A PATTERN COLORING METHOD USING RANK-BASED INTERACTIVE EVOLUTIONARY ALGORITHM

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Abstract. Interactive evolutionary algorithm (IEA) is a form of evolutionary computation designed to utilize information provided through human subjective assessments. This study proposes a design method based on an interactive evolutionary algorithm using a non-dominated sorting method that is well-known in the context of multi-objective evolutionary algorithm. The method developed is applied to a coloured geometric pattern as a graphic design element. The aim of this experiment is to investigate and evaluate a pattern coloring method using IEA that have the potential to augment creativity by providing robust support for exploration process of designers. The questions to the participants were designed to capture participants' perspectives on various aspects of the experiment, including satisfaction with the IEA, confidence in the exploration process, inspiration drawn from the generated designs in terms of visual pattern perception and color combinations. The results from the questionnaire showed that IEA can contribute the designers creative exploration process, become influential in visual perception of the patterns and supports initial design phase.

Keywords. Evolutionary algorithm, pattern, interactive design, pattern colouring, creative exploration

1. Introduction

Evolutionary algorithms, acknowledged as a stochastic search methodology, have been extensively explored and applied within the realm of engineering design. Notably, their benefits have transcended engineering domain and found relevance in diverse fields such as design. Whether optimizing engineering parameters or enhancing various design aspects, in both, purpose of evolutionary algorithms is to maximize the fulfilment of one or multiple objectives. IEAs, a subset of interactive evolutionary computation, aim to integrate human subjective evaluations into the optimization process. Unlike conventional evolutionary algorithms, interactive evolutionary algorithms (IEAs) emerge as a distinctive approach designed to bridge the gap between human and computer. This integration allows for the inclusion of tacit knowledge of human; including their psychology, emotions, preferences, and intuition.

ACCELERATED DESIGN, Proceedings of the 29th International Conference of the Association for Computer-Aided Architectural Design Research in Asia (CAADRIA) 2024, Volume 1, 19-28.

In the realm of digital art and design, the quest for aesthetically pleasing pattern coloring methods are to be an area of exploration. The intersection of computational intelligence and artistic expression this paper presents a novel approach to pattern coloring, by using of a rank-based interactive evolutionary algorithm. The objective of the study is to empower individuals to explore diverse coloured pattern designs that they may not have been considered through conventional methods. In this approach, IEA is used to augment the aesthetic appeal of the pattern based on the user's aesthetic judgment and preferences.

2. Background

In the subsection 2.1, we gathered background information about patterns, color and visual perception. In the subsection 2.2, we described genetic algorithms, how designs are generated by using genetic algorithm, a specific type of of genetic algorithm, known as non-dominated sorting Genetic Algorithm (NSGA-II) which is used in this work. We also reviewed a number of interactive genetic algorithms studies focusing on the implementation.

2.1. PATTERN

2.1.1. Patterns in Graphic Design

Pattern implementation in graphic design has viewed as a pervasive and dynamic area of exploration. Early works by design theorists such as William Morris emphasized the significance of patterns in creating visual interest and conveying specific aesthetic intentions. In contemporary graphic design, patterns are employed across various mediums, from print to digital, to enhance visual appeal, communicate brand identity, and evoke emotional responses (Lupton & Phillips, 2015).

2.1.2. Role of Colors in Patterns

Colors play a pivotal role in the effectiveness and aesthetic impact of patterns. Research by Albers (1975) and Itten (1961) laid the groundwork for understanding color interactions within patterns, emphasizing the significance of color harmony and contrast. The selection and arrangement of colors contribute to the visual hierarchy within a pattern, guiding the viewer's focus and conveying specific meanings (Landa, 2019). Studies by Palmer and Schloss (2010) have investigated the subjective nature of color perception within patterns, suggesting that individual differences in color preferences can influence the overall visual experience.

2.1.3. Color Perception in pattern

The role of color in pattern perception is grounded in literature. Research by Itten (1961) and Albers (1975) laid the foundation for comprehending color interactions and their effects on visual perception.

Moreover, Adams (2012) and Smith et al. (2018) have explored cultural influences on color interpretation within patterns, revealing the ways in which societal norms and individual experiences contribute to the subjective understanding of color in different contexts.

