Abstract

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Chapter 1

Introduction

Procedural generation of game (PCG) content has become a widely used tool for video-game developers. Automatically generating content allow game developers to provide more content, with more differentation, from a limited supply of assets, most often by helping to produce levels, maps or dungeons for their games. Additonally PCG is often used to maintain a challenge for the player by presenting an unpredictable and renewed game experience on re-playing the games in which it is used. Rogue [1980] is one of the earliest examples on proceduraly generating game levels (or dungeons). Several highly popular games has since used procedural level generators, some as a main part of their game-play (The Seven Cities of Gold [**?**], Civilazation II(-V) [**?**], Minecraft [2011], Spelunky [2009] and many others), while other has used PCG tools to create finished levels (Rescue on Fractalus! [**?**], Farcry 2 [**?**]. PCG has also been used to create a wider array of weapons and items (Borderlands-series [**?**], Diablo-series [**?**], Torchlight-series [**?**], Dark Age of Camelot [**?**]), or event to create graphical or audio assets (RoboBlitz [**?**], .kkrieger [**?**]).

1.1 Introduction to game generation

An interesting next step to take is to not only generate content for games, but generate the games themeselves. A way to generate complete games might be to search through a space of games represented in a programming language like C or Java. However, the proportion of programs in such languages that can in any way be considered a game is quite small. Increasing the density of games in the search space can be achieved by searching programs defined in a a game description language (GDL) designed to encode games.

Even searching a reasonably well defined space of games still supposes that we have a way of automatically telling good games from bad games (or not-quite-so-bad games from really bad games). In other words, we need a fitness function. Part of the fitness function could consist in inspecting the rules as expressed in the GDL, e.g. to make sure that there are winning conditions which could in principle be fulfilled. But there are many bad games that fulfil such criteria. To really understand a game, you need to play it. It seems the fitness function therefore needs to incorporate a capacity to play the games it is evaluating.

1.2 Research Objectives

The main objectives of this study was to create a generator being able to create simple games and levels, enjoyable for human players. The focus of the study was to create fitness functions able to differentiate between games (and levels) of different quality, to be able to create interesting content. Making the generator able to create a large amount of games, and then select the ones with the highest quality.

1.2.1 General Evaluation - Arcade-/Action Games

The first goal was to use the results of a series of general game-playing (knowledge free) algorithms to value a given game.

1.2.2 Breadth First Search - Puzzle Games

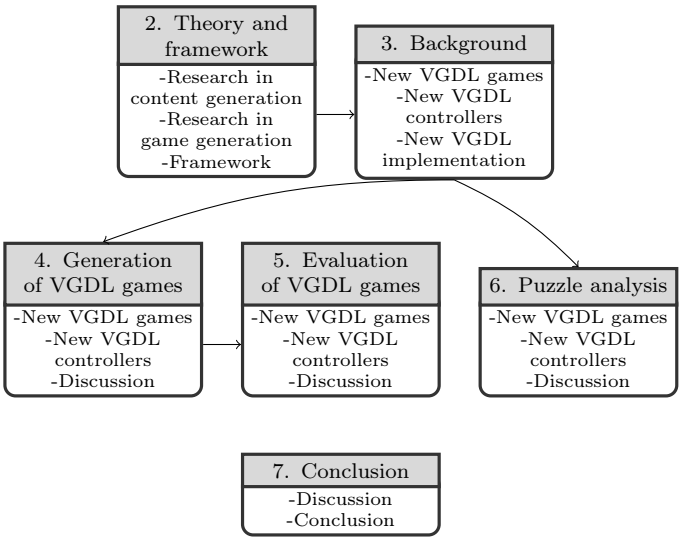
The second goal was to

1.2.3 Assumptions

We assume that the games metioned are of high quality (i.e. highly enjoyable for human players). This is not always clear when playing the games in their form, since they need crucial element to keep a game fun: Audio, graphic effects, control-scheme fiiting to the games. We reason this because they are clones of existing games.

1.3 How to read this thesis

In the following chapters the research goals are being fulfilled. The figure below shows the structure of the thesis, explaining how each chapter fits in to the larger picture:



Chapter 2

Existing research and framework

In this chapter we describe the existing research on the topic of procedural content generation (PCG) for games, and specifically game- and level-generation, which is of relevance to the project. Additionally the framework used for game- and level-generation, and testing is described thoroughly.

2.1 Content generation

Before discussing generation of complete games, the research on procedural content generation (PCG) for games are investigated. The task of PCG is to create elements for specific parts of a game, for instance levels, weapons, environments, textures and sounds. Hendrikx et al. [2013] proposes a layered taxonomy to describe PCG of different depths in games, while performing a survey of different ways in which PCG has been implemented in commercial games, noticing that some layers has not been thoroughly explored.

Several different approaches are used in PCG (both in commercial games and in research), however the "search-based" approach (explored by Togelius et al. [2011], Nelson et al. [2014a]) dominates the problem. In search-based generation a *fitness function* is used to score generated content by their quality, making it possible to ensure a high quality of the generator, by either simply generating a large amount of content and choosing the best, or using an evolutionary strategy to evolve better content.

