Evolutionary Developmental System for Structural Design

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Abstract

This paper discusses the results of extensive computational experiments involving evolutionary developmental representations for structural design. In particular, it describes developmental representations based on one-dimensional cellular automata applied to three complex structural design problems in the domain of steel structural systems in tall buildings. In the experiments conducted with the developmental encodings, several of their key parameters were tested, including the impact of the configuration of the design embryo and the importance of the symmetry constraint on the quality of produced designs. The obtained results were also compared to the results of evolutionary design experiments involving traditionally used direct representations. These comparisons focused primarily on the compactness and evolvability properties of both types of design representations. The results have shown that developmental encodings produce quantitatively better results for the majority of the investigated design problems and also generate structural designs with distinct shaping patterns.

Introduction

The problem of choosing an appropriate representation for complex engineering designs has been studied extensively by many evolutionary design researchers (Bentley 1999; Eggenberger Hotz 2004; Hornby 2004; Parmee et al. 2000). During more than 40 years of research in this field various types of encodings have been proposed and empirically analyzed. Also, in the field of structural design, various ways of representing structural systems were investigated, from simple direct, or parameterized, encodings (Goldberg and Samtani 1986) to much more elaborate and Voronoi-based and fractal representations (Hamda et al. 2002).

Recently, together with a growing complexity of structural design problems and emerging interest in the development of novel/creative designs, new methods of representing designs have been proposed and investigated. Several examples of such novel representations of complex structural systems are discussed and empirically investigated in this paper. They are inspired by the processes of biological development and utilize simple models of constructive/generative processes to develop complete design structures from initial sets of simple elements (called here design embryos) using sets of instructions (called here design rules). Specifically, design representations studied in this paper are based on various types of cellular automata which generate complete designs of steel structural systems in tall buildings.

The paper is organized as follows. First, the problem of structural design of steel structures in tall buildings is introduced. Next, its traditional direct encodings and new developmental representations are presented and compared. Further, results of extensive computational experiments involving key parameters of developmental representations are discussed. These results are subsequently compared to the results produced in traditional evolutionary design experiments. Finally, initial conclusions are presented together with some recommendations for future research.

Steel Structural Systems in Tall Buildings

Design of steel structural systems in tall buildings is one of the most complex design problems in structural engineering. Such steel structures are designed to provide a structural support for tall buildings and they have to satisfy numerous requirements regarding the building's stability, transfer of gravity, wind, and earthquake loads, deformations, vibrations, etc. (Arciszewski and Ziarko 1988; Taranath 1998). Usually, structural systems consist of vertical members called columns, horizontal members called beams, and various diagonal members called wind bracings, which are added in order to increase the flexural rigidity of the entire system.

In the process of evaluation of each structural design, an analysis of its behavior under various combinations of loading is conducted. Usually, simplified two-dimensional analysis of this three-dimensional design problem is performed due to the fact that full three-dimensional analysis is computationally very expensive and the simplified planar analysis provides relatively good approximation of structure's behavior. Thus, in this paper, two-dimensional models of steel structural systems were considered as shown in Figure 1. Traditionally, such

structures were represented using direct, or parameterized, representations in which there was one-to-one mapping between genes and structural members (beams, supports, and wind bracings) (Kicinger et al. 2005; Murawski et al. 2001).

The objective of design processes investigated in this paper was to determine an optimal configuration of structural members in a tall building. Each gene representing a structural member could assume only one of several possible symbolic values. These values encoded different types of a given structural member and determined its structural behavior. In the experiments reported here, optimal configurations of wind bracing elements were sought and the remaining elements (i.e. beams, columns, and supports) were kept fixed. Figure 2 shows the types of wind bracing members and their corresponding symbolic values used in the design experiments reported in this paper. The fitness of each design was defined by the total weight of a steel structural system (a good approximation of its cost) and the objective was to find a minimum weight design.

