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From Inspired Modeling to Creative Modeling

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Creativity isn't a talent, it's a way of operating.
– John Cleese

1 Introduction

An intriguing and reoccurring question in many branches of computer science is whether machines can be *creative*, like humans. Machines can compute much faster than humans, thus in the realm of content creation, they can generate many models much faster than we can. However, can a well-designed machine reach the point where a bar is crossed so that the produced contents exhibit true creativity?

This is one of the central questions that motivates the study of *computational creativity*. The "computational creativity" wiki [42] clearly articulates a set of three-tiered goals of this emerging field. The ultimate goal is to construct a computer or program capable of human-level creativity. Certainly, such a goal may prove to be too elusive. A less ambitious goal is to have a better understanding of human creativity and to formulate an algorithmic perspective of creative behaviors in humans. Further down the list, perhaps the "lowest hanging fruit" of the pursuit, is to design programs that can enhance human creativity without necessarily being creative themselves.

In this exploratory paper, we examine the problem from a computer graphics, and more specifically, geometric modeling, perspective. We focus our discussions on the weaker but still intriguing question: "Can machines assist or *inspire* humans in a creative endeavor for the generation of geometric forms?" Similar questions can also be asked for other creative tasks, e.g., to compose arts, music, or narratives, and they have been [26]. In the field of computer graphics, while the question is quite new, it is not un-touched. However, we are not aware of previous efforts to explore answers to the question in breadth or depth.

Fully answering the above question is highly challenging since it would require us to first understand what creativity, as well as inspired modeling, is exactly. In the following, we refrain from defining and qualifying these terms in a formal way; instead, we leave them to

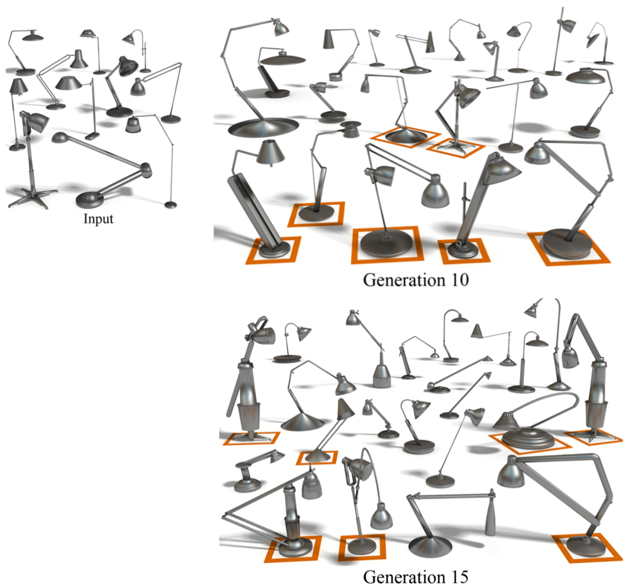

Fig. 1 An evolution-based, example-driven creative modeling tool [45] allows generations of 3D models to be created. The highlighted models exhibit diversity from the input set.

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