2.1.1 Game-level generation

Almost all video games are highly dependent on designed level or map (or levels/map) in which the game play takes place. Levels are often responsible for creating increasingly challenging situations, and thereby entertaining game play. Super Mario would be way less interesting if enemies and platforms were spread randomly across each level, which would almost certainly result in the game being ether too easy or too difficult.

In recent years, game developers have begun using automatic generation of game-levels, to decrease the human work-load while still creating interesting content for games. Using PCG for creating "dungeon"-type maps have long been a successful endeavor for certain type of games as seen in *Rogue* [1980], the *Diablo*-series, and in newer times *Minecraft* [2011] and *Spelunky* [2009]. PCG were additionally successfully implemented in strategy games like "Civilization II", "Command & Conquer: Tiberian Sun" and "XCom: UFO Defense", but otherwise automatically generating levels have not been hugely successful in other game genres.

Several scientific projects have focused on the topic as well with an array of different approaches, some requiring player-input, or simply a helper for human level-designer. In addition to the other game genres mentioned above, a lot of work has been done in generating levels for puzzle games (ie. Sokoban and Cut The Rope). Most of the work is focused on generating levels for single game, where some attempt to create general level generation procedures.

2.1.2 Other uses of PCG

Other games have been published applying PCG in different ways. In *Borderlands 2* [2012] the player have access to an extreme amount of different weapons, designed by automatic generation.

2.1.3 Advantages and disadvantages using PCG

Having a procedure for generating content in games has a number of advantages:

- Content generation allows games to potentially have an endless amount of possibilities, often resulting in higher re-play value than linear games.
- PCG can help game designers generate game levels, often simply by letting the designer explore possible layouts, add decorations or finishing up human-designed levels.

PCG also has some problems for generating content for levels:

- Generated content can have a feeling of being unauthentic and/or too random. For instance, the positions of decorations in a level (barrels, paintings etc.) can be important for humans, while they are not for computers.
- In games where the player follows a story it can be difficult to automatically generate levels, that follow what the game designer intend to happen

2.2 Game generation

Generating complete games through algorithms is a problem that is being increasingly researched, but work has been done on the topic for last decade. Because the problem is in general quite large, a subset of the problem is usually handled: Only generating certain types of games-, or using different (restricted) frameworks. Video games may consist of a large number of tangible and intangible components, including rules, graphical assets, genre conventions, cultural context, controllers, character design, story and dialog, screen-based information displays, and so on Cook and Colton [2014], Liapis et al. [2014], Nelson and Mateas [2007].

In this project we look specifically at generating the game-play and -setting of games, i.e. defining a set of game-rules and -objects, and specifying the levels in which the game-play takes place. The two main approaches that have been explored in generating game rules are reasoning through constraint solving Smith and Mateas [2010] or search through evolutionary computation or similar forms of stochastic optimisation Togelius and Schmidhuber [2008], Browne [2008], Font et al. [2013]. In either case, rule generation can be seen as a particular kind of procedural content generation Nelson et al. [2014b].

It is clear that generating a set of rules that makes for an interesting and fun game is a hard task. The arguably most successful attempt so far, Browne's Ludi system, managed to produce a new board game of sufficient quality to be sold as a boxed product Browne [2008]. However, it succeeded partly due to restricting its generation domain to only the rules of a rather tightly constrained space of board games. A key stumbling block for search-based approaches to game generation is the fitness/evaluation function. This function takes a complete game as input and outputs an estimate of its quality. Ludi uses a mixture of several measures based on automatic playthrough of games, including balance, drawishness and outcome uncertainy. These measures are well-chosen for two-player board games, but might not transfer that well to video games or single-player games, which have in a separate analysis been deemed to be good targets for game generation Togelius et al. [2014]. Other researchers have attempted evaluation functions based on the learnability of the game by an algorithm Togelius and Schmidhuber [2008] or an earlier and more primitive version of the characteristic that is explored in this paper, performance profile of a set of algorithms Font et al. [2013].

A typical approach for generating complete games is searching in a space of possible games. This basically requires two things: That the ratio of enjoyable games in the set is not too low - otherwise those games might never be found. To increase this ratio a game description language (GDL) is often used (searching through all possible Java or C programs would lead to an enormous amount invalid games). Also, to search through a set of games it is necessary to be able to calculate a fitness value for each game, valuing how enjoyable the game is.

2.2.1 Analyzing games using performance profiles

A large amount of games contain puzzle-elements, but only a few has puzzles as the main game-play.

2.2.2 Something to note: Levels

The problem of generating complete games is heavily linked to the problem of generating levels since most games are deeply tied to the geometry and object-placement defined in levels. A part of the success of Ludi stem from the fact that levels (boards) were as much in focus, as the game-rules themselves.