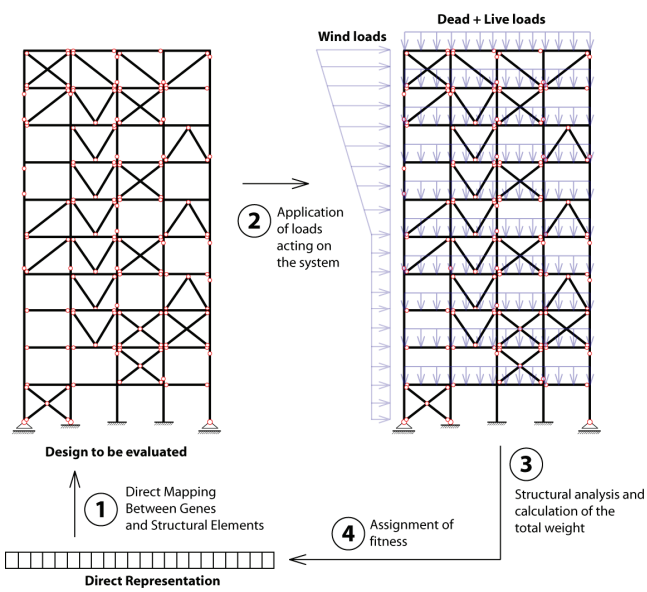

Figure 1: Traditional direct representation of a steel structural system in a tall building and the process of design evaluation and fitness assignment

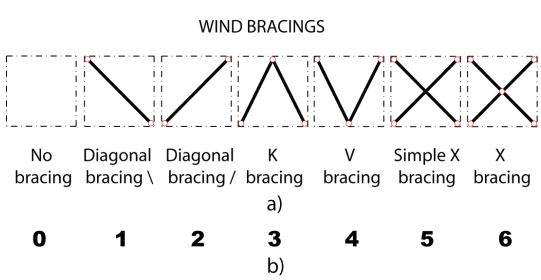

Figure 2: Types of wind bracing elements and their symbolic representation.

Three types of design problems were considered: the design a wind bracing system in which only simple X bracings were used (Problem 1), the design of wind bracing system composed only of K bracings (Problem 2), the design of the wind bracing system with all types of wind bracing elements shown in Figure 2 (Problem 3).

Developmental Representations of Designs

Results produced in design experiments involving direct design representations introduced in the previous section were compared to the developmental/generative encodings shown in Figure 3. These representations were initially proposed in (Kicinger et al. 2004). Bottom part of Figure 3 shows the structure of the genome representing a wind bracing design. It consists of two parts: encoding of the design embryo and encoding of the design rule. The design embryo represents a configuration of wind bracing members located at the first story in a tall building. The design rule, which forms the second part of the genome, is applied to this configuration and the result produced by the application of the rule determines the configuration of wind bracing members at the second story in a tall building. The process is subsequently repeated to define the configuration of the third story, etc. until the complete configuration of wind bracing members in a tall building has been generated.

Once the design development process has been concluded, the symbolic representation of wind bracings is translated into structural members, the loads are applied to the resulting structural system, and its structural behavior is analyzed (see Figure 3). During the analysis process, the cross-sections of all structural members are calculated so that the structural system satisfies all requirements of relevant design codes.

When the structural analysis is completed, the fitness of the design is determined by its total weight as discussed above.

Cellular Automata Representation

The general concept of a developmental representation of a structural system in a tall building presented in the previous section was instantiated using cellular automata (CAs). CAs were chosen because of their simplicity, inherent capability to model local and spatial interactions, and ability to generate emergent patterns. All of these properties are highly relevant for structural design problems investigated in this paper.

Figure 4 shows a specific example of a CA representation of a wind bracing system for Problem 1. In this case, one-dimensional CAs were used to develop a complete configuration of wind bracing members composed only of simple X bracings. Figure 4a shows the genome of a specific structural design (individual) whose developmental process is depicted in Figure 4c.

