Rehashing Design Through Evolutionary Computation

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Abstract: Evolutionary computation has made its way into design curricula in the last two decades. However, questions remain on how evolutionary computation can be made more accessible to design students and its potential to transform design thinking and learning beyond optimisation. This paper examines how the formulation and implementation of evolutionary systems can contribute to students’ learning of historical and theoretical aspects of design. The paper reviews evolutionary computation in design and presents genetic algorithms (GAs) as a design tool. Opportunities are identified on how to teach design students to create and implement basic GAs. Strategies that can help design educators to identify and build on these opportunities are discussed. Design activities aimed at applying GAs to rehash the learning of historical and theoretical aspects of design are described.

Keywords: evolutionary computation; genetic algorithms; design learning; design thinking

1 Introduction

Design students and practitioners can formulate and implement evolutionary computational systems to generate design solutions that are suitable for specific contexts. Evolutionary computational systems can assist in the design of architectural solutions whose performance aligns with the characteristics of the local environment (e.g. wind speed, amount of sunlight, etc.) (Ercan & Elias-Ozkan, 2015). However, it is still unclear how evolutionary computational systems can extend the understanding that design students have on qualitative aspects of design solutions (e.g. an artefact’s meaning, historical relevance, etc.). In view of the above, this paper examines how the formulation and implementation of evolutionary computational systems may enhance the learning of design history and theory. To do so, Section 2 reviews approaches to evolutionary computation and describes Genetic Algorithms (GAs). Since the formulation and implementation of GAs relies heavily on a clear understanding of how their constituent parts interact, Section 3 presents strategies for physically representing a GA for design. Section 4 assesses how design activities that involve the development of basic GAs can enhance the understanding that design students have on the stylistic parameters of specific historical periods. Section 5 explores how GAs can assist the exploration of the concept of “innovability” and how in turn, such concept can be used to extend the scope of traditional GAs (Wagner & Rosen, 2014).
2 Evolutionary Computation and Genetic Algorithms

Evolutionary computation integrates principles from evolutionary biology and computer science to develop search heuristics and algorithms. Evolutionary algorithms perform search by evolving candidate solutions to problems. Currently, these techniques are used in design for optimising existing solutions and for producing new ones (Ercan & Elias-Ozkan, 2015; Petre, Sharp & Johnson, 2006). These two approaches are respectively known as evolutionary design optimisation and creative evolutionary design. Both evolutionary design optimisation systems and creative evolutionary design systems can be implemented by means of genetic algorithms (GAs) (Bentley, 1999). A genetic algorithm (GA) is an evolutionary computation technique where candidate solutions for a given problem are stochastically combined and evaluated in successive generations. Due to its combinatorial approach, GAs tend to produce solutions that are increasingly fit for the purpose defined in the evaluation function. The search for design solutions in a GA initiates from a number of randomly selected points in the design space. As a GA runs, regions of the design space are further explored combining randomness with guidance from the relative fitness of candidate solutions (Bullock, Denham, Parmee & Wade, 1995). A usual stopping rule for GAs is when the increase of fitness of new candidate solutions slows down, indicating a convergence to a region of good-enough solutions in the design space. Several techniques exist to prevent early convergence and to pursue an extensive exploration of the design space. Evolutionary approaches in design are distinguished between routine design where the fitness function and the design space are fully defined at the start state and remain unchanged, and creative design where the search process may transform the design space, the evaluation function, and even the problem formulation.

In its most basic form, a GA is composed by an initial population of candidate solutions generated randomly when the GA is initialized. Candidate solutions are usually represented as strings of information that form their genotypical expression. Genotypes are composed of N number of variables or solution features each of which contains a randomly allocated value or design parameter. The values or design parameters at each locus are referred as alleles and may be of different types including numerical, Boolean (on/off), and nominal. Together, all the design parameters contained in the genome represent the characteristics of a candidate solution (Mitchell, 1998). As an example, the genome of a computer keyboard may contain genes to represent the total number of keys, their size and the spacing, whether characters are engraved or printed, whether keys are lighted or not, the type and colour of materials, layout characteristics, whether it uses capacitive, mechanical or membrane switches, whether it connects wirelessly or not and if so the length of cable and type of connector, and even the key bounce rate. The genome of candidate solutions represent their structural description, whilst the evaluation function can include criteria of performance (Gero, 1990). This means that search can be guided by the phenotypical expressions of candidate solutions. In the case of keyboards, phenotypical expressions include ergonomic performance, design language or style, and the audible and tactile qualities of the typing experience.

