Applications of Cellular Automata: Wildfire Spread simulation

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December 9, 2019

1 Abstract

2 Introduction

By implementing a 6-state based model of fire spread across a variable-height terrain with wind and areas of varying flammability, we have been able to simulate the spread of real forest fire across a simulated environment, dictated by the specification given.

By using a minimal state set and an auxiliary 20-value cell attribute grid, we can model complex relationships between the properties of an area in a forest fire to create a stochastic state transition function for each cell in the next time step.

Attempting to relate our simulation to the real world values of forest fires across a similar terrain, we have gradually improved the weighting of various factors to generate a suitable fire spread.

3 Introduction and Background: Literature Review

Consulting existing research into the field of cellular automata can give us a valuable insight into how best to proceed when considering the formulation of a model which can describe the spread of wildfire. Considering what properties are being modelled and the ways in which transitions between state are decided can give us a grounding in this specific problem area. Research into the real world applications of forest fires are fruitful and well explored: using CA to explore forest fires is something that is well researched [(Ntinas, Moutafis, Trunfio, & Sirakoulis, 2017) (Clarke, Brass, & Riggan, 1994) (Trunfio, D'Ambrosio, Rongo, Spataro, & Di Gregorio, 2011)].

Considering the evidence existing papers have used to justify their results, including their empirical values formulated by authors familiar with the problem domain, can provide a good metric for the accuracy of our results.

There are two notable papers in this field whose outcomes seem to overlap strongly with our intentions. Both of these papers consider simulating real world forest fires using cellular automata, but have different approaches to the use of neighbourhoods and states, and their relationship with the real world properties that affect forest fires.

(Encinas, White, del Rey, & Sánchez, 2007) seeks to model forest fires using a hexagonal grid, modeling various different fuel values as states. By using a hexagonal model, the size of each cells' neighbourhood is increased - allowing more complex calculations to be derived on the basis of a 'near neighbourhood' and 'distant neighbourhood'. The authors of the paper opt to use 3 properties when considering the flammability rate of a cell: wind, topography, and the rate of fire speed. This simplistic model differs from that of (Alexandridis, Vakalis, Siettos, & Bafas, 2008), which includes spread and shape of a forest fire front; the fuel type (type of vegetation); humidity; wind direction and magnitude; terrain topography (slope and natural barriers), fuel continuity (vegetation thickness); and spotting - a phenomenon where burning material is transferred by the wind or other reasons such as the fling of flaming pinecones to areas that are not adjacent to the fire front.

Although the inclusion of additional parameters in (Alexandridis et al., 2008) allows an implementation with greater accuracy in relation to real forest fires, this is only true if the correct relationships and weightings are defined.

(Encinas et al., 2007) following states are defined in the paper:
$\{0, 0.1, 0.2, 0.3, 0.4, 0.5, 0.6, 0.7, 0.8, 0.9, 1\}$, where each value represents a fuel value. This differs from (Alexandridis et al., 2008), where four states were used ($\{0, 1, 2, 3\}$), which represent differing functional states. This choice of state representation is based on the paper's approach to the functional implementation of what means to 'be on fire'.

(Alexandridis et al., 2008)'s model was designed to include the most impactful properties when considering the spread of wildfire. By comparing their results against that of the 1990 Spetses island wildfires, and iteratively changing constants in their transition functions, the authors simulated forest fire spread to a high degree of accuracy - their final results occupying $5.4km^2$, with the actual fire occupying $5.9km^2$.

To calculate the chance of a cell being 'on fire', (Encinas et al., 2007) uses the following approach. Each parameter [listed above] is given a weighting and a probablistic model is used for each parameter to calculate the total chance of a cell being set on fire in the next time step $(t + 1)$.

The chance of fire, p_{burn}, is given as:

$$p_{burn} = p_h(1 + p_{veg})(1 + p_{den})p_w p_s$$

where:
p_h = constant probability that a cell adjacent to a burning cell containing a given type of vegetation and density will catch fire at the next time step under no wind and flat terrain
$p_{den}, p_{veg}, p_w, p_s$ = the density of vegetation, the type of vegetation, the wind speed and the slope, respectively.

In contrast, (Encinas et al., 2007) looked to find the optimal values in any forest fire, using purely mathematical models which consider heavily the boundary conditions of each of the hexagon cells in an inhomogeneous forest neighborhood.