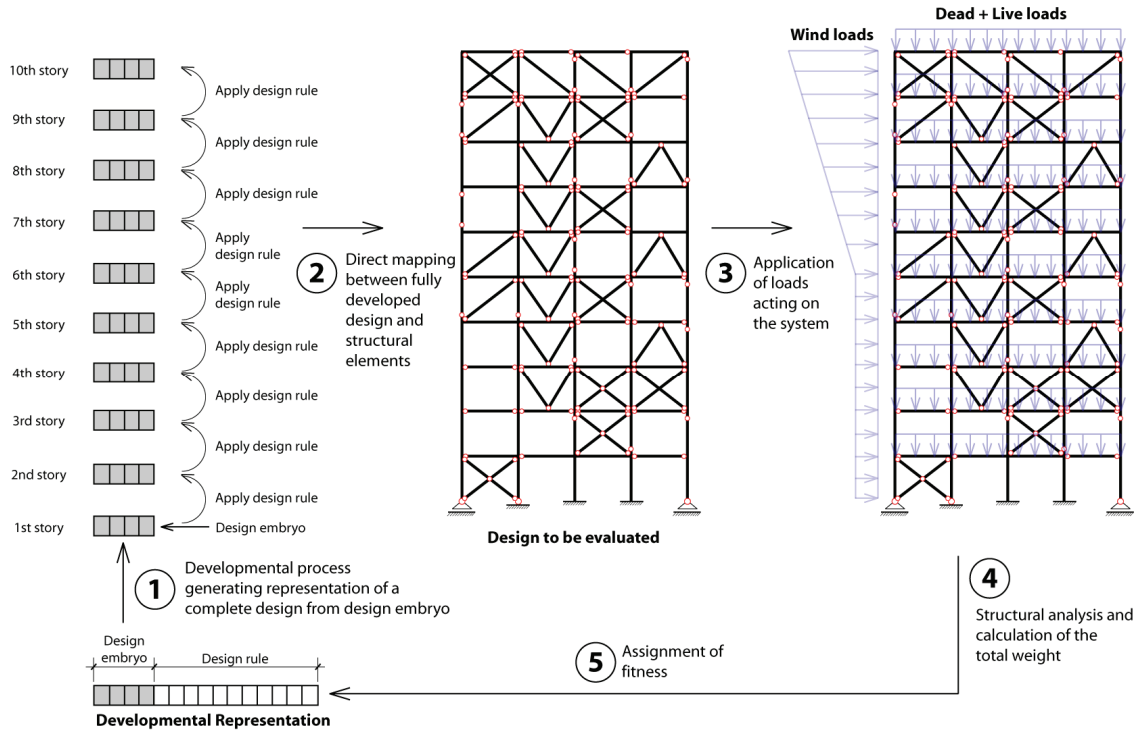

Figure 3: Developmental representation of a steel structural system in which a complete design is constructed from a design embryo by the repeated application of a design rule