Basic GAs operations include the selection, crossover and mutation of candidate solutions. The selection operator chooses pairs of candidate solutions within a population. Selected solutions may be referred as parents because they inherit some of their characteristics to the upcoming generation of candidate solutions. The higher the fitness of a solution, the more likely it is to be selected to pass its genes to the next generation. The genetic material of candidate solutions that are not selected as parents is gradually lost. Once parents are selected, the crossover operator randomly picks a locus and exchanges the substrings before and after that locus between each pair of parents. As a result of this, offspring are created by combining increasingly fitting genetic material. The mutation operator introduces novelty by randomly switching the value of design parameters stored in one or more locus of the genotype. The cycle is iterated with evaluation of solutions to produce new generations.

3 Learning Evolutionary Design

Design education relies heavily on physical interaction with models, materials, tools, etc. Through this interaction, students develop an understanding of design practice that would not be easily achieved with other approaches to learning (i.e. verbal, written, etc.) (Klemmer, Hartmann & Takayama, 2006). Because of this, tasks like computer programming that heavily rely on text and where physical interaction is limited may be less intuitive and present learning barriers for design students (Jacobs, Brandt, Mech & Resnick, 2018). In our experience, teaching design students to formulate and implement GAs is best achieved via four types of learning experiences. The first type is characterised by the learning goal of developing an understanding of what evolutionary systems are and their potential applications in design. The second allows students to understand what GAs are, their main components and dynamics, and how they model design by evolution. The third type of learning experience enables students to build and link their understanding of design knowledge and design activity with the formulation and implementation of GAs and other evolutionary systems. In this process, students learn how GAs can support design practice (Belmonte et al.,
2014; Bernal, Haymaker & Eastman, 2015). The fourth learning experience seeks to develop programming skills and more broadly, computational thinking for design.

**Strategies for Evolutionary Design**

The learning outcomes described above can be achieved in design education via strategies that are compatible with how designers learn. For instance, design educators can select an everyday artefact (e.g. a pair of scissors) and ask students to develop a GA aimed at producing candidate solutions for such an artefact. As a preliminary stage, students can use visual diagrams and cardboard models to develop an analogic version of the GA. An example of an analogic GA is presented below. Figure 1 shows from left to right “generation g” that includes candidate solutions A to D. The genome of each candidate solution is shown above the corresponding image. The values at the different locus of these genomes represent the type and shape of handles and blades. Specifically, each position in genomes A to D encode a phenotypical feature expressed in this case by material (M), size (Z), colour (C), symmetry (Y), and shape (S) respectively. Solution A shows a genetic makeup indicating that its handle is metallic (M), small size (Z), blue (C), symmetrical (Y), and that its blade shape is straight (S). Following this notation, solution B shown in Figure 1 is genetically encoded as {M, Z, C, Y, S} and physically expressed by a metallic, medium size, no colour, symmetrical handle and straight blades. Solution C is genetically encoded as {M, Z, C, Y, S} which physically expresses as a plastic, medium size, red, asymmetrical handle and curved blades. Solution D is encoded as {M, Z, C, Y, S} and expressed by plastic, large size, grey and yellow, asymmetrical handle and straight blades. Notice that this one-to-one representation of genetic code into physical features is a rather basic implementation. Section 5 introduces genetic interaction to capture the more complex reality of physical design features expressing via the complex interaction between genes and the environment.

![Figure 1. Genetic encoding and Phenotypic expression of scissors design.](image)

Cardboard models can be used to physically represent genetic operators. Figure 2 shows a cardboard version of the selection operator known as roulette-wheel sampling (Holland & Goldberg, 1989). The parts that comprise the roulette are organized in subsets that are proportional to the level of fitness of candidate solutions A, B, C, and D. Assume that based on their manufacturing cost and cut precision, the fitness of these candidate solutions is: A=2, B=3, C=2 and D=1. The fitness of A, B, C and D has to be added (i.e. 2+3+2+1=8). The result of the sum is then matched to the number of parts that make up the roulette (i.e. 8 =16). Finally, the number of parts of the roulette that correspond to the fitness of A, B, C and D is calculated using a rule of three. Once this is done, students can proceed with parent selection.
Figure 2. Cardboard model of roulette-wheel sampling operator.

Table 1. Genomes, Fitness, No. Roulette Parts

<table>
<thead>
<tr>
<th>Genomes</th>
<th>Fitness</th>
<th>No. Roulette Parts</th>
</tr>
</thead>
<tbody>
<tr>
<td>A:</td>
<td>2</td>
<td>4</td>
</tr>
<tr>
<td>B:</td>
<td>3</td>
<td>6</td>
</tr>
<tr>
<td>C:</td>
<td>2</td>
<td>4</td>
</tr>
<tr>
<td>D:</td>
<td>1</td>
<td>2</td>
</tr>
</tbody>
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In Selection, solutions CB and AB are paired up based on their level of fitness. Notice that genome D was not selected and thus, its genetic material will be discarded. In Crossover, a point is randomly defined for each pair of solutions. Substrings before and after this crossover point are exchanged between pair members producing two offspring from each pair. In Mutation, the value at a randomly chosen position or locus is changed. The right-most segment shows the new characteristics of individuals in “generation g+1”. Notice that cardboard models may be fabricated to physically represent the Crossover and Mutation operators.