2.2. GENETIC ALGORITHM

When a search problem involves objectives that are characterized by non-linearity, uncertainty or discreteness, point-by-point search lacks in robustness, so that parallel search strategies apply (Goldberg, 1989) Treating a problem by means of a GA conventionally requires expressing the design criteria in the form of one or multiple objective functions (Deb, 1995; Coello, Veldhuizen, and Lamont 2003). In the genetic algorithm framework, a design solution is represented as a chromosome, comprising individual genes. The collection of solutions constitutes the optimization's set of possible solutions, referred to as a population. Each gene within the chromosome denotes a value corresponding to a specific design variable. In the context of genetic algorithms, usually values represent in binary form, i.e., as a string of bits.

2.2.1. NSGA-II Algorithm

This work uses the non-dominated sorting genetic algorithm II (NSGA-II), a widely used genetic algorithm known for its effectiveness across diverse applications. NSGA-II, specifically designed when the objective functions are multiple. The essential mechanism for such algorithms to cope with the multitute of solution directions that arise due to multitute of objective functions, is a comparison among population members known as Pareto ranking. In the case of Pareto ranking the fitness values obtained from multiple objective functions and are used to establish a higher order fitness criteria, known as the degree of non-dominance. Non-dominance refers to the relative superiority of a solution compared to the rest of known possible solutions with respect to the simultaneous superiority with regards to all objective functions. Explicitly a solution A is said to dominate a solution B, when A is equally fit as B with respect to the objective functios, while at least in one of the objective functions A is superior to B. Then a solution C is said to have superior Pareto rank compare to solution D, when the number of solutions that dominate C is lower compared to the number of solutions that dominate D. With this definition of a higher order "fitness," namely fitness in a multiobjective sense, it is clear that the "fitness," of an individual solution is not independent from the other solutions.

2.2.2. Interactive Evolutionary Algorithm

A design problem presents challenges for computational design, especially while expressing aesthetical criteria. Since aesthetics cannot be translated into mathematical expressions, in the absence of a objective function, a genetic algorithm is to be implemented in interactive manner, by a human. In the realm of Interactive Genetic Algorithms (IGAs) applied to design, various studies have explored diverse domains. Leelathakul and Rimcharoen (2020) focused on ornamental motifs, employing a population size of 9 individuals who selected 1 out of 3 options nine times. Their assessment involved statistical analysis of shape features and questionnaire responses. Dou et al. introduced an IGA the context of car dashboard design. They utilized six real numbers in order to get input from designers judgement in their approach of customization of product. Brintrup et al. proposes an algorithm within the realm of furniture design to determine the ergonomics of a chair. They took into account both qualitative and quantitative objectives. Yoon and Kim, focused on generation of shape of buildings in a video game. They used 12 integers from the interval between 0 and 5 to format designer's judgement. Hernandez et al. proposed an interactive algorithm in order create solution for facility layout. They use 9 integer numbers from the interval of 1 and 5 as a human input. Gong et al. used interactive genetic algorithm for women's fashion elements with a multi-population approach. Their grading scale is in between 1 to 20 in order to format human preference. Kim and Cho, also studied IGA in the field of fashion design. The diverse dress styles, was displayed on a screen, and users assigned fitness values to each. Except for the Brintrup et al. and Quiroz et al. the interactivity is not to let the grading of chromosomes be accomplished by a human in place of a fitness function but to refine the application of the objective functions.

3. Methodology

This section presents our methodology for generating designs using IEA. The interactivity of proposed IEA and selection scheme developed in this work are explained.

3.1. INTERACTIVITY

Interactive ranking fitness function decided according to human preferences and judgements. In this approach, chromosomes within the population are ranked according to user preferences. The most favored chromosome receives the highest rank (Rank 1), the second-best obtains Rank 2, and the remaining non-preferred chromosomes are assigned Rank 3. This method establishes non-dominancy among chromosomes through human preferences. The algorithm is laid out in the Figure 1.

