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Co-Creative Product Design with Interactive Evolutionary Algorithms: A Practice-Based Reflection (Preprint)

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Abstract

Progress in AI has brought about new approaches for designing products via co-creative human–computer interaction. In architecture, interior design, and industrial design, computational methods such as evolutionary algorithms support the designer's creative process by revealing populations of generated design solutions in a parametric design space. However, the benefits and shortcomings of such algorithms for designers are not yet fully understood. This paper reports the in-depth, in-situ and longitudinal experiences of one industrial designer using an interactive evolutionary algorithm in a non-trivial creative product design task. Our study sheds light on the intricate interaction between algorithm, human designer and their environment. It identifies, amongst others, the algorithm's contributions to design inspiration and to overcoming fixation. We contribute concrete proposals for the future study of co-creative AI in design exploration and creative practice.

Keywords: Co-creativity, Interactive Evolutionary Algorithm, Introspection, Autoethnography, Longitudinal Study, Design.

Introduction

Although the potential of evolutionary algorithms has long been recognized in design [33], only during the last decade solutions have become sophisticated and flexible enough to find their way into commercial computer-aided design (CAD) software. Evolutionary algorithms have the capacity to transform CAD software from creativity support tools [14, 44, 7] to *co-creative* systems [21] capable of not only augmenting but also complementing the creativity of human designers [3].

When new tools and technologies for human–computer co-creativity are applied, designers' working methods are transformed. Evolutionary algorithms are likely to induce profound shifts in the designers' process, creativity and experience of agency (e.g. [41]). One particular notable development are *interactive* evolutionary algorithms, which allow the designer to intervene in the optimization process by selecting the best performing candidates, thus implicitly injecting performance criteria that may be tedious, hard or impossible to formalize explicitly. However, interactive evolutionary algorithms are a rather recent addition to the commercial design practice. They are not yet provided as standard features in established design software, but have to be included through third party extensions. Moreover, they are rarely covered in contemporary design school curricula. Overall, we have little understanding of how existing interactive evolutionary algorithms can be incorporated into design practice, and, vice-versa, how design practice could inform algorithm development.

This paper addresses these shortcomings through a researcher introspection study of an industrial designer's use of an interactive evolutionary algorithm in a real-world creative design task. The analysis covers the first author's experiences from using a design software equipped with evolutionary design support software over a period of 11 weeks, during which they solved the design problem of creating a pendant lamp, with the aim of ultimately fabricating a physical prototype. As is typical of creative design processes, this work involved focus and incubation phases as well as high amounts of iteration and exploration.

Our contributions are threefold. Firstly, we support the adoption of interactive evolutionary algorithms in design practice by documenting an algorithm's use, benefits and shortcomings in a real-world design task. We particularly focus on the algorithms' ability to complement the designer's creativity and avoid fixation. Secondly, we inform the further development of these algorithms by computer science researchers to support future design practice. We particularly highlight opportunities for supporting the meta-evolution of parametric design definitions, and the effective visualization and manipulation of design instances. Thirdly, we shed light on how emerging work practices can be studied in-situ, as we see it necessary to establish a foundation for longitudinal studies on practice-based experiences of emerging CAD tools. In particular, we posit that, when humans are included in the loop, it is essential to investigate designers' experience of creativity within the design process on multiple time-scales.

Background

To ease the readers' understanding of the designer's actions in our longitudinal study, and how evolutionary algorithms can transform design, we highlight the most relevant features of design as a creative practice. We draw parallels between the conceptualisation of design practice and evolutionary algorithms, and particularly relate the dynamic construction of design spaces and the co-evolutionary construction of the problem and the solution within a design process.

The interaction of our designer with the evolutionary system is substantially guided by their *reflection* on the design. In his classic book on design theory, Schön [37] presents design as a practice where reflection has a prominent role both in-action, i.e. during the activity, as well as on-action, i.e. prior to, and after the activity. Reflection leads to what Schön describes as a "re-framing of the design problem" [37, pp. 94-95]. *Framing* here refers to the process in which a designer makes sense about the problem at hand, imposes their interpretation, and uses it to generate ideas for small design experiments to probe the value of possible trajectories towards more substantial solutions. Schön describes this method as "reflective conversation with the materials in a design situation" [38].