2.3 Framework: VGDL and the GVG-AI framework

Regardless of which approach to game generation is chosen, one needs a way to represent the games that are being created.[1] For a sufficiently general description of games, it stands to reason that the games are represented in a reasonably generic language, where every syntactically valid game description can be loaded into a specialised game engine and executed. There have been several attempts to design such GDLs. One of the more well-known is the Stanford GDL, which is used for the General Game Playing Competition Genesereth et al. [2005]. That language is tailored to describing board games and similar discrete, turn-based games; it is also arguably too verbose and low-level to support search-based game generation. Another attempt at an VGDL is called PuzzleScript, created by game designer Stephen Lavelle. The language (as its name suggest) is focused on turn-based puzzle games, but the engine allows for simple forms of animation and movement. The language is relatively high level compared to Stanford GDL, but does not support that large set of video games.

2.3.1 VGDL game description

The various game generation attempts discussed above feature their own GDLs of different levels of sophistication; however, there has not until recently been a GDL for suitably for a larger space of video game types- and genres. The Video Game Description Language (VGDL) is a GDL designed to express 2D arcade-style video games of the type common on hardware such as the Atari 2600 and Commodore 64. It can express a large variety of games in which the player controls a single moving avatar (player character) and where the rules primarily define what happens when objects interact with each other in a two-dimensional space. VGDL was designed by a set of researchers Levine et al. [2013], Ebner et al. [2013] (and implemented by Schaul Schaul [2013]) in order to support both general video game playing and video game generation. In contrast to other GDLs, the language has an internal set of classes, properties and types that each object can defined by, which the authors suggest the user to extend.

Objects have physical properties (i.e. position, direction) which can be altered either by the properties defined, or by interactions defined between specific objects. Playing the games also required a specified level which defines a set of game-tiles deciding the initial locations of sprites. When running games sprite can move in between game-tiles (if the **speed** is a fraction).

A VGDL description has four parts:

SpriteSet Defines which sprites can appear in the game. Each sprite must be designated by a class, in which a set of predefined actions exists. Also a set of parameters can be fed to each sprite, configuring for instance the speed or how often the sprite takes an action, and the parameters used for the different sprite-classes – for instance, for the class **Flicker** (a simple extension to the base sprite, the sprite is destroyed after a speecifed amount of time) the lifetime can be adjusted. Sprites can additionally be designed in a tree structure, where multiple sprites have the same parent sprite, making more possibility for the interactions and terminations described below.

InteractionSet Each line defines what happens when a set of two sprites collide with each other (located on the same game-tile). Each interaction is represented by a class defining the action to take (i.e. push back, or kill sprite), and a set of parameters specific to each interaction-class, as well as the score achieved for letting the interaction happen.

[1] See Nelson et al. [2014b] for a discussion of game-rule representation choices.

TerminationSet Defines how the game can end. Each line in this set has a win parameter, which is set to true or false; winning or losing the game. Each termination-function is represented by a class defining under which conditions the game should end, which can for instance when there exists 0 of a certain sprite (when all of the sprites are killed).

LevelMapping The job of the `LevelMapping` is to translate from a character (`char`) in a level-file (explained below), to sprites from the `SpriteSet`. A single mapping can be shared by several sprites, causing the sprites to be created on the same game-tile.

```
1  BasicGame
2    SpriteSet
3      city  > Immovable color=GREEN img=city
4      explosion > Flicker limit=5 img=explosion
5      movable >
6        avatar  > ShootAvatar stype=explosion
7        incoming >
8          incoming_slow  > Chaser stype=city color=ORANGE speed=0.1
9          incoming_fast  > Chaser stype=city color=YELLOW speed=0.3
10
11   LevelMapping
12     c > city
13     m > incoming_slow
14     f > incoming_fast
15
16   InteractionSet
17     movable wall  > stepBack
18     incoming city > killSprite
19     city incoming > killSprite scoreChange=-1
20     incoming explosion > killSprite scoreChange=2
21
22   TerminationSet
23     SpriteCounter stype=city    win=False
24     SpriteCounter stype=incoming win=True
```

Figure 2.1: Example of VGDL description - a simple implementation of the game Missile Command

Additionally each game can only be played using level files. A level file is written using the `LevelMapping` characters, where each character defines a tile of the game, and spaces defines empty tiles.

```
1  w     m   m    m   m   m m mw
2  w                          w
3  w                          w
4  w                          w
5  w                          w
6  w                          w
7  w            A             w
8  w                          w
9  w                          w
10 w                          w
11 w   c c c c c c c c        w
12 wwwwwwwwwwwwwwwwwwwwwwwww
```

Figure 2.2: Example of VGDL level description - a level for the implementation of the game Missile Command

2.3.2 GVG-AI: AI controllers and testing

The GVG-AI framework is a testbed for testing general gameplaying controllers against games specified using VGDL. Controllers are called once at the beginning of each game for setup, and then once per clock tick to select an action. Controllers do not have access to the VGDL descriptions of the games. They receive only the game's current state, passed as a parameter when the controller

is asked for a move. However these states can be forward-simulated to future states. Thus the game rules are not directly available, but a simulatable model of the game can be used.