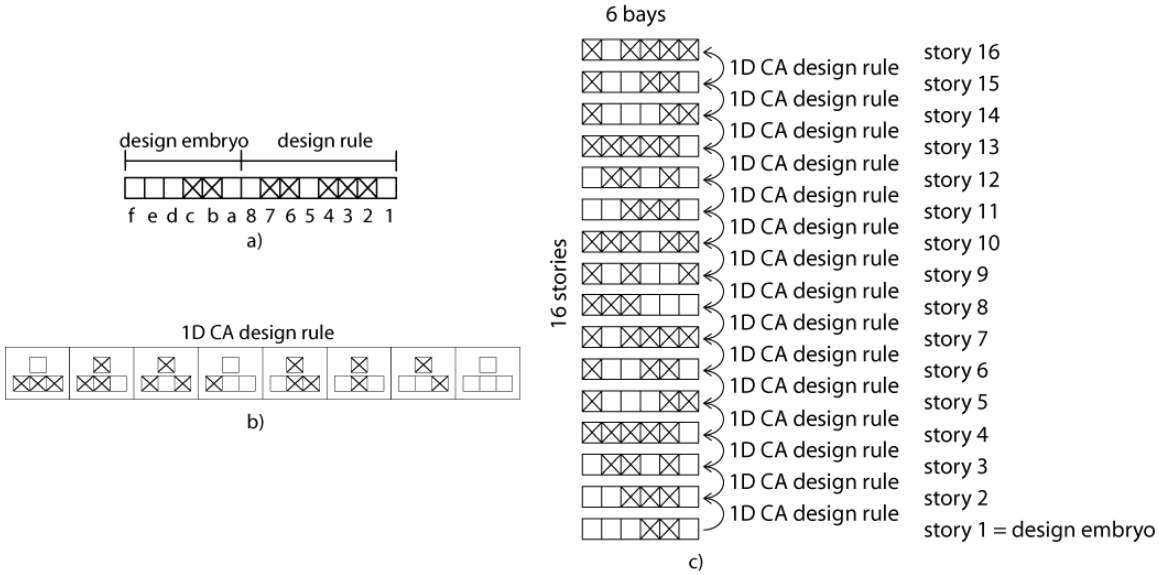

Figure 4: Cellular automata representation of a steel structural system in a tall building and the process of design development encoded by this representation

The design embryo, as stated earlier, is formed by the configuration of wind bracing members at the first story of a tall building. The design rule encodes the outcome values (the upper row of cells in Figure 4b) of a one-dimensional CA rule shown in Figure 4b. Since cellular automata are deterministic systems, the design embryo and the design rule shown in Figure 4a uniquely specify the structural design of a wind bracing system shown in Figure 4c.

One of the advantages offered by cellular automata representations is their reduced size when compared to traditional direct encodings described earlier. For

example, CA representations of wind bracing systems with 30 stories and 5 bays have length of 13 genes for problems 1 and 2. The length of the corresponding direct representations is equal to 150. However, when we increase the number of types of wind bracing members to 7 (problem 3), the size of CA representation increases to 348. It can be significantly reduced when totalistic CAs are used in place of standard CA discussed above. In this case, the length of the representation decreases to 24 genes only.

Another advantage of CA encodings, important from structural design perspective, is the simplicity of enforcing symmetry constraint on cellular automata representations. In order to obtain symmetric designs, we simply need to use symmetric design embryos and constrain the outcome values of CA rules. Figure 5 shows the way in which elementary CA rules can be constrained in order to generate symmetric designs from symmetric design embryos. The symmetry constraint also reduces the size of the CA rule spaces. For example, by using the symmetry constraint for elementary CA rules we effectively reduce the number of possible elementary CA rules from 256 to 64.

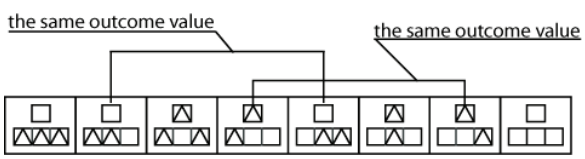

Figure 5: The process of constraining elementary CA rules so that they generate symmetric designs

Table 1: Parameters and their values used in the experiments

Domain	Values	EA	Values
# of bays	*5*	Represen-tation	*CA or Direct*
# of stories	*30*	CA rule types	*Standard or Totalistic, Radius 1 or 2*
Bay width	*20 ft*	EA type	*Evolution Strategies*
Story height	*14 ft*	Populatio n sizes	*(1,5), (1,25), (5,25), (5,125), (50,250)*
Structural analysis	*1st order*	Mutation rates	*0.025, 0.1, 0.3, 0.5*
Beams	*Fixed*	Crossover rates	*0.0, 0.2, 0.5*
Columns	*Fixed*	Fitness	*Total weight*
Supports	*Fixed*	Runs	*5*
Types of wind bracings	*See* Figure 2	Termina-tion	*1,000 (short-term), or 10,000 (long-term) evaluations*

Design Experiments

The conducted design experiments investigated various properties of developmental representations of steel structural systems and their impact on the fitness of produced structural designs. Specifically, the following parameters were tested:

1. The impact of the configuration of the design embryo (arbitrary configuration vs. randomly generated configuration) on the fitness of generated designs.
2. The impact of the symmetry constraint on the fitness of generated designs.
3. The evolvability of developmental encodings.