Through framing, the designer constructs a mental image of the design and solution spaces within which the desired design can be explored and identified [12]. Studies have revealed that the design space is not static, and that also the solution space may be re-framed based on insights gathered when trying to solve a specific problem. Consequently, the problem space and the solution space may co-evolve [13, 9]. In an evolutionary algorithm, re-framing the solution space corresponds to altering the objective function measuring the success of generated solutions. The typical design process thus encompasses more than the search for optimal solutions to a given and fixed problem and the traditional use of evolutionary algorithms for optimization captures only a part of the process.

The work of a designer can be considered as "satisficing" rather than optimizing [40]. Design spaces are vast and the amount of possible designs is substantial [45]. Also, design is often concerned with *wicked problems*, where intricate, sometimes contradictory systemic relationships render any solution sub-optimal or downright harmful in different situations or changing environments [35]. For example, industrial design requires trading-off product manufacturing efficiency, material characteristics, cost, human factors, sustainability concerns, aesthetic vision and styling trends, amongst others. These manifold requirements are typically very tedious, hard or impossible to formalize in the objective function of a standard evolutionary algorithm for the optimization of a design problem. Together with our observation in the previous paragraph, this renders the study of how designers can benefit from employing *interactive* evolutionary algorithms as co-creative partners in their practice particularly worthwhile.

Related Work

At present, evolutionary algorithms cannot substitute real-world human design practice. However, they allow designers to *articulate* (i.e., to spell out and arrange in a structured way, cf. [39]) and to *explore* the characteristics of problem and solution spaces. This can potentially counteract designers' fixation on a smaller set of possible solutions [29]. While evolutionary algorithms are popular in architecture, there are only few examples of real-world applications in product design. We survey related work to distinguish different types of such algorithms and to reveal a gap in the study of their application.

Industrial product design has prominently adopted *Genetic Algorithms*, e.g. to explore the design space of lamp holders [26]. A particular challenge has been to formalize subjective experiences such as human aesthetic preference in the GA's objective function. While there have been theory-inspired attempts to formalize aesthetics of e.g. product shapes [27], there is space for improvement. An alternative solution for dealing with such features that characterize *wicked problems* in design is to complement algorithmic selection via an explicitly stated objective function with human selection in *Interactive Genetic Algorithms* (IGAs).

IGAs have been leveraged in designing cameras [25], cars [8], fragrance bottles [22], wine glass profiles [42] and fashion [15, 43], amongst others. Existing studies in this field focus on *only one use* of IGAs – to explore the design space (e.g. [24, 1, 2]). Moreover, they typically emphasize the system's architecture and implementation from the *perspective of its engineers*, but do not study how it is experienced by designers as their end-users. Existing work focuses on the use of IGAs in *only one or few stages* of product design, covering only a *short period* of time. It primarily covers the conceptual design stage (e.g. [8]) and rarely the early embodiment stage, where the structural and product architecture design establishes a myriad of opportunities and requirements for the following process. When optimization is the focus, these reports typically address the late detail design stage, focusing on e.g. finite element analysis. In the center is a design system of designer and their computer, trying to create an integrated design specification which addresses objectives, requirements, and limitations, considering the available resources and environment of the product [32].

Based on our analysis of related work, we attest a lack of first-hand, *longitudinal* studies of the *designer's experiences* in applying IGAs to *real world* industrial design problems *outside the lab*. However, only such studies can inform the (a) design of such algorithms and their (b) adoption by practitioners.

Design Study

We address this research gap with a longitudinal study of the designer's experiences when employing an IGA in an industrial product design task.

Design Task

We study the realistic, real-world task of designing a pendant lamp fixture. The fixture had to be made primarily of plywood, using manufacturing methods suitable for mass personalization. We note that this framing already constrains the design space substantially. In interior design, a pendant lamp fixture is functionally a rather mature basic concept. One typically has a fixture of one or more light sources, like bulbs, hanging from the ceiling from electrical wire or supports, and a configuration of shades and reflectors attached to it. However, structurally, there are a wide variety of pendants, and a certain constant interest in the market for new designs. With these characteristics, the design of a pendant lamp provided an ecologically valid design problem for this design study.