GVG-AI example games

The framework additionally contains 20 hand-designed games, which mostly consist of interpretations of classic video games. Figure 2.2 shows the VGDL description of the game *Missile Command*. Most of the games are inspired by classic arcade- and Atari games (e.g. Boulderdash, Frogger, Missile Command and Pacman), while some are original creations by the General Video-Game AI Competition's organizers. The games can in general be described (except for *Sokoban*) as action arcade games, in that the player controls a single avatar which must be moved quickly around in a 2D-setting to win, or to get a high score (the player is able to increment a score counter in all of the games).

Below is a short summary of each of games, describing the winning conditions, and how the player can increase his/her score:

Aliens VGDL interpretation of the classic arcade game *Space Invaders*. A large amount of aliens are spawned from the top of the screen. The player wins by shooting all the approaching aliens.
Goal Destroy all the incoming aliens, without being hit by them or their projectiles.
Scoring Destroy all the incoming aliens, without being hit by them or their projectiles.

Boulderdash VGDL interpretation of *Boulder Dash*. The avatar has to dig through a cave to collect diamonds while avoiding being smashed by falling rocks or killed by enemies.

Butterflies The avatar has to capture all butterflies before all the cocoons are opened. Cocoons open when a butterfly touches them.

Chase About chasing and killing fleeing goats. However, if a fleeing goat encounters the corpse of another, it get angry and start chasing the player instead.

Digdug VGDL interpretation of *Dig Dug*. Avatar collects gold coins and gems, digs his way through a cave and avoid or shoot boulders at enemies.

Eggomania VGDL interpretation of *Eggomania*. Avatar moves from left to right collecting eggs that fall from a chicken at the top of the screen, in order to use these eggs to shoot at the chicken, killing it.

Firecaster Goal is to reach the exit by burning wood that is on the way. Ammunition is required to set things on fire.

Firestorms Player must avoid flames from hell gates until he finds the exit of a maze.

Frogs VGDL interpretation of *Frogger*. Player is a frog that has to cross a road and a river, without getting killed.

Infection Objective is to infect all healthy animals. The player gets infected by touching a bug. Medics can cure infected animals.

Missile Command VGDL interpretation of the classic arcade game *Missile Command*. Player has to destroy falling missiles, before they reach their destinations. If the player can save at least one city, he wins.

Overload Player must get to the level after collecting coins, but cannot collect too many coins, as he will be too heavy to traverse the exit.

Pacman A VGDL interpretation of *Pac-Man*. Goal is to clear a maze full with power pills and pellets, and avoid or destroy ghosts.

Portals Objective is to get to a certain point using portals to go from one place to another, while at the same time avoiding lasers.

Seaquest VGDL interpretation of *Seaquest*. Avatar is a submarine that rescue divers and avoids sea animals that can kill it. The goal is simply to a high score.

Survive Zombies Player has to flee zombies until time runs out, and can collect honey to kill the zombies.

Whackamole VGDL implementation of the classic arcade game *Whac-a-Mole*. Must collect moles that appear from holes, and avoid a cat that mimics the moles.

Zelda VGDL interpretation of *Legend of Zelda*. Objective is to find a key in a maze and leave the level. Player also has a sword to defend himself against enemies.

Camelrace Player needs to get to endpoint to win.

Sokoban The objective is to move the boxes to holes, until all boxes disappear or the time runs out.

2.3.3 Restrictions of VGDL

The VGDL implementation of the GVG-AI competetion is essentially (without great extension) only able to describe certain action-arcade games, and puzzle games. For instance, the lack of possibility to traverse different levels make **Adventure** games impossible to make, and the restriction of only being able move a single character with the keyboard (the avatar) makes great restriction in creating **Strategy** games.

In this project we will focus on the two main type of games describable in VGDL: Action-arcade games and turn-based puzzle games. We make the simple distinction that arcade games contain elements (sprites) that move by themselves, whereas interactions only occur as a result of the avatar moving in puzzle games. This puts the game *Portals* in the arcade genre, even though it contains puzzle elements.

Chapter 3

Extending VGDL

We created a series of extensions to VGDL during the project.

3.1 Writing new VGDL games

To increase the size of the set of designed games, and to allow for more precise analysis we created a series of fourteen new game descriptions in VGDL.

Another important reason for creating new descriptions, was to introduce a series of *puzzle games* to be analysed, since, as mentioned in Section 2.3.1 the example games from the GVG-AI competetion has a severe lack of that game-genre.

3.1.1 Describing existing games in VGDL

The main goal when developing a game - which also applies in this case - is to ensure that it is enjoyable to human-players. Therefore the games implemented are all interpretations of published existing games (and not original creations). As described in **Section 2.3.3** VGDL can only describe relatively simple games of certain type/genre, and so only a limited number of games can be translated without severely changing the game-play. The games are in general "exact" copies of the original ones - containing all the game-play features and interactions but lacking elements like audio, graphics and controls. However many lack certain (non-essential) game-play features like bonus point sprites, infrequently appearing enemies or features which only appear in some levels of the games.