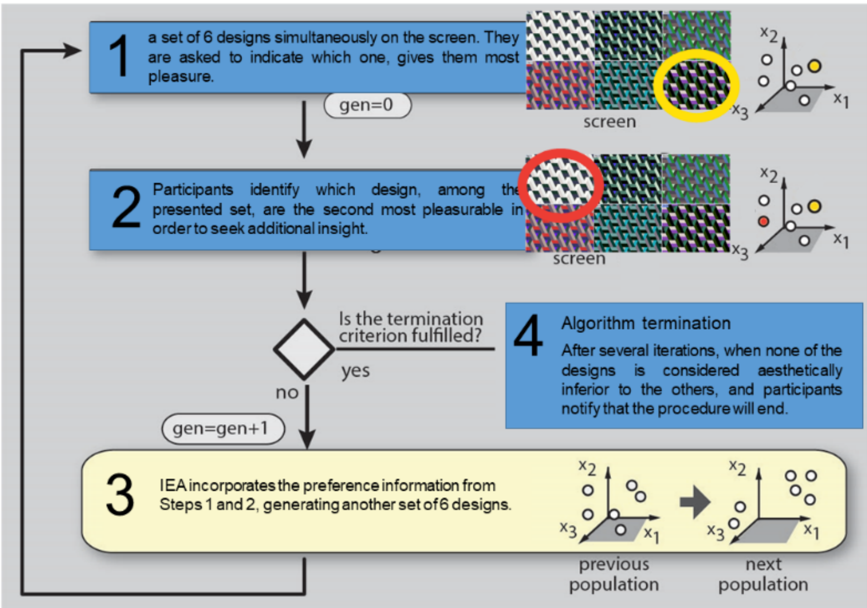

Figure 1. Interactivity Flow Chart of the proposed interactive evolutionary algorithm.

3.2. SELECTION SCHEMA

Aesthetic judgement is a measurement of a pleasure due to humans' perception. Given the absence of abstraction in this evaluative process, it is challenging on determining exact scores on an abstract scale but rather on identifying the design that offers a more aesthetically pleasing experience, in other words, which one is superior to the others.

Taking this perspective, the method of ranking based tournament selection, as it is implemented in NSGA-II, is deemed appropriate in this work since it allows comparative assessments.

3.3. BINARY TOURNAMENT SELECTION

Within genetic algorithms, the selection process can take different forms, among them two major ones are fitness proportionate selection and tournament selection. A key distinction lies in tournament selection, where the selection pressure is consistently maintained throughout the entire search process (Deb, 1995).

3.3.1. Tournament Formation

In each generation, 6 binary tournaments occurs, where two contenders compete to be the winner. Binary tournaments, a popular form of tournament selection (used in algorithms such as NSGA-II), involve determining a single winner per tournament. The winner contender is then copied into the mating pool for subsequent genetic operations, this process referred to as selection in genetic algorithm terminology.

The two contenders for winning the tournament are determined as follows: The first contender in the first tournament is pre-determined to be chromosome number one; in the same way, the first contender in the second tournament is chromosome number two;, the first contender in the ninth tournament is the chromosome number nine. This deterministic element is done to ensure that every chromosome at least is selected at one time into a tournament, so that it has at least some chance to be selected. The second contender, is randomly chosen from the remaining chromosomes to avoid repetition within the same tournament.

In a binary tournament featuring chromosomes A and B, the ranking hierarchy is established: Rank 1 is the highest, followed by Rank 2, and Rank 3 as the lowest. The tournament outcome is determined as follows: if Rank(A) < Rank(B), A wins; if Rank(A) = Rank(B), the probability of A winning is equal to the probability of A losing (both are 0.5); if Rank(A) > Rank(B), A loses.

It is important to note that in the case of a chromosome holding Rank 1 and being the sole occupant of this top rank, it is guaranteed to win at least one tournament. However, if there are multiple Rank 1 solutions, it is possible that a particular Rank 1 solution may not participate in next generation, depending on its opponents, if it contends against another.