Study Method

We chose to perform a *researcher introspection* study within the *Research through Design* (RtD) framework. Evolving from design-oriented Human–Computer Interaction research, RtD focuses on building knowledge through design practice [47]. It shares characteristics with what Koskinen and Krogh consider *constructive design research* [23], which tackles design problems with design-specific means, producing design outcomes. The main accountability is directed towards design practice, rather than other fields. Efforts to develop a more rigorous theoretical basis for RtD and design research are underway (e.g., [20, 30]).

In the past, think-aloud protocol studies have been particularly popular in studying the design process and creativity within [13]. Crucially, this method assumes a split between the researcher and the designer subject. While this allows for reflection-in-action within one phase of the design process and on toy problems, the impossibility for the researcher to accompany the designer for a prolonged period renders the think-aloud method unsuitable for longitudinal, reflection-in-action studies on real-world design problems.

We instead leverage *researcher introspection*, a family of methods through which the researcher investigates their ongoing self-experiences as the primary means to generating knowledge. Xue et al. [46] particularly promote this as a means for Human-Computer Interaction researchers to access insider experiences in a specific domain. For this study, we chose to perform *researcher introspection* through *autoethnography*, a method that joins autobiographic with ethnographic principles, inquiring into cultural phenomena (such as design) through self-observation and reflexive investigation [28]. The subject in our study conducted autoethnography based on 1) screenshots from the software, containing interim genotype versions and phenotypes developed within by an evolutionary algorithm, and 2) text notes during and right after each design session. The use of text notes, e.g. in the form of diary entries, has been recommended by other design researchers (e.g. [46, 31]). Hence, our study relies on both concurrent and retrospective introspections, with an emphasis on retrospection.

Crucially, this study design serves our goal to *exploring* areas of future study, rather than identifying generalisable conclusions on a specific question. We describe the next steps required to further the latter goal in our discussion section.

Participant: The Designer

Our researcher introspection through autoethnography is done by the first author who is both, a designer and a researcher. The remaining paper and in particular the later discussion of the study findings has been shaped by all authors. The designer has ten years of industry experience as a consulting and in-house industrial designer in Europe and the US. They moreover have gathered experience in human-centred design research for eight years. The designer's expertise in surface and parametric solid CAD is on an expert level, based on consulting work as a surface modeler in the car industry, and as an industrial designer in the occupational protective equipment industry. They can be considered an advanced user of the software employed in our study, but not an expert. The designer has been teaching different CAD tools in design universities part- and full-time.

Software Tools and Algorithm

One of our primary goals is to foster the adoption of IGAs in industrial product design. To this end, we must enable other designers to apply our insights to their own practice, in the spirit of constructive design research [23]. We consequently leverage a set of readily available software tools that are popular in design.

The designer's co-creative partner in our case study consists of multiple components. *Grasshopper* [16] is a visual programming extension for the 3D modeling system *Rhinoceros 3D* [34], enabling the creation of parametric definitions of shapes. The definition is constructed by connecting parametrized nodes into a directed acylic graph, with nodes representing shape grammar rules. The freely available add-on *Biomorpher* [18] provides an IGA to optimize these parameters (Fig. 1). To this end, *Biomorpher* encodes all parameters in a normalized real number genotype vector. It provides a user interface for manipulating the algorithm's initial parameters such as mutation rate, pop-