3.1.2 Results

A series of fourteen commercial games was re-created in VGDL to be used in future tests. Figure 3.1 shows one of the games translated to VGDL. Minor changes to the GVG-AI framework was made for a small number of the games, to be able to correctly copy the games' gameplay features. The original game levels were additionally translated into VGDL level description, with five levels being created for each game. For some of games the levels could not be completely copied, for instance because the levels were too large in size (*Bolo Adventures*), or because a lack of game features implemented in the clones (*Chip's Challenge*), and the resulting levels are therefore simplifications of the originals..

Action-arcade games

A set of four Atari -arcade and -2600 games were found to be suitable for interpretation; *Solar Fox*, *Crackpots*, *Centipede* and *Astrosmash*, and a VGDL game description was written for each. A description of each of the games and their interpretations can be seen in Appendix B

Puzzle games

A set of puzzle games from several different platform, all featuring a single avatar, was found to be suitable to be described in VGDL. Several of these games can be described as *Sokoban*-clones

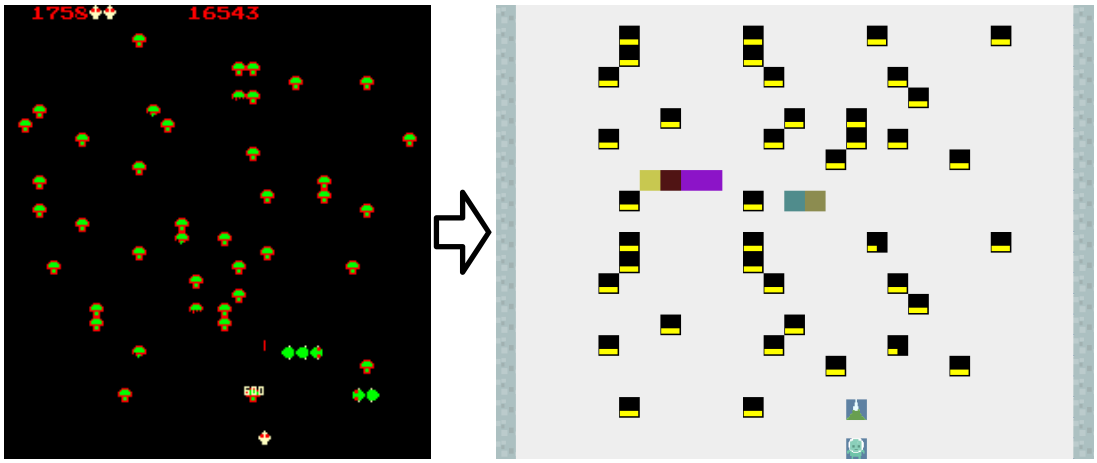


Figure 3.1: Interpretation of the classic arcade game *Centipede* [1983]

with different spins on the gameplay. The games interpreted were *Sokoban*, *Bait*, *Bombuzal*, *Bolo Adventures*, *Zen Puzzle*, *The Citadel*, *Brainman*, *Chip's Challenge*, *Modality* and *Painter*.

3.2 Creating new VGDL controllers

To be able to probe VGDL games in more detail, we created a series of new AI controllers with various approaches to finding a results. In total five new controllers was generated: Three to play the action-arcade style games, and two only focused on turn-based puzzle games.

3.2.1 Action-arcade controllers

Three controllers of an increasing degree of cleverness was introduced: *One-step* (least clever), *Deep-search* and *Explorer* (most clever). The controllers greatly differ in their strategy in simulating the forward model (accessible when running the GVG-AI framework) using different actions, and different series of actions.

One-step

The One-step AI only attempt to advance the forward model once, for each allowed action in the game. The score and win/lose state of the resulting game states are then considered, and the action with the resuling best state is chosen – and a random action is chosen when no state is better than others. The controllers approach can be seen below:

```
for action : PossibleActions do
    newGameState = gameState.copy().advance(action)
    value = newGameState.score
    if newGameState.gameEnded then
        value += newGameState.won ? 1000 : -100000
    end
end
return action leading to highest value
```

Deep-search

This controller starts out in a similar fashion as the One-step, by expanding using all possible actions by copying the initial game-state. However the resulting game-states are then continuosly explanded from.

Explorer

The Explorer was proven to be of a decent quality by getting a 2nd / 7th place in the GVG-AI competition.

3.2.2 Puzzle controllers

Breadth first

Best first

3.3 FastVGDL

Since the GVG-AI framework has some functions and properties which are not interesting for some parts of this work, we created an implementation of a lighter version of VGDL, solely focused on analysing puzzle games in more detail. The implementation is basically a clone of the GVG-AI framework, but with several time- and memory consuming features removed, which in part was possible due to the puzzle games being relatively more simple (for instance, only movement from one tile to another is possible in FastVGDL, whereas sprites can move and collide in-between tiles in the GVG-AI framework).