This difference in approach, applied versus maximum mathematical, shows the effect of the fuzzy nature of real life. (Alexandridis et al., 2008), which looked towards a case study to generate its values, relied on empirical constants, whereas (Encinas et al., 2007) focused entirely on a formulaic approach.

When considering the use of CA in our study, the question of whether a case study based approach has to be answered. Due to the greater knowledge of the existing authors on the topic, ensuring the work presented here is the best position to build on their findings is essential.

The use of additional parameters such as humidity to predict the spread of the forest fire, along with their use of real world GIS values gives rise to a greater accuracy of results (in relation to the real world spread of forest fires) when compared to the default criteria to be implemented.

To meet the criteria given, the insights regarding the weighting of different parameters and the use of a probabilistic model to calculate the chance of a cell burning offer a credible starting point.

The two papers discussed above implement the idea of 'fuel' in different ways. (Alexandridis et al., 2008) structures fuel as a property of the states, whereas (Encinas et al., 2007) provides different states for different levels of fuel.

The advantage of moving the fuel state into an attribute of the cell is the greater precision of fuel that can be stored, while also maintaining a smaller amount of states. By limiting fuel state to discrete variables, the forest fire spread will lose valuable resolution which can be maintained with a different data structure.

4 Methodology

Cellular Automata is a term to describe the simulation of a discrete number of cells and interactions across a cell space (grid). Each cell can have one state at any one time step (generation). Cells can change state. The permitted changes from any one state to another state is determined by a transition function. The transition function can consider global properties, such as the current time step, as well as local properties, such as the cell's current state, as well as its neighbourhood - a set of cells near the cell.

By representing small sections of the terrain as cells, cellular automata can be used to simulate the spread of the fire across the grid. The amount of cells can be thought of as the resolution of the simulation.

After consulting existing literature, the following functional states were devised.

0. **Burnt out** - cells which were once on fire, but have no fuel remaining.

1. **Burnable grass** - the default state for the terrain, as listed by the specification
2. **Dense Forest** - Thick forest with more 'fuel' than burnable grass, but which is harder to ignite.
3. **High Flammable Scrub** - A low fuel but highly flammable substance, found in the valley in the specification
4. **On fire** - cells which are on fire
5. **Buildings** - cells which are buildings, this represents the town on the map.
6. **Water** - a state which can never be on fire.

These states represent the same approach as that of (Alexandridis et al., 2008), where each state represents a functionally different cell. This state model is an extension of a binary state CA given as a starting point for this assignment. The migration away from a two state model was necessary to capture the detail provided in the specification and also to implement some of the core findings from existing literature.

Burnable grass, Dense Forest and High Flammable Shrub are all variations of a burnable substance, and although this could be managed entirely within the attribute grid for each cell, having dedicated states allows the representation of the differing areas with different colours with the CaPyle simulation engine (*CAPyLE | cross-platform teaching tool*, 2016).

State	**Valid transition states**
Burnt Out	Burnt out
Burnable grass	Burnable grass, On fire
On fire	On fire, Burnt out
Buildings	Buildings, On fire
Water	Water

Figure 1: Valid state transitions for each of the states in the CA.

To produce a performant simulation which can cope with many generations, values which can be precomputed are done so in a setup function, and are then added to the attributes grid as an additional dimension.

The transitions between states are then calculated using these attributes for each cell (along with the local properties of the cell, such as number of neighbours in a certain state), which are stored in an 20-value array for each cell in a grid equal in width and height to the grid.

0. Height - Scalar value (m)

1. Flammability
2. Humidity
3. Fuel

4-12. Wind difference vectors (difference between wind in cell and neighbours) (ms^{-1})

13-20. Height difference vectors (difference between height in cell and neighbours) (m)

4.1 Modelling the effect of wind in the model

Wind has a significant effect on wildfires, with research suggesting that even a wind speed of 2 to 6ms^{-1} can increase the spread of the fire by an additional 50% (Beer, 1991). As wind heavily is discussed in both (Alexandridis et al., 2008) and (Encinas et al., 2007), factoring wind into this model would effectively build on their findings.

By computing wind vectors for the whole grid at setup time, we can then use the difference in wind angle and 'flame angle' to predict the effect that the wind will have on the fire, and consequently, the resultant directional changes.

