MAPPING TEXTURES ON 3D TERRAINS:

A HYBRID CELLULAR AUTOMATA APPROACH

A Thesis

by

SWAPNIL SINVHAL

Submitted to the Office of Graduate Studies of
Texas A&M University
in partial fulfillment of the requirements for the degree of

MASTER OF SCIENCE

December 2005

Major Subject: Computer Science

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Approved by:

Chair of Committee,	John Keyser
Committee Members,	Ricardo Gutierrez-Osuna
	Charles Culp
Head of Department,	Valerie E. Taylor

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ABSTRACT

Mapping Textures on 3D Terrains:

A Hybrid Cellular Automata Approach. (December 2005)

Swapnil Sinvhal, B.Arch., Indian Institute of Technology, Roorkee, India

Chair of Advisory Committee: Dr. John Keyser

It is a time consuming task to generate textures for large 3D terrain surfaces in computer games, flight simulations and computer animations. This work explores the use of cellular automata in the automatic generation of textures for large surfaces. I propose a method for generating textures for 3D terrains using various approaches – in particular, a hybrid approach that integrates the concepts of cellular automata, probabilistic distribution according to height and Wang tiles. I also look at other hybrid combinations using cellular automata to generate textures for 3D terrains. Work for this thesis includes development of a tool called "Texullar" that allows users to generate textures for 3D terrain surfaces by configuring various input parameters and choosing cellular automata rules.

I evaluate the effectiveness of the approach by conducting a user survey to compare the results obtained by using different inputs and analyzing the results. The findings show that incorporating concepts of cellular automata in texture generation for terrains can lead to better results than random generation of textures. The analysis also reveals that incorporating height information along with cellular automata yields better results than using cellular automata alone. Results from the user survey indicate that a

hybrid approach incorporating height information along with cellular automata and Wang tiles is better than incorporating height information along with cellular automata in the context of texture generation for 3D meshes.

The survey did not yield enough evidence to suggest whether the use of Wang tiles in combination with cellular automata and probabilistic distribution according to height results in a higher mean score than the use of only cellular automata and probabilistic distribution. However, this outcome could have been influenced by the fact that the survey respondents did not have information about the parameters used to generate the final image - such as probabilistic distributions, the population configurations and rules of the cellular automata.

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I INTRODUCTION

Generating textures for terrains to be used in computer games, animations and renderings can be painstaking and laborious. Often a user has a broad idea of the kind of end result she needs, but needs to create the final texture map by piecing together different textures. In such applications, the terrains usually do not have to exactly match a real-world scene; they only need to be sufficiently realistic and "believable" to be used.

Texture can help us in adding interest to terrains without having to render extra geometry. For example, we easily add elements like flowers, rocks and grass through textures. While rendering large expanses of terrain, a user may want to generate many textures and select one out of them. A user may also want to be able to get slightly different results in different scenarios, for instance a slightly different backdrop terrain in a car game every time a new game is played. Ideally, it would be easier for a user to generate these texture-mapped terrains with minimal effort and by changing easily-configurable parameters. This work explores the application of the concept of cellular automata to the generation of terrain textures.

Cellular automata have been studied as models of various natural phenomena (See Section II). This work explores whether extending this idea to texture generation for terrain surfaces can yield effective results.

This thesis follows the style and format of *IEEE Transactions on Visualization and Computer Graphics.*

Wolfram [97] pointed out that randomness and complexity can make a population more robust. This inspired me to explore the effect of adding a degree of randomness to the output, in an attempt to achieve better results.

I also explore the use of Wang tiles [11] in texture generation for large surfaces, as they reduce periodicity while allowing reuse of texture tiles. The Wang tile placement is decided in accordance with the final state of the cell.

As a part of this research, I developed a tool called "Texullar" – a texture building tool using the concept of cellular automata, the name being derived from a play on the words "texture" and "cellular". The tool allows a user to render a terrain surface using different cellular automata rules, combining them with a choice of other parameters for randomness, Wang tiles and height information drawn from the terrain.

I propose a set of hypotheses regarding the generation of textures for 3D terrain surfaces. Using Texullar, I generated many sets of images using various combinations of parameters to validate these hypotheses.

I evaluated the validity of the hypotheses by conducting a user survey to compare the results obtained by using different inputs and texture generation logic. The findings show that incorporating concepts of cellular automata in texture generation for terrains can lead to better results than random generation of textures. The analysis also reveals that incorporating height information along with cellular automata yield better results than using cellular automata alone, and also better than only a probabilistic distribution of texture tiles according to height.

Results from the user survey, however, did not yield enough evidence to indicate whether a hybrid approach incorporating height information along with cellular automata and Wang tiles is better than incorporating height information along with cellular automata in the context of texture generation for 3D meshes.

II BACKGROUND

II.a Cellular Automata

II.a.1 Introduction

Mathworld [58] defines a cellular automaton as “a collection of ‘colored’ cells on a grid of specified shape that evolves through a number of discrete time steps according to a set of rules based on the states of neighboring cells”.

In general, this relationship can be expressed [101] as:

$S_i(t+1) = f(S_i(t) + S_{neigh(i)}(t))$

Where Si denotes the state of the ith cell

t denotes the number of generations that have evolved

$S_{neigh(i)}$ denotes the set of neighbors (according to the chosen neighborhood) of the ith cell

2D cellular automata are cells arranged on a 2D grid, and are affected by neighbors in both the X and Y dimensions. I have used the rules of 2D cellular automata in this work. Throughout this text, “cellular automata” refers to 2D cellular automata unless explicitly mentioned otherwise.

Wolfram pointed out [96] that:

- Very simple rules often generate great complexity
- Simple ideas tend to be reused much more often than complicated ones
- The simpler the system, the more likely a version of it will recur in a wide variety of more complicated contexts

These ideas about simplicity and its use have inspired me to explore the use of simple cellular automata in texture synthesis. The idea of self-reproducing automata, as explained by von Neumann [84] and [85], illustrates how simple rules can lead to great complexity.

Different rules of cellular automata have different characteristics. The entropy of some unpredictable patterns generated by cellular automata has been studied by Crutchfield et al. [16] and Melanie et al. [60], [61]. A ‘chaotic’ system has been described [99] as one in which “activity doesn't die down into a regular pattern, but yet it also doesn't explode all over the place. We seem to be able to pick out individual 'things' in the space. These things grow and shrink and interact in 'interesting' ways. These worlds are the ones that get everyone all excited about CAs [cellular automata].” The author also describes an 'exploding' universe as one in which “… no matter what we start with (other than a few pathological cases), the patterns grow and expand until they fill up the whole space”.

Using cellular automata, we can define an initial configuration of cells and evolve them according to pre-defined rules with known characteristics.

The application of evolutionary strategies like genetic algorithms [34] and cellular automata to solve complex problems has generated a lot of interest [36], [41], [69].

Figure 1 shows an example of a cellular automata rule found in real life. The Conus textile shell follows Rule 30, which is illustrated and explained in Figure 2.

Figure 1   Conus textile shell: Rule 30 cellular automaton

Picture taken from [94]

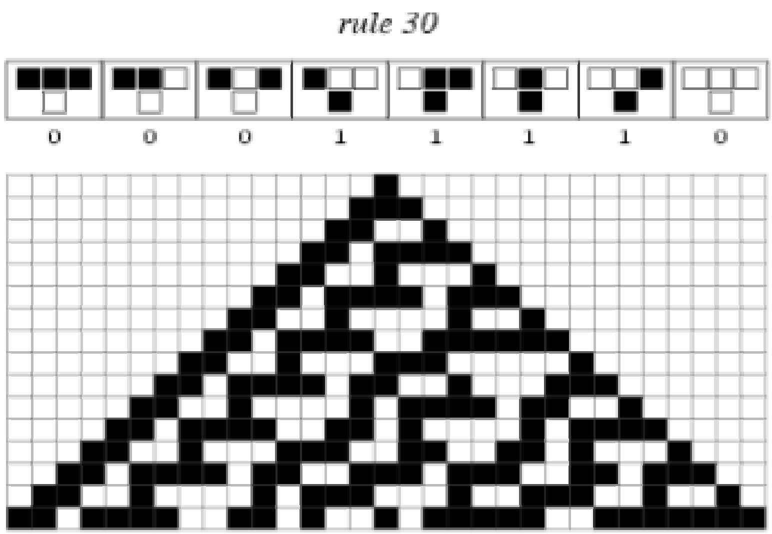


Figure 2   Rule 30 Cellular automaton

Picture taken from [58]. Rule 30 is a 1D cellular automaton. The diagram at the top row shows various configurations of the initial state of a cell and its 2 immediate neighbors on either side, with the final state of the cell shown below. For instance, a black cell whose left and right neighbors are also black will be white in the next generation. There are 4 configurations that lead to a final state of 1. The diagram below is a representation of the growth of the automaton, starting from a single black cell in the top row. Subsequent rows show the evolution of the cell population, one generation at a time.

II.a.2 Neighborhoods

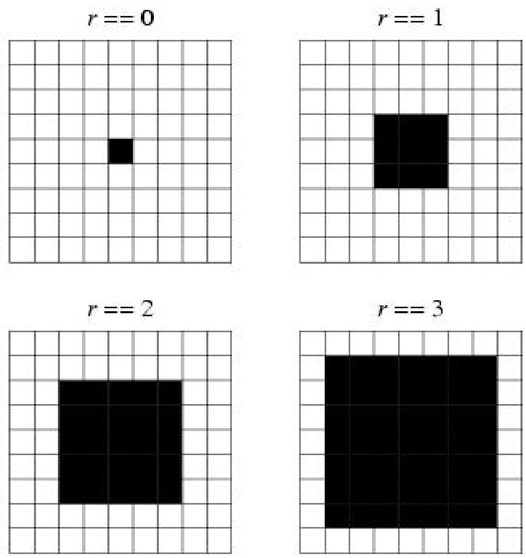


Figure 3 Cellular automata: Moore neighborhood

Picture taken from [91].

A Moore neighborhood (Figure 3) is a square-shaped set of neighboring cells that can affect the state of a cell in consideration. This set is defined [91] as:

$N^{M}_{(x0,\, y0)} = \{(x,y): |\ x\text{-}x_0| \leq r,\ |y - y_0| \leq r\}$

where N^{M} denotes the set of cells in the Moore neighborhood

x_0 denotes the x – coordinate of the current cell

y_0 denotes the y – coordinate of the current cell

x denotes the x – coordinate of another cell

y denotes the y – coordinate of another cell

r denotes the range

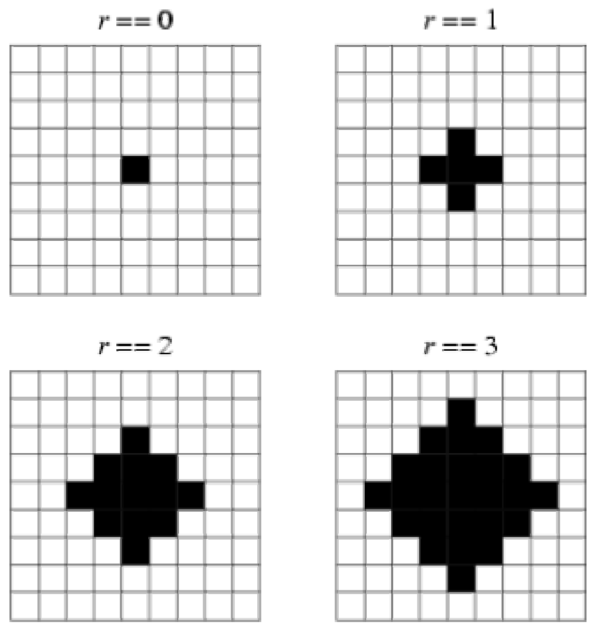


Figure 4 Cellular automata: von Neumann neighborhood
Picture taken from [91].

Other kinds of neighborhoods like the von Neumann neighborhood, as illustrated in Figure 4, have also been defined [96].

II.a.3 Lexicon for Cellular Automata

The “Life” family of rules [96] for 2D cellular automata uses 1 bit for state and is defined in the "S/B" form, where:

S is the number of neighbors that should be alive for a cell to survive

B is the number of neighbors that should be alive for a cell to be born

E.g., the Conway's Game of Life is defined [29] over a Moore neighborhood as 23 / 3. We consider a state of 1 to indicate a surviving cell and a state of 0 to indicate a cell that is not living. The rule defines that a living cell with exactly 2 or 3 surviving neighbors will survive in the next generation; else it will die. A non-living cell will come to life if exactly 3 cells in its neighborhood are alive.

II.a.4 Applications of Cellular Automata

Toffoli and Margolus [81] state that "in spite of their wide interdisciplinary appeal, cellular automata would have remained at the level of a parlor game if they had not been shown to be capable of playing a serious role in the modeling of physics". Benati [7] showed that cellular automata can be used to model phenomena typical of living communities like reproduction, self-organization and a complex evolution. An interesting relation between fractals and cellular automata has been discussed by White et al.[92] in the context of urban form.

Cellular automata have been studied as models of biological growth for plants [12, 13], urban elements [5, 6, 7], bush fires [31, 44, 53, 74] and other natural phenomena. Parameters for cellular automata to model the spread of invasive plant species have been studied by Cole et al. [14]. Cellular automata have also been studied as evolution strategies [3], [45], [46], [50], [80] and in the area of artificial life [24], [39], [49] and [83]. Thus, I felt that cellular automata could be effectively used to "grow" textures representing flower patches, shrubs or groups of buildings.

Other areas of research in which studies have been done regarding the concept of cellular automata include physics [26], economics [15] and sociology [25].

II.a.5 Texture Synthesis Using Reaction-Diffusion

The process of reaction-diffusion, which is a biologically motivated method of texture synthesis, models the diffusion of two or more chemicals at unequal rates over a surface and their mutual reactions to form stable patterns such as spots and stripes. The Rufenacht website [68] shows examples of applying cellular automata rules to generate textures that look like animal skins. Reaction-diffusion methods for texture generation also use the concept of cellular automata [75, 77 and 82]. Figures 5 and 6 illustrate some examples of texture synthesis using reaction-diffusion.