4 Learning Design History through GAs

From the perspective of actor-network theory (ANT), designed artefacts are aimed at propitiating that daily events unfold in accordance with programs of action established by social institutions. Programs of action are usually deployed not through a single artefact but several. The ways in which people drive are jointly shaped by seatbelts, car brakes, traffic lights, traffic signs, speed bumps, roads, etc. (Latour, 1992; 2007). Thus, artefacts from a historical context may share a common design rationale. One aspect of designed artefacts that clearly reflects this idea is “design style”. Asides from integrating the components of an artefact into an overall pattern, style resolves conflicts among people’s shared values and concerns. For example, during the period between the two World Wars, industrialized societies tried to incorporate the looks and rhythms of industrial machines into daily life. Consequently, stylistic traits were transferred from industrial machines to everyday artefacts of the epoch. At the most basic level, style can be said to be the visual synthesis of two elements: shapes and lines. This is because both the proportion and decoration of designed artefacts can be described in terms of the interplay of these elements (Cranz, 2000).

Considering the above, design educators can organize design activities (Telenko et al., 2015) to develop students’ understanding and use of GAs. This can be done to design everyday objects (e.g. chairs) that reflect the stylistic parameters of specific historical contexts. These new designs can be assessed by contrasting them to taxonomies and catalogues of designs from that epoch. To formulate the fitness function of these GAs, students can revise historical
texts and documents, catalogues of products, photographs, etc. In addition to providing students the chance to familiarize themselves with the design style from different historical contexts, this may increase their understanding of how designed artefacts incarnate people's values and concerns (Juez, 2002). A brief that can be used at the beginning of this type of learning activities is presented below.

Brief: Implement a GA that evolves an initial population of 20 randomly generated structures into design proposals for office chairs. Structures that make up the initial population should be made from sets of 20 to 30 cubes of the same size. When formulating the fitness function, keep in mind that the office chairs produced by the GA should match the stylistic parameters of the average American workplace of the 1950s. For a general overview of the American workplace of such time, review (Saval, 2014a; 2014b). Additionally, refer to product catalogues, furniture ads, magazines and movies from the epoch.

To evaluate active-learning activities as the one above, educators can compare the proportion of the solutions produced by GAs with the proportion of design solutions from the examined epoch. Additionally, educators can consider the structural similarity between GA and real-world design solutions. Structural similarity can be examined by contrasting the overall composition of solutions produced by GAs with the overall composition of design solutions from a given epoch. That is to say, design educators can look at whether solutions produced by GAs exhibit the same components as the ones that are characteristic of particular historical periods. A more detailed evaluation can be made by independently comparing the components of solutions generated by GAs with the components of real-world design solutions. Besides allowing students to get familiar with stylistic parameters of different epochs, active-learning activities with GAs can increase students' awareness of other historical aspects of design (e.g. the role of materials and manufacturing technologies). To maximise learning of design history, work with GAs can be complemented with activities such as group discussions, poster making, etc.

5 Learning Design Theory through GAs

In this section, we refer to Wagner’s concept of “innovability” to illustrate how the use of GAs may enhance the learning of design theory (Wagner & Rosen, 2014). Innovability emerges from the organization of the design space. The design space has been defined elsewhere as the set of all the possible genotypes that can produce one type of design solution. Since differences between some genotypes can be very subtle, two or more genotypes can produce virtually the same phenotype of a designed artefact (Raman & Wagner, 2010; Wagner & Rosen, 2014). Genotypes that produce phenotypes that exhibit no observable differences are integrated in networks within the design space. These networks are referred as genotype networks. When navigating a genotype network, the slightest change in a design parameter (i.e. allele) can lead the search to a neighbouring genotype. Progressively, mobilization towards neighbouring genotypes can cause the search to switch from one genotype network to another. Once the switch between genotype networks occurs, phenotypes may exhibit entirely new characteristics. What this means is that sequences of changes that cause no observable or significant differences between phenotypes can still lead to major innovations (Wagner, 2011).

Analogic work with components of GAs may enhance students’ comprehension of the concepts above. For instance, design educators can select an everyday artefact (e.g. a chair) and ask students to represent such artefact as a genome. As an example of this consider genome “S”. Genome “S” is composed by N locus that together regulate the characteristics of wood chair phenotypes. In contrast to the scissors' genome presented in section 2, genome “S” does not constitute a one-to-one representation of genetic code into physical features. That is to say, in genome “S” physical features are not regulated by values at single locus. Instead, physical features are regulated by the interaction of values expressed at various locus. Figure 4 shows the section of genome “S” that contains the genes that interact to regulate three physical features of chair phenotypes: the length of the legs (LL), the angle between the legs and the seat (ALS), and the height of the backrest (HB).