The flame angle can be defined as the angle of between the direction of the fire spread and the current cell.

By initially setting wind to be two scalars, an $\pm$ value for wind in the X axis, and in the Y axis, and then converting this to a vector, we can then use $acos(v_1, v_2)$ where our wind vector = v_1, and our 'fire angle' = v_2, to calculate the possible 'magnitude' of fire for each neighbour of each cell. As each cell has 8 neighbours, an 8-value array is generated, and added to our cell attributes grid.

4.1.1 Modelling the effect of height in the model

The implementation of height in this model begins with an assumption: rate of flammability is inversely proportional to the height difference.

By calculating the difference in the heights between a cell and its neighborhood, a cell's chance of setting on fire can be affected by the number of on fire cells and this distance.

4.2 Calculating transitions

Using the methods defined in (Alexandridis et al., 2008) as a basis for our transitions, our grid is computed at every interval using two behaviours, `ignite` and `reduce_fuel`, which perform as their names suggest, both returning new, computed versions of the grid.

4.2.1 Ignite

Ignite works by calculating an ignition probability for each cell, then generating a random threshold probability for each cell. If the calculated ignition probability is larger than the random threshold, then in the next time step that cell is to catch fire.

The ignition probability of cell c is calculated as follows:

$$prob(c) = 0.5n(c) * f(c) * w(c) * h(c) * v$$

where $n(c)$ is returns a 1 if the cell has any on fire neighbours, or 0 if it has none; $f(c)$ is the rate of flammability for the cell (`rate_of_flam`); $w(c)$ is the wind weight for that cell; $h(c)$ is the height weight for the cell, and v represents a degree of randomness.

The height weight for a cell is computed by comparing the current cell against its on fire neighbours' heights. For every neighbour that is on fire, the `height_weight` is increased by a factor of the height difference ($0.0051*$ height difference).

Similarly, the wind weight for a cell is computed by consulting the 8-dimensional wind magnitude grid attributes generated at setup. For each on fire neighbour of a cell, the associated wind value from the 8-dimensional grid attributes grid is summed.

4.2.2 Reduce Fuel

The fuel reduction technique considers every cell in the grid whose fuel attribute is greater than 0. The algorithm subtracts the `rate_of_flam` attribute from the current `fuel` value, clipping the results to 0.

5 Results

After devising a model which can allow for differing wind speeds, heights and various different types of flammable land on a cellular automata grid, investigations into the possible scenarios requested by the town officials can begin. It has been suggested that a forest fire can travel anywhere between $0.46ms^{-1}$ (Viegas et al., 2009) to $2.60ms^{-1}$, depending on wind speed. As listed by the provided specification, the proposed location of the incinerator is $70.71km$ away from the furthest edge of the town.

5.1 Dense forest locations

5.2 Best water locations

Due to the small size of the water available, ensuring the timely deposit of the water is essential to its effectiveness.

By experimenting with different water locations across the grid, and comparing the amount of time it takes for the fire to reach the city, it is possible to devise an optimal location.

Due to the nature of this solution's implementation, the time step at which water can be dropped can be adjusted. Because this system simulates an 'airdrop' of water, it was important to try and simulate the effects of the water being dropped at various different points in time, and at different points on the fire front.

If the water is in place when the fire arrives at a location, the fire would migrate around it. Modelling the effect of the airdrop shows that dropping the water at the right time does make a difference.

5.2.1 Choosing locations

It is important in our assessment of optimal water location to choose the best areas to sample, not least due to the small size of the water available ($10km^2$)(Christopher, 2016) suggests the optimal placing of water in a forest fire is near the source, and on the 'attacking front' of the fire.

To this end, the following water placements were devised:

(130,10). The northern end of the canyon - This is to try and make a blockade which extends the journey of the fire.

(130,140). The southern end of the canyon - similar tactic.

(190, 200). The top right. What would happen if the fire could be stopped early into its journey?

(10,182). The top of the town. If for whatever reason it wasn't feasible for the crews to reach the start of the fire, would an effective preventative measure be blocking the surrounding area near the town?

(10, 190). Bottom right hand side of the town. A similar tactic as above. These are the nearest two sides to the wildfire front.

(80, 100). Between the lake and the dense forest - Does decreasing this area make a difference?