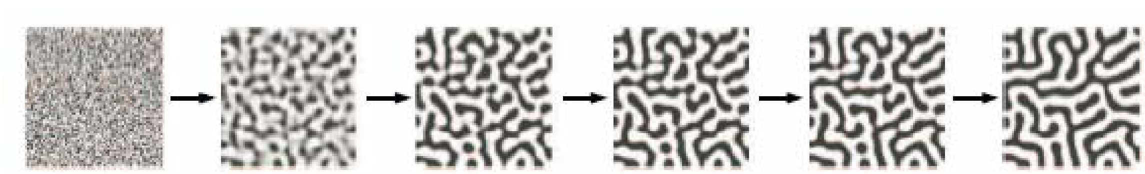


Figure 5 Striped pattern using reaction-diffusion method
Picture taken from [75]

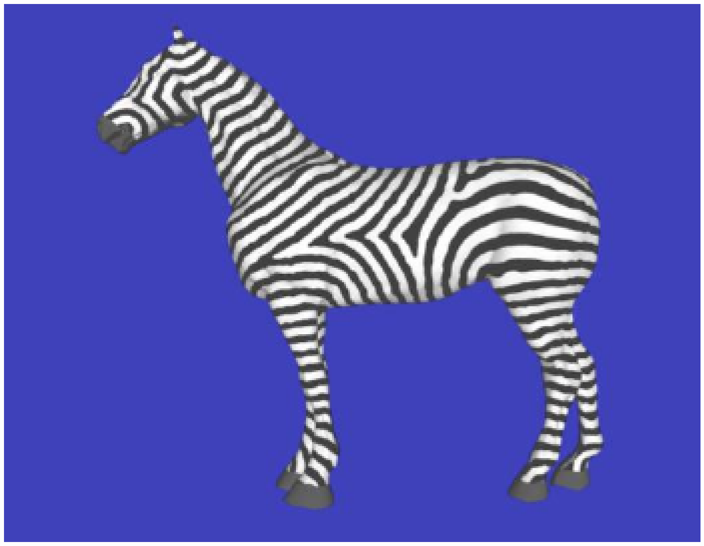


Figure 6 Pseudo zebra - texture synthesis using reaction diffusion
Picture taken from [82]

II.b Hybrid Approaches Using Cellular Automata

Sullivan et al. [74] use a hybrid model to compute the spread of bush fire using 2D cellular automata with a semi-physical model of convection. Colasanti et al. [13] propose a hybrid model of plant growth using cellular automata with the C-S-R-model. Both of these studies found that a cellular automata process alone was not sufficient to simulate the natural evolution of the phenomenon under consideration. Probabilistic cellular automata have been studied by Takai et al. [76].

This suggests that augmenting the concepts of cellular with the application of domain-specific information can lead to better results. Hence, the texture generation algorithms used in this work incorporate terrain information (in this case, height) in the generation of texture.

Gobron et al. [33] use a 3D surface cellular automata approach to represent a model. This gives the advantage of direct texture simulation on the model.

II.c Terrain Generation

Fractals [57] have been used to generate terrains by many terrain generation engines like fracPlanet [1] and FracHill [9]. Fractals lead to smooth height transactions, and are also sometimes used to color the terrain as an alternative to texturing.

A cellular automata approach to generating terrains is described by Wijaya et al. [93]. Various volumetric approaches to terrain generation have also been explored [95].

II.d Generating Textures for Large Surfaces

The Neyret-Cani approach [64] for aperiodic texture mapping of a 3D object uses triangular textures as inputs and maps them onto a triangular mesh. The edges of the triangular textures match up seamlessly with each other and tile up as a texture for a large area. Figures 7 and 8, taken from [64], illustrate this method of texture mapping. The Akleman-Kaur method [47] uses square texture tiles, applying background tiles for a seamless base, and then blending another texture in the center of each tile. Further work in the same direction by Green [32] illustrates aperiodic texture tiling using different complexities of matching edges.

Figure 7 Neyret-Cani's method applied to map textures on an arbitrary mesh

Figure 8 Neyret-Cani's method applied to map textures on a set of tori

Recent work [51], [52], [59] on texture blending has made it easier to generate textures that seamlessly blend into one another. This work could be extended to generate texture tiles that "blend" well. This work simplifies the problem of matching up seams of adjacent tiles by choosing input texture tiles that have been pre-generated and are seamless. A technique called "TextureMontage", proposed by Zhou et al. [100] can be used to seamlessly map a patchwork of texture images onto a 3D model.

Litwinowicz et al. [55] describe algorithms for the placement and distortion of textures, using affine transformations of a texture and localized warps to align features in the texture with features of the model. Sander et al. [71] propose a method for texture mapping that minimizes texture stretch and texture deviation.

Texture mapping through Wang tiles [86], [87] uses "color-coded" texture tiles to indicate textures that can be placed adjacent to each other seamlessly, and is an effective way to tile a surface aperiodically. Cohen et al. [11] show how Wang tiles can be used to generate a texture for a 3D surface which is not periodic. A minimal set of Wang tiles required to aperiodically tile an infinite plane is illustrated in Figure 9 below.

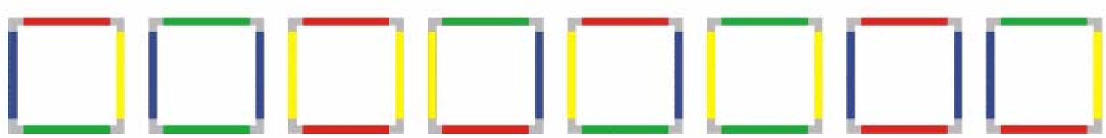


Figure 9   A minimal set of 8 Wang tiles that can aperiodically tile an infinite plane

Efros et al. [23] explain a method for texture synthesis and transfer that works by rendering an object with a texture taken from a different object, illustrating its use on 2D surfaces. Various texture mapping methods have been discussed by Heckbert [38].

Figure 10 shows a comparison of a plane tiled according to the stochastic and aperiodic considerations. The figure shows that using a purely stochastic tiling gives a greater impression of aperiodicity as compared to a strictly aperiodic set assembled using a minimum set of tiles that follow the Wang tile constraints.

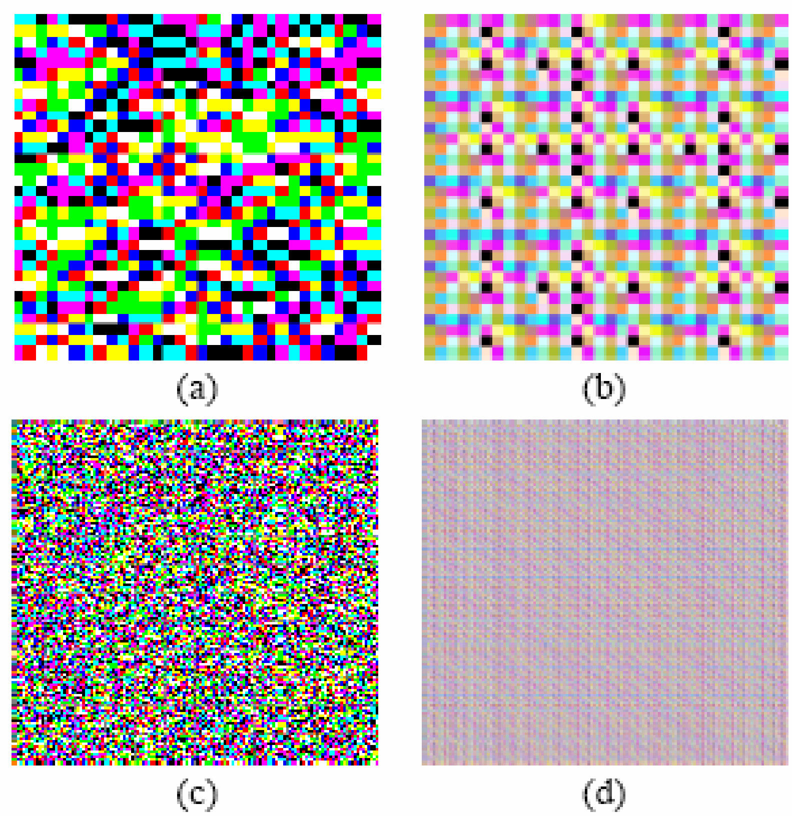


Figure 10 Comparing stochastic and random assembly of tiles

(a) 32×32 tiles stochastically assembled
(b) 32 × 32 strictly aperiodic set (taken from [37])
(c) 256 × 256 stochastic
(d) 256 × 256 aperiodic.
Picture taken from [11]

II.e Texture Mapping Terrain

Large surfaces can be mapped with different textures by creating one large texture that wraps well around the geometry of the object. Until recently, this was done manually by choosing textures that conformed to simple geometry, e.g. using a map of the earth that wraps perfectly onto a sphere. Recent work by Zhou et. al. [100] shows how to generate a "texture atlas" that corresponds to models with complex geometry such as animals. Terrain Engine [78] uses a very large terrain texture with a tiling detail texture. Some game engines use a large texture map to render the terrain, and later add detail like roads by fine-tuning geometry. Kajiya et al. [43] use a volumetric approach to rendering fur and Decaudin et al. [17] use a volumetric approach to rendering large forests.

Ong's work [65] on applying Genetic Algorithms for texture generation used an approach that evolved textures over time. [19] shows a blending technique used to texture map terrains. Worley [98] discusses a basis function that can be used for solid texturing as a complement to Perlin's fractal noise [67].

The advent of GPU (Graphics Processing Unit)-based processing has given birth to new rendering techniques that are usually faster than CPU (Central Processing Unit) -based rendering techniques. Asirvatham et al. [2] and Losasso et al. [56] discuss terrain rendering using GPU-based geometry clip maps. Bloom [8] describes terrain texture compositing by blending in the frame buffer using "splatting"- another GPU-intensive technique.

Lindstrom et al. [54] describe how a view-dependent refinement can be combined with view frustum culling and triangle stripping for effective visualization of terrains. Pajarola [66] uses a restricted quadtree triangulation for high performance terrain visualization. Other high performance techniques to render large meshes have been described using multi-resolution point rendering [70] and view-dependent level-of-detail [40].

II.f Physically-Based Simulation

Various physically based approaches to weathering of surfaces have been explored, which also produce the effect of using more than one texture. Lichen growth [18] using an Open Diffusion Limited Aggregation model on 3D surfaces adds geometry to the existing surface. Another approach [20] uses thickness maps and rendering layers to simulate weathering of metallic surfaces, particularly in relation to copper. Simulating water flow as a particle system and incorporating information about chemical reactions (like exposure to sunlight) [22] can be used to alter the appearance of the original textures. In a related study [21], the authors use a volumetric data structure to simulate weathering of stone incorporating effects like flow of moisture and mineral dissolution. Jensen et al. [62] illustrate the rendering of wet materials by taking into account the water on the surface and a concentration of water beneath the surface.

All these simulations achieve the result of adding interest to the surface texture. Being physically-based simulations, these methods require some prior knowledge of parameters like the geometry, surface conditions, the environment and the interplay of these factors.

II.g User Studies

User studies related to effective visualization of computer-generated artifacts are being done by many researchers [72], but are not yet a standard practice [48]. User surveys in the area of visualization [88], [89], [90] have explored some of the issues regarding how we perceive surfaces under environments with different parameters like orientation and texture.

III THEORY

III.a Characteristics of Terrains Desirable for Texture Generation

I have studied various types of terrains to identify the main "ingredients" that could make computer-generated textures for large terrains look realistic. Broadly, I conjecture that the following characteristics make a terrain surface look natural:

a) Natural terrains usually have a strong "characteristic" e.g. large expanse of sand on a beach, flower patches on a hill.

b) There is some unpredictability (or randomness) in a landscape that makes it look natural.

c) When viewed at a large scale, terrain surfaces can show features that are influenced by height. For instance, a mountain is more likely to have snow at higher elevations and rocks at lower elevations than the other way round.

d) Natural features on terrains are generally aperiodic. Even planned cities with grid-like road patterns usually have some differences from location to location.

I use cellular automata to define a broad set of characteristics for a terrain and evolve the initial population over several generations to simulate natural growth. I use randomness or probability to make the results look less formal, and I use Wang tiles to model (d) above. To incorporate (c) above, I have used probabilistic distributions of texture tiles, defined in terms of height intervals of the terrain.

Based on these ideas, I have formulated a set of hypotheses. These are detailed in the following section.

III.b Research Hypotheses

I formulated four sets of hypotheses regarding placement of texture tiles on a 3D terrain mesh. To compare images generated using different approaches, I proposed to compare the mean of the scores assigned to them on a 10-point scale.

Throughout this document,

CA denotes cellular automata

H_0 denotes the null hypothesis

H_a denotes the research hypothesis (also called the alternative hypothesis)

μ_R denotes the mean score for images generated using random placement of texture tiles

μ_{CA+R} denotes the mean score for images generated using cellular automata approach

μ_{Ht} denotes the mean score for images generated with a probabilistic distribution of texture tiles according to height of the terrain

μ_{CA+Ht} denotes the mean score for images generated using cellular automata approach combined with a probabilistic distribution of texture tiles according to height of the terrain

$\mu_{CA+Ht+W}$ denotes the mean score for images generated using a cellular automata approach combined with a probabilistic distribution of texture tiles according to height of the terrain and using the Wang method for placing texture tiles

The research hypotheses are:

$H1_{a:}$ For the assignment of texture tiles on a 3D terrain mesh, a hybrid approach combining cellular automata and random placement leads to a higher mean score than a random placement alone.

$H2_{a:}$ For the assignment of texture tiles on a 3D terrain mesh, a hybrid approach combining cellular automata and probabilistic distribution of texture tiles according to height of the terrain leads to a higher mean score than a hybrid approach combining cellular automata and random placement.

$H3_{a:}$ For the assignment of texture tiles on a 3D terrain mesh, a hybrid approach combining cellular automata and probabilistic distribution of texture tiles according to height of the terrain leads to a higher mean score than an approach using a probabilistic distribution of texture tiles according to height of the terrain alone.

$H4_{a:}$ For the assignment of texture tiles on a 3D terrain mesh, a hybrid approach combining cellular automata, probabilistic distribution of texture tiles according to height of the terrain and Wang tiles leads to a higher mean score than a hybrid approach combining only cellular automata and probabilistic distribution of texture tiles.

The formulation of the null and research hypotheses are:

$H1_{0:}$ $\mu_{CA+R} \leq \mu_R$

H1$_{a:}$ $\mu_{CA+R} > \mu_R$

H2$_{0:}$ $\mu_{CA+Ht} \leq \mu_{CA+R}$

H2$_{a:}$ $\mu_{CA+Ht} > \mu_{CA+R}$

H3$_{0:}$ $\mu_{CA+Ht} \leq \mu_{Ht}$

H3$_{a:}$ $\mu_{CA+Ht} > \mu_{Ht}$

H4$_{0:}$ $\mu_{CA+Ht+W} \leq \mu_{CA+Ht}$

H4$_{a:}$ $\mu_{CA+Ht+W} > \mu_{CA+Ht}$

As the nature of the response is highly subjective, an α value of 0.20 was chosen.

