:

1. Symbolic AI (also "traditional AI")

2. Neural networks

3. Evolutionary Computing (under which Genetic Algorithms fall)

4. Fuzzy systems

5. Rough sets

6. Chaos

Symbolic AI is the umbrella term for the traditional methods dating from the field's inception, focusing on abstracting the world and applying logic and rules to reach decisions.

The following two methods (Neural Networks and Evolutionary Computing) are different reactions to the insufficiencies of Symbolic AI by attempting to more closely modelling biological processes, so they can be called "biology-inspired AI".

The remaining three methods are more recent developments which attempt to attack the problem from a different angle, collectively called "soft AI" due to their focus on not giving "hard answers" and reliance on uncertainty. These methods are less relevant to the topic of my thesis, and as such will not be covered further.

2.2.1   History

Before going further it would be useful to go through the history of Artificial Intelligence, to see its roots, and how closely it has developed alongside the field of computer science itself. (Buchanan, 2002; Luger, 2005)

The field has traces back to antiquity with Greek myths about artificial beings such as the golems and homunculus, which were "programmed" to perform tasks through occultic writing, and to the writings of many ancient scholars (Aristotle and Euclid, among others) on the topic of reasoning,

logic and the mind. Further there have been many people working on mechanical automaton through the ages, attempting to have them emulate human behaviour.

There was early work on intelligent machines from the very time computers existed, but computer AI as a field didn't really come into existence until 1950, through a pair of papers.

1. A very important paper was published by by Alan Turing named "Computing machinery and intelligence" (Turing, 1950), where the he defined the "Turing Test" as a way to test whether a machine was truly intelligent.

2. Claude Shannon publishes a paper on programming a computer to play chess, by representing it as a search problem. (Shannon, 1950)

The term "artificial intelligence" wasn't coined until six years later when John McCarthy used the term for the first conference on the topic in 1956, where the first running AI program (the Logic Theorist) was demonstrated.

It didn't take long for AI programs to challenge humans at board games, with the first program to challenge a human world champion being made in 1962 by Arthur Samuel The program was aimed at the game of checkers and utilizing machine learning to improve its performance.

Further works into computer-assisted problem solving led to SAINT, that solved calculus at a freshman level (Slagle, 1963); ANALOGY, that solved the kind of analogy questions found on IQ tests Evans (1964); and ELIZA, which could simulate conversation (Weizenbaum, 1966).

Later, there was work into "knowledge-based programs" for artificial reasoning, which described programs able to interpret mass spectra of chemical compounds, solve integration problems in math, and play chess well enough to reach a class-C rating.

In 1969, the beginnings of Neural Networks were appearing with Minsky and Papert (1969) which defined Perceptrons, while several papers on natural language understanding were published during the next few years, along with the introduction of "expert systems" using rule-based programming, and the creation of the first computer to make a scientific discovery, the Meta-Dendral learning program (Buchanan et al., 1976).

Through the 70s and into the 80s, an explosion of well-known AI programs occurred. Many "expert systems" were made that were capable of reasoning within a limited knowledge space on the same

level as a human expert, using the traditional symbolic methods, before Neural Networks become widely used using backpropagation (first introduced in WERBOS (1974)).

Around the 80s, the American Association for Artificial Intelligence (AAAI, now named the Association for the Advancement of Artificial Intelligence after a name change in 2007) was founded. The AAAI hosts many conferences and symposia each year, and supports several journals on AI.

Another boom in AI research happened in the 90s with major advances in all areas of AI, with significant demonstrations in machine learning, intelligent tutoring, case-based reasoning, multi-agent planning, scheduling, uncertain reasoning, data mining, natural language understanding and translation, vision, virtual reality, games, and other topics.

The 90s also had two significant accomplishments of AI programs for playing games: Deep Blue beat Garry Kasparov in 1997, and TD-Gammon, an AI that played backgammon at championship-level, was written. In addition, AI was starting to see use in cataloguing the internet.

This brings us to today, where AI is proliferating, seeing use in toys (such as robotic pets) and other forms of entertainment (most notably video games), but is still far away from the goal of creating a truly human machine.

2.2.2   Symbolic AI

This sub-field of AI is also known as "traditional" or "classic" AI, and was the approach that was used during the inception of AI and is still heavily used today. It is characterized by a top-down focus on logic and reasoning, and relies on a symbolic description of the world, such as a set of rules, and is thus often said to be "knowledge-based".

Techniques included under Symbolic AI are knowledge-based systems, logical reasoning, symbolic machine learning, search techniques, and natural language processing.

2.2.3   Biology-inspired AI

This term describes two sub-fields of AI, "Neural Networks" and "Evolutionary Computing", both of which attempt to mimic biological processes, although not in a way that attempts to emulate them faithfully. The two are also part of a branch of Artificial Intelligence called Machine Learning, alongside techniques such as "Decision Trees" and "Bayesian Learning".