4. Experiment

In this experiment, we utilize a geometric pattern composed of multiple geometric elements. A pattern with geometric elements are selected due to its regular arrangement of geometric shapes. Each geometric element within the pattern is assigned a color parameterized in the HSL color model using Grasshopper. Each shape has following paremeters: hue, saturation, luminance and alpha value between 0 and 1. At the first phase of the experiment, participants experiment colour combinations on the pattern by changing slider values for each shape. A total number of 6 geometric shapes with 4 different slider values, makes 24 number of parameters. At the second phase, the experiment with IEA was implemented as the steps followed which are mentioned in the section 3.1. Through the experiment, the distribution index (n_c) used by the SBX (Simulated Binary Crossover) operator is kept constant. The n_c distribution index significantly influences convergence speed; smaller values of n_c result in slower convergence as offspring solutions move away from their parents. In our experiment, we set $n_c = 2$ to foster a variety of design solutions that are distinct from their parents. Mutation probability set as 0.1. The mutation operation introduces a parameter called the mutation index which is n_m (Deb, 2001). When n_m is set to a lower value, the diversity of mutated solutions increases, and they deviate more from their parent solutions. This is the rationale behind setting n_m to 10, aiming to enhance the diversity among mutated solutions and reduce their resemblance to the parent solutions. These values are determined by a number of test runs using trial and error, not by systematic tuning. In Figure 2, one of the experiment screen is shown.

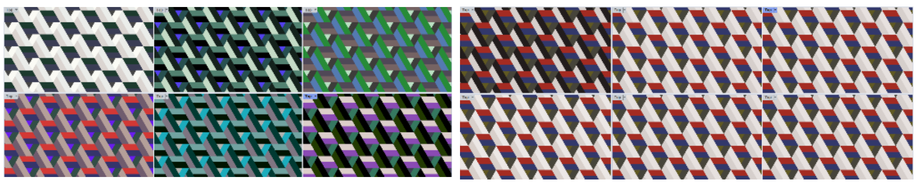

Figure 2. First generation (left), last generation (right) of one of the experiments

5. Results

5.1. OVERVIEW OF THE SURVEY

A total of 27 participants took part in the survey, representing diverse professional backgrounds, including graphic designers, artists, architects, interior architects, and industrial designers. The participant breakdown included 3 undergraduate students, 8 graduate students, and 16 professionals. Among the professionals, 10 had 1-5 years of experience, 4 had 5-10 years of experience, and 2 had more than 10 years of experience in their respective fields. They are asked the following questions:

- How satisfied are you with the generated colored patterns?
- Do you find the number of design solutions provided sufficient? Would you prefer fewer or more choices? If so, why?

- Do you believe that IEA can take your aesthetic judgement? (Did the colored patterns become more aesthetically pleasing as the search progressed? and/or Do the patterns become similar to each other when the search goes on?)
- When comparing the process of coloring patterns using the conventional method (selecting each parameter individually) with the interactive algorithm, how do the two techniques differ in terms of your confidence in throughly exploring possible solutions?
- Did the colored pattern generated solutions inspire you? If so, how?
- Do you think that IEA could contribute your explorative creative process?
- When exposed to different coloring combinations on the pattern, do you perceive them differently? How does your perception affected?
- Do you have any additional comments or suggestions regarding your experience with the IEA algorithm in pattern coloring and the overall experiment?

5.2. RESULTS OF THE SURVEY

5.2.1. Satisfaction

Participants were asked about their satisfaction with the generated coloured patterns. Out of the total 27 participants, 2 were very satistfied (7.4%), 14 participants reported being satisfied (51.9%), 9 indicated a neutral stance (33.3%), and the remaining 2 participants (7.4%) reported dissatisfaction with the experience.

In response to the question about the sufficiency of design solutions provided, the participants' preferences varied. Out of the total 27 participants, one participant (3.7%) expressed a preference for fewer design choices, citing a desire to concentrate more on the pattern. Conversely, 12 participants (44.4%) expressed a preference for more design solutions, expressing a desire for increased diversity in the design set. The majority, comprising 14 participants (51.9%), found the number of design solutions provided to be satisfactory.

In response to the question regarding the capability of IEA to take aesthetic judgment, a significant majority, comprising 22 participants (81.5%), affirmed that they believed the IEA could take their aesthetic judgement. In contrast, 3 participants (11.1%) expressed a neutral stance on the matter, while 2 participants (7.4%) disagreed with the notion that the IEA could effectively take their aesthetic judgement. Participants who held a neutral stance on this question provided feedback indicating that, through the search, although the designs become more similar to each other, the designs did not entirely align with their individual aesthetic preferences. Furthermore, the participants that agreed with this question noted that as an overall, the designs were progressively becoming more aesthetically pleasing, however, they expressed a desire for more pleasing options.