These hypotheses are broadly based on the major characteristics of terrains that I have observed (Section III.A). The characteristic of the terrain can be defined using cellular automata, and evolved using pre-defined rules – thus a "method" is followed to generate a final result derived from initial conditions (Hypotheses I and III). Terrain – specific information can be added by incorporating a probabilistic distribution of the texture tiles based on the terrain height (Hypotheses II). I have used Wang tiles to eliminate periodicity in the process of texture generation (Hypothesis IV).

III.c Program Structure

This work explores the mapping of more than one texture on to 3D surfaces to achieve realistic and aesthetically pleasing results. The inputs to the program are:

1. A gray scale image defining the geometry (a height map)
2. A set of rules for the evolution of cellular automata
3. Images to be used as “texture tiles” (e.g. snow, grass, flower patches)
4. User-defined parameters. These include:
    - Initial cell population
    - Number of generations (evolution cycles)
5. Optional parameters, depending on choice of algorithm used to generate textures. These include:
    - A probabilistic distribution of texture tiles according to height of the terrain
    - Wang tile information

The program uses a two-dimensional cellular automata approach to generate a texture placement map. The images used as texture tiles match up seamlessly with each other and are always used in the same orientation (North always remains North). Seamless texture tiles are used so that the joints between texture tiles are not visible along the edges. In case Wang tiles are used, the edges of the tiles follow the rules of Wang tiles.

Terrain geometry can be easily defined in terms of height maps, which are 2D gray scale images. In a height map, a lighter color usually indicates a higher elevation. A height map can be thought of as "two-and-a-half dimensional" information [10], or height information over a 2D grid, which needs to be translated into a three-dimensional mesh (see Figure 11).

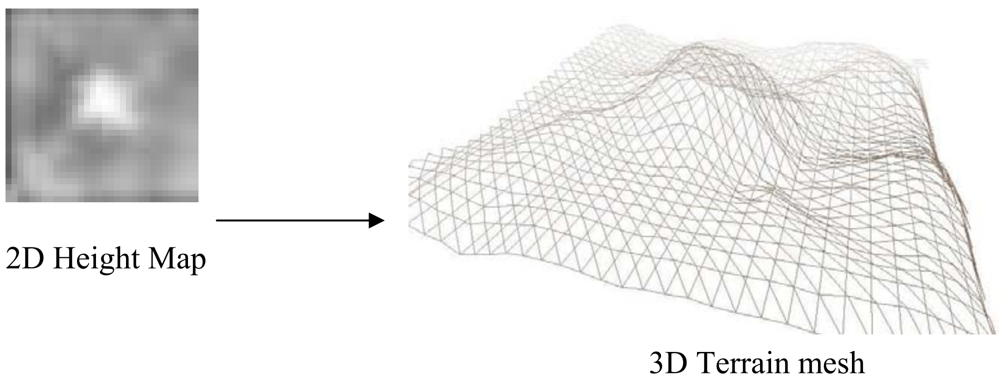


Figure 11 Generating a 3D mesh from a height map

The final texture placement map is then juxtaposed with the height map to define which texture tile gets placed on which part of the geometry.

III.d Choosing Rules for Cellular Automata

Many rules for generating interesting patterns using cellular automata have been proposed. The growth patterns and major characteristics of some of these rules and their applications have been studied by researchers. The website for Mathworld [58] provides online documentation on some of these rules and their characteristics.

For this research, I chose cellular automata rules with characteristics that are more likely to be found in nature. So, I favored rules that evolved an initial population to a chaotic or exploding population as opposed to those that led to stable growth.

For simplicity, I used rules with 2 states in this work. The rules that I chose have been taken from [96] and are reproduced below in Tables 1, 2 and 3: [for lexicon rules, see Section II.A.2]:

Table 1 Cellular automata rule: Conway's Game of Life

Rule	:	23/3
Character	:	Chaotic
Neighborhood	:	Moore neighborhood
Author	:	John Conway
Description	:	This rule was proposed by John Conway [29], [30]. Even though the rule looks simple, it generates interesting results. Informally, it has been defined in terms of a cell surviving if it is surrounded by 2 or 3 surviving neighbors; and a cell becomes alive if it has exactly 3 neighbors that are alive. I chose this rule because it is one of the most popular rules of cellular automata. It was even mentioned in the popular Time magazine [79].

Table 2 Cellular automata rule: Coagulations

Rule	:	235678/378
Character	:	Exploding
Neighborhood	:	Moore neighborhood
Author	:	(Unknown)
Description	:	Cells seem to coagulate as the population expands forever. I chose this rule because it leads to groups of cells with the same state; I thought that would be useful in simulating some features like patches of flowers or buildings on a terrain surface. Figure 12 illustrates a population that has been evolved using this rule.

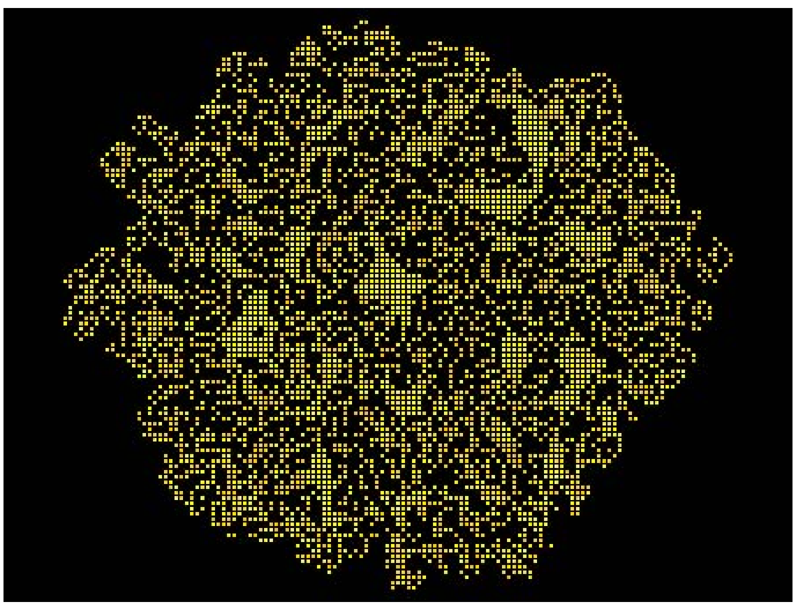


Figure 12 Cellular automata: The Coagulations rule

Adapted from [96]. The coagulations of the cells are visible.

Table 3 Cellular automata rule: Amoeba

Rule	:	1358/357
Character	:	Chaotic
Neighborhood	:	Moore neighborhood
Author	:	(Unknown)
Description	:	The population oscillates wildly. I chose this rule because the growth pattern looked natural (see Figure 13).

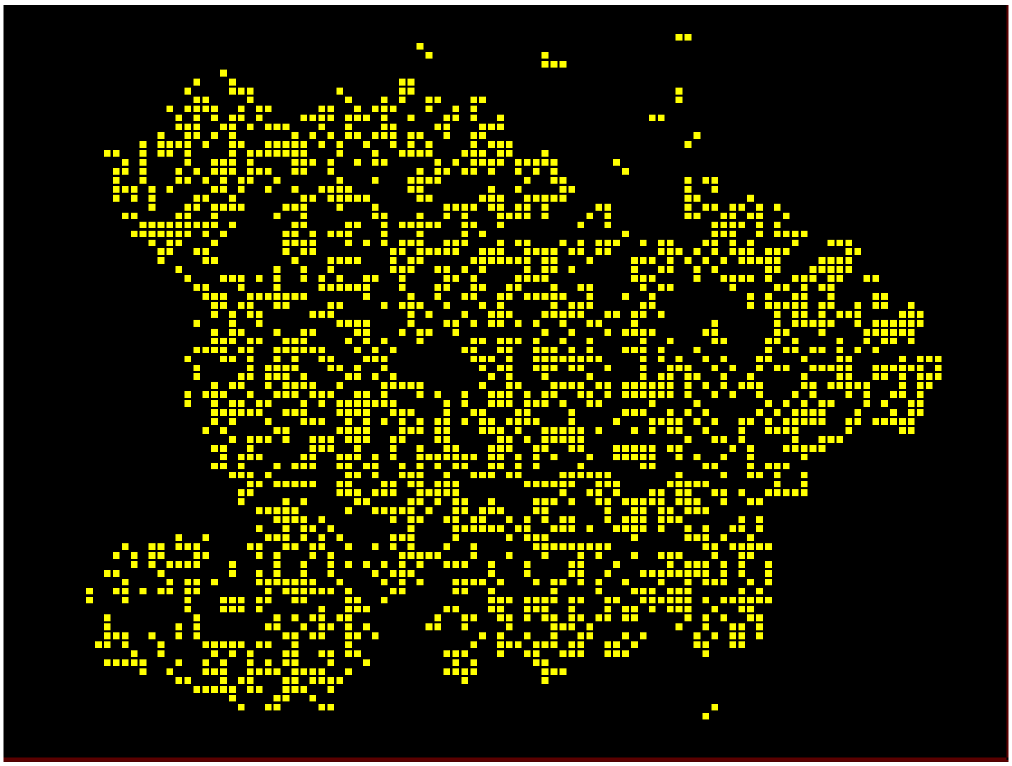


Figure 13 Cellular automata: The Amoeba rule

Adapted from [96].

III.e Cellular Automata with Height Information

I noticed that, in some cases, elevation has an effect on the natural features (like vegetation) on a terrain surface. I define a “family” of textures with similar characteristics that map to each state of the cellular automata. Section III.F contains details on the algorithms used to incorporate height information in the placement of texture tiles on the terrain mesh. Figures 14 and 15 below shows examples of real landscapes, where the terrain features (that can be represented by textures in a computer-generated rendering) vary with height.

Figure 14 A snowy landscape

Picture taken from: [28]. The "texture" varies according to the height – there are more trees on the lower elevations. There is more snow on the higher elevations. The peaks have snow exclusively.

Figure 15 San Francisco. Picture taken September 2005

Trees and shrubs appear on lower elevations. The higher areas are devoid of vegetation.

III.f Algorithms

III.f.1 Algorithm for Texture Mapping with Cellular Automata and Random Selection

Input: A height map to define the terrain

A set of rules for evolution of cellular automata

The number of generations of evolution

A set of texture tiles for each possible state of the cellular automata

Output: A texture-mapped 3D mesh

Algorithm:

1. Applying the chosen cellular automata rules to the initial population, evolve it over the specified number of generations to compute the final population.

2. Construct a 3D terrain mesh by interpreting the height map.
3. Map the final cell population one-to-one with the quadrilaterals that define the 3D terrain mesh.
4. For each cell,

   According to the final state of the cell, randomly choose one texture tile that corresponds to the set of texture tiles for that state.
5. Apply the chosen texture tiles on the terrain mesh.

III.f.2 Algorithm for Texture Mapping with Cellular Automata and Probabilistic Distribution According to Height

Input: A height map to define the terrain

A set of rules for evolution of cellular automata

The number of generations of evolution

A set of texture tiles for each possible state of the cellular automata

A probabilistic distribution of texture tiles for each state, according to the terrain height

Output: A texture-mapped 3D mesh

Algorithm:

1. Applying the chosen cellular automata rules to the initial population, evolve it over the specified number of generations to compute the final population.
2. Construct a 3D terrain mesh by interpreting the height map.

3. Map the final cell population one-to-one with the quadrilaterals that define the 3D terrain mesh.
4. For each cell,
    a. Consider the set of texture tiles that map to the final state of the cell.
    b. Find the height of the cell on the terrain and consider the subset of texture tiles that map to the given rules of probabilistic distribution of texture tiles according to the height of the terrain mesh.
    c. Choose a texture tile from this subset.
5. Apply the chosen texture tiles on the terrain mesh.

III.f.3 Algorithm for Texture Mapping with Probabilistic Distribution According to Height

Input: A height map to define the terrain

A probabilistic distribution of texture tiles for each state, according to the terrain height

A set of texture tiles for each interval defined in the probabilistic distribution

Output: A texture-mapped 3D mesh

Algorithm:

1. Construct a 3D terrain mesh by interpreting the height map.
2. Choose a texture tile according to the given rules of probabilistic distribution of texture tiles according to the height on the terrain mesh.
3. Apply the chosen texture tiles on the terrain mesh.

III.f.4 Algorithm for Texture Mapping with Cellular Automata, Using Probabilistic Distribution According to Height and Wang Tiles

Input: A height map to define the terrain

A set of rules for evolution of cellular automata

The number of generations of evolution

A set of texture tiles for each possible state of the cellular automata and the color codes of their edges (according to the Wang tile description)

A probabilistic distribution of texture tiles for each state, according to the terrain height

Output: A texture-mapped 3D mesh

Algorithm:

1. Applying the chosen cellular automata rules to the initial population, evolve it over the specified number of generations to compute the final population.
2. Construct a 3D terrain mesh by interpreting the height map.
3. Map the final cell population one-to-one with the quadrilaterals that define the 3D terrain mesh.
4. Start from the North West corner of the mesh. According to the probabilistic height distribution, choose any texture tile from the set of tiles that corresponds to the final state of the cell.
5. Continue to the next cell to the immediate East of the current cell, until the end of the row. For each cell,
    a. Consider the set of Wang tiles that map to the final state of the cell.

b. Find the sub set of texture tiles (for the same state) such that the West edge matches the East edge of the tile placed to the West.

c. Apply the given rules of probabilistic distribution of texture tiles according to the position of the cell on the terrain mesh. Choose a texture tile that corresponds to the set of texture tiles for that state from within the subset chosen in the step above. (Thus, the chosen tile satisfies both the probabilistic height distribution <u>and</u> the Wang tile constraints.)

6. Go to the next row. Continue on from West to East. For each cell,

   a. Consider the set of Wang tiles that map to the final state of the cell.

   b. Find the sub set of texture tiles (for the same state) such that the North edge matches the South Edge of the tile immediately to the North, and the West edge matches the East edge of the tile placed to the West.

   c. Apply the given rules of probabilistic distribution of texture tiles according to the position of the cell on the terrain mesh. Choose a texture tile that corresponds to the set of texture tiles for that state from within the subset chosen in the step above. (Thus, the chosen tile satisfies both the probabilistic height distribution <u>and</u> the Wang tile constraints.)

7. Repeat Step 6 until the texture tiles for all cells are chosen.

8. Apply the chosen texture tiles on the terrain mesh.

III.g A Conceptual View

Figure 16 below illustrates the steps followed in the initial stage of Texullar. The initial population is evolved according to the set of rules chosen by the user. A 3D mesh is generated by interpreting the height map. Figure 17 shows how the output from Stage 1 is used as input to Stage 2 of Texullar and combined with other parameters to yield the final result. Details of the algorithms used to generate the final textures are described in Section III.F.

III.h Texture Tiles

Cohen et. al. [11] use a set of 18 tiles to map a large texture area; they note that even though only 8 tiles are theoretically enough to aperiodically tile a surface, it helps to use more tiles to achieve better results. While using cellular automata with 2 states, I use 8 tiles for each state – leading to a total of 16 tiles.