SMALL TEST SHOWING TIME AND MEMORY DIFFERENCE PL0X!!!

Chapter 4

Automatic generation of VGDL descriptions

This chapter describes the experimental- setup, and methodology used in generating VGDL descriptions. The chapter is focused on action-arcade games - puzzle games will be discussed and analysed in Chapter 6.

4.1 Automatic generation of VGDL descriptions

This section explain the setup used in generating new VGDL games (i.e. game descriptions). We used two different approaches in generating new game description in VGDL: Mutating existing (designed) games, and randomly generating games from scratch. In both approaches several constraints were set upon the generation process to prevent crashes, and to increase the chance of a human playable game.

4.1.1 Mutation of example games

A set of VGDL games were used to mutate new game descriptions, analysed in this section.

Designed arcade-action games

After our addition of new games to GVG-AI framework (Chapter 3) we have access to 34 games, with five levels each. However, only 23 of the games are of the arcade-action genre explored in this section. Additionally, as mentioned in Section 2.3.1 a few of the example games from the GVG-AI competition are original creations, which cannot equally be assumed to be human-enjoyable.

Thirteen interpretions of existing games are left, and used as a baseline for testing and game generation: Aliens, Boulderdash, Frogs, Missile Command, Zelda, DigDug, Pacman, Seaquest, Eggomania, Solar Fox, Crackpots, Astrosmash and Centipede

Generating approach

A process was built for mutating the different parts of game descriptions, i.e. changing the sprites available of the `SpriteSet`, the interactions rules (`InteractionSet`) and the termination rules (`TerminationSet`). The process additionally allowed for changing the amount of rules, i.e. generating new rules or removing existing ones.

Since the sprites and rules of each game description is described by both a class and a series of parameters, several partly subjective decisions was made on defining probabilities of different parameters' values to try reach "realistic" values. For instance it was decided that a sprite being mutated or generated only has a 25% chance of using the `cooldown` parameter (making sprites have pauses between acting), and that the parameter have a random value between 1 and 10. The values and probabilities used were mostly decided by examining the set of designed games descriptions. Several constraints were also used to avoid game with non-valid descriptions (which can cause crashes in the GVG-AI framework), for instance by ensuring that avatar-sprites cannot

be spawned and sprites cannot transform to an avatar, but an avatar sprite can still transform to another type of avatar sprite.

When testing mutated games the original games' levels were used. Therefore the amount of sprites and the `LevelMapping` was not changed.

4.1.2 Random game generation

A similar process a mentioned above was used to randomly put game descriptions together creating new games completely from scratch, constructing the textual lines for different parts of a VGDL description: Generating an array of sprites (for the SpriteSet), interaction-rules (InteractionSet), termination-rules (TerminationSet) and level mappings (LevelMapping). When generating descriptions, we used similar constraints to those mentioned in section 4.1.1, partly to avoid generating descriptions with invalid elements, and partly to increase the proportion of interesting outcomes. As for the mutated games, some partly subjective decisions were made on defining the possible amount of sprites and rules, the proportion of sprites that has a level mapping, and when generating new sprite definitions.

To simplify the sprite creation process, no parent-child structure was used in the `SpriteSet`. However, the goal of the parent-child structure is only to make rule definitions less verbose, and does not make actual new game features possible.

Level generation

As mentioned in Section 2.2.2 the problem of generating a game is more often than not intimately linked to a generation of levels.

A simple level generator were constructed with the simple goal of making the randomly generated games playable. The generator designates a level built using a given size, and inserts sprite mappings in different positions which takes all the level mappings from a game description and put a random (but small) amount of each sprite defined, in a random location(s).

4.2 Experimental setup and initial results

In this section we present a set of initial results from playing through both designed and generated games using different AI controllers, and discuss different ways to analyse the resulting data.

Controllers

Eight general videogame controllers were used to test the games. The controllers use different approaches, with a varying degree of intelligence. Four of the controllers are included in the GVG-AI framework, while the remaining were implemented for this work. Except for *OneStep-Heuristic*, the controllers only evaluate a given state according to its score and win/loss status. Each controller was marked with one of four types of intelligence for later tests: Intelligent (complex searches in game space are taken), semi-intelligent (game space search uses simple approach), random and do-nothing.

MCTS GVG-AI sample controller. "Vanilla" MCTS using UCT.

GA GVG-AI sample controller. Uses a genetic algorithm to evolve a sequence of actions.

OneStep-Heuristic GVG-AI sample controller. Heuristically evaluates the states reachable through one-step lookahead. The heuristic takes into account the locations of NPCs and certain other objects.

NoStepBackSearch Explained in Section 3.2.1. Marked as *semi-intelligent*

OneStep-Score Similar to *OneStep-heuristic*, but only uses the score and win/loss status to evalue states.

Random Chooses a random action from those available in the current state.

DoNothing Returns a nil action. Literally does nothing.