(80, 75). The same tactic but closer to the lake

5.2.2 Results

Top left	Bottom right	gen reached	dump gen	gen diff	gens to reach	+/-
130, 140	140, 150	172	182	10	298	-8
190 ,200	200, 10	0	14	14	302	-4
80,75	90,85	150	0	-150	303	-3
130,10	140,20	77	0	-77	303	-3
130, 140	140, 150	172	172	0	304	-2
-	**-**	-	**-**	**-**	**306**	**0**
10,190	20,200	295	305	10	306	0
80,100	90,110	157	167	10	306	0
130,10	140,20	77	87	10	306	0
10, 182	20, 192	290	300	10	307	1
10, 182	20, 192	290	0	-290	308	2
80,100	90,110	157	0	-157	309	3
80,100	90,110	157	157	0	309	3
80, 75	90, 85	150	160	10	309	3
10,190	20,200	295	300	5	310	4
80, 75	90, 85	150	150	0	310	4
130,10	140,20	77	77	0	311	5
190 ,200	200, 10	0	15	15	312	6
190 ,200	200, 10	0	20	20	312	6
130, 140	140, 150	172	0	-172	312	6
10, 182	20, 192	290	295	5	313	7
10,190	20,200	295	0	-295	314	8
190 ,200	200, 10	0	0	0	-	-
190 ,200	200, 10	0	13	13	-	-

5.3 Wind Direction

The town is situated 70.81km away from the incinerator in a south easterly direction - a wind in this direction would increase the velocity towards the town. Although the specification presented does not specify a region of the United States, a report by (Thompson, Calkin, Finney, Ager, & Gilbertson-Day, 2011) suggests the state of California is most prone to wildfires (50.22%).

Research by Guzman-Morales et al. proposes the average wind speed in wildfire season in California (traditionally September to January) is about $6ms^{-1}$, and also creates three boundaries: Low winds ($< 5ms^{-1}$), moderate winds ($5 - 15ms^{-1}$), and extreme winds ($\geq 15ms^{-1}$) (Guzman-Morales, Gershunov, Theiss, Li, & Cayan, 2016).

By assessing the impact of these differing wind speeds, the impact of an incinerator fire can be shown in realistic boundaries. Results were taken for three different wind speeds based on the values above. These are listed as $mgen^{-1}$, or meters per generation.

CD	$\pm 6mgen^{-1}$	$\pm 10mgen^{-1}$	$\%\Delta$	$\pm 15mgen^{-1}$	$\%\Delta$	Avg. gens	AVG$\%\Delta$
SW	298	280	-6.43%	**329**	14.89%	226.73	4.23%
W	325	349	6.88%	385	9.35%	264.77	8.11%
S	335	379	11.61%	388	2.32%	275.53	6.96%
N	460	600	23.33%	921	34.85%	495.31	29.09%
E	478	669	28.55%	1085	38.34%	558.07	33.45%
NE	465	748	37.83%	**2337**	67.99%	887.59	52.91%

Various wind directions and magnitudes and resultant number of generations taken to reach the city.

The results presented above suggest a successful wind technique has been implemented: the winds that blow away from the town do result in an increased number of generations before the fire hits.