5.2.2. Exploration

In comparison of the conventional parametric method (selecting each parameter individually) with the IEA, the participants provided insights in their confidence regarding exploring possible solutions, over the 27 participants, 24 of them (88.89%) agreed on that. The conventional parametric method, which involved selecting each parameter individually using sliders, deemed confusing by the respondents. Despite control, participants found the process tiresome, particularly due to high number of parameters involved. In contrast, the IEA method was appreciated by the participants since the generations produced by the IEA were explorative. 3 of the participants (11.11%) commented IEA is not exploratory due to high speed of convergence.

For the question whether participants found the IEA process inspirational or not, the majority of them, 25 out of 27 respondents (92.59%) agreed on that the IEA method inspire them while 2 of the respondents (7.41%) stay neutral. None of the participants disagreed with it. Some of them reported that interacting with generated colour options on the triggered imaginative thinking and influenced their own creative process.

The view on whether the IEA could contribute to the explorative creative process varied among participants. Out of 27 participants, 9 of them (33.3%) responded agree, 12 of them (44.4%) responded partially agree and 4 of them (14.81%) had neutral stance. Although the majority partially or not partially agreed on the contribution of IEA, 2 of the participants (7.41%) expressed a preference for selecting the color pallette before the design process and, as a result, did not feel that the IEA significantly contributed to their creative design process. On the other hand, another participant highlighted seeing different options as a contribution to design. The ability to explore various design alternatives through the IEA was considered a positive influence on their explorative creative process. Another view from the participants was noted that while the IEA was inspirational, it couldn't fully lead the design process; its impact was more pronounced during the initial conceptual phase.

In the study with 27 respondents, we investigated the impact of various coloring combinations applied on pattern as visual perception. 26 of the participants (96.29%) reported participants did, in fact, perceive patterns differently when exposed to different coloring combinations. (20 of them responded " Significantly enhances perception and 6 of them responded "enhances perception") They commented that variations in color seemed to have an effect on their overall perception so that it become inspirational in the design process.

5.2.3. Suggestions

The feedback from participants regarding their experience with the IEA algorithm in pattern coloring and the overall experiment highlighted a desire for increased options. In that manner some of the participants suggested that conducting the experiment for multiple times could be beneficial due to the potential wideness of the exploration space. Additionally, a few participants expressed the idea that it would be helpful if they could remove designs they did not like. Another participant provided feedback suggesting the option to limit certain parameters based on their design criteria.

6. Discussion

6.1. RANDOMIZED SOLUTIONS

Regarding slider-based design, the starting point within the decision variable space is arbitrary, with a single trajectory. In case of interactive evolutionary algorithm, the starting points are also arbitrary, and more specifically they are random. Furthermore, there are numerous starting points, ensuring that randomness covers the entire search domain. The search process within the space, due to the parallel evaluation of designs, implies the simultaneous pursuit of multiple trajectories. In each generation, in other words, at every turn of a trajectory in decision variable space, the designer's evaluation information comes into the process. Among each turning point, those that are relatively close to a desirable design solutions are distinguished from those that are relatively distant. As the search is a multi-trajectory search, the probability of reaching a desirable region should be somewhat higher than in case of the single trajectory search, which parametric design is. Participants commented that the presence of multiple sliders complicates the design process. Consequently, they believe that the IEA method has the potential to be influential, considering it a beneficial tool for conceptual exploration.

6.2. INITIAL POPULATION

The randomly generated initial population may not be satisfactory for the participants. However, due to the experimental evaluation process, participants are still required to choose designs based on their aesthetic judgments among the alternatives. This could potentially misdirect the algorithm in a wrong trajectory. Consequently, some participants commented that, despite the algorithm could take their preference information, the results did not entirely reflect their aesthetic preferences or the designs could be better. Selecting worst design or conduct the experiment with a different the initial population could be helpful to address this issue.

