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TOWARDS THE IMPLEMENTATION OF A COMPOSITE CELLULAR AUTOMATA MODEL FOR THE EXPLORATION OF DESIGN SPACE

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Abstract. In this paper, we introduce a novel composite Cellular Automata (CA) model to explore the space of design for human environments. Consisting of multiple, regularly spaced, interleaved 1D CA, our model provides a mechanism to evolve flexible spatial units, where the 'cells' are not defined as programmatic elements but as 'form-making' elements. The efficacy of this approach is evaluated via a standard methodology, typically used in the study of complex adaptive systems. We systematically examine the dynamics of a series of instances of the composite CA by varying initial conditions and transition rules. A measure of entropy is used to validate emergent patterns. Subsequently, we investigate whether the composite CA is capable of generating aggregate spatial units to match specific spatial configurations, using a well-known example as a benchmark. This phase allows us to bring an understanding of the results into the context of architectural design.

Keywords. Cellular automata; generative design; design space.

1. Introduction

Design can be conceived as a purposeful, constrained, decision-making process where the aim is to transform an existing situation into a desired one (Press, 1995, Simon, 1996). When designing environments for humans, such transformations are typically developed by generating some sort of physical form (Woodbury, 1991), where the aim is to characterise the space and make it suitable for different forms of inhabitation to take place.

Given the 'wicked' nature of most design problems (Buchanan, 1992), designers are forced to use a combination of data and intuition in order to generate an outcome to satisfy intended purposes (Alexander, 1964). In order to test their assumptions, they go through a synthetic process, generating a series of potential candidates, and evaluating them to find the most suitable for their purposes (Swann, 2002). Under this perspective it can be said that design is not problem solving, but it relates to art, as defined by Danish author Piet Hein: 'Art is solving problems that cannot be formulated before they have been solved. The shaping of the question is part of the answer' (cited byArup, 1972). More succinctly, architectural design can be thought of as a particular method of problem solving that considers the search through a set of alternatives in order to find a desired output: architecture then, appears as a generative process (Mitchell, 1977).

In this paper, we introduce a novel composite Cellular Automata (CA) model to explore the space of design for human environments. Our generative system is capable of producing a design space by defining initial conditions, rules and design criteria. This approach represents a departure from the oversimplification that the 'form-follows-function' paradigm, main design motto of the modern movement (Coates et al., 1996), as it explores new techniques, capable of enabling the discovery of emergent structures suited for a contemporary conception of human inhabitation. Significantly, the overarching goal of this research is to define a way in which low-level design elements (Lynch, 1981) interact in, and with space, in order to enable the exploration of a design solution space.

2. Background

CA are an abstract mathematical framework or 'generative method' that have been used with some success, in the production of search spaces, especially during the early stages of the design process. They are discrete dynamical systems comprising a number of typically identical simple components (cells), with local connectivity over a regular lattice whose global configuration changes over time, according to a local state transition rule. CA implementations and functions, regardless of their complexity, regularity and constraints, require the definition of characteristics (cells, cell-states and neighbourhood) that can be directly interpreted as spatial configurations, which makes them appear suitable for applications in design-related fields (O'Sullivan and Torrens, 2001).

In architecture, 3D implementations of CA have been typically used to produce diagrams of spatial configurations in early design stages. In these applications, the cells of the CA generally represent 3D spatial units with programmatic characteristics (e.g. housing units, rooms, public spaces, circulation spaces, etc.), which results in functionally deterministic outputs. Examples include work by Coates et al. (1996), Krawczyk (2002), Herr et al. (Herr and Ford, 2015, Herr and Kvan, 2007) and Araghi and Stouffs (2015).

There are a few examples that use ‘Game of Life’-based 3D CA models for the generation of diagrams at early design stages. Coates et al (1996) developed one to search for emergent patterns, as Conway did with his original model (Gardner, 1970). For this purpose, a series of rule combinations and neighbourhood manipulations are explored, aiming to understand the possibilities they open for architecture. Krawczyk (2002) uses CA to generate a starting point for design, but the main focus is on how the outcomes of the model can be translated into architectural form, by changing the characteristics of cells. The desired outcomes or other parameters that allow for the evaluation of the system’s performance are not defined.