Neural Networks

Neural Networks, more correctly called Artificial Neural Networks (ANN) to separate them from the biological variety, are computer simulations that attempt to mimic biological neural networks through a variety of algorithms, but they all revolve around small units called "neurons" linked in networks of some sort, trained by a learning algorithm.

The simplest variety of ANN is called a Feedforward Neural Network (Wikipedia, 2011b), and consists of one or more layers of neurons connected in a network where information only moves in one direction. The kind of neuron most commonly used in such a network is the Perceptron (Minsky and Papert, 1969), and one usually uses the Backpropagation (Wikipedia, 2011a) algorithm to train these kinds of networks.

Other kinds of ANN are:

- Radial Basis Function Network.

- Kohonen Self-organizing Network.

- Learning Vector Quantization.

- Recurrent Neural Network.

- Modular Neural Networks.

ANNs are usually trained against a set of data containing both inputs and outputs, using a learning algorithm that dictates how the neurons in the network are to be updated based on the training data. The network is then tested against a separate "validation set" where the input data is sent through the network and compared with the output data to test the network's error rate. This process is then repeated as long as necessary to generate an acceptable error rate.

ANN can used for multiple purposes, such as function approximation, classification, and robotics, but require a large and diverse set of data to train on to be useful, as ANN have a proclivity towards temporarily overfitting if presented with a long series of less diverse data.

Evolutionary Computing

In Evolutionary Computing the aim is to mimic the biological process of evolution to evolve solutions to problems. There are many approaches that fall under this name, among others Genetic

Algorithms, Genetic Programming and Evolutionary Algorithms, but the common trait is that they use, to a certain extent, the four mechanics of biological evolution: reproduction, mutation, recombination and selection.

These methods present the problem by taking a starting point towards a solution, (which can be of any complexity, from nonexistent to a "best-known" program), then "reproduce" it by applying a random set of mutations to generate a certain amount of new solutions (called individuals). These individuals are then tested with a fitness function defined by the person attempting to solve the problem, that measures the individual's performance at the problem, and the result of this is used to rank the individuals. We further choose one of the individuals in the list, and "reproduce" it to create new individuals either by way of mutations or by using an algorithm to combine it with another individual in a way that mimics the biological process of recombination. The newly generated individuals are then tested for fitness and put into the list of individuals, which is then culled to a specific length by removing the least fit individuals. This process reproduction and culling is repeated until the solution is deemed good enough or, on rare occasion, an optimal solution is found.

The system used in my thesis, ADATE (Olsson, 1995), is an Evolutionary Computing system that fits into a sub-field of Artificial Intelligence called Inductive Programming, which will be described in section 2.7.

2.3   Game AI techniques

The approaches to AI used in video games (as opposed to more traditional board/card games) are often very different from the academic approaches, where AI programs can take a long time to reach a decision, might require massive amounts of resources and usually have as a goal to perform as excellently as possible at a task.

In games the AI actors might only have a handful of microseconds of CPU time available to reach a decision without harming the performance of the game, and the AI must fulfill the twin goals of being challenging (but beatable by the majority of players) and entertaining (by employing novel methods and seeming human-like).

In addition, game AI is a comparatively recent field when compared to the volume of research on AI work using traditional board and card games, which evolved alongside computer science, as

"solving" board games was one of the driving forces behind computer science, as mentioned in Schaeffer and Van den Herik (2002).

2.3.1 History

Before covering specific techniques, it is prudent to go through a history of AI as used in games, to show the field's evolution in contrast to the field of traditional AI which has a long history of strong scientific focus. The majority of this information comes from Tozour (2002).

When it comes to video game AI, the methods employed have been, and still are, marked by the heavy performance requirements and the fact that very little emphasis has been put on AI sophistication until recently, as quipped about in the following quote:

> Even today, game AI is haunted by the ghosts of Pac-Man's Inky, Pinky, Blinky and Clyde. Until very recently, the video game industry itself has done all too little to change this perception.

Continuing on through the article, it is explained that many of the popular early games used very crude AI, basically just consisting of a handful of simple rules, with the exception of games that just digitized board games with well established AI research such as chess.

More sophisticated AI in video games was first embarked upon in the context of turn-based strategy games (such as *Civilization*), then in real time strategy games (such as *Age of Empires 2: The Age of Kings* and *WarCraft II*). Further, good AI started showing up in First Person Shooter games (*Half-Life* and *Unreal: Tournament*) that showed tactical ability and the ability to model several actors simultaneously, while *Thief: The Dark Project* had actors that emulated sense of sight and sound in a human-like fashion, and *SWAT 3: Close Quarters Battle* featured randomized AI parameters that allowed each actor to have a slightly different personality every time the game was played.

After that the variety of different AI exploded, with games focusing entirely on nurturing "AI life" in a manner the player decided, with *SimCity* and *The Sims* being very well known staples. Another well-known AI life game was *Creatures* which is famous for being one of the few games that actually used a biological model for its "Norns", both modelling biological processes with great detail and using neural networks for the AI (see Grand et al., 1997). Other games fit into the "God games" category, such as *Populous* and *Dungeon Keeper*, alongside *Black & White*, which has the

distinction of being the first major game to focus the player's attention entirely on the game's AI capabilities, and including a learning AI, a topic which is considered to be the next "Big Thing" in gaming.