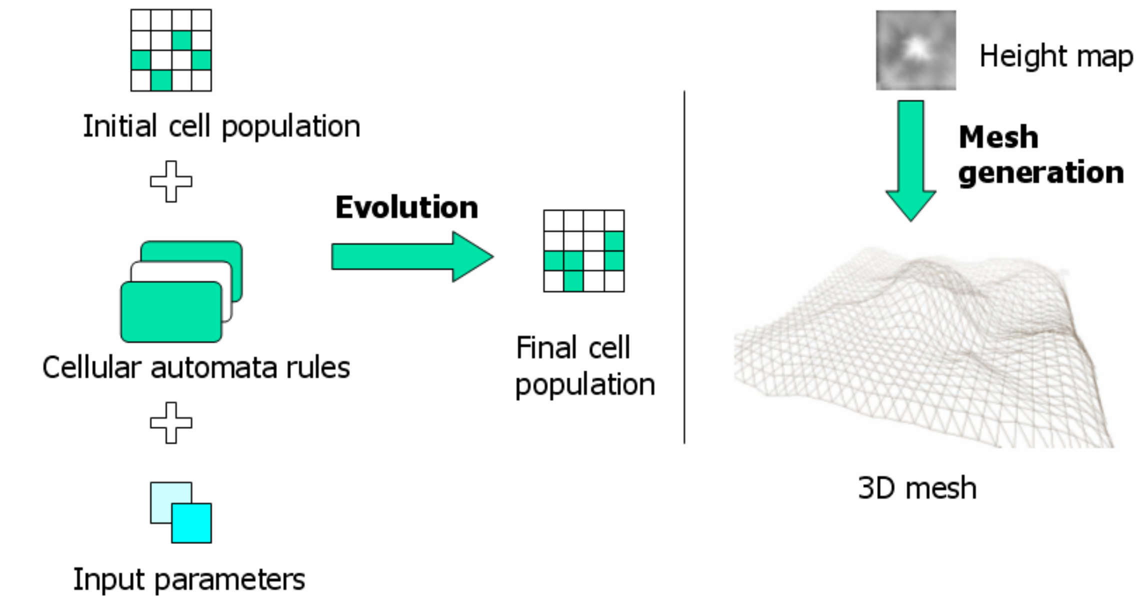


Figure 16 Conceptual diagram of the Texullar system: Stage 1

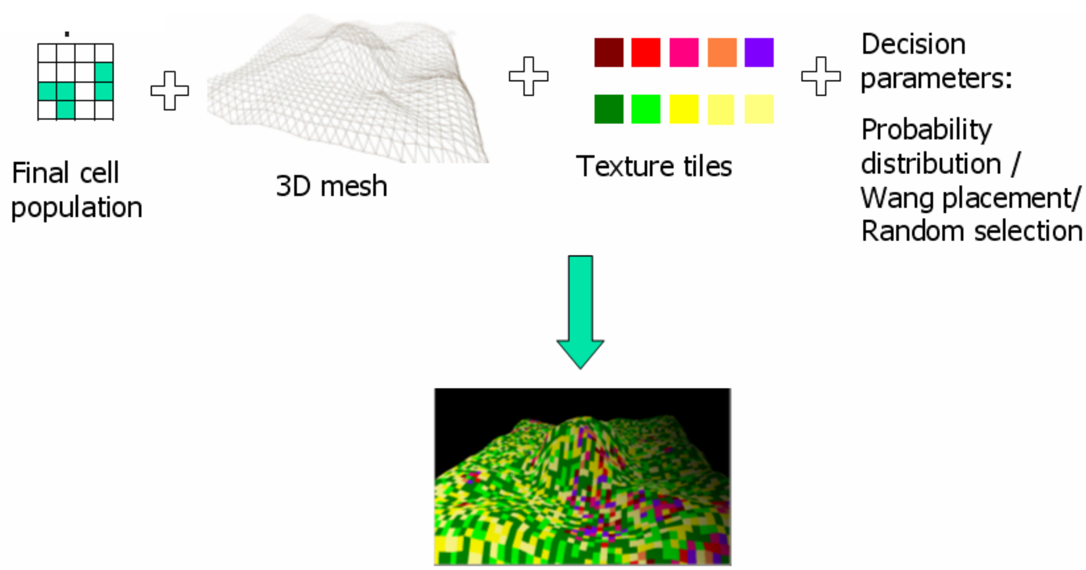


Figure 17 Conceptual diagram of the Texullar system: Stage 2

III.i Wang Tiles and Cellular Automata

After evolving a population using cellular automata, I generated textures for terrains using a set of 8 Wang tiles for each state. Thus, I used a total of 16 texture tiles. The tiles were designed in a way such that the Wang tiles for each given North configuration of one state would blend in seamlessly with the South-East configuration of its own state as well as other states of the cellular automata. No rotations were allowed for the Wang tiles.

IV IMPLEMENTATION

IV.a Implementation Details

I have developed a program called Texullar in C++ using the OpenGL libraries and Windows API. I used Visual Studio .NET 2003 as the Integrated Development Environment. I used Adobe Photoshop and MS Paint to generate the images used as texture tiles.

At the end of stage 1, the program outputs a file that contains details of the state of the cell population used to generate the final texture. The user can manipulate this file to “tweak” the final result. However, it is the responsibility of the user to ensure that the changes made are valid, i.e., the states used conform to the valid set of states for the rule used.

The state of a cell depends on the state of its neighbors in the previous generation. Since the neighbors are not completely defined for edge cells, the program “wraps around” the neighbors for cells on the boundary of the terrain map. For example, the neighbors of the top left cell in the terrain map that used a Moore neighborhood of 8 cells would include cells from the bottom left corner, the top right corner and the bottom right corner. While this approach may lead to slightly inaccurate results, particularly in the case where elevation information is also incorporated in the placement of texture tiles, it provides a simplification in the implementation.

The program uses MIP maps [27] to apply the appropriate level of detail while rendering the view. MIP stands for "multum in parvo" - Latin for “many in a small place”. MIP mapping is a texture mapping technique that uses multiple texture maps (MIP maps), where each MIP map is half the size of the one at the previous level. This provides several texture maps for various levels of depth. For my thesis, I have generated the MIP maps using OpenGL libraries.

The user can define an initial population using a configuration file. The number of states that can be defined depends on the rule being used. For example, a 1-bit cellular automata rule like Conway’s Game of Life is defined using 0 and 1.

When the 2D height map defining the terrain is read by the program, one polygon is created in the 3D mesh for each pixel in the height map. The program allows the subdivision of polygons using bilinear interpolation to achieve a higher density 3D mesh. If the resolution of the 3D mesh is the same as the texture placement, there is a one-to-one mapping between the polygons on the geometry mesh and the texture placement mesh. However, each polygon can be subdivided into smaller polygons to map more textures onto the same surface. For instance, the program reads in a height map of 32 x 32 pixels – by default, this maps one-to-one with a cell population of 32 x 32 cells. If the size of the cell population is 64 x 64, each quadrilateral on the 32 x 32 terrain mesh is subdivided into a 2x2 grid using bilinear interpolation to obtain 64 x 64 quadrilaterals.

IV.b The User Interface

The user interface allows users to generate textures over terrain surfaces defined by a gray scale terrain map. The user can alter any of the input parameters. Figure 18 shows how a user can pick a cellular automata rule and the number of generations for the evolution of the initial cell population. Figure 19 illustrates the various options that can be used to generate textures through Texullar.

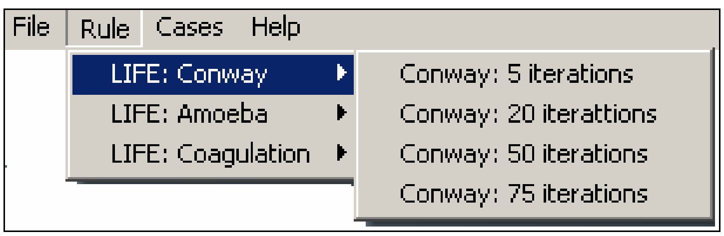


Figure 18 Texullar: (Menu) Picking a Rule

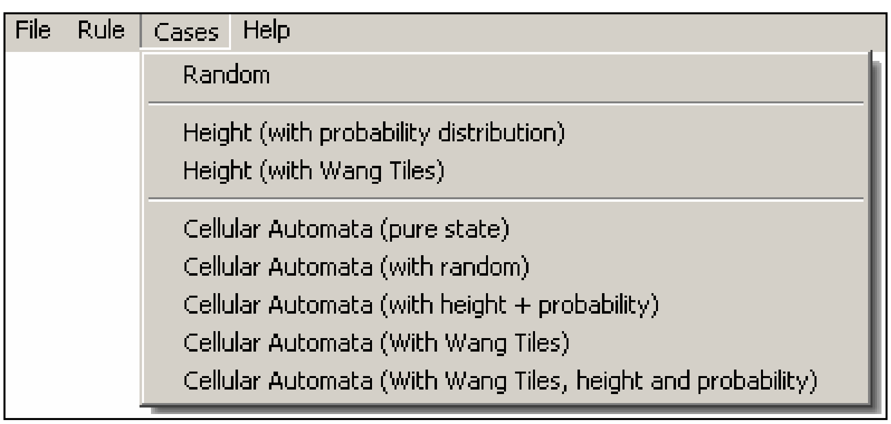


Figure 19 Texullar: (Menu) Choosing a type of method for texture generation

Using the mouse, a user can zoom in and out to view the results – clicking in the "up" direction zooms in and clicking in the "down" direction zooms out. The view can be rotated by clicking the left mouse button in the desired direction (left or right) of rotation.

The initial configuration of the cell population can be defined through a text file (ca_initpop.txt). This file contains the initial state of each cell, corresponding to the set of states applicable to the chosen rule.

V RESULTS

V.a Results

I have generated textures for different terrains to study the effect of varying different parameters on the output. All the results presented in this section were generated using a height map of 32 x 32 pixels which was subdivided to generate a set of 64 x 64 quadrilaterals, each cell mapping one-to-one with a quadrilateral.

Figures 20 and 21 illustrate the set of texture tiles used to generate the terrain textures for Figures 23 – 25. While defining probabilistic distributions for the texture tiles according to height, the texture tiles were sub-classified according to the density of flowers on the tiles. The cellular automata rules of Amoeba were applied to an initial population and evolved over 10 generations for these images. These three figures have been shown with the terrain mesh in the same orientation to illustrate how the choice of inputs influences the final results.

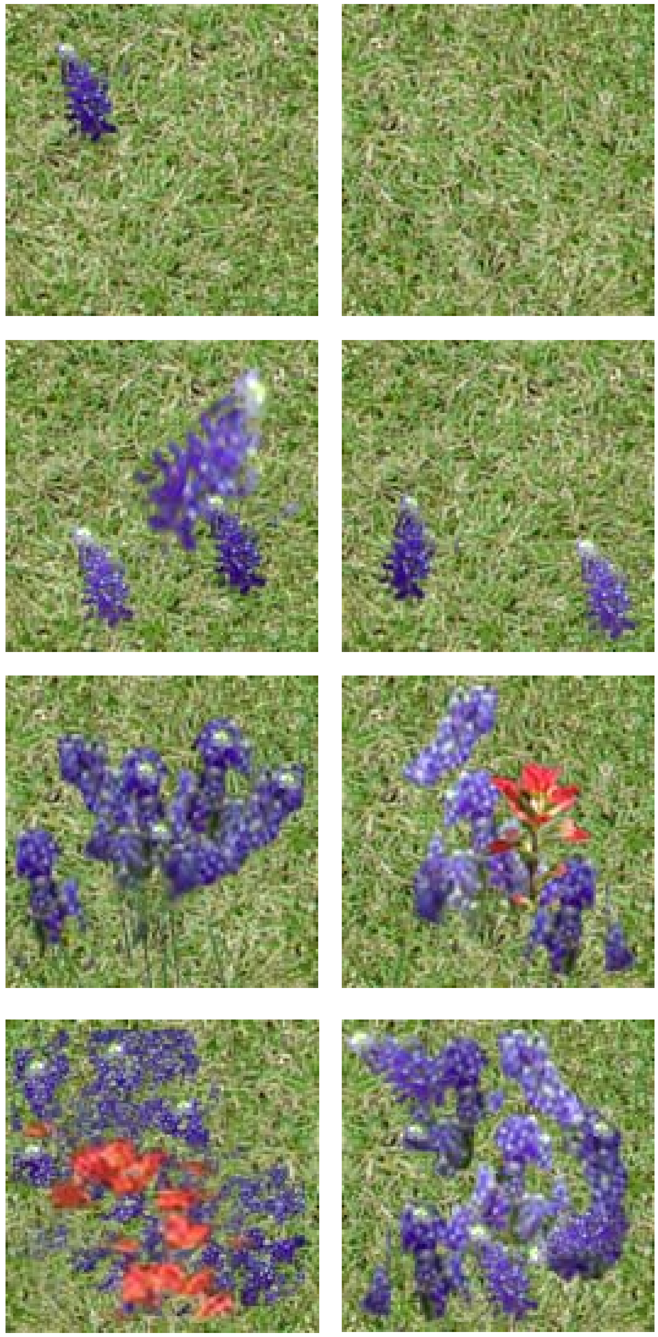
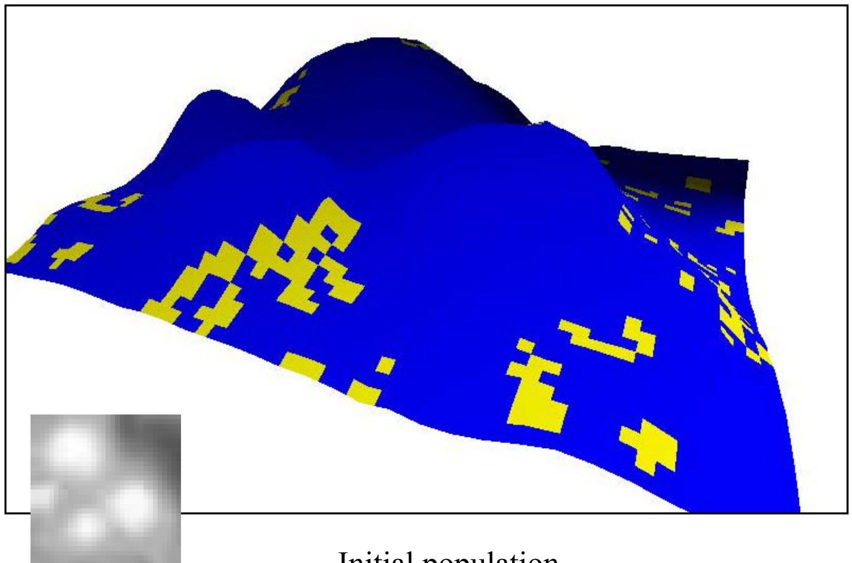