Herr and Kvan (2007) present an approach where the designer is provided with a certain degree of freedom to reconfigure the lattice and to intervene in the process, steering the evolution of the CA to attain design goals. This implementation iterates between solving and reformulating the design problem, which helps reducing the post-processing of outcomes to detailing.

Araghi et al (2015) present a CA that generates variety for the development of high density housing, by addressing accessibility and lighting as additional design requirements. These requirements translate into cell states that depend on the configuration of the neighbourhood, as well as update rules that inform the development of the system. The definition of 3D cells implies a design operation that binds the form of the cell to a function, rendering the results of the development of said models functionally static.

3. Composite CA model

We introduce a composite CA model, consisting of multiple, regularly spaced, interleaved 1D CAs (Fig 1a) arranged in a horizontal-vertical configuration (Fig 1b). This composite model provides a mechanism to evolve flexible spatial units, where the ‘cells’ are not defined as programmatic elements but as ‘form-making’ elements. This represents a departure from how CA models are typically used in architecture and urban design. Our approach focuses on the ways in which space can be physically reshaped and reconfigured, where its characteristics (such as open/closed, fragmented/continuous, exterior/interior etc.) emerge from the evolution of the system, rather than being prescribed by design.

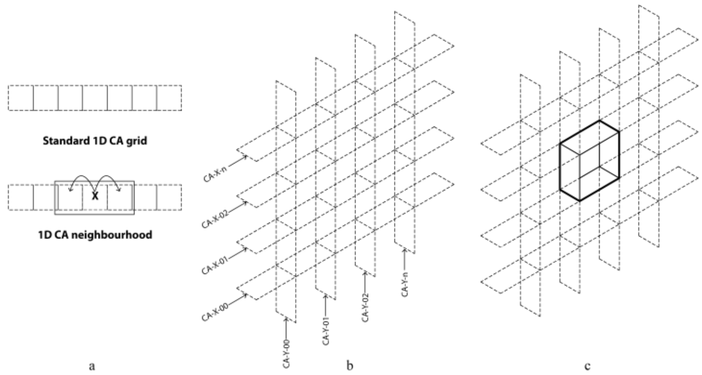

Figure 1. (a) Standard 1D CA. (b) Configuration of composite 1D CA: interleaved horizontal and vertical 1D CAs. (c) Representative example of one spatial unit, (four active boundaries).

What differentiates our approach from a standard 2D CA is the fact that the multiple 1D CA act as the edges of encapsulated 'spatial units' (Fig 1c). This approach is similar in some respects to bond percolation models in that the state of the cells in the 1D CA (edges of the individual spatial units) are either active (*on*) of inactive (*off*). If a cell in a 1D CA is off, the spatial units on either side of it are connected. If the cell is on, the spatial units are separated. The main difference between a traditional 2D CA and the composite CA model proposed is that in the former, the states of the cells are predefined, whereas in the latter the individual spatial units embedded do not have prior meaning; their characteristics are defined by the configuration of the 1D CAs that constitutes their boundaries.

In our composite CA, there are two possible states for each cell (k=2). Given the configuration of the interleaved 1D CAs, this results in 16 different possible configurations for each of the encapsulated spatial units. In Fig 2, we illustrate these configurations in 3D to emphasise the boundaries of the encapsulated 2D spatial units, rather than their faces. Significantly, our approach provides a robust and flexible alternative to a k=16 state 2D CA.

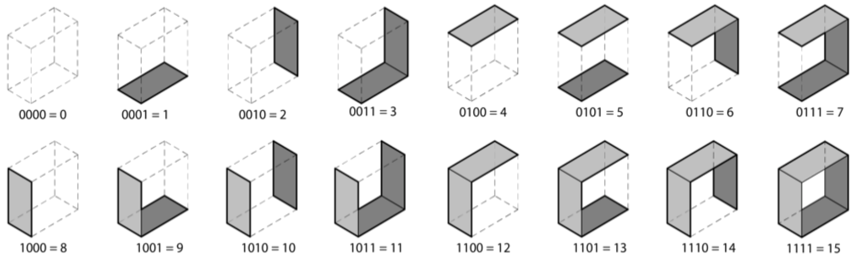

Figure 2. 3D representation of the 16 spatial configurations the model is capable of producing for a single 2D spatial unit. Binary counting is used to number the active edges.