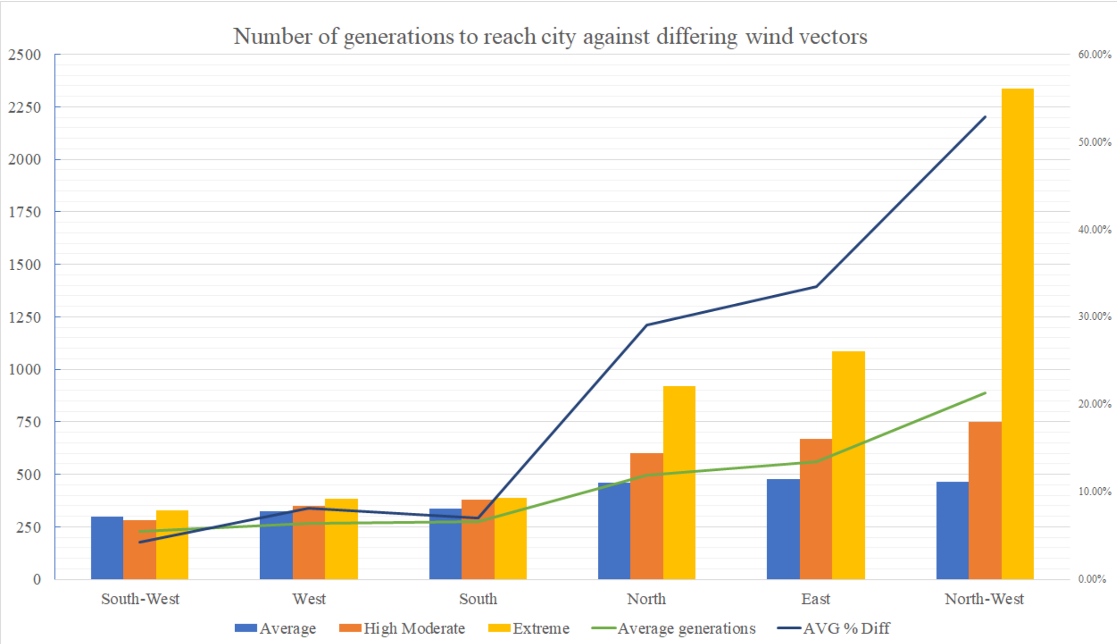

Figure 2: Graph showing the number of generations taken to reach the city against differing wind speeds.

There are two notable values in the wind data that could be seen as outliers, and such deserve discussion.

Figure 3: In extreme South Westerly winds, the fire is affected by the placement of the dense forest, canyon, and water, such that the spread towards the town is slower than that of a fire with lower wind speeds.

6 Discussion of model and conclusions

7 Conclusion

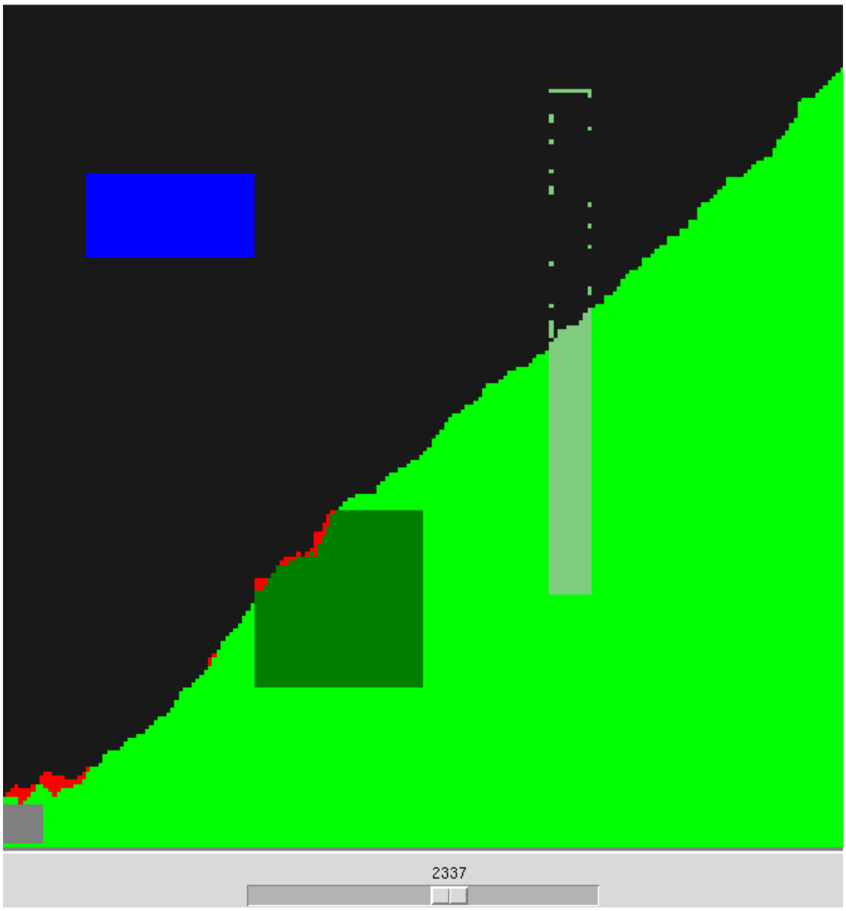

Figure 4: In extreme North Westerly winds, the majority of the fire spread misses the town. It is only after roughly 2100 generations does the fire eventually spread in the south direction enough to reach the town.

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