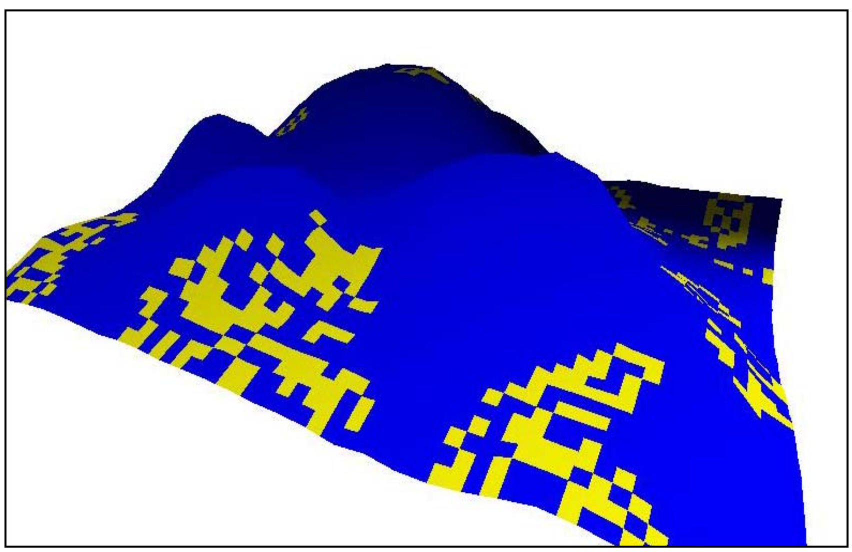
Figure 20 Texture tiles used for bluebonnets (Cellular automata state = 0)

Figure 21 Texture tiles used for yellow flowers (Cellular automata state = 1)



Height map

Initial population



Final population

Figure 22 Evolution of cellular automata

The gray scale inset shows the height map used to generate the terrain geometry. The figure on top shows the initial cell population over the terrain mesh. The figure below shows the initial population evolved over 10 generations using the Coagulation rule.

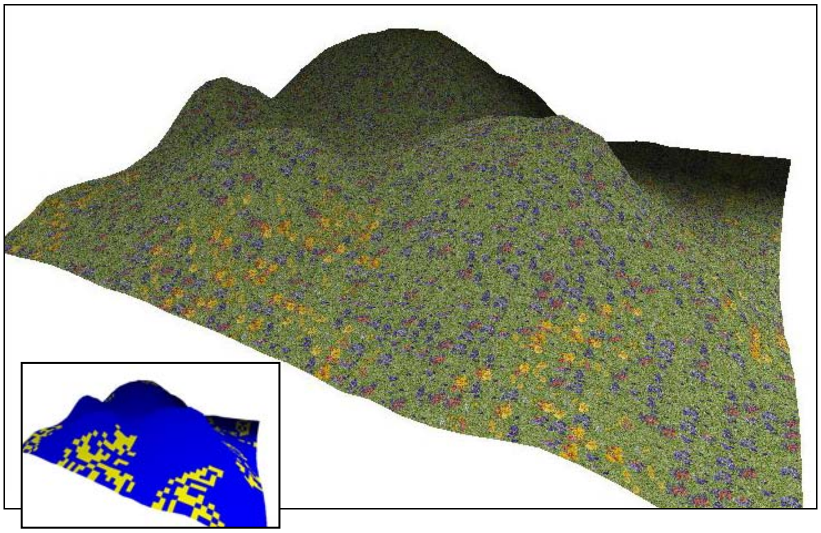


Figure 23 Texture generation using a random selection of texture tiles

The inset shows the final population (blue indicates the cells with state =0, yellow indicates the cells with state = 1). This is the same final population and terrain mesh as shown in Figure 22.

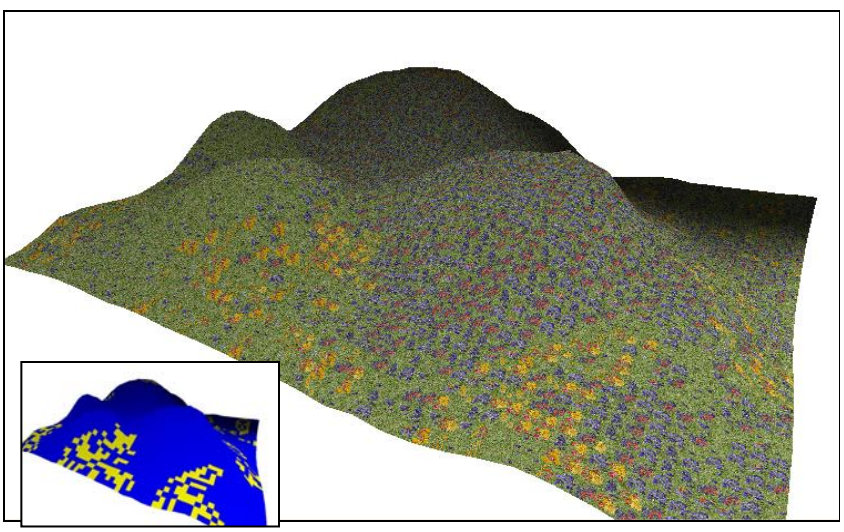


Figure 24 Terrain texture generated using cellular automata and probabilistic distribution according to height.

The texture was generated using the same final population as in Figures 22 and 23. The probabilistic distribution scheme favors bluebonnets at higher elevations and yellow flowers at lower elevations

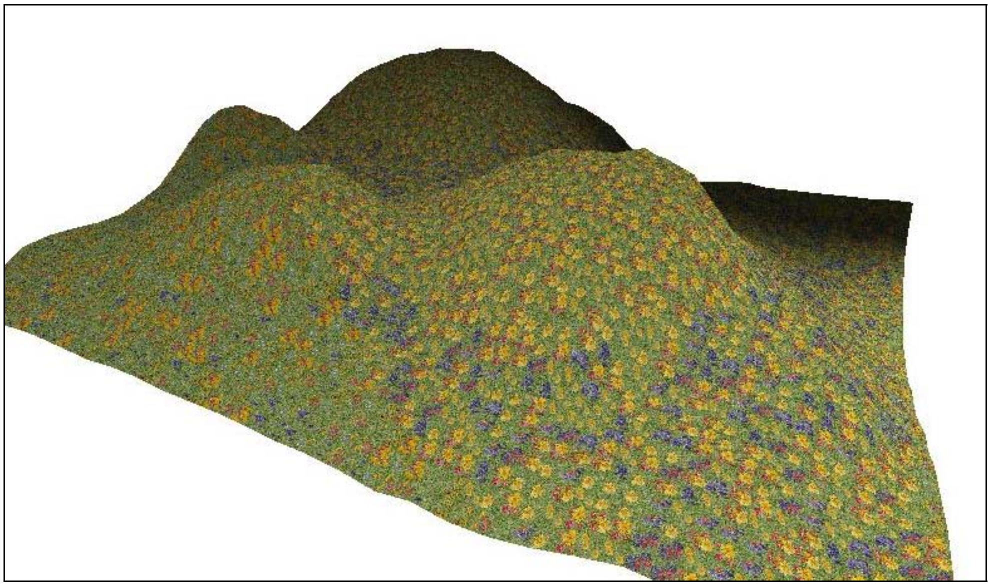


Figure 25 Texture generation using a probabilistic distribution according to height

The probabilistic distribution scheme favors bluebonnets at lower elevations and yellow flowers at higher elevations. This image uses the same terrain mesh as in Figure 22.

Figures 26 and 27 show the Wang tiles used as texture tiles. The tiles for the state 1 have show buildings (with the exception of one). The tiles for the state 0 have no buildings; they only have roads and trees. Figures 28 and 29 were generated by texture mapping through a hybrid approach involving cellular automata, Wang tiles and probabilistic distribution.

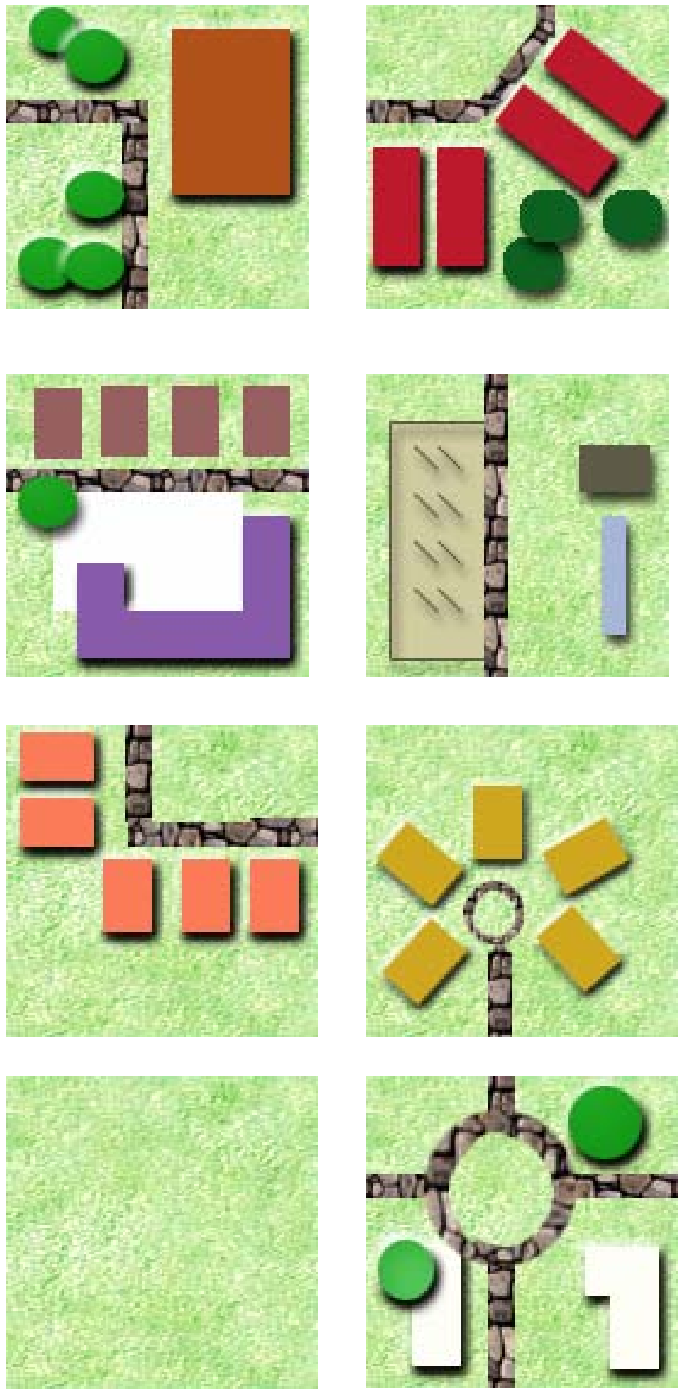


Figure 26 A set of 8 Wang tiles, corresponding to state = 1

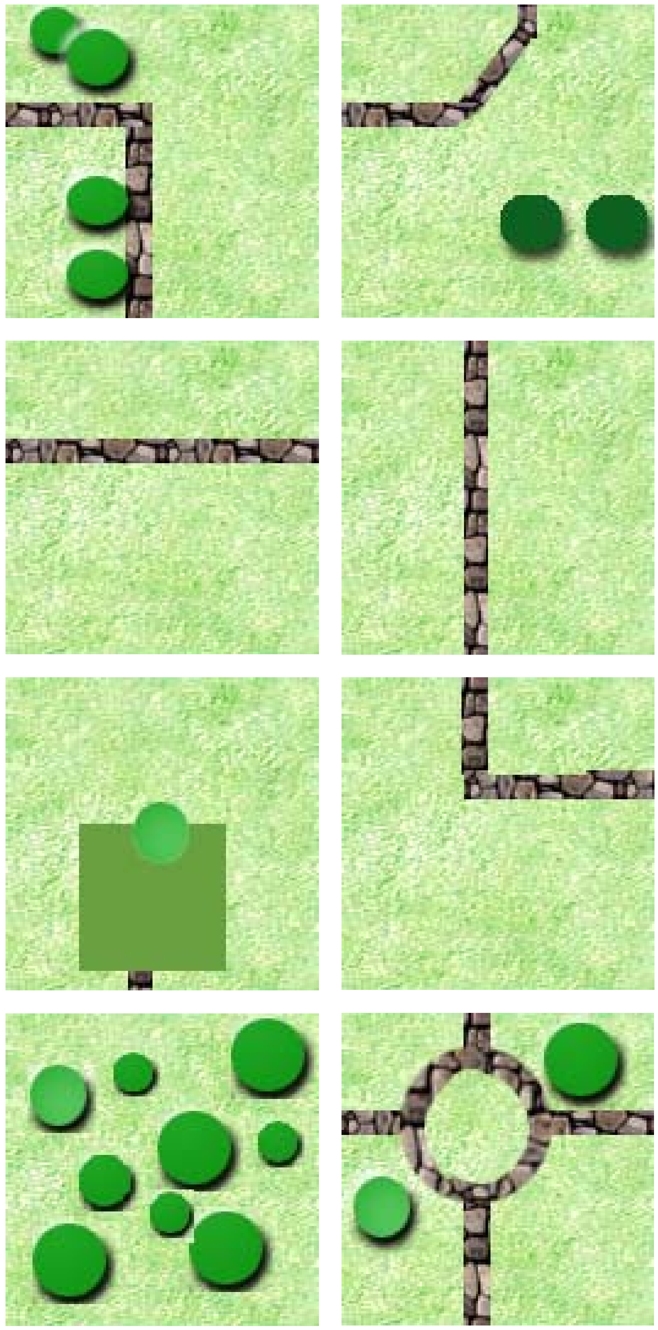


Figure 27 A set of 8 Wang tiles, corresponding to state = 0

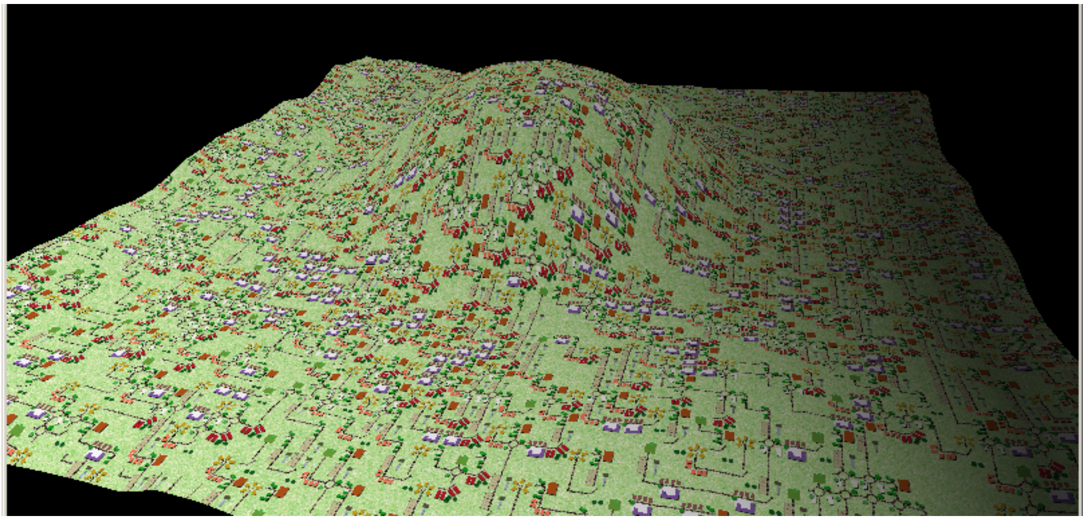


Figure 28 Texture mapping using cellular automata, Wang tiles and probabilistic height distribution. Purple buildings are preferred for lower elevations while red buildings are preferred for higher elevations. Due to the use of Wang tiles, the roads meet up to form a connected network, even though individual tiles contain small segments of the road.