Table 1 shows parameters and their values used in the reported experiments. In all experiments, 30 story buildings with 5 bays were considered. The height of each story was equal to 14 ft and the width of each bay was equal to 20 ft. The values of evolutionary computation parameters are shown in columns 3 and 4.

Configuration of the Design Embryo

Arbitrary Design Embryo. The impact of the configuration of the design embryo was investigated in the context of problems 1 and 2. Specifically, Figure 6 shows examples of design embryos used in the experiments with arbitrarily selected design embryos for problems 1 and 2, respectively. In this case, CA representations had binary values (no bracing and simple X bracing for problem 1 and no bracing and K bracing for problem 2) and the set of all possible design rules based on elementary CA with binary values and the local neighborhood of size 1 was equal to 256 for each problem. Thus, it was feasible to conduct exhaustive search of all possible structural designs generated by CA representations with arbitrary design embryos shown in Figure 6.

Figure 7 shows the best structural designs, in terms of the total weight, produced from the design embryo shown in Figure 6a. The least weight design was produced by elementary CA rule 51 and its total weight was equal to 560,646 lbs. An interesting property of all best designs shown in Figure 7 is that they exhibit three different patterns which are relevant from structural design perspective. In particular, designs produced by rules 177, 163, 99, and 57 developed a pattern of so-called macro-diagonal bracings used in several existing structural systems in tall buildings.

a) *b)*

Figure 6: Arbitrarily selected design embryos for problems 1 and 2, respectively

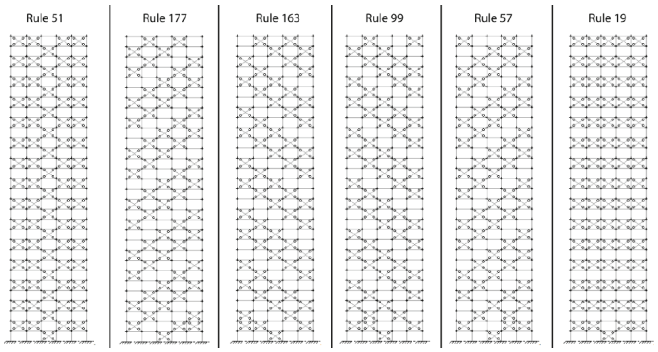

Figure 7: Best designs for problem 1 produced from the arbitrary design embryo

On the other hand, the best designs developed from the arbitrary embryo for problem 2 are presented in Figure 8. In this case, the best design was developed by several CA rules and its total weight was equal to 450,234 lbs. A closer look at best designs shown in Figure 8 reveals that the patterns associated with best designs for problem 2 are qualitatively different than the ones found for problem 1. Here, the vast majority of designs exhibit a fully-braced pattern in which the entire configuration of wind bracing elements is occupied by K bracings.

Randomly Generated Design Embryo. In this group of experiments, the same set of 256 CA rules was applied to 5 randomly generated design embryos. As before, the experiments were conducted separately for problems 1 and 2. Figure 9 shows best designs with randomly generated design embryos for problem 1. Here, the total weight of the best design was equal to 550,366 lbs and was about 10,000 lbs. better (lower) than the total weight of the best design produced from the arbitrary embryo. In fact all of the designs shown in Figure 9 had better fitness than the best design produced from the arbitrary embryo. Also, even though most of the patterns shown in Figure 9 are similar to the macro-bracing diagonal pattern found earlier, there are two distinct patterns associated with best designs produced from randomly generated embryos, namely the pattern generated by rules 154 and 186.