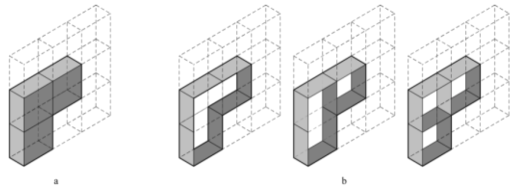

Figure 3. (a) Standard 2D CA. Each cell is a spatial unit in itself. 3 cell configuration depicted. (b) 3D representation of three possible spatial unit configurations that can be produced with the proposed composite CA model.

In Fig 3, we illustrate the exploratory power embedded in the composite CA model. Here, we show representative examples of the complex spatial topologies that emerge as a result of the concatenation or combination of multiple edges being active/inactive at the same time. It is this formation of aggregates or clusters of 'enclosed space' that subsequently generates a volumetric matrix for spatial organisation to be used by the designer.

Given the description of the composite CA (*cell states*=2, *neighbourhood*=3, a fixed number of horizontal and vertical 1D CAs), all that remains is a definition of the state transition rules and initial conditions. In our prototype model, we use random initial conditions and have selected representative rules from each of the four Wolfram's (1984, 2002) elementary 1D CA classes: Class I (uniformity) contains rules that generate uniform patterns (i.e. cell states become constant after a number of generations); Class II (repetition) contains rules that produce repetitive patterns, making the outcomes completely predictable. Class III (random) contains rules that generate outcomes with no discernible patterns. Finally, Class IV (complexity) contains rules that generate discernible patterns that repeat as the system develops. However, the frequency and location where these patterns occur is unpredictable.

4. Experiments

4.1. METHODOLOGY

A key feature of our composite CA model is its ability to evolve (or generate) spatial configurations, defining by spatial boundaries, rather than by using the state of cells to characterise that space. To test the efficacy of this approach, a standard methodology typically used in the study of complex adaptive systems has been followed. We start by systematically examining the dynamics of instantiated instances of the composite CA by varying the initial conditions of each CA and transition rules. We use a measure of entropy to validate emergent patterns.

In the second phase of our investigation we examine whether the composite CA can generate aggregate spatial units to match specific spatial configurations, which allows us to bring an understanding of the results into the context of architectural design. As a benchmark spatial configuration, we use the typical section of the interlocking units of the 'Unité d'habitation' by Le Corbusier (Fig 4a). This choice of benchmark was motivated by its formal characteristics that allow for a series of potentially desirable attributes in terms of lighting, ventilation and circulation performance that could be further investigated as input parameters to be implemented into the proposed system. As shown in Fig 4b, the selected cross section has been 'translated' to the 'language' of the composite CA model, using the alphabet of the 16 possible spatial units illustrated in Fig 2. Model performance is described using standard machine learning similarity measures.

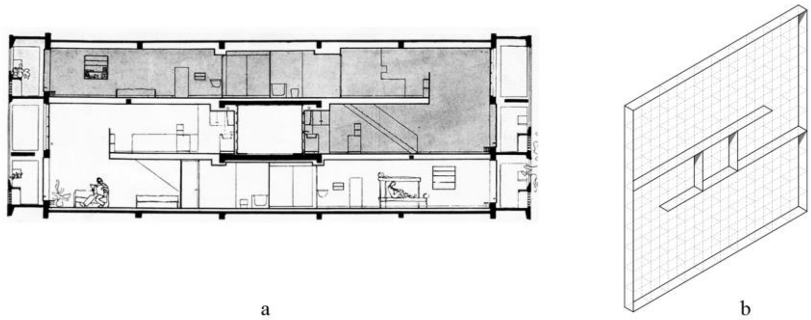

Figure 4 (a) Typical cross section of interlocking units from the Unité d'habitation in Marseille (Le Corbusier). (b) The abstract representation of the benchmark cross section. The numbers correspond to the key described in Fig 2