It should also be noted that for all the recent complexity, it is still the case that the game AI community favours simple "traditional" methods implemented through finite state machines, decision trees and rule systems, for their excellent performance and relative simplicity. These are then further augmented to add human-like behaviour, simulating planning and learning (see Isla and Blumberg, 2002; Khoo et al., 2002; Mateas and Stern, 2002; Orkin, 2003).

2.3.2   Traditional game AI

Traditional game AI or "simple AI" is what game AI started out as, and still to this day mostly is. It's based upon simple rules or simple logical systems, and has traditionally used a sampling of simple techniques, such as simply hard coding the AI in a single routine, utilizing Finite State Machines, or using rule-based systems. In addition, path finding has always been a topic with AIs, where simple, well known, algorithms such as A* have been dominant for a long time.

The common factor in traditional game AI techniques is that they tend to be static, the NPCs are only capable of the things they were programmed to do beforehand, and have little capability for learning or planning.

Hard-coded AIs

The first game NPCs utilized simple hard-coded AIs, which were basically a short routine that ran every tick of the game with simple behaviours for the opponents, not following any formalized methods for AI. This method is still used to this day, as it's easy to create, and usually many minor opponents in games don't need more sophistication than this method creates.

A good example of this technique is Pac-Man's ghosts, which used simple path finding, and a selection of "modes" for the ghosts globally, then four different targeting rules to give each ghost a "personality" as their entire AI (Birch, 2010; Pittman, 2011). Even this very simple AI created the interesting behaviours and engaging game play which propelled Pac-Man towards becoming one of the most recognized games in video game history, evidence that you don't need fancy high-powered algorithms to create interesting and engaging games.

Finite State Machines

Finite State Machine (FSM) systems are the most commonly used systems in game AI, although the FSM systems used by game developers do not necessarily work the same as the ones described by Computer scientists. They take certain shortcuts which violate the traditional definition of FSM, which make them more applicable to games (Rabin, 2002).

FSM are used to formalize an NPC's behaviour in a simple way, as states and transitions. States correspond to a specific behaviour or action, whereas a transition correspond to a change in behaviour due to an event in the game. Using this, one can easily map up simple behaviours that allow an NPC to act in a manner that can be deemed "intelligent," as long as the programmer thinks of all the transitions necessary and makes them seem natural.

This method of AI creation has the benefits of being simple to understand, create and debug, as well as being very versatile by virtue of being a general method that can lend itself to most any problem. Of course, there are downsides to FSM as well. They can easily grow out of hand in more complex AI systems, need to have every necessary transition programmed in, and they don't have the capability of combining states (so you can't have an NPC be in the *run away* and *attack* states at the same time, to have it do a tactical retreat, without explicitly programming the option in).

For a more thorough coverage of implementing an FSM system, one can consult Rabin (2002) or Kirby (2011, chap. 3).

Rule-based systems

As with FSM, Rule-based systems stem from traditional AI research, but are used in a more loose form in video games (Christian, 2002). The basic idea of rule-based systems is that of a database (the data can be information, actions or other things), where each piece of data has a "matching rule" used by the system to infer which pieces of data apply to the current situation.

In the context of games, this boils down to series of rules coupled with actions or behaviours, many of which can apply at the same time, which together make up the AI for the given NPC. These are formally named *reaction rules*, and are just one type of rule, with the other major one being *consequent rules* that deal mostly with information.

Usually there is some method of discerning which rules are the most relevant at the current time if many of them match the current situation, to prevent the NPC from doing too many things at

once (many simple AIs only allow the NPC to do a single action per tick). These can range from randomly choosing a rule, to weighting each rule based on its specificity and choosing the most applicable one (Freeman-Hargis, 2002).

The biggest benefit of rule-based systems is that you can create a good set of behaviour with a comparatively small amount of rules. This means you aren't suspect to the "state explosion" you might have in an FSM, where adding a single new state will result in a cascade of new transitions having to be written to handle every single case where the NPC can switch in and out of the new state. In a rule-based system you just add the new rule and write one matching function for it, and let your system handle the rest.

Of course, the downside in this case is that creating a good AI like this requires a bit more thinking to create a set of actions that acts well in the most common cases, and still handles uncommon and unexpected cases decently well, since one can't write a rule for every situation. This usually requires a human with some expertise to either formulate or actually code the rules.

More info on writing rule-based systems can be found in Kirby (2011, chap. 4).

2.3.3   Towards more human game AI

In recent times there has been efforts towards making game NPCs act more human-like, by introducing planning and learning behaviours (making the AI adaptable), making their decisions be more unpredictable (but rational), culling any obviously stupid behaviour, as well as engineering the NPCs to introduce more human elements such as adding the feeling of emotion and body-language (Spronck, 2005).