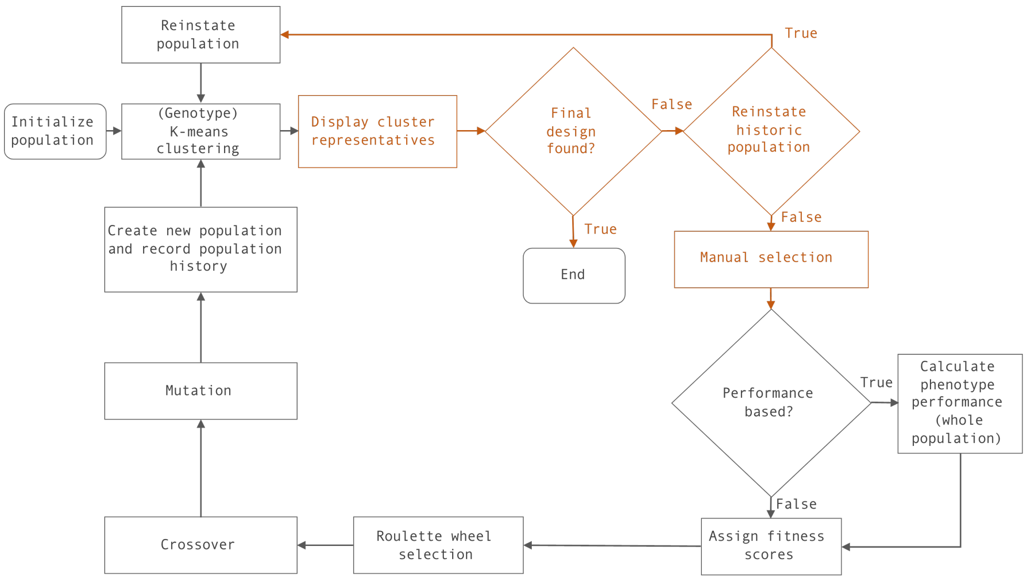

Figure 1: The *Biomorpher* process with human interaction stages in red. Figure adopted and extended from Harding and Brandt-Olsen [18].

ulation size, and single-point crossover. The interface moreover facilitates the evaluation and selection of design candidates that were worth of retention and further evolution.

Generative design algorithms in general can effortlessly produce innumerable design candidates. However, their review and the selection of the best candidates for further development can become an overwhelming task [15]. *Biomorpher* counteracts user-fatigue by leveraging a *Cluster-Orientated Genetic Algorithm* (COGA) [6]. Here, k-means clustering is applied to the whole population, and only twelve instance if the clusters' centroids are presented to the designer for review along with additional information such as the number of other, hidden instances in the cluster. These clusters bear similarity with Krish's *represented regions* of the solution space [24], where different designs assume different locations in a multi-dimensional space of quality characteristics. The designer can optionally complement their selection of design candidates to evolve further by specifying objective performance criteria – corresponding to the objective function in standard evolutionary algorithms. All user-selected candidates are assigned a maximum fitness of 1.0. If optional, objective performance criteria have been specified, they are transformed and equally weighted in a single fitness value and applied to all candidates that have not yet been selected by the user. When creating a new population from the fittest individuals, *Biomorpher* records the previous population in a history. This allows the user to return to previous generations if evolution leads to an undesired part of the design space. Once the designer has terminated the process, they can use the 3D geometry of an instance in further design or fabrication. Fig. 1 documents *Biomorpher's* operation and interaction with the designer. Further technical details can be found in [18].

Findings: Introspective Design Reflections

The following experiential account of using the above-introduced IGA software is written in the first person singular, emphasizing the reflections of the designer. The project was not commissioned and had no significant time pressure, but was of personal interest with the aim to inspire some prototyping later.

Aesthetic Objectives.

The pendant would need to be rather large: the actual interior I had in mind was 9 by 5m, with a ceiling that is 5m high on average, in a lakeside cabin with a contemporary ethos. The particular harsh northern lakeside locale of the interior for some reason took my mind to the northern Atlantic coast. The initial conceptual ideas for the design borrowed from the aesthetics of aviation, of the wing foil and truss structures of aeroplanes. Another design cue was a whale, even a carcass of a whale with the rib-cage showing as mere bones. Vaguely linked to this was an Inuit kayak, as reflections of some old films of Inuits occasionally flashed in my mind during the intentionally low-key incubation process. The cues were not particularly vivid, and I intended maintaining pure conceptuality in them, wanting to avoid the direct reproduction of any particular artefact.

I made no visual searches from e.g. the Internet for images at the early stage of design, as this might have led to constraining mental imagery of the constructions, at what I saw was a very sensitive phase of the design process. My objective was to channel the experience of the people enjoying the interior with subtle visual cues, leading to interpretations stemming from their personal experience. I deemed that the artefact should raise questions, not be a model of something existing. The success of the design intent of the pendant depends on these multi-interpretive semantics.