4.2. VALIDATION OF THE COMPOSITE MODEL

In our experiments, we set the number 1D CAs to 22 (11 vertical and 11 horizontal), where each 1D CA consisted of 12 cells. Thus, each of the possible encapsulated spatial units can be uniquely defined on one boundary by a cell located at the end of its automaton (see Fig 1b). Table 1 lists the rule combinations/pairing from Wolfram's 1D elementary rules and classes (two rules from each of class II, III and IV), used for sensitivity analysis.

TABLE 1. Rule sets for analysis with corresponding rule classification in parentheses.

Horizontal Rule	62 (II)	94 (II)	62 (II)	62 (II)	30 (III)	30 (III)	54 (IV)	54 (IV)
Vertical Rule	94 (II)	62 (II)	30 (III)	54 (IV)	60 (III)	54 (IV)	30 (III)	110 (IV)

For each iteration of the composite CA, the cells are updated synchronously, using the given rule associated with the specific orientation (horizontal or vertical). Each of the rule combinations was run for 100 time steps (generations), using three different seed values for the random initial conditions. We refer to a generated time-series data set as an iteration of the system. The key validation step is carried out by calculating the entropy of the system, as it is understood in information theory, where a high value means that a large amount of information is needed to represent the state of the system (Cilliers, 1998). Here, we calculate entropy at each time step using Shannon's equation (Equation 1), which allows us to visualise how the system changes over time.

$$H(x) = -\sum p(x_i) \times log_2 p(x_i) \tag{1}$$

In Fig 5 we can observe that where rules from class II are in use (solid line), the plot shows the value of entropy entering a periodic cycle after a few time steps. However, when combining rules from classes II and III (dashed line), the plot shows that the variation in the value of entropy describes an unpredictable pattern. These observations are consistent with what is expected in the system dynamics from the Wolfram's classes, thus we can conclude that the composite CA is performing as expected.

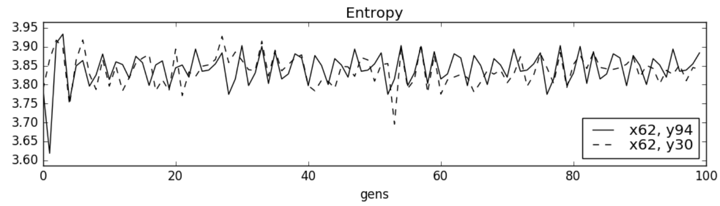

Figure 5. Entropy calculated for two different sets of rules over 100 generations: solid line shows combination of class II rules. Dashed line shows combination of class II and III rules.

4.3. EVOLVING SPATIAL UNITS

To evaluate the form generating capabilities of the composite CA model, the benchmark configuration described in Fig 4b acts as the target, where the goal is to measure the similarity between this benchmark and the evolved spatial unit configurations.

$$similarity = \frac{\sum A_i \times B_i}{\sqrt{A_i^2} \times \sqrt{B_i^2}} \tag{2}$$

The plot in Fig 6, illustrates the distribution of spatial unit configurations corresponding to the best result obtained from the simulation experiments (similarity = 0.87). Despite this relatively high similarity score, there are significant differences between the evolved and target configurations. However, an interesting observation is that the evolved configuration encapsulates examples of each of the spatial units listed in Fig 2, whereas the benchmark does not. The graphic representations of both configurations, shown in Fig 7, highlight these differences.