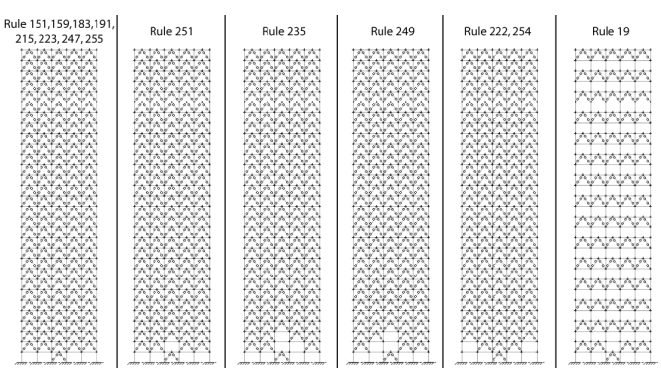

Figure 8: Best designs for problem 2 produced from the arbitrary design embryo

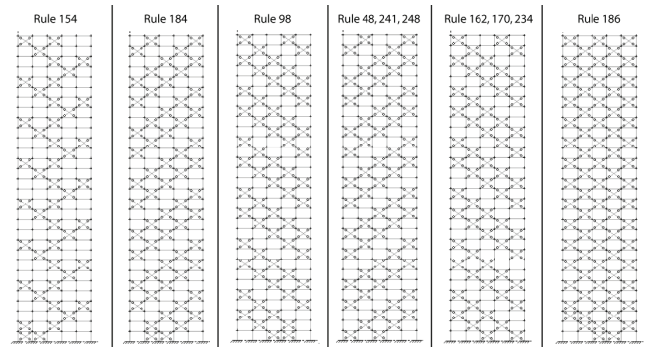

Figure 9: Best designs for problem 1 produced from randomly generated design embryos

The situation was different for problem 2. Here, the best design produced from randomly generated design embryos had the total weight of 449,521 lbs., which was only slightly (by about 1,000 lbs.) lower than the best design developed from the arbitrary design embryo. Also, all best designs developed from randomly generated design embryos showed the same fully-braced pattern discussed earlier. Hence, the figure showing the structures of best designs for problem 2 was omitted.

The results produced with arbitrary and randomly generated design embryos proved that the configuration of the design embryo is important for structural design problems considered in this paper. Hence, both the optimal configuration of the design embryo and the optimal design rule should be sought.

Symmetry Constraint

The experiments involving symmetry constraint used a subset of 64 CA rules obtained by applying symmetry constraint to the set of 256 CA rules as discussed earlier. These 64 rules were applied to eight symmetric design embryos presented in Figure 10. As before, these experiments were conducted for problems 1 and 2 only.

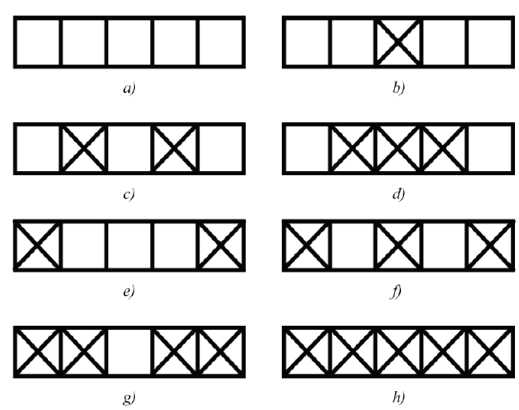

Figure 10: Eight types of symmetric design embryos used in experiments with symmetric design rules

Figure 11 shows the best symmetric designs generated for problem 1. The total weight of the least weight design was equal to 556,177 lbs. and was in fact worse (higher) than the total weight of the best design produced from random design embryo. On the other hand, several new patterns associated with best symmetric designs were found, as shown in Figure 11. Slightly different results were produced for problem 2. Here, the total weight of the best symmetric design was equal to 449,376 lbs. and was about the same as the total weight of the best design produced from randomly generated design embryos. All best symmetric designs for problem 2 exhibited the same fully-braced pattern discussed earlier. Hence, the results of the experiments with the symmetry constraint have shown that by imposing this constraint we do not obtain better results for the structural design problems investigated here.