6.3. POPULATION SIZE

Determining the population size is a crucial aspect of interactive evolutionary computational processes. The population size should not be too large to maintain user's focus on the task, yet not too small, as a low population hinders the user's ability to explore diverse alternatives for solutions. The limited number of design solutions creates a lack of diversity, therefore the randomized solutions might direct the process as it is biased. In order to prevent from the disadvantage of low population size, the experiment could be conducted multiple times.

7. Conclusion

The intricacy of design arises from the simultaneous evaluation of multiple parameters and the incorporation of tacit knowledge, which are encompassing human preferences and judgments. To address this challenge, the interactive evolutionary approach emerges as a unique solution. This is primarily because the interactive evolution incorporates the judgment of preference directly into the computational process, eliminating the need for an explicit explanation of the preference.

We had applied a rank-based interactive evolutionary algorithm (IEA) to generate colour combinations for patterns. Exploring each color applied to the pattern is a challenging task because visual perception is influenced. In the examplary design study, it addresses the challenge of considering multiple color parameters for each geometric element of the pattern. This task is inherently complex due to the intricate relationships between colors, geometric shapes and the number of parameters. In this regard, the IEA stands out as an effective process for design exploration for color selection and visual appeal in the final pattern. When compared to conventional parametric design methods, experimental results showed that this approach facilitates creative exploration and inpire the initial phases of design due to IEA's ability to start with randomized design solutions and due to fitness according to human preferences.

References

Albers, J. (1975). Interaction of Color. *Yale University Press.*

Brintrup, A. M., Ramsden, J., Takagi, H., & Tiwari, A. (2008). Ergonomic chair design by fusing qualitative and quantitative criteria using interactive genetic algorithms. *IEEE Transactions on Evolutionary Computation*, 12(3), 343-354.

Deb, K. (2001). Multi-objective optimization using evolutionary algorithms. *John Wiley & Sons.*

Deb, K., & Beyer, H. G. (2001). Self-adaptive genetic algorithms with simulated binary crossover. *Evolutionary computation*, 9(2), 197-221. https://doi.org/10.1162/106365601750190406

Dou, R., Zong, C., & Nan, G. (2016). Multi-stage interactive genetic algorithm for collaborative product customization. *Knowledge-Based Systems*, 92, 43-54. https://doi.org/10.1016/j.knosys.2015.10.013

Goldberg, D. E. (1989). Genetic Algorithms. *Addison-Wesley*: Massachusetts.

Gong, D.-W., Hao, G.-S., Zhou, Y., & Sun, X.-Y. (2007). Interactive genetic algorithms with multi-population adaptive hierarchy and their application in fashion design. *Applied Mathematics and Computation*, 185(2), 1098-1108.

Hernandez, L. G., Morera, L. S., & Azofra, A. A. (2011). An Interactive Genetic Algorithm for the Unequal Area Facility Layout Problem. *Soft Computing Models in Industrial and Environmental Applications, 6th International Conference SOCO 2011* (pp. 253-262). Advances in Intelligent and Soft Computing (AINSC), 87.

Itten, J. (1961). The Art of Color: The Subjective Experience and Objective Rationale of Color. *John Wiley & Sons.*

Kim, H. S., & Cho, S. B. (2000). Application of interactive genetic algorithm to fashion design*. Engineering Applications of Artificial Intelligence*, 13(6), 635-644.

Landa, R. (2019). Color, Space, and Style: All the Details Interior Designers Need to Know but Can Never Find. *Rockport Publishers.*

Leelathakul, N., & Rimcharoen, S. (2020). Generating Kranok patterns with an interactive evolutionary algorithm. *Applied Soft Computing*, 89, 106121.

Lupton, E., & Phillips, J. C. (2015). Graphic Design: The New Basics.

Quiroz, J. C., Louis, S. J., Shankar, A., & Dascalu, S. M. (2007). Interactive Genetic Algorithms for User Interface Design. *2007 IEEE Congress on Evolutionary Computation* (pp.1366-1373). IEEE. DOI: 10.1109/CEC.2007.4424630

Yoon, D.-M., & Kim, K.-J. (2013). Interactive Evolution of 3D Models based on Direct Manipulation for Video Games. *Procedia Computer Science*, 14 (1), 1-16. https://doi.org/10.1016/J.PROCS.2013.10.036