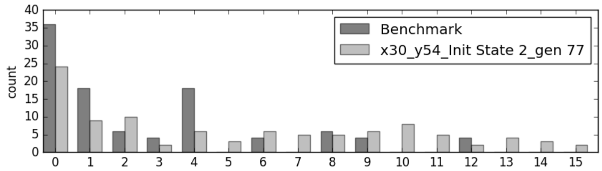

Figure 6. Distribution of 2D spatial units by type (according to Fig 2) for the benchmark and the composite CA: rules 30 (horizontal), 54 (vertical), with initial state 2, after 77 generations

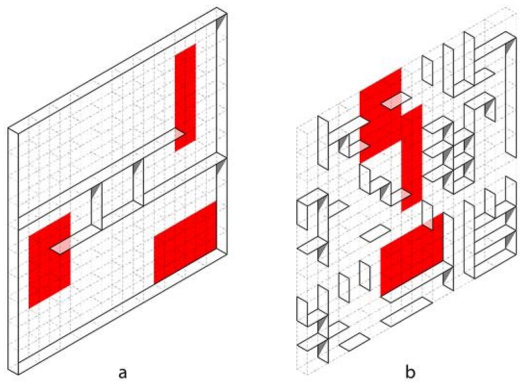

Figure 7. (a) Spatial representation of benchmark. (b) Spatial representation of configuration with highest cosine similarity score.

In the next stage of our analysis, we compare the benchmark and the evolved configurations 'element by element' by counting how many different spatial units are identical in both topology and location.

An inspection of the vector of spatial unit counts shows that the minimum number of matches was 6, achieved when using class II rules (94 horizontal/ 62 vertical), initial state 0, and it repeats every 7 generations. On the other hand, a maximum number of 19 matches was reached in two simulation trials: i) Class III and IV rules (30 horizontal/54 vertical), initial state 2, and it appears after 21 and 52 generations; ii) Class IV rules (54 horizontal/110 vertical), initial state 0 and it appeared after 84 generations. Fig 8 presents a visual comparison between the benchmark and trial ii.

Similar to the comparative patterns presented in Fig 7, it is possible to observe in Fig 8 that most of the matching elements are part of sub-patterns. Therefore, the exploration of a search strategy focused on sub-structures, rather than on the configuration of the complete pattern, appears as a method suitable for generating a wider range of usable results. It is significant to note that in the case illustrated in Figs 7 and 8, the sub-patterns only appear as result of the comparison process, as their boundaries are not clearly defined. However, looking at the benchmark configuration, there are three substructures clearly defined by their boundaries, the most obvious being the square in the centre.

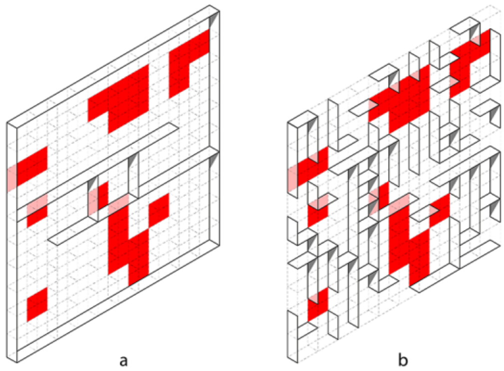

Figure 8. Matching elements between (a) benchmark configuration, and (b) composite CA: for rules 54 (horizontal), 110 (vertical), with initial state 0, after 84 generations.

5. Discussion

In this paper, we have introduced a novel composite CA that can be used to generate a variety of spatial unit configurations, defining the boundaries of space, rather than by prescribing spatial characteristics of the constituent elements of the system. Our goal was to explore the formation of aggregates (clusters) of 'enclosed' space, representing an 'interesting' spatial organization, which can be detailed, developed or interpreted by a designer at a later stage. Significantly, our model was able to produce a wide variety of aggregate patterns.

It can be argued that the strength of the composite CA system is based on informing a designer about the inherent complexity rather than acting as a tool for generating completed design solutions. The ability to generate/search the state space is defined by transition rules and the time evolution of the model. In our experiments, the benchmark target was pre-defined. Searching for a fixed, static configuration limits the possibilities as to what can be imagined by the user, defeating the ultimate purpose of the model – generating a design space, and searching through it using design criteria, looking for emergent spatial configurations. Therefore, introducing protocols for searching for characteristics of the space (e.g. open vs. closed space), rather than specific patterns, is seen as a goal to pursue in order to enable the emergence of unexpected spatial configurations. In this regard, the development of mechanisms to incorporate modifications to the rules as the system evolves, as well as the introduction of external influences, are seen as plausible paths to pursue in order to extend the system's capabilities.

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