Evolvability

The final group of experiments investigated evolvability of cellular automata representations for problems 1, 2, and 3. Here, the genomes consisting of design embryos and design rules (without symmetry constraint) were evolved by evolutionary algorithms. The evolutionary parameters used in these experiments were presented earlier in Table 1.

Figure 12 shows average best-so-far fitness curves obtained in the experiments with direct and developmental representations for problem 2. In this case, CA representations using both standard and totalistic CA rules (Wolfram 1994) were employed. Figure 12 shows that evolutionary developmental processes produced significantly better results than traditional evolutionary design processes involving direct representations. They not only found better solutions in terms of designs' fitness but also converged to the optimal region much faster. Similar results were obtained in the case of more complex problem 3 as shown in Figure 13.

On the other hand, results obtained for problem 1 were much different. Figure 14 presents average best-so-far fitness curves obtained in these experiments. It shows that in this case the best results were achieved with direct encodings rather than the developmental ones. Even though the initial progress produced in the first stages of evolution was better for developmental representations, they quickly converged to suboptimal regions of the design spaces and subsequently produced little evolutionary progress.

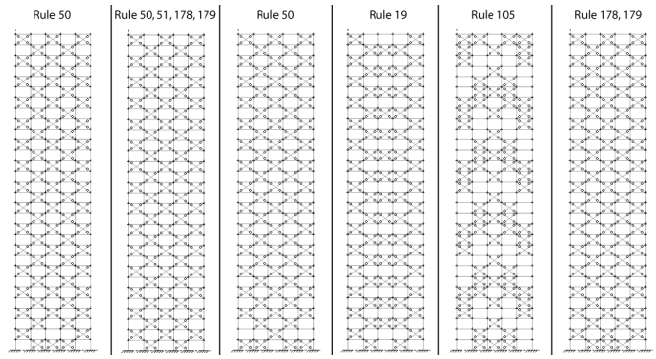

Figure 11: Best symmetric designs for problem 1 in the experiments with the symmetry constraint

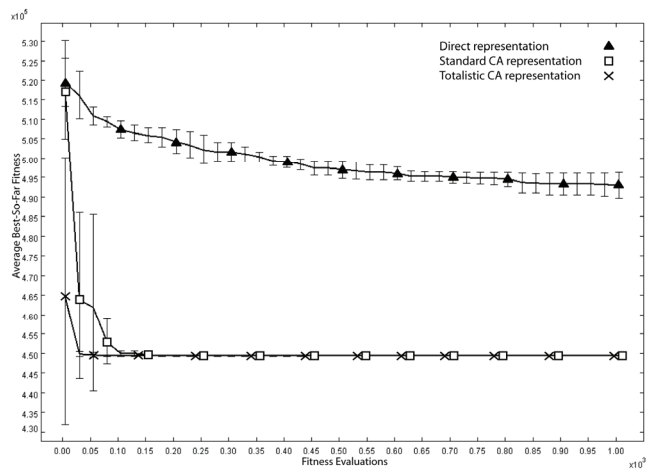

Figure 12: Comparison of average best-so-far fitness curves obtained in the experiments with direct and CA representations for problem 2

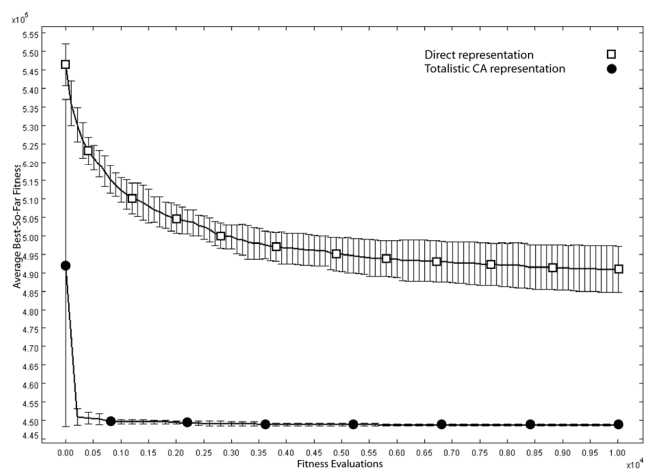

Figure 13: Comparison of average best-so-far fitness curves obtained in the experiments with direct and CA representations for problem 3