The initial design space was not informed by visual cues and form semantics; materials and manufacturing technology often constrain the design space significantly. In a product architecture as in the present case, visual and different structural functions cannot be separated. For me, this was a rather special product, as functional requirements were somewhat secondary to aesthetics and personal motivations played a role.

I contemplated plywood as the material and considered its affordances for design. It can be bent, but not in two ways simultaneously. Thin (less than 1mm) sheets can let through some light. The material is lightweight, hydrostable enough for this use, relatively inexpensive, long lasting, easily and safely disposable, and rather sustainable from a manufacturing point of view. Cutting it accurately from a sheet is easy e.g. by laser cutting. Assembly can then be done either without separate fittings or with simple ones if needed. Visually, the material suits many environments. Even high quality plywood is available locally.

Definition and Genotype from Conceptual Cues.

I used the IGA in the fixture design from January to early March 2021, as a low intensity process with often days in between consecutive sessions. The above-presented initial design cues, aesthetic considerations and the material selection had limited the concept to a point where I could proceed with the embodiment design [19], and I hence developed the initial parametrization of the model. My objectives for the grammar and its genes were to 1) create valid geometry, 2) enable easy growth of the design space, and 3) follow the capabilities and limitations of the material on one hand, and support manufacturing and assembly opportunities on the other.

While I had the aforementioned cabin interior as an environment cue, I was not primarily focusing on delivering a single design. Instead, my objective was a robust parametric representation and genotype, capable of covering a sufficiently large design space to enable mass personalization. This requires the co-creative system to seamlessly fit into the later stage of detail design [19], as it would be inconvenient to manually finalize the individual phenotypes for production.

I therefore planned to extend the system to generate the routing for laser cutting the parts and stacking the cutting paths space-efficiently on raw sheets. This would enable the generation of ready-to-manufacture individual variants. That effort is not part of this report, however, as the process reported here covers only the parts that related to the co-creative design with the IGA in *Biomorpher*.

I generated the initial populations during the first design session with the computer, after parametrizing the design and setting up the initial gene configuration. This led me to an iterative process with the IGA, where, after I had created a few generations from one parametric definition, I collected insights to re-frame the problem. Once they had served their purpose in assisting this re-framing, I discarded the generated populations. The insights led me to either add more features to the grammar, and to change the gene value domain limits.

I enjoyed exploring the design space by having the IGA generate populations even without clear objectives. I paid notice to unexpected versions and details, while the initially very limited solution space motivated me to grow the variety the system is capable to produce. The visual representations and ability to both manipulate and render them at different degrees of fidelity on screen were imperative for assessment, and for making decisions for future changes to the definition. In the majority of cases, the visualization provided by the *Biomorpher* user interface was sufficient (Fig. 2).

It took me three consecutive evenings to create the basic parametric definition through the described process. After this sprint, the further development of the design took place in individual sessions with multiple days in between. In these sessions, I generated some populations, but did not make changes to the parametric definition. This was an inspiring stage as it allowed me to explore variations to my primary design. At the same time, finding the boundaries of the current solution space increased my motivation to apply changes.

A Period of Botched Efforts.

On the experiment's third week, after the five separate design sessions (of 2–4h each) described above, I created a new definition with a wider design space from scratch. Unfortunately, I had to discard it after a few hours, as it revealed a critical mistake with regard to the objective constraints of the materials: the new approach created double-curvatures, a geometry which plywood does not allow for. The resulting instances were thus beyond the viable design space. I back-pedaled to the old version, and re-factored it to increase its capability to produce variations, and robustness. I was aware of the constraints stipulated by material choices, but this time I had forgotten why I had done the initial parametric definition the way I had. Showing the respective state of the working evolution to three peers in separate occasions led to a demotivating response, as they did not see anything particularly creative in the output. This was disappointing,