In the last decade or so, game AI has started incorporating planning and learning behaviour to make NPCs seem smarter and more human-like. Games such as F.E.A.R (using Goal-Oriented Action Planning as described in Orkin (2006)) utilize planning to make their opponents behave in a more realistic manner, while other projects have used planning to make AI for previously released games, such as WarCraft II (using Hierarchic Task Networks as described in Brickman and Nishant (Unknown year)).

Planning allows the AI programmer to specify "action sets" and "goals" which together make up the bulk of the AI for the NPCs. Action sets contain actions which satisfy goals, and each action may have preconditions which are also classified as goals. Using this information, the NPCs can plan its actions by what it knows of the world (which it can learn over time) and which actions have been

defined as being accessible to it, instead of having to have the AI programmers code every possible such path.

An example of the benefit of using a planning system is described in Orkin (2006), where they describe an NPC being shot while sitting at a computer desk. In the traditional FSM-based system, the NPC had to fully exit its current state before being able to transition to the next, so it would exit its "work" state by turning off the computer, pushing out the chair, and standing up, before letting out a death groan and falling over dead. Not really what one would consider human-like, or even believable, behaviour. In a planning system, that transition would be dynamically created, and the NPC would just slump over dead from its chair, as one would expect.

Introducing emotion into games can be done in various ways, not just through having the NPC itself show emotion, but also by having various "AIs" change the mood of the game by altering lighting, music, and texture (Kirby, 2011, chap. 9).

NPC AI itself can also introduce emotions in the players by virtue of their difficulty or other behaviours that rise to player experiences such as "hard fun", "soft fun" and "serious fun" (Lazzaro, 2004). NPC difficulty can alter itself according to player skill to fulfill any of these goals, something which many modern games utilize in what's called "Difficulty scaling", which can refer to anything from simply giving you enemies with higher levels (in RPG-style games such as Fallout 3), spawning more or less enemies and changing where they appear (such as the AI Director in Left 4 Dead), to evolving NPC AI that uses the player's performance as a parameter in a fitness function to create better AI (one component of the thesis topic, and will be described in more detail later)

2.3.4 Advanced game AI

More advanced game AI utilizes more heavy-duty AI techniques such as Genetic programming or Neural Networks that learn and train as the game goes by, in an effort to create an ever-changing experience for the gamer. The most well known games which utilize these kinds of techniques are, as described earlier, Creatures (Grand et al., 1997) and Black & White.

One technique used to allow these advanced agents is called Reinforcement Learning (Merrick and Maher, 2006; Sutton and Barto, 1998), which differs from the normal learning/training method of machine learning (termed Supervised Learning) in that it isn't given any examples to learn from to learn how to behave. In Reinforcement Learning the agents start out with a defined set of actions and goals, and have to learn through trial and error which ones are the best series of actions to fulfill

a certain goal, which can easily change during play as the human player changes its tactics.

Beyond this, the usage of more advanced AI techniques in games has been mostly within the realm of research and done after the release of the games, either through altering the source code of released games, or by creation of bots that use a certain AI technique for research purposes and pitting it against humans and/or other bots in a multiplayer setting.

2.4   Making NPCs Entertaining

When AI is used for NPCs in games, the main goal is not to perfectly emulate a human, nor to create the most skilled opponent possible, but rather to create an opponent that *seems* human, and possesses behaviour that creates an entertaining experience, without being unduly challenging.

There are many methods of doing this, some of which have been described in previous subsections under section 2.3. These range from simple difficulty-scaling methods to match the player's skill level, through having NPCs that perform "human" tasks such as planning and cooperating smartly, to having NPCs and AI that show emotion and alter their behaviour and how they are perceived based on their moods.

2.5   Evaluating entertainment

Before you can make AI more entertaining, you need a way to measure if you're actually reaching your goal. This can be done in one of two ways, you can measure the response from real human beings playing your game, or you can try to quantify entertainment value through various scientific means in an objective manner.

2.5.1   Measuring people's entertainment

Measuring a real human being's response to a game will give you the most accurate measurement of entertainment, but it comes at a cost. The methods of doing so can be very expensive, in equipment, time, or both. There is also ample room for bias either by the one doing the measurements or the measured person, conscious or subconscious.

Techniques employed here can range from very primitive to very advanced, and include everything from surveys, to hooking a player up to gear to measure brain waves.

Simple surveys or questionnaires are easy and cheap to implement, but suffer from not being able to capture complex data. In addition, and suffer from bias on the part of the person filling out the data, where they subconsciously fill out data closer to what they think you might be looking for than what they actually think (Mandryk et al., 2006).

Another technique that can be used is recording a person playing the game, and analyzing the recording to pull out data about how the person playing the game feels about it. This can provide a very rich source of data, but suffers from drawbacks, the biggest of which is that time spent analyzing is very high compared to the amount of video recorded, ranging from 5 times to 100 times longer. Another problem, as always, is bias, this time on part of the researcher (Mandryk et al., 2006).