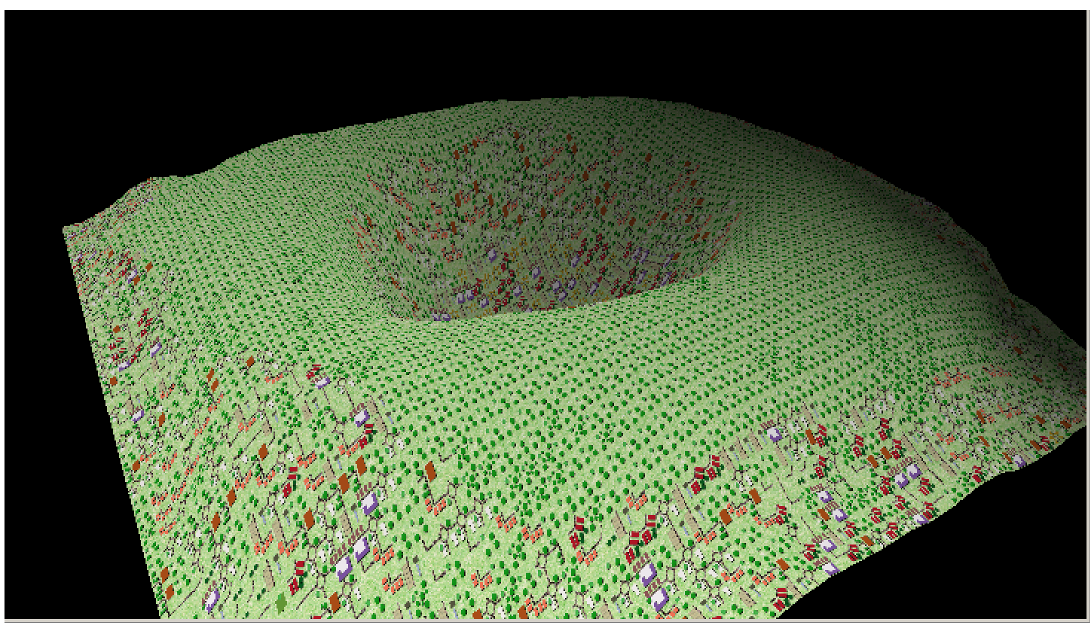


Figure 29 Texture mapping using cellular automata, Wang tiles and probabilistic distribution of texture tiles according to height.

The higher elevations strictly favored the use of texture tiles with no buildings at all. Thus, cells at the higher elevations with state = 1 also use the texture tile with no buildings

VI EVALUATION AND ANALYSIS

VI.a User Survey

To evaluate the effectiveness of the method used for generating textures and to test the hypotheses discussed in Section III.B, a user survey was conducted. The survey was conducted according to the specifications laid down by the Institutional Review Board at Texas A&M University. As the survey was deemed to pose minimal risk to participants, an exemption from full review was granted.

VI.b Participant Group

The survey was publicized through notices and the respondents were selected on a first-come-first-served basis. Participation in the survey was voluntary, and the respondents were offered neither incentives nor compensation for participation. No personal information about the users was collected. All participants were required to be above 18 years of age. A total of 17 people participated in the survey.

VI.c The Questionnaire

Survey participants were shown sets of images, and asked to evaluate the visual quality of the images through a questionnaire. All questions had four options, each of which was to be assigned a score on a scale of 1 to 10, depending on how "realistic and visually pleasing" they looked. It may be noted that this instruction could have been interpreted differently by different participants. The respondents were asked to score the images relative to each other within a question. The respondents were allowed to look at all the images before they scored any of them, and were also allowed to look at images they had already scored.

I used different rules of cellular automata and used multiple images generated using cellular automata in the questions for the survey. This was done in order to get a more representative set of results. For instance, in Question 1, I used three different rules of cellular automata to analyze the effect of using cellular automata. I also used different terrain types and different sets of texture tiles to eliminate bias.

Across the images generated for a set, I used an identical height map. The same initial populations were used for (a), (b), (c) and (d) within the same set and all of them were evolved over the same number of generations. Survey participants were not told of the change in parameters and were asked to grade the images on a scale of 1 to 5 (1 = Poor, 5 = Excellent). The users were allowed to view the images in any order to avoid any bias due to a specified sequence of images. Users were also free to change their responses to previous questions after viewing images for subsequent questions.

While constructing the questions for the survey, I used multiple images using different rules of cellular automata to get a better representation of the 2-state cellular automata.

The questionnaire and the complete set of images used for the survey is available in Appendix 1. The parameters used for texture mapping are described in Table 4.

Table 4 Parameters for images used in survey

Ques		Choices			
		(a)	(b)	(c)	(d)
Q 1	Terrain 1	Random	CA (Conway's Game of Life) + Random	CA (Amoeba) + Random	CA (Coagulation) + Random
	Terrain 2	Random	CA (Conway's Game of Life) + Random	CA (Amoeba) + Random	CA (Coagulation) + Random
Q 2	Terrain 1	CA (Conway's Game of Life) + Random	CA (Amoeba) + Random	CA (Conway's Game of Life) + $Height_{prob}$	CA (Amoeba) + $Height_{prob}$
	Terrain 2	CA (Conway's Game of Life) + Random	CA (Amoeba) + Random	CA (Conway's Game of Life) + $Height_{prob}$	CA (Amoeba) + $Height_{prob}$
Q 3	Terrain 1	$Height_{prob}$	CA (Conway's Game of Life) + $Height_{prob}$	CA (Amoeba) + $Height_{prob}$	CA (Coagulation) + $Height_{prob}$
	Terrain 2	$Height_{prob}$	CA (Conway's Game of Life) + $Height_{prob}$	CA (Amoeba) + $Height_{prob}$	CA (Coagulation) + $Height_{prob}$
Q 4		CA (Conway's Game of Life) + $Height_{prob}$	CA (Coagulation) + $Height_{prob}$	CA (Conway's Game of Life) + Wang tiles + $Height_{prob}$	CA (Coagulation) + Wang tiles + $Height_{prob}$
Q 5		Wang tiles	CA (Conway's Game of Life) + Wang tiles + $Height_{prob}$	CA (Coagulation) + Wang tiles + $Height_{prob}$	Wang tiles

Abbreviations used in Table 4:

CA: Using cellular automata rules; the name of the rule used is indicated in parentheses.
$Height_{prob}$: Applying height information to define a probabilistic distribution of texture tiles
Random: Random placement of textures
Wang tiles: Texture placement defined by Wang tiles

VI.d Analysis of Survey Results

The scores given to the images were analyzed at the end of the survey. One of the participants volunteered the information of being color blind. Scores from this participant showed very little variation, all scores being within a range of 2 to 4. I interpreted this as an indication of the fact that the participant was not able to distinguish enough detail to judge the images appropriately. Hence, I did not consider scores from this participant while compiling the results; the analysis was done on the basis of responses from the remaining 16 respondents.

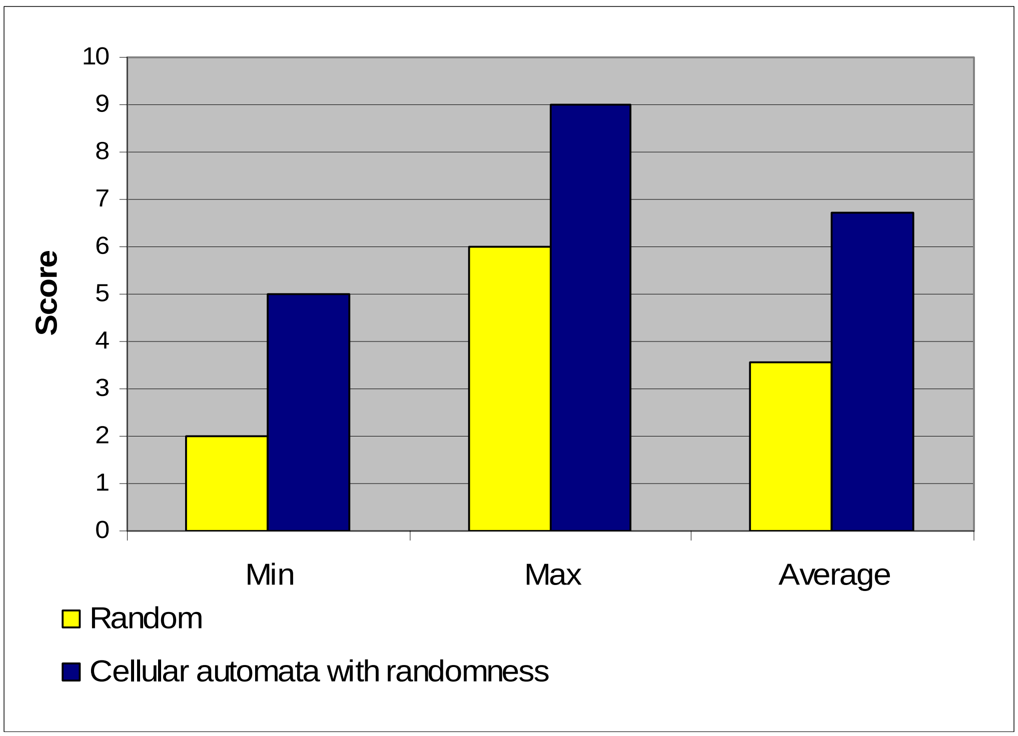


Figure 30 Comparing Random against CA + Random

Figure 30 above shows that the minimum, maximum and average scores given by respondents to images with random placement of textures is lower than those for cellular automata with randomness. An analysis of the scores given to images using only random placement against those using cellular automata rules and randomness showed a p-value of 0.15. Since $p < \alpha$, I reject the null hypothesis ($H1_0$) in this case. Thus, there is sufficient evidence to support the research hypothesis ($H1_a$) and conclude that, for the assignment of texture tiles on a 3D terrain mesh, a hybrid approach combining cellular automata and random placement leads to a higher mean score than a random placement alone.

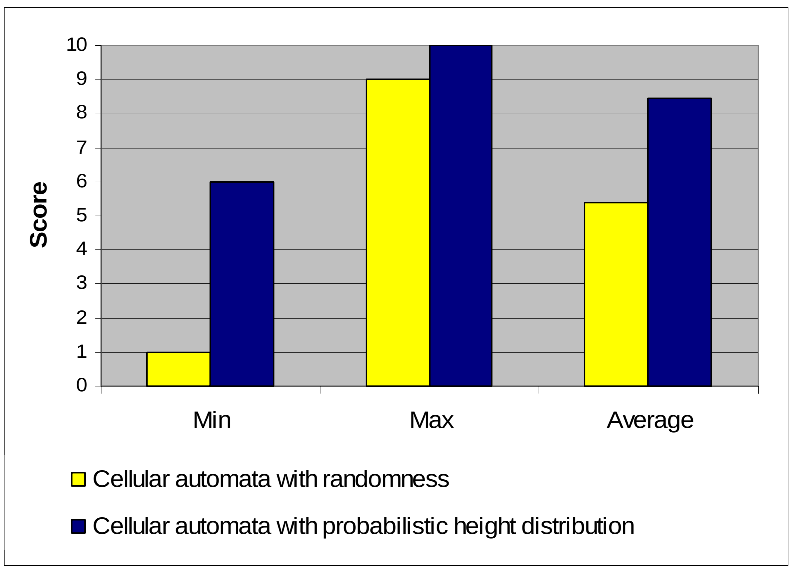


Figure 31 Comparing CA + Random against CA + height

Figure 31 shows that the minimum, maximum and average scores given by respondents to images with random placement of textures is lower than those for a hybrid approach using cellular automata with a probabilistic distribution of texture tiles according to height. Further analysis shows a p-value of 0.14. Since $p < \alpha$, there is enough evidence to reject the null hypothesis ($H2_0$) in this case. Thus, there is sufficient evidence to support the research hypothesis ($H2_a$) and conclude that, for the assignment of texture tiles on a 3D terrain mesh, a hybrid approach combining cellular automata and probabilistic distribution of texture tiles according to height of the terrain leads to a higher mean score than a hybrid approach combining cellular automata and random placement.

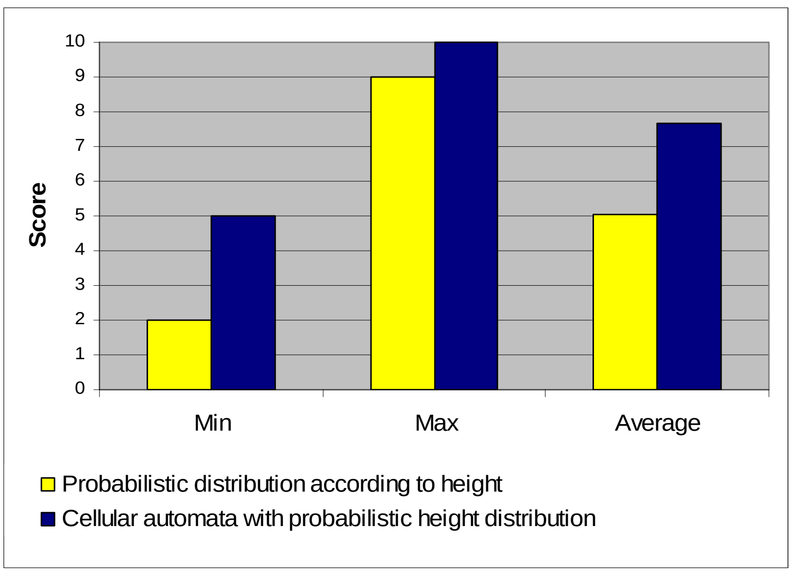


Figure 32 Comparing CA + height against Height

Figure 32 above shows that the minimum, maximum and average scores given by respondents to images generated using a probabilistic distribution of texture tiles according to height is lower than those generated using a hybrid approach integrating cellular automata with a probabilistic distribution of texture tiles according to height. An analysis of the scores given to images using only random placement against those using cellular automata rules and randomness showed a p-value of 0.17. Since $p < \alpha$, the null hypothesis ($H3_0$) can be rejected in this case. Thus, there is sufficient evidence to support the research hypothesis ($H3_a$) and conclude that, for the assignment of texture tiles on a 3D terrain mesh, a hybrid approach combining cellular automata and probabilistic distribution of texture tiles according to height of the terrain leads to a higher mean score than an approach using a probabilistic distribution of texture tiles according to height of the terrain alone.