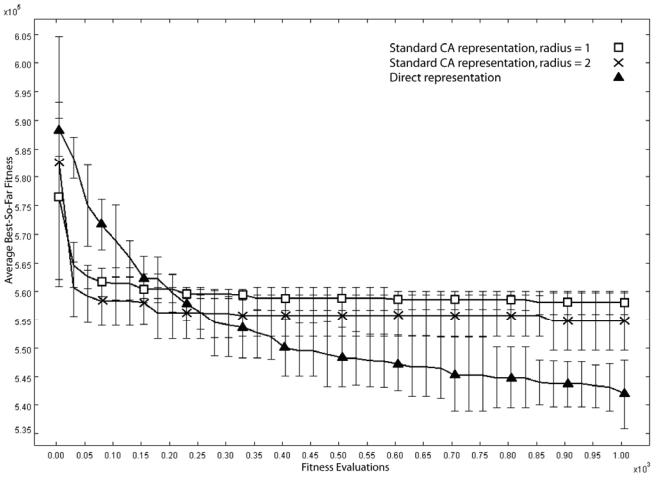

Figure 14: Comparison of average best-so-far fitness curves obtained in the experiments with direct and CA representations for problem 1

The author's explanation of this fact is the following: The three design problems, i.e. the design of a wind bracing system composed of simple X bracings, the design of a wind bracing system composed of K bracings, and the design of a wind bracing system composed of 7 types of bracings represent two different classes of problems. The optimal solutions for the first and third problems have regular structures composed of configurations of K (or V) bracings (variations of the fully-braced or periodic patterns). CA encodings, particularly the ones utilizing totalistic CA rules, can generate these structures readily and hence they find optimal solutions very quickly. On the contrary, the optimal designs for the second problem exhibit very elaborate patterns of simple X bracings.

In some cases (e.g., problem 2), the patterns associated with optimal solutions cannot be generated by simple CA encodings based on elementary CA rules and hence these developmental representations produce inferior results. Additionally, direct representations can more easily exploit the possibilities of fine-tuning of the best solutions found so far as compared to the developmental encodings in which a small change at the genotypic level usually produces much larger change at the phenotypic level. In this way, direct representations may be more successful in finding structural designs with slightly reduced weight at the cost of disrupting the structure's pattern. On the contrary, when aesthetic criteria, relevant from design perspective, are somehow embedded in the fitness function, it may be the case that developmental encodings will generate better solutions than direct representations even for problem 2.

Conclusions

In this paper, an evolutionary developmental system for structural design was introduced and empirically tested on three complex structural design problems. In particular, the impact of several key parameters of cellular automata representations on the fitness of developed designs was investigated. These representations consists of an initial configuration of structural members (called design embryos) and a set of instructions based on CA rules (called design rules) which iteratively develop complete designs from the corresponding design embryos. Extensive computational experiments have shown that the configurations of design embryos have big impact on the fitness of generated designs and hence they should be optimized together with design rules in order to produce best results. On the contrary, the symmetry constraint frequently used in structural design did not produce superior results.

Developmental encodings were also compared to the traditionally used direct encodings in terms of their compactness and evolvability. It was found that CA representations are usually much more compact that direct representations for the considered design problems. Also, they produced better results when evolved by evolutionary algorithms in the majority of design experiments. Moreover, they biased the search towards the regions of design spaces in which highly patterned solutions were found. Several structural patterns associated with best designs for each design problem were also reported.

The research presented in this paper will be continued, including the extension of the scope of the empirical studies to other types of developmental representations. In particular, more sophisticated types of developmental encodings based on CA will be investigated, e.g., utilizing non-uniform CAs or encodings with a self-adaptation mechanism.

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