Explorer Design specifically to play the arcade-style games of the GVG-AI framework. Unlike the other controllers which utilise open-loop searches, it stores information about visited tiles and prefers visiting unvisited locations. Also addresses a common element of the VGDL example games, randomness. The controller gains an advantage by simulating the results of actions repeatedly, before deciding the best move.

Testing and result analysis

The eight controllers were used to play through different set of example-, mutated and randomly generated games. Because of CPU budget limitations, each game was played with a maximum amount clock ticks (values between 200-2000 was used), and each controller was restricted to use 50 ms on each tick. For each playthrough only the default data from the GVG-AI framework was retrieved: The score, the win-lose value, the amount of ticks and a list of actions performed.

A program to analyse the data was built, to calculate averages and std. deviations of each of the values, for each controller, with the possibility of caculating averages across several levels or games.

To more accurately compare the score for the different controllers when playing across a range of different games, we calculate a normalised score using a max-min normalisation. Normalised averages and win rate averages are shown in Figures **??** and **??**, respectively. In Figure **??**, it is possible to see that the difference between the highest and lowest scores is greater in the example and mutated games than in the generated games. On the other hand, the average win rate of generated games surpasses both examples and mutated games, as shown in Figure **??**.

In addition to the score and win-rate, the average entropy of actions chosen for the player avatar is shown in the tables below.

In the following sections, we show results of these tests, analyse the average of all play-throughs for each controller, and compare the results with each other.

4.2.1 Designed games

controller	*score mean*	*std.dev.*	*normalised-mean*	*winrate*	*act-entropy*
Explorer	15.36	30.53	0.8295	0.1011	0.9796
MCTS	5.76	10.48	0.5052	0.0389	0.9954
GA	4.76	7.90	0.5004	0.0189	0.8318
Onestep-S	7.17	16.55	0.4603	0.0161	0.9780
Onestep-H	−2.77	22.76	0.2985	0.0556	0.2632
Random	3.02	7.69	0.3136	0.0033	0.9997
DoNothing	−1.44	5.03	0.1630	0	0

Figure 4.1: Results from the 20 example games

Averages and win-rates from the 18 human-designed example games are shown in Figure 4.1. The distributions of normalised scores show that more intelligent controllers tend to have more success. It is worth noticing that the *score mean* and *normalised score mean* have slightly different orderings. Notice also that distributions are slightly different when analysing the results of individual games. For instance, in *Aliens*, Random has a higher average than Onestep.

4.2.2 Generated games

Figure 4.2 shows results for the 65 randomly generated games, with problematic games removed according to the same criteria as in the previous section.

First of all, *score std. deviations* are much higher than in the previous games, with the minimum being 199,406.58, over 1500 times larger than the highest in the set of example games (i.e. 121.55, by Explorer). Clearly, only the *normalised mean* can be on this set to compare scores across the

the different game types. The *normalised score means* and *win-rates* both have values that are more closely clustered togther, than in the previous game sets.

controller	*score mean*	*std.dev.*	*normalised-mean*	*win-rate*	*act-entropy*
Explorer	319.44	4852.31	0.5583	0.1967	0.8674
MCTS	542.32	5773.92	0.4401	0.2200	0.9818
GA	581.33	6263.91	0.4514	0.1978	0.7783
Onestep-S	344.16	5026.86	0.4132	0.1622	0.9640
Onestep-H	689.14	6159.38	0.4309	0.1744	0.5591
Random	322.81	4492.68	0.3195	0.1611	0.9981
DoNothing	566.19	5065.79	0.3625	0.1667	0

Figure 4.2: Results from randomly generated games

4.2.3 Mutated games

When mutating games, two types of games are problematic: Games where the controllers never increase their score (and never win), and games where too many objects are created and each frame end up taking too long ($>$ 50ms). We exclude both types of games in the following analysis.

Averages from playing the remaining 146 mutated games (of 200 total) are shown in Figure 4.3. The scores have higher means and standard deviations, indicating outliers in the data. The ordering of the *normalised score mean*, however, shows a similar pattern as for the example games, with Explorer again excelling.

controller	*score mean*	*std.dev.*	*normalised-mean*	*win-rate*	*act-entropy*
Explorer	45.22	203.71	0.8049	0.0736	0.9491
MCTS	24.14	168.33	0.4495	0.0267	0.9957
GA	26.13	170.08	0.4545	0.0226	0.8179
Onestep-S	30.21	156.71	0.4200	0.0130	0.9466
Onestep-H	10.87	147.38	0.3037	0.0863	0.2376
Random	17.47	176.04	0.2567	0.0127	0.9978
DoNothing	13.59	159.16	0.1889	0.0068	0

Figure 4.3: Results from mutated games

4.2.4 Outcome

The conclusion of the above tests is that the the result distribution of controllers can be used to score a game, with a high probability.

Chapter 5

Evaluation of games (fitness functions)

The initial tests of the previous chapter shows that there is reason to explorer the relationship of AI's perfomance profiles to analyze a given VGDL game. This chapter focuses on creating fitness function to analyze different generated games and evolve enjoyable games by evolving game descriptions. The resulting games are then discussed in detail.