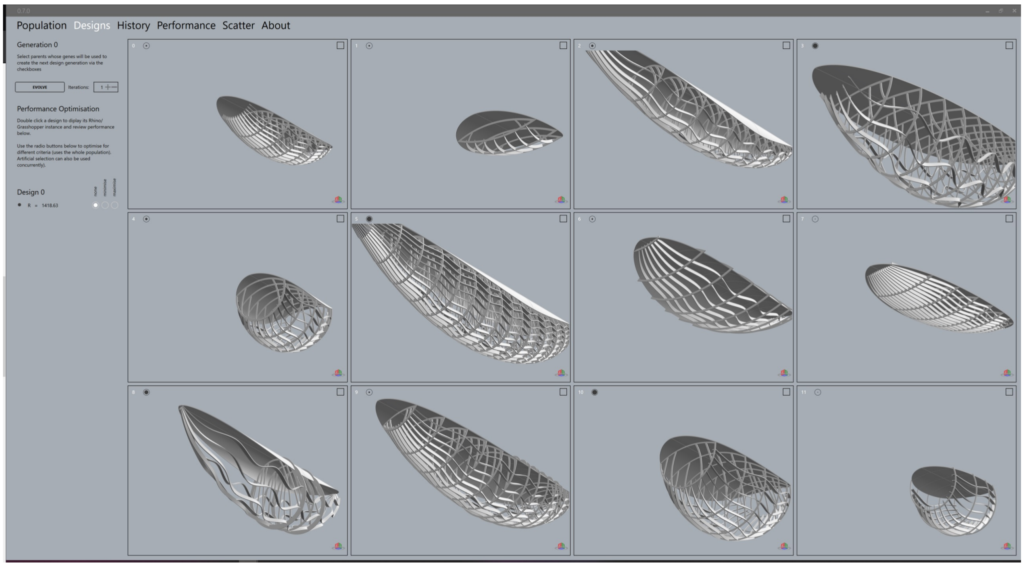

Figure 2: *Biomorpher's* selection view, showing 12 samples from a generation of 48 instances as centroids resulting from k-means clustering. Screenshot taken and used with permission from the authors [18].

leading to pressure to pursue more novel output. However, this was out of reach due to time resources available for the project.

Inspiration from the Wild.

I added longitudinal ribs to the bottom of the form late in the process, only during the sixth and after nine separate design sessions in total. I noticed some resemblance with a whale's chest-skin corrugations but the insight did not lead to action until a few days later when I was watching a TV-program of actual whales swimming under water. It led me to add wave-form to the geometry (Fig. 3). The IGA proved valuable in the process of finding a suitable range for the genes that would define the wave-form. I had been concerned about the lighting experience, i.e. shading the bulbs of the fixture. While this visual cue towards the whale was welcome in aligning with one of the initial aesthetic cues, the lighting-study renderings with selected phenotypes proved a visually intriguing shading performance which aligned well with the affordances of plywood.

Specifying Objective Performance Criteria.

Having reached this far, I introduced the laser cutting length as an objective performance criterion to be minimized. The definition evolved as the material and other requirements and the geometrical opportunities and constraints were considered and revealed during the process, as a result of repeated cycles of population generation, and subsequent definition development. In the resulting definition and genotype, the genes of the grammar control the length, width, and height of the pendant. Other genes control the amount and curvature of various ribs in the structure, and the final ones the longitudinal, wavy

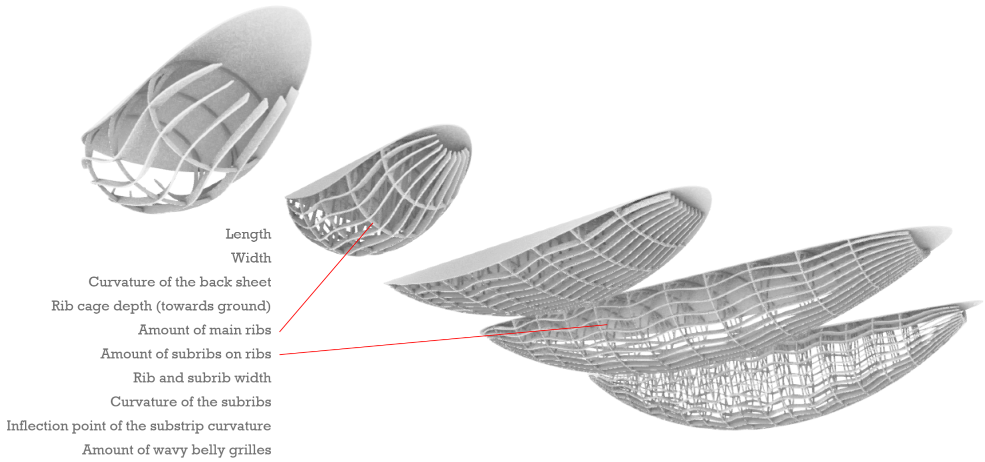

Figure 3: Some generated instances. The genes guiding the generation are listed.

grilles. Fig. 3 illustrates the genes on example solutions, i.e., the design outcomes generated by the final algorithmic definition.