The previous techniques are mostly indirect measurements, but there are ways to directly measure a person's enjoyment of a game, by utilizing physical measures such as Galvanic Skin Response, Electrocardiography and respiration. This involves hooking the players up to a lot of equipment, and is thus a lot more expensive, time consuming and intrusive. One way of doing this is described in Mandryk et al. (2006), another in Yannakakis et al. (2008).

2.5.2 Quantifying entertainment

There is also work going into methods of quantifying entertainment in games, with several articles proposing theories on what makes a game fun (e.g. Federoff, 2002; Koster, 2004; Lazzaro, 2004; Malone, 1981; Read et al., 2002), and others proposing methods for augmenting or optimizing entertainment value in games (e.g. Yannakakis, 2008; Yannakakis and Hallam, 2004b, 2007b, 2009).

The presentation "Why we play games" (Lazzaro, 2004) states that there are four keys to making a fun game: "Hard Fun", in which the joy of overcoming difficult challenges drives the player; "Easy Fun", where immersion into the game world is more important than challenge; "Altered States", in which the game elicits some change of the player's internal state; and "The People Factor", where the social aspect of the game adds to, or creates, the entertainment. These could be used as loose measures of how fun a game is, and to whom it appeals, by quantifying the amount each of these keys are exhibited in the game. These views are echoed and expanded heavily upon by Federoff (2002), which mostly comments on the first two keys, as "challenge" and "immersion".

A related view, as argued by Yannakakis and Hallam (2004a,b), is that interactive or interesting opponents is the key to making fun games, and the key to having interesting opponents is for them to adapt to the player, so that the player doesn't get to a point where the AI is too simple for them. The key to doing this, it's argued, is having a way of directly quantifying "fun".

As demonstrated in the reports, being able to do this quantification is important for being able to evolve "fun" AI offline. It is prohibitively difficult to make a fitness function for entertaining NPCs otherwise, as it is unreasonable to expect to be able to have a player play against every new individual and rate the AI's fitness.

The method utilized in the reports is to pit the evolved NPCs against a sampling of pre-programmed AIs standing in for the player, and then using a quantification formula of the NPC's interestingness and difficulty as the fitness function or "measure of fun".

2.6   Making entertaining NPC

As noted in the section 2.5, one of the primary factors in a game NPC's entertainment level is realized by having them be "interactive" opponents. In that vein there is some work on increasing how human-like game AI is behaving, as a way of increasing entertainment value, which involves planning behaviours, anticipation, learning and adapting (Orkin, 2003, 2004; Spronck, 2005; Yannakakis and Hallam, 2009), as described in previous sections.

There is an approach called character-based AI collecting many of these techniques (Isla and Blumberg, 2002), which is gaining grounds in the game industry as a way to give the game's AI agents a reasonable facsimile of human behaviour and personality, or a "character", to make game opponents and allies more entertaining. The term is applied to AI which collect many techniques and behaviours that make the AI seem more human, like the aforementioned planning, learning and adapting, but also the ability to sense patterns, the ability to anticipate, and a certain model of the AI actor's perception that limits its available information to a more "realistic" amount.

Another way of making NPCs more entertaining is by having them present a constant challenge to the player, without them being too challenging. One way of doing this is having the NPCs utilize Reinforcement Learning (Merrick and Maher, 2006; Sutton and Barto, 1998) to present a continuously learning opponent. Another is to use one of the methods of difficulty scaling to present different NPC opponents that correspond to the player's skill level, a technique already utilized in

many games at various levels of sophistication.

Another possible way of increasing an NPC's entertainment level is by increasing the NPC's inter-estingness by making them act in interesting ways by way of automatic programming. This method would utilize offline learning, and possibly online learning, to generate NPC behaviours that would create a more interesting experience. This method has been described by Yannakakis (2005), and is going to be described in more detail in Section 2.10.

2.7 Inductive Programming

As noted in section 2.2.3, ADATE (Olsson, 1995) fits into a sub-field of Artificial Intelligence called Inductive Programming, which is actually a field recently emerging from being fragmented across Inductive Logic Programming, Genetic Programming, and Machine Learning (Kitzelmann, 2010).

2.8 Introduction to Inductive Programming

As described by Approaches and Applications of Inductive Programming (AAIP, 2010), the aim of Inductive Programming is to create programs based on incomplete specifications. These specifica-tions are given in the form of a set of inputs with matching outputs or an output evaluation function that are used to evaluate a generated program's fitness. This is opposed to Deductive approaches which start with a high-level description of the wanted system, then have the system generate code that matches the description.

The biggest difference between the two approaches is that the Deductive approach guarantees that a solution is correct, although it requires the problem to be well-understood and a specification to be written, whereas the Inductive approach does not guarantee a fully correct solution, but only requires input and output data to create its solution.