5.1 Fitness function features

From the above tests we can see that it is interesting to write a fitness function for controllers results, to be able to find out if new generated games are of a high quality.

5.1.1 Action-arcade games: Generated levels

Results of what happens when generating levels for the example games.

Chapter 6

Puzzle generation

6.1 Turn-based puzzle games

Definition of games

The games described in this section are games where the puzzles are the only game-play. There is no fast movement, or quick reaction time required to win. Additionally, because the games are described using the GVG-AI framework, the games focus around a player avatar which can only move up, down, left or right (also, in the games described below, all movement are from one game-tile to another).

6.1.1 Games

Description of the puzzle games used in tests.

6.1.2 Puzzle solving AIs

As mentioned in (WHERE ITS MENTIONED), the controllers from the GVG-AI competietion are not well-suited for playing puzzle games, because the goal can often only be achieved by applying a specific series of moves, which the controllers are not very good at. Two general puzzle solving algorithms were implemented. The overall goal of the controllers were to analyze the game as much as possibl, rather than finding a solution fast, or using as low memory as possible They controllers use fact that wall-sprites in the different games always push back the player, and so the controllers do not try to move into a wall – this is achieved by storing the positions of every wall-sprite at the start of the game. Also, the controllers store each path it is had tried. For each path a game state is calculated and stored, by finding the position and type of each (non-wall) sprite in the game. A path is cut off if the calculated game state is the same as has appeared before.

Breadth-first search A breadth-first search algorithm was implemented by using a queue and letting each node expand to the adjacent tiles, using the "tricks" described above. Additionally the controller was given a low- and high-memory option: In the high memor

Best-first search

6.1.3 Level generation

A setup for creating levels for a given game were constructed using an evolutionary algorithm. The level generator described in section **??** was used to generate simple levels for games. In addition two extra options were added: Wall-sprites and ground-sprites. This reduces a lot of troubles since the avatar would otherwise be able to escape the level in a lot of the games. Ground-sprites signify which sprite should appear on empty locations.

The fitness function used in evolving levels was found by letting the two "puzzle solving AIs" play through the level.

Mutation

Crossover

Two different levels were constructed into a new, by going over each tile on the level and with 50% chance take the sprite residing in the two different original levels.

The setup was as follows:

```
while not at end of this document do
    read current;
    if understand then
        go to next section;
        current section becomes this one;
    else
        go back to the beginning of current section;
    end
end
```

Algorithm 1: How to write algorithms

6.1.4 Level generation for generated games

The Title

Put here cool text like what is going on in the wauw

This is subsubsection with title “Level generation for generated games”.

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Appendices

Appendix A

GVG-AI example games

The contents...

Appendix B

Games designed during thesis

B.1 Action arcade games

Crackpots [1983] VGDL implementation of the classic arcade game *Whac-a-Mole*. Must collect moles that appear from holes, and avoid a cat that mimics the moles.

Solar Fox VGDL interpretation of *Legend of Zelda*. Objective is to find a key in a maze and leave the level. Player also has a sword to defend himself against enemies.

Astrosmash [1981] The player controls a laser cannon at the bottom of the screen, with the goal of shooting down as many incoming meteors, bombs and other objects. Points are earned by destroying objects, but lost if the objects reach the ground. The game ends if the laser cannon is hit a few times by the incoming objects.

Centipede The objective is to move the boxes to holes, until all boxes disappear or the time runs out.

B.2 Puzzle games

Bait VGDL interpretation of the classic arcade game *Space Invaders*. A large amount of aliens are spawned from the top of the screen. The player wins by shooting all the approaching aliens.
Goal Destroy all the incoming aliens, without being hit by them or their projectiles.
Scoring Destroy all the incoming aliens, without being hit by them or their projectiles.

The Citadel VGDL interpretation of *Boulder Dash*. The avatar has to dig through a cave to collect diamonds while avoiding being smashed by falling rocks or killed by enemies.

Bombuzal The avatar has to capture all butterflies before all the cocoons are opened. Cocoons open when a butterfly touches them.

Chip's Challenge About chasing and killing fleeing goats. However, if a fleeing goat encounters the corpse of another, it get angry and start chasing the player instead.

Bolo Adventures VGDL interpretation of *Dig Dug*. Avatar collects gold coins and gems, digs his way through a cave and avoid or shoot boulders at enemies.

(Real) Sokoban VGDL interpretation of *Eggomania*. Avatar moves from left to right collecting eggs that fall from a chicken at the top of the screen, in order to use these eggs to shoot at the chicken, killing it.

Brainman Goal is to reach the exit by burning wood that is on the way. Ammunition is required to set things on fire.

Modality Player must avoid flames from hell gates until he finds the exit of a maze.

Painter VGDL interpretation of *Frogger*. Player is a frog that has to cross a road and a river, without getting killed.

Zen Puzzle Objective is to infect all healthy animals. The player gets infected by touching a bug. Medics can cure infected animals.