Discussion

In the following, the team of authors summarizes their collective reflections on the nature of the reported design process, on the co-creative relationship between the designer and the IGA, and on the study's limitations.

Our researcher introspection through autoethnography study revealed that the IGA performed several roles in the design process. It helped the designer to articulate the design space and thereby also to understand its boundaries. It also helped to visualize and conceptualize the landscape of possibilities in that space. The designer also used the IGA as a pathfinder whereby they could take a passive role and let the IGA offer its suggestions, which then could be turned down or picked up for further exploration. Finally, the IGA helped the designer to visualize and fine-tune their vision of the final design. These roles invite the following further considerations on designer–IGA co-creation.

Early Constraining of the Design Space

The designer defined the initial objectives by having particular visual cues (e.g., aviation aesthetics) about the design direction. In this sense, the design process seems to have been informed by a *primary generator* [11], i.e., by a promising conjecture that designers have often been noted to use as a basis for their design. The designer did not use the typical method of collecting visual material to generate or develop these primary generators, but instead developed a parametric definition and the ensuing population generations. Only then they searched for visual images of the design cues. In their diary notes, the designer mentioned a concern that actual images would be constrictive. Because of this, they found it beneficial to use the IGA in creating further aesthetic direction. This observation supports the use of IGAs as partners to help fulfilling and redefining designer visions (or, primary generators).

Support in Problem–Solution Co-Evolution

The design process took place over 11 weeks, with intermittent bursts of activity, typically of two to three evenings each, with some days of non-activity in between. The initial parametric definitions took only a few hours to develop, after which the designer utilized the IGA for the population generation and evolution. The process of developing some populations and after that again returning to develop the definition further, or to correct the gene scales thus affecting the design space constraints, resembles the problem–solution co-evolution that e.g. Bernal et al. [4] have written about. They note that "although it is an approximation to the co-evolving dialog between problem and solution that characterizes expert designers, it lacks reformulation mechanisms" [4]. Because collaboration with an IGA naturally shapes a design process towards this direction, IGAs may help some of the designers' processes gain more expert characteristics.

Using an IGA in the design process also had another beneficial impact: the design space was *informed* and *filtered* [17] by the constant process of population generation and the ensuing editing of the genotypic representation. By filtering the design space, the IGA exposed areas of inquiry and thus motivated the designer to redefine the constraints of the space. It thus realized a different role than merely serving as a meta-heuristics to find unexpected but iteratively optimized solutions to quantifiable problems. Here, in contrast, the IGA was helpful in redefining the problems themselves in addition to offering solutions.

Escaping and Falling in a Fixation Trap

As presented above, genetic algorithms offer a possibility for their users (e.g., designers) to notice unexpected, serendipitous solutions to problems. This was observed several times also in our case study, as the introspective report attested. However, in hindsight, we also identified three "modes" through which the interaction with IGAs has negatively impacted the design process. These modes have been coined by Robertson and Radcliffe in CAD more generally [36].

Firstly, a form of *bounded ideation* shows in the session where the designer started creating an alternative genotype from scratch, but later recognized the solution to be outside the limits of the planned fabrication possibilities. This can be considered a novice mistake; expert designers intuitively recognize the many constraints and frame their problem accordingly [10]. Here the designer had attended to the constraints initially, but became captivated and immersed by the engaging computational design task of defining a parametrization with a large enough solution space so that they forgot a fundamental constraint.

Secondly, while the initial reason for devising a new genotype was to open up new lanes of inquiry to the design space in order to avoid *premature fixation* [36] to the initial genotypic representation, the designer became distracted from the actual creative tasks due to being immersed in interacting with the software. Combined with time constraints, the designer returned to the older version of the genotypic representation, rather than creating a new one. This fits premature fixation, i.e. exactly the mode which the designer aimed to avoid.