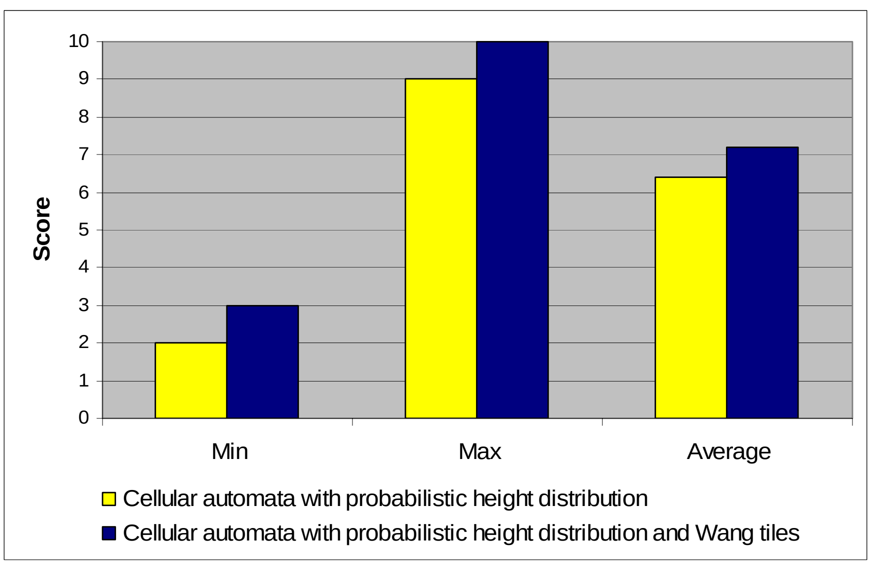


Figure 33 Comparing CA + height against CA + height + Wang tiles

Figure 33 above shows the minimum, maximum and average scores given by respondents to images generated using a hybrid approach of cellular automata and a probabilistic distribution of texture tiles according to height against a hybrid approach integrating cellular automata, a probabilistic distribution of texture tiles according to height with randomness and Wang tiles. An analysis of the scores given to images using only random placement against those using cellular automata rules and randomness showed a p-value of 0.46. Since $p > \alpha$, there is not enough evidence to reject the null hypothesis ($H4_0$) in this case. Thus, for the chosen α, the research hypothesis ($H4_a$) cannot be validated.

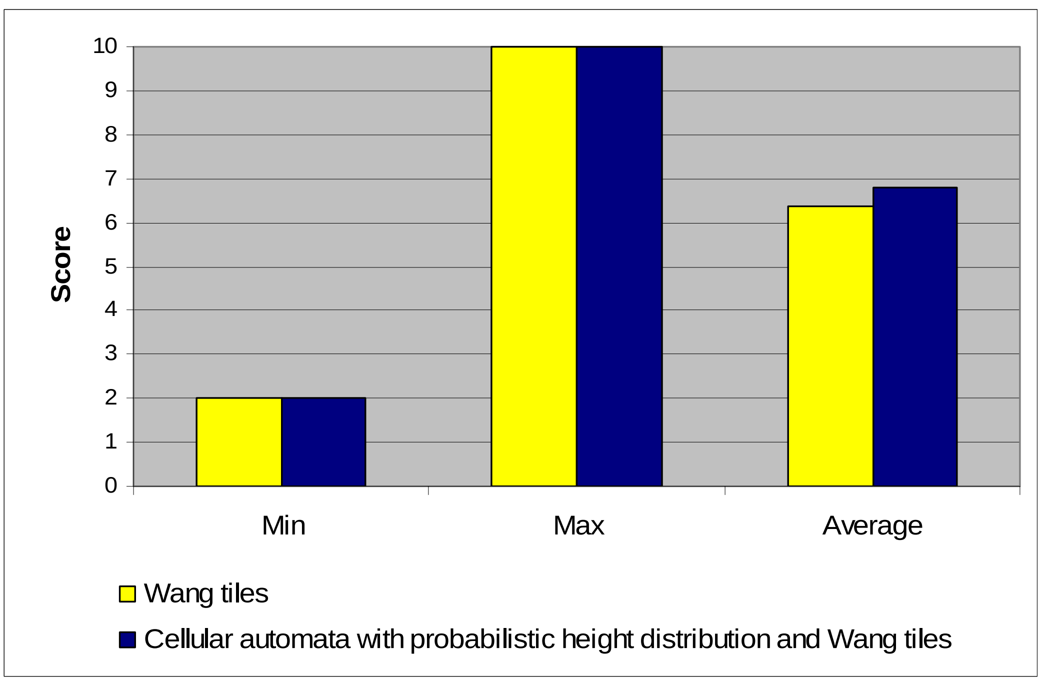


Figure 34 Comparing Wang tiles against CA + height + Wang tiles

The results of Figure 34 are interesting, as they show a very insignificant increase in the mean score of images using Wang tiles when cellular automata and probabilistic distribution of texture tiles using height information is added to the algorithm for texture generation. However, this may have been the case because the respondents did not know the desired distribution patterns of textures used to generate the images. The use of Wang tiles eliminated periodicity and the respondents of the survey may not have been able to detect the subtle changes brought into effect by the use of cellular automata and the probabilistic distribution of texture tiles.

VII PROBLEMS AND LIMITATIONS

I note that the effectiveness of the final results is likely to depend on the actual texture tiles used as inputs. The results can also be influenced by the choice of rules for the cellular automata used.

This work explores only those terrains that can be represented by height maps – thus eliminating terrain features such as cliffs and caves. The probabilistic distributions according to height for such terrain types would also be different. For instance, the texture tiles used for an elevation interval may be different in case of a cave and an undulating hill slope.

Since the quality of images is a very subjective domain, it is difficult to score images by giving the quality a numerical value. In some of the survey questions, the images used for the options (a, b, c and d) were similar with minor variations. If a survey respondent were to re-score the images, it would be likely that the scores might be different. The fact that all participants responded to the invitation notice for the survey indicates that they have an interest in the area of computer graphics – this may have influenced their scoring pattern because they might have already had extensive exposure to computer-generated images.

Some questions in the survey had more than one image per option. This was done with the intention of having a greater representative set of images generated using the given parameters. However, in a few cases, the quality of images within an option was different. Some respondents remarked that this made it difficult to evaluate the results.

In the images used for the survey questions, I noticed that even a minor change in the orientation or lighting for one of the options affected the response of some users. For instance, one respondent gave a lower score to one of the options in Question 4 because it was darker than the others. The use of particular textures may also have influenced the responses of participants; similar problems have been noted by Bair et al. [4] and House et al. [42].

The survey images illustrated only a small subset of all the possible options to generate textures using the given set of parameters. Many different possibilities still exist that have not been explored. For instance, instead of using a uniform random distribution, other options like Perlin noise could be investigated. Various options for the probabilistic distribution of texture tiles according to height can also be explored. Results can also be generated using cellular automata algorithms with different rules, number of states, characteristics and growth rates. Different terrain types and texture patterns can also be studied.

VIII CONCLUSIONS

VIII.a Conclusions

An analysis of the survey results (Section VI.D) shows that using cellular automata concepts can, in some cases, potentially yield better results than random placement of texture tiles alone as well as probabilistic distribution of texture tiles based on height information alone.

I noticed that using Wang tiles with cellular automata and probabilistic distribution of texture tiles based on height information reduced periodicity of texture tiles while following a theme defined by the final cell population. However, this did not necessarily translate into higher mean scores as compared to images generated using only Wang tiles. This hypothesis could be re-evaluated by conducting another survey in which respondents can be asked to generate a terrain texture using Wang tiles by evolving an initial population by choosing parameters for evolution. Respondents may be able to achieve more customized results using this approach – more so by also defining their own probabilistic distributions according to height – than by the use of Wang tiles alone. Images generated in this fashion might lead to a higher mean score than images generated using Wang tile information alone.

Some advantages of using the approaches described in this work for texture mapping include the fact that it allows the user to define an initial configuration and evolve it according to the growth patterns desired. It also gives the user options to customize various parameters to change the final outcome. Most importantly, using cellular automata can save a lot of user input from hand painting textures over large surfaces. Since cellular automata can be evolved using parallel computation techniques, they can be processed in short intervals of time and can yield quick results.

VIII.b Future Work

The use of texture tiles with rotations can give greater aperiodicity in texture generation, while using fewer texture tiles. This can lead to a potential saving of memory – a critical resource in interactive computer graphics applications.

The application of 3D cellular automata can also lead to interesting results and can be a future direction of research. The effects of adding Perlin noise [67] and randomness in the evolution of the cellular automata can also be investigated.

Another idea is to pre-define some terrain features (like lakes or major roads) and the placement of texture tiles that map to them. Then, we can evolve only the cells that map to the rest of the terrain mesh. This, however, would need special consideration for the rules to be applied when there is a break in continuity in the cell population due to the pre-defined features.

REFERENCES

1. Fracplanet, http://www.bottlenose.demon.co.uk/share/fracplanet, accessed on October 7, 2005.
2. A. Asirvatham and H. Hoppe, "Terrain Rendering Using GPU-based Geometry Clipmaps," *GPU Gems 2*, M. Pharr and R. Fernando, eds., Boston, MA: Addison-Wesley, pp. 27-45, 2005.
3. T. Bäck, F. Hoffmeister, H. Schwefel, "A Survey of Evolution Strategies," in L. B. Belew, R. K. Booker, eds., *Proc. Int'l Conf. Genetic Algorithms*, pp. 2-9, 1991.
4. A. Bair, D. House and C. Ware, "Perceptually Optimizing Textures for Layered Surfaces," *Applied Perception in Graphics and Visualization*, pp. 67-74, 2005.
5. M. Batty and Y. Xie, "From Cells to Cities," *Environment and Planning B*, 21, s31-s48. 1994.
6. M. Batty and Y. Xie, "Possible Urban Automata," *Environment and Planning B*, 24(2), pp. 175-192, 1997.
7. S. Benati, 1997, "A Cellular Automaton for the Simulation of Competitive Location," *Environment and Planning B*, 24(2), pp. 175-192.
8. C. Bloom, "Terrain Texture Compositing by Blending in the Frame-Buffer," http://www.cbloom.com/3d/techdocs/splatting.txt, accessed on October 1, 2005.

9. P. Bourke, "Fractal Landscapes," 1991, http://astronomy.swin.edu.au/~pbourke/modelling/frachill/, accessed on October 5, 2005.

10. A. Carosio, "Three-Dimensional Synthetic Landscapes: Data Acquisition, Modelling and Visualisation," D. Fritsh and D. Hobbie eds., *Photogrammetric Week '95*, pp. 293-302, 1995.

11. M. F. Cohen, J. Shade, S. Hiller and O. Deussen, "Wang tiles for Image and Texture Generation," *Proc. ACM SIGGRAPH*, vol. 22, no. 3, pp. 287-294, 2003.

12. R. L. Colasanti and R. Hunt, "Resource Dynamics and Plant Growth: A Self-Assembling Model for Individuals, Populations and Communities," *Functional Ecology 11*, pp. 133-145, 1995.

13. R. L. Colasanti, R. Hunt and A.P. Askew, "A Self-Assembling Model of Resource Dynamics and Plant Growth Incorporating Plant Functional Types," *Functional Ecology 15*, pp. 676-687, 2001.

14. V. Cole and J. Albrecht, "Modelling the Spread of Invasive Species — Parameter Estimation Using Cellular Automata In GIS," 1999. http://www.geo.hunter.cuny.edu/people/fac/albrecht/DMGIS99.pdf, accessed on October 1, 2005.

15. R. Conte and R. Hegselmann, "The Dynamics of Sharing," *SimSoc '97*, 1997.

16. J.P. Crutchfield and J.E. Hanson, "Turbulent Pattern Bases for Cellular Automata," *Physica D 69*, pp. 279-301, 1993.

17. P. Decaudin and F. Neyret, "Rendering Forest Scenes in Real-Time, Rendering Techniques," *Proc. Eurographics Symp. Rendering*, pp. 93-102, 2004.

18. B. Desbenoit., E. Galin, and S. Akkouche, "Simulating and Modeling Lichen Growth," *Computer Graphics Forum*, vol. 23, no. 3, pp. 341-350, 2004.

19. J. Dexter, "Texturing Heightmaps," http://www.gamedev.net/reference/articles/article2246.asp, accessed on October 1, 2005.

20. J. Dorsey and P. Hanrahan, "Modeling and Rendering of Metallic Patinas," *Proc. ACM SIGGRAPH,* pp. 387-396, 1996.

21. J. Dorsey, A. Edelman, H. Jensen, J. Legakis, and H. Pedersen, "Modeling and Rendering of Weathered Stone," *Proc. ACM SIGGRAPH*, pp. 225-234, 1999.

22. J. Dorsey, H. K. Pedersen, and P. Hanrahan, "Flow and Changes in Appearance," *Proc. ACM SIGGRAPH*, 1996.

23. A. A., Efros, and W. T. Freeman, "Image Quilting for Texture Synthesis and Transfer," *Proc. ACM SIGGRAPH*, pp. 341-346, 2001.

24. C. Emmeche, "The Garden in the Machine: The Emerging Science of Artificial Life," *Princeton University Press*, translated from the Danish by S. Sampson, 1994.

25. G. Engelen, R. White, I. Uljee, and P. Drazan, "Using Cellular Automata for Integrated Modelling of Socio-Environmental Systems," *Environmental Modelling and Assessment*, vol. 34, pp. 203-214, 1995.

26. E. Fredkin and T. Toffoli, "Conservative logic," *Int'l J. Theoretical Physics*, vol. 21, no. 3/4, pp. 219-253, 1982.