To help guide it towards an acceptable solution the Inductive Programming system can also take other inputs in their specifications, in the form of constraints on efficiency and complexity; back-ground information about data types, functions available for use in the generated code and informa-tion about the flow of the intended program; heuristics or bias to guide the system towards a certain solution. These are, however, not required.

As my thesis will be using the ADATE system, I will be explaining the details of Inductive Programming in context of the ADATE system, as described in Olsson (1994) and Vattekar (2006).

2.9   The ADATE system

ADATE's approach to Inductive Programming, formally named Evolutionary Inductive Programming (Crossley et al., 2009), applies evolutionary computing to the problem of making computer programs and the units which are manipulated (the "genes" if you will) are computer code operations. Apart from that, the process which is followed is very much like the one described in the previous section about evolutionary computing (section 2.2.3).

All Inductive Programming system generate code in a specific programming language, usually simplified or streamlined for the purpose, and ADATE is no exception. It uses a subset of Standard ML, called ADATE-ML, for its generated code, as well as for parts of its specification.

As mentioned before, all Inductive Programming systems make use of a specification with the input and output necessary to frame the problem. ADATE's specifications only make use of an output evaluation function, it does not support, out of the box, the simpler variety of matching input data with output data, although it is trivial to write an output evaluation function that works in such a manner. ADATE also requires an initial program to be part of its specification, although this program may be as simple as an empty function, as the method it uses to generate programs is a form of local optimization, in which a program is continuously improved to find better and better solutions.

ADATE's specification is written in two parts, one in ADATE-ML and the other in Standard ML, separated by a "*%%*" token.

The ADATE-ML part contains three different things:

1. Definitions of data types and functions that can be used by the code that is generated by ADATE.

2. The initial program, called f, that the ADATE system will start from and improve, which takes the inputs and returns an output.

3. A function $main$ which is called by the ADATE's evaluation cycle, and can provide a scaffolding or a context around f. This comes in handy if f is supposed to be a small part of

a larger program, but the performance of the program is dependant on the performance of $main$ itself, which may call f several times (perhaps not a constant or determinable amount) during its execution.

The Standard ML part of the specification can contain any user supplied code that might be used as part of the evaluation, but must define a certain set of callbacks that are called by the ADATE system. These callbacks define things such as the input data, any validation inputs, the set of functions that should be available for generated code, the evaluation function, the parameters governing amount and complexity of generated individuals, and other minor things (consult Vattekar (2006, sect. 4.2) for details).

As ADATE is an evolutionary system, it uses the same general process as other genetic systems, being that of a cycle of procreation, evaluation and culling in the search for ever improving performance. These steps will now be described as they apply to ADATE.

The process of creating new individuals in ADATE functions like most other Evolutionary Computing solutions, in that it utilizes both mutation and genetic crossover (albeit only in a limited fashion). When ADATE creates a new individual it starts out with an individual from the "kingdom" existing individuals (which at the beginning is only one program), then applies a series of transformations called "compound transformations" to create the new individual.

The six basic transformations available for use by ADATE are as follows:

R is the only transformation that can actually change the semantics of a program, and it does this by replacing a part of the program with a new synthesized expression.

REQ is an R transformation that is guaranteed to not make the program worse.

ABSTR abstracts a piece of the program out into a separate function which can then later be reused by the program in several places.

EMB updates an existing function by adding a new parameter to it, and updates all calls to the function to take into account the new parameter.

CASE-DIST rearranges code within $case$ and let expressions in a way such that semantics are preserved.

Crossover takes a series of REQ transformation and treats them as alleles in a genetic recombination.

The individuals are then evaluated by running the evaluation function specified in the specification file on $main$, using the current individual as f, over all the examples given. The evaluation value from this function is then used to compute a few values regarding the individual's performance (among others the time it takes to run and the complexity of the program).

If the individual evaluates better than any of the solutions currently in the kingdom, the evaluation value is then used to group the individual with others of similar performance in the kingdom. The kingdom is then culled by removing the lowest ranked individual. The process then continues by creating a new individual from the same base individual as before, until a given time limit is elapsed, at which point a new base individual is chosen.

This loop continues forever until the program is halted and output is written to disk while the program runs. This output shows the current state of the system and the current best individuals, along with their code. By evaluating this output, the user of the system can decide if a good enough solution has been created, or if the system needs to be stopped for other reasons.

2.10   Evolving Game AI

Using evolutionary techniques for game AI is not an entirely new topic, although doing it with the goal of creating entertaining or fun AI is a more recent development. The major body of research on this topic focuses on evolving an agent that can successfully play a game, or execute certain maneuvers, in a human-seeming manner.

Much of the research on evolution in game follows the research on learning in games, by focusing on First Person Shooter games, in particular well-known ones with good facilities for creating "bots". Examples of such research include using evolution to tune the parameters given to a bot for the game *Counter Strike* (Cole et al., 2004), using evolution to teach a bot to do rocket jumps and dodge fire in an unspecified game (Champandard, 2003).