Thirdly, *circumscribed thinking* [36] might also be present in the observed process, although this is harder to confirm. All possible ways of using *Grasshopper* considered (including plugins), the designer, based on their prior experience, chose to approach the design task primarily through parametric solid modelling. This previous experience circumscribed their thinking, potentially resulting in missed opportunities to develop a genotype for a wider design space exploration.

Thus, while the general benefits of genetic algorithms lie in their capacity to generate unexpected, seemingly creative, design solutions, they may also limit the designer's field of vision, make them complacent and inattentive to biases, and lead them to suboptimal working practices.

The IGA as Creative Partner

Traditional tools in product design – pen and paper, graphics and CAD software – operate deterministically and can therefore be mastered with high precision and virtuosity. However, they do not produce *unexpected novelty* and *value*, the key characteristics of creativity [5]. IGAs in contrast realize unexpectedness in their output through randomness, and value through selection based on their objective function. This is why we consider them *partners* in co-creative interaction.

In order for the IGA to work as creative partner, the algorithm must encode some of the human designer's knowledge of the design space. The success in making the IGA reach the necessary level of expertise depends on the designer's ability to encode the design space in a creativity-conducive manner. This succeeded in the present study, but we do not consider it universally achievable. Being a rather new addition to designers' toolboxes, IGAs will probably undergo a significant amount of experimentation in design communities before the best practices of representing design spaces will be discovered.

Our study has uncovered several additional areas to improve this creative partnership, particularly related to avoiding fixation modes, supporting design co-evolution, and inspiring designers e.g. through visualization. We believe that this can foster the successful adaptation of IGAs in co-creative design.

Study Limitations

Our study only reports the experiences of a single designer and design case. We deem this method particularly useful for tool creators to explore a tool's use, and how it is experienced, in practice and to highlight areas for further study. However, to identify generalising conclusions, the present approach must be extended to multiple, diverse participants and cases.

In our study, the researcher was part of the experiment. While separating the designer-participant and the researcher would have alleviated the risk of bias, it would also have removed the researcher from the experience. In future studies, it would be sensible to mix designers who also act as researchers with independent participants to reduce bias while still offering some researcher introspection.

A further limitation is the low documentation of reflection in action, and how it is collected. Most notes and insights were retrospective reflections on the activities, even if done just shortly after the design session. A think-aloud method with a simultaneous screen-capture of the software could have led to different and a larger number of insights. However, such a method would need to deal with a large volume of data, given the project's length that may cover several weeks and involve incubation periods during which insights may also develop.

Furthermore, such data collection could also pose validity threats to the study at inopportune moments. For instance, as things get interesting and a certain flow state is achieved, note-taking may inhibit the flow [31].

To circumvent the problems listed above on note-taking granularity and the validity of introspections, we used a secondary round of *reflection on action* [37] while preparing this article as well as when framing the collected diary notes against design literature. Additional in-situ documentation methods, such as video-recording of the activities and subsequent analysis, would provide higher fidelity in the results. We intend to implement these improvements in future work, as discussed in the next section.

Conclusion and Future Work

We employed a researcher introspection through autoethnography study to provide insights into a designer's use of an interactive evolutionary algorithm in a real-world design task. Through this endeavor, we contribute methodology and practical insights to the emerging body of research on how AI impacts the experience, and perceived agency, of product design practitioners.

We have reflected our findings against theory from design research, and computational design. We found that the relative ease of applying interactive evolutionary algorithms to support design space articulation and exploration improved the designer's capabilities, and provided alternative paths in the design process. On the contrary, we also revealed how the use of such algorithms can negatively impact design practice, e.g. by fostering bounded ideation, as a first step towards avoiding these pitfalls by informing appropriate use or changes to the software.

In future work, we want to provide further, generalising and actionable insights on how AI algorithms can augment and complement human creativity in design practice. To this end, we aim to conduct a larger longitudinal, protocol study which overcomes the shortcomings of the present study through, amongst others, expanded in-action reflection by multiple designers.

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