27. J. Foley, and A. van Dam, "Computer Graphics: Principles and Practice," *Addison-Wesley*, 1990.

28. Fotograferen.net: Wallpapers: Snow, http://www.fotograferen.net/, accessed on October 1, 2005.

29. M. Gardner, "Mathematical Games: The Fantastic Combinations of John Conway's New Solitaire Game 'Life'," *Scientific American*, pp. 120-123, Oct. 1970.

30. M. Gardner, "Mathematical Games: On Cellular Automata, Self-Reproduction, the Garden of Eden, and the Game 'Life'," *Scientific American*, pp. 112-117, 1971.

31. G. Guariso and Baracani, "A Simulation Software of Forest Fires Based on Two-Level Cellular Automata," *Proc. Int'l Conf. on Forest Fire Research 2002 and Wildland Fire Safety Summit*, pp. 100-101, 2002.

32. L.A. Green, M. Saslow, J. Keyser, and E. Akleman, "Tiled Texture Synthesis," *Thesis Report, Texas A&M University*, 2004.

33. S. Gobron and N. Chiba, 3D Surface Cellular Automata and Its Applications, *J. Visualization and Computer Animation*, pp. 143–158, 1999.

34. D. Goldberg, "Genetic Algorithms," Boston, MA: Addison Wesley, 1988.

35. G. Gabriele, V. Interrante, and G. Sapiro, “Texture Synthesis for 3D Shape Representation,” *IEEE Trans. on Visualization and Computer Graphics*, vol.9 no. 4, pp. 512-524, 2003.

36. L. Gray, "A Mathematician Looks at Wolfram's New Kind of Science." *Not. Amer. Math. Soc. 50*, pp. 200-211, 2003.

37. B. Grunbaum B., and G.C. Shephard, *Tilings and Patterns*, New York: W. H. Freeman and Co., 1987.

38. P.S. Heckbert, “Survey of Texture Mapping,” *IEEE Computer Graphics and Applications*, vol. 6, no. 11, pp. 215-223, 1986.

39. J.H. Holland, *Adaptation in Natural and Artificial Systems: An Introductory Analysis with Applications to Biology, Control, and Artificial Intelligence*, 2nd ed., Cambridge, MA: MIT Press, 1992.

40. H. Hoppe, “Smooth View-Dependent Level-Of-Detail Control and Its Application to Terrain Rendering,” *Proc. IEEE Conf. on Visualization*, pp. 35-42, 1998.

41. W. Hordijk, J.P. Crutchfield, and M. Melanie, “Mechanisms of Emergent Computation in Cellular Automata”, *Lecture Notes in Computer Science*, vol. 1498, pp. 613-622, 1998.

42. D. House, A. Bair, and C. Ware, “On the Optimization of Visualizations of Complex Phenomena,” *Proc. IEEE Visualization*, 2005.

43. J. T. Kajiya, and T. L. Kay, “Rendering Fur with Three Dimensional Textures,” *Computer Graphics*, vol. 23, no. 3, pp. 271-280, July 1989.

44. I. Karafyllidis, and A. Thanailakis, “A Model Predicting Forest Fire Spread Using Cellular Automata,” *Ecological Modelling 99*, pp. 87-97, 1997.

45. S. Kauffman, *At Home in the Universe: The Search for Laws of Self-Organization and Complexity*, New York: Oxford University Press, 1995.

46. S. Kauffman, *The Origins of Order*, New York: Oxford University Press, 1993.

47. A. Kaur, J. Chen, D. House, and E. Akleman, “Texture Mapping Using Tiled Textures,” M.S. Thesis, Texas A&M University, College Station, TX, 2004.

48. R. Kosara, C.G. Healey, V. Interrante, D.H. Laidlaw, and C. Ware, “Thoughts on User Studies: Why, How and When,” *Proc. IEEE Computer Graphics and Applications*, vol. 23, no. 4, pp.20-25, 2003.

49. C. Langton, “Studying Artificial Life with Cellular Automata,” *Physica D*, vol. 22, 1986, pp. 120-149, 1982.

50. C. Langton, “Self-Reproduction in Cellular Automata,” *Physica D*, vol.10, pp. 135-144, 1984.

51. S. Lefebvre, and H. Hoppe, “Parallel Controllable Texture Synthesis,” *Proc. ACM SIGGRAPH*, vol 24, no. 3, pp. 777-786, 2005.

52. S. Lefebvre, and F. Neyret, “Pattern Based Procedural Textures,” *Proc. ACM Symp. Interactive 3D Graphics*, pp. 203-212, 2003.

53. X. Li, and W. Magill, “Modelling Fire Spread Under Environmental Influence Using A Cellular Automaton Approach,” *Complexity International 8*, pp. 1-14, 2000.

54. P. Lindstrom, and V. Pascucci, "Visualization of Large Terrains Made Easy," *Proc. IEEE Visualization*, pp. 363–370, 2001.

55. P. Litwinowicz, and G. Miller, "Efficient Techniques for Interactive Texture Placement," *Int'l Conf. Computer Graphics and Interactive Techniques*, pp. 119-122, 1994.

56. F. Losasso and H. Hoppe, "Geometry Clipmaps: Terrain Rendering Using Nested Rectangular Grids," *ACM Trans. Graph*., vol. 23, no. 3, pp. 769-776, 2004.

57. B. Mandelbrot, *The Fractal Geometry of Nature*, San Francisco, CA: W. H. Freeman, 1982.

58. Mathworld, http://mathworld.wolfram.com, accessed on Oct 01, 2005.

59. W. Matusik, M. Zwicker and F. Durand, "Texture Design Using a Simplicial Complex of Morphable Textures," *Proc. ACM SIGGRAPH*, vol. 24, no. 3, pp. 787 - 794 , 2005.

60. M. Melanie, J. P. Crutchfield, and R. Das, "Evolving Cellular Automata with Genetic Algorithms: A Review of Recent Work," *Proc. First Int'l Conf. Evolutionary Computation and Its Applications*, 1996.

61. M. Melanie, P. T. Hraber, and J. P. Crutchfield, "Revisiting the Edge of Chaos: Evolving Cellular Automata to Perform Computations," *Complex Systems 7*, pp. 89-130, 1993.

62. H. W. Jensen, J. Legakis, J. Dorsey, "Rendering of Wet Materials," *Proc. 10th Eurographics Workshop on Rendering*, pp. 273-282, 1999.

63. F.K. Musgrave, C.E. Kolb, R.S. Mace, "The Synthesis and Rendering of Eroded Fractal Terrains," *Proc. Int'l Conf. Computer Graphics and Interactive Techniques*, pp. 41 – 50, 1989.

64. F. Neyret, M. Cani, "Pattern-Based Texturing Revisited," *Proc. 26th Annual Conf. Computer Graphics and Interactive Techniques*, pp. 235-242, 1999.

65. T. J. Ong, "Using Genetic Algorithms to 'Auto-Generate Textures' for Predetermined Environment," Project Report, Texas A&M University, 2003.

66. R. B. Pajarola, "Large Scale Terrain Visualization Using The Restricted Quadtree Triangulation," *IEEE Visualization*, pp. 19–26, 1998.

67. K. Perlin, "An Image Synthesizer," *Proc. ACM SIGGRAPH*, pp. 287 – 296, 1985.

68. www.rufenacht.com/CA/AnimalSim.html, "And What If Animal Skins Were Cellular Automata?" (as viewed on Aug 26, 2005)

69. Rucker Rudy, "Symbiotic Programming: Cross-Breeding Cellular Automaton Rules on the CAM-6," *J. Complex Systems*, vol. 3, pp. 79–90, 1989.

70. S. Rusinkiewicz and M. Levoy, "Qsplat: A Multiresolution Point Rendering System for Large Meshes," *Proc. ACM SIGGRAPH*, pp. 343 – 352, 2000.

71. P. Sander, J. Snyder, S. Gortler, H. Hoppe, "Texture Mapping Progressive Meshes," *Proc. ACM SIGGRAPH*, pp. 409-416, 2001.

72. B. Shneiderman, and C. Plaisant, *Designing the User Interface: Strategies for Effective Human-Computer Interaction*, 4th ed., Boston, MA: Addison Wesley, 2004.

73. J. Sharman, “How to Render Landscapes,” http://www.gamedev.net/reference/articles/article678.asp, accessed on October 1, 2005.
74. A. L. Sullivan and I.K. Knight, “A Hybrid Cellular Automata/Semi-Physical Model of Fire Growth,” *Proc. Conf. Complex Systems*, pp 64-73, 2004.
75. Y. Suzuki, T. Takayama, I.N. Motoike, and T. Asai, “Striped and Spotted Pattern Generation on Reaction-diffusion Cellular Automata – Theory and LSI Implementation,” *Int’l J.Unconventional Computing*, 2006, in press.
76. Y. Takai, T.Saito, Y.Tomikawa, and N.K.Takai, “A Particle Cluster Deformation Model by the Probabilistic Cellular Automata,” *IEICE Trans. Inf. and Sys.*, vol.J83-A, 2000.
77. Y. Takai, N.K. Takai, and K.J. Nakamori, “Exploration of the Reaction-Diffusion Textures,” *Proc. Int’l Conf. on Modelling and Simulation*, 1998.
78. Terrain Engine, http://ohad.visual-i.com/exper/exper.htm, accessed on October 1, 2005.
79. "The Game of Life,” *Time*, January 21, 1974.
80. T. Toffoli, “Nothing Makes Sense In Computing Except In The Light Of Evolution,” *Int’l. J. Unconventional Computing 1*, pp. 1-29, 2005.
81. T. Toffoli, and N. Margolus, *Cellular Automata Machines*, Cambridge, MA: MIT Press, 1987.
82. G. Turk, “Generating Textures on Arbitrary Surfaces Using Reaction-Diffusion,” *Proc. ACM SIGGRAPH*, pp. 289-298, 1991.

83. L. Vepstas, Notes on Artificial Life & Cellular Automata, accessed on October 1, 2005, http://linas.org/plants/observe.html, 1996.
84. J. von Neumann, "The General and Logical Theory of Automata," *Collected Works, vol. 5,* New York: Macmillan, pp. 288-328, 1963.
85. J. von Neumann, *The Theory of Self-reproducing Automata,* Urbana: Univ. of Illinois Press, 1966.
86. H. Wang, "Games, Logic, and Computers," *Scientific American* (November), pp. 98–106, 1965.
87. H. Wang, "Proving Theorems by Pattern Recognition II," *Bell Systems, Technical Journal 40*, pp. 1–42, 1961.
88. C. Ware, and G. Sweet, "View Direction, Surface Orientation and Texture Orientation for Perception of Surface Shape," *Proc. Graphics Interface*, pp. 97-106, 2004.
89. C. Ware, E. Neufeld, and L. Bartram, "Visualizing Causal Relations," *Proc. IEEE Information Visualization, Late Breaking Hot Topics*, pp. 39-42, 1999
90. C. Ware, and W. Knight, "Using Visual Texture for Information Display," *ACM Trans. on Graphics*, vol. 14, no. 1, pp. 3-20, 1995.
91. E. W. Weisstein, "Moore Neighborhood," From MathWorld--A Wolfram Web Resource. http://mathworld.wolfram.com/MooreNeighborhood.html. Last accessed on October 1, 2005

92. R. White and G. Engelen, “Cellular Automata and Fractal Urban Form: A Cellular Modelling Approach to the Evolution of Urban Land-Use Patterns,” *Environment and Planning A*, vol. 25, no. 8, pp. 1175-1199, 1993.

93. M. Wijaya, and D. Callele, “Semi-Random Terrain Generation,” Poster Abstract, Graphics Interface, 2005.

94. Wikipedia, “A New Kind of Science,” http://en.wikipedia.org/wiki/A_New_Kind_of_Science [Last accessed on October 1, 2005].

95. J.R. Wright and J.C.L. Hsieh, “A Voxel-Based, Forward Projection Algorithm for Rendering Surface and Volumetric Data,” *Proc. 3rd Conf. Visualization*, pp. 340–348, 1992.

96. M. Wojtowicz, Cellular Automata Gallery - part II, http://psoup.math.wisc.edu/mcell/ca_gallery2.html [Last accessed: October 5, 2005]

97. S. Wolfram, *A New Kind of Science*, Champaign, IL: Wolfram Media, 2002.

98. S. Worley, “A Cellular Texture Basis Function,” *Proc. Conf. Computer Graphics and Interactive Techniques*, pp.291-294, 1996.

99. http://www.carleton.ca/ics/courses/cgsc5001/lecture2.html, CGSC 5001 Lecture 2, Cellular Automata [Last accessed on October 10, 2005]

100. K. Zhou, X. Wang, Y. Tong, M. Desbrun, B. Guo, H. Shum, “TextureMontage: Seamless Texturing of Arbitrary Surfaces From Multiple Images,” Proc. ACM SIGGRAPH, pp. 1148-1155, 2005.

101. K. Zuse, *Rechnender Raum*, Braunschweig: Friedrich Vieweg & Sohn Verlag, 1969 [English translation: Calculating Space, MIT Technical Translation AZT-70-164-GEMIT, MIT (Proj. MAC), Cambridge, MA 02139, Feb. 1970.].

APPENDIX A

Questionnaire

Please take a look at Exhibits and answer the questions below. For questions that ask you to rate images, please rate them on a scale of 1 to 10 [Poor = 1 or 2, Fair = 3 or 4, Good = 5 or 6, Very Good = 7 or 8, Excellent = 9 or 10].

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1. Exhibits A, B, C and D are computer-generated images of textures on a terrain surface. Please rate these images according to how realistic and visually pleasing they look.

	Excellent	Very Good	Good	Fair	Poor
Exhibit A					
Exhibit B					
Exhibit C					
Exhibit D					

2. A, B, C and D are computer-generated images of textures on a terrain surface. Please rate these images according to how realistic and visually pleasing they look.

	Excellent	Very Good	Good	Fair	Poor
Exhibit A					
Exhibit B					
Exhibit C					
Exhibit D					

3. Exhibits A, B, C and D are computer-generated images of textures on a terrain surface. Please rate these images according to how realistic and visually pleasing they look.

	Excellent	Very Good	Good	Fair	Poor
Exhibit A					
Exhibit B					
Exhibit C					
Exhibit D					

4. Exhibits A, B, C and D are computer-generated images of textures on a terrain surface. Please rate these images according to how realistic and visually pleasing they look.

	Excellent	Very Good	Good	Fair	Poor
Exhibit A					
Exhibit B					
Exhibit C					
Exhibit D					

5. Exhibits A, B, C and D are computer-generated images of textures on a terrain surface. Please rate these images according to how realistic and visually pleasing they look.

	Excellent	Very Good	Good	Fair	Poor
Exhibit A					
Exhibit B					
Exhibit C					
Exhibit D					

6. Comments ____

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