Other research on using evolution to create game AI, using other kinds of games, include the use of evolution to create an AI to play the RTS game *WARGUS* (a *WarCraft II* clone implemented in the *Stratagus* engine) (Spronck et al., 2004). Another example is the use of an ice hockey environment to explore evolutionary learning (Blair and Sklar, 1999). There are a couple pieces of research on using online co-evolutionary methods against human players over the Internet, using the game Tron (Funes and Pollack, 2000; Funes et al., 1998). In addition, there has been research into using offline

and online co-evolution with action games (Demasi and Cruz, 2003).

There does not exist much research on evolving game AI with the express purpose of creating entertaining NPC behaviour, as most of the body of work on evolving game AI focuses on creating human-like behaviour. Of course, as Bauckhage et al. (2003) states, one component of human-like behaviour is to be unpredictable, which is a component of interesting or entertaining NPCs, as noted in section 2.5.2. It all comes down to how you define "human-like", a definition that could be either as simple as "seems to exhibits intelligence" or one that requires having an agent that simulates most human traits and capabilities to learn and adapt well enough to pass a Turing test. No matter how you define it, however, the majority of existing research use fitness functions that do not specifically test for entertainment value or interestingness.

One body of work that does explore this specific topic is the work of Georgios Yannakakis, in collaboration with John Hallam, who wrote his PhD dissertation (Yannakakis, 2005) on this topic. He has also authored a few articles regarding this and related topics, such as on how to measure and quantify entertainment (Yannakakis, 2008; Yannakakis and Hallam, 2007a; Yannakakis et al., 2008), how to use these models to increase a player's satisfaction with a game (Yannakakis, 2008; Yannakakis and Hallam, 2009) and of course further articles regarding the use of evolution in creating games (Yannakakis and Hallam, 2004a,b).

Chapter 3

Methodology

This chapter presents the methodology used to complete the aims of the thesis, primarily the use of inductive programming, via ADATE, to evolve interesting game opponents. With that in mind, we describe a prototype game to be used for simulation and the learning method in detail. In addition, we will briefly cover the simulation platform (ADATE).

3.1 The Dead End Game

The simulation environment we will be using is an adapted version of the Dead End computer game used in Yannakakis (2005), a predator-prey game where the player (the prey) has to reach the goal before being captured by a group of opponents (the predators). This game environment is sufficiently simple that it's easy to model, but also sufficiently complex and dynamic to provide a good basis for using evolutionary techniques to create interesting AI strategies. The game will be considered from the viewpoint of the opponents (the predators) in an attempt to evolve characters that exhibit the ability to cooperate based on partial information, with the capability to play effectively against a player following a fixed strategy.

3.1.1 Game Description

In this section we will describe our implementation of the Dead End game in sufficient detail to give a good understanding for how it works, as well as in which ways it differs from the reference

implementation. (see Yannakakis, 2005, Chap. 5)

The game is played on a two-dimensional field of size 16cm x 16cm (while we use the unit cm to refer to the units within the game, this is purely for convenience and is a completely virtual unit with no physical correspondence), with a rectangular area at the top representing the goal . The characters in the game are the player character, named *'Cat'*, represented as a circle of radius 0.75 cm, and an arbitrary number of enemy characters, named *'Dogs'*, represented as squares of dimension 1.5 cm.

The aim for the Cat is to reach the exit from its starting position, situated randomly at the bottom of the map, by avoiding the Dogs or to survive until the end of the simulation, i.e. after a certain amount of simulation steps. On the other hand, the aim of the Dogs is to capture the Cat before it reaches the exit or the simulation ends.

Since there are more Dogs than there are Cats on the playing field, they are given a handicap to even the playing field. In our implementation, the Cat moves at a fixed rate of 2 cm per simulation tick, while the dogs move at $3/4$ that speed (1.5 cm per simulation tick). In addition, it is important to note that the Dogs have the property of permeability, i.e. they can occupy the same space as other Dogs. Given the speed handicap the Dogs have, it is impossible for a single Dog to catch the Cat, so the Dogs must cooperate to trap and catch the Cat. This is where the opportunity arises for emerging interesting AI behaviour.

At the beginning of the game the characters are positioned so they are sufficiently spaced out. As mentioned, the Cat starts at a random position flush with the bottom of the field, whereas the Dogs start at a random position in the upper half of the playing field.

Then, for each simulation tick, the following happens:

1. All entities (Cat and Dogs) in the game gather information from the playing field, run their AI routine, and produces a movement decision: up, down, left, or right.

2. All entities are moved according to their movement decisions.

3. The field is checked for any collisions. If there are any, the game is marked as over, and the win condition is checked. If the Cat has collided with the goal, the game is considered won, if any of the Dogs collided with the Cat, the game is considered lost, and if both occurs the tie is broken by considering the game won. (The Cat narrowly escapes, with a suspiciously teeth-shaped mark)

4. If the game is not over yet, but the amount of simulation ticks is greater than 50, the game is considered over and won.

5. If the game is over, a new game is started with a new random cat position, but the same dog positions.

Should we do this?