![Figure 4. Section of genome “S” that contains genes that regulate LL, ALS and HB.](image)
Once the genome is completed, educators may establish different criteria for measuring fitness. Depending on the established criteria (e.g. comfort, stability, etc.), students can progressively modify the values of the alleles that regulate specific physical features. For example, if the fitness of chair phenotypes depended on the height of the seat, the genes that regulate LL would progressively exhibit values whose interaction results in phenotypes with longer legs. Sketches can be made to illustrate the effects that these changes exert on chair phenotypes. Notice that interactions of genes that regulate one physical feature may affect the values of genes that regulate other physical features. For instance, as LL increases, values at the genes that regulate ALS may be recombined or modified so that the measure of stability of chair phenotypes remain adequate. Trade-offs between sections of genome “S” can progressively lead to design solutions whose physical features drastically differ from those of archetypical chairs. At some point, these differences may be significant enough to characterise resulting designs as new types of solutions (a new species). Figure 5 illustrates how changes in the values of the genes that regulate LL, ALS and HB may gradually lead to a different type of design solution.

Active-learning with GAs may as well enhance aspects of design practice. For example, the logic for implementing crossover operators may be used during studio-based courses as a method for systematically combining design variables in order to produce novel solutions (Hybs & Gero, 1992; Smith, Smith & Shen, 2012). In view of the above, a set of guidelines to design active-learning activities with GAs would include:

- Design activities based on artefacts composed of few components that are connected in standardized ways.
- Design activities based on artefacts whose components can be organized in different ways to produce the same or almost the same behaviour.
- Design activities with GAs as part of larger learning experiences that include other approaches to learning (i.e. verbal, auditory, etc.).
- Consider how the logic to formulate selection, crossover and mutation operators may be linked with design practice and align the stages to formulate and implement GAs with the activities scheduled in studio-based courses.
- Consider how the assessment of the solutions produced by a GA can be used to revisit specific theoretical aspects of design.

Just as GAs can enhance the learning of design theory, design theory can contribute to extend the scope of GAs. One way to do so is to implement innovability as a measure of fitness. That is to say, parent selection can be based on the level of adequacy of current candidate solutions and that of their neighbouring genomes. In this approach, the fitness of each candidate solution would be established through a two-stage evaluation process. In the first stage, the adequacy of a genome is evaluated in relation to fitness criteria. Assume that the fitness of genome “S” is dependent on the amount of “1s” it exhibits at the section shown in figure 4. That being the case, the fitness of this particular instance of genome “S” would be 6. In the second stage, the value at the first locus of S is switched from 1 to 0 (or correspondingly from 0 to 1) and the fitness of such genome which can be referred as S₁ is evaluated. The same process is repeated with the rest of the locus so as to evaluate the fitness of genomes S₁ to S₁₂. The average fitness of S to S₁₂ is then calculated. Genome “S” is then assigned with a selection probability that is proportional to the averaged fitness. This approach to parent selection can enhance the results produced by GAs because larger regions of the design space are explored at each time. GAs that incorporate this approach to parent selection can be viewed as devices for systematically navigating the design space.
6 Discussion

This paper shows opportunities for teaching evolutionary design in ways that are compatible with how designers learn. Specifically, visual diagrams and cardboard models are examined as means that can make the formulation and implementation of GAs more accessible to design students. Notice that other low-fidelity prototyping techniques may as well facilitate the formulation and implementation of GAs and other evolutionary systems (e.g. agent-based models, neural networks, etc.). The identification of which low-fidelity prototyping techniques better suit the characteristics of the different evolutionary systems may be the topic of future research projects and is not addressed here. Opportunities to relate the formulation and implementation of GAs with learning on design history are also highlighted in this paper. In specific, GAs can be used to generate design solutions that reflect the stylistic parameters of specific historical periods. Likewise, the paper stresses how the representation of design solutions as genomes may improve the understanding that students have on the concept of innovability. Notice that a better understanding of the concept of innovability may be achieved by means of other evolutionary computational systems.

Complementarily, we argue that design theory can contribute to extend the scope of traditional GAs. To illustrate the above, we propose to implement innovability as a measure of fitness. This approach to selection can enhance the results produced by GAs because larger regions of the design space are explored at each time. Overall, we suggest that the development of computational thinking skills can enhance the learning experience of design students. Some general guidelines on how to design active-learning activities with GAs are presented. The effectiveness of these guidelines will be assessed in future studies within the classroom.

References

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