3.1.2 The Cat

To be able to evolve good behaviour for our characters (the Dogs), it is necessary to have a competent player character, as the behaviour of the Dogs is strongly related to the behaviour of the player character. As it isn't feasible to provide the player character with human input during the simulation process, it is necessary to provide one or more strategies for the player to execute in an attempt to reach its goal. For the Dogs to be capable of diverse behaviour it is preferred to have several behaviour for the player, so in our case we have implemented two fixed strategy behaviours for the Cat.

These strategies are implement as AI functions which take as input a complete state of the field containing the following:

Maybe a list like this is overkill?

Self The (x, y) coordinates of the current Dog.

Cat position The (x, y) coordinates of the Cat.

All Dogs A list of the (x, y) coordinates of all the Dogs.

Goal position The (x, y) coordinates of the Goal.

and produce as its output a movement direction: left, right, up, or down.

Exit-Achieving Cat

This is a very simple Cat behaviour. It simply chooses the movement direction that reduces the coordinate which has the greatest relative direction from the Goal. (If the Goal has position $(8, 1)$ and the cat has position $(7, 10)$, the Cat would choose to move up, as the Y direction has the biggest difference)

Potential Field-Based Cat

This is a more complex and efficient Cat behaviour based on a Artificial Potential Field (APF), where the cat is attracted or repelled by objects in the playing field, and moves along the path of least resistance towards the Goal. The implementation is heavily based on the one in Yannakakis (2005, Chap. 5.1.1.3) and considers points along the path to the Goal as attractive, and the Dogs as strongly repulsive.

The overall effect of the forces on the field gives the cat a map of movement costs by plotting the function $C(x, y)$:

$$C(x, y) = \Delta_E(x, y) + D(x, y) \tag{3.1}$$

$$\Delta_E(x, y) = \sqrt{(x_e - x)^2 + (y_e - y)^2} \tag{3.2}$$

$$D(x, y) = \sum_{i=1}^{N} \frac{\rho}{|x_{d,i} - x| + |y_{d,i} - y|} \tag{3.3}$$

where N is the number of Dogs, (x_e, y_e) is the center of the Goal, $(x_{d,i}, y_{d,i})$ is the center of the ith dog, ρ is the cost of a dog in the APF (which in our implementation is 1000, as it is in the reference implementation).

This field allows the Cat to select the direction that will incur the lowest costs by plotting $C(x, y)$ at 0.5 cm intervals for 2 cm in each movement direction from the Cat's center coordinate, computing the average cost of moving in that direction, and selecting the direction with the lowest movement cost.

This strategy is intended to represent a very good strategy for the Cat, on level with the performance of a Human player, and as such is well suited as a surrogate for a human player in the simulation.

3.1.3 Inducted Dogs

This point marks the biggest deviation from the reference implementation, which utilized Dogs controlled by Feed-forward Neural Networks. (Yannakakis, 2005, Chap. 5.1.2) Our dogs will instead be controlled by a Standard ML function synthesized via ADATE. This function will accept input

similar to the input given to the the neural network described in the reference implementation, and produce similar output.

Input

The input to the Dogs AI function is a snapshot of the state of the field with the following values:

Self The (x, y) coordinates of the current Dog.

Cat position The (x, y) coordinates of the Cat.

Nearest k dogs A list of the (x, y) coordinates of the k closest dogs.

Goal position The (x, y) coordinates of the Goal.

Take notice that the Dogs do not have access to the position of all the dogs in the field, but only the nearest k dogs, this places limitations on how closely they can cooperate.

Output

The output is the Dog's chosen movement direction: left, right, up, or down.

3.2 Experiment

3.2.1 Specification

3.2.2 Testbed

Chapter 4

Results

Chapter 5

Discussion

Chapter 6

Discussion, Future Work and Conclusions

Wrap up (in separate sections, or integrated in one final section):

Discussion Explain in the discussion section of your document information presented in the results section, commenting on significant data and experience produced by the study.

Conclusions Include a conclusion as the final part of the body of your document. Because some readers of documents, particularly managers, will sometimes not read the entire document but, instead, focus on the conclusion, this part of the document should summarize all essential information necessary for your audience's purpose. In your conclusion:

- Relate your findings to the general problem and any specific objectives posed in your introduction.

- Summarize clearly what the report does and does not demonstrate.

- Include specific recommendations for action or for further research. Sometimes these recommendations will constitute a separate section of a document.

Recommendations Include appropriate and specific recommendations as part of your conclusion or, in feasibility and recommendation reports, as a separate section preceding the conclusion.

Many types of scientific and technical documents conclude by pointing to further action. Research reports often recommend further studies to confirm tentative explanations or to answer

questions presented in the discussion section. Feasibility and recommendation reports always have one or more specific recommendations as the principal aim of the document.

Recommendations should always be specific and appropriate to the document's audience. Separate each specific recommendation. Often authors present recommendations in bulleted or numbered lists. Organize recommendations either in the order of importance or in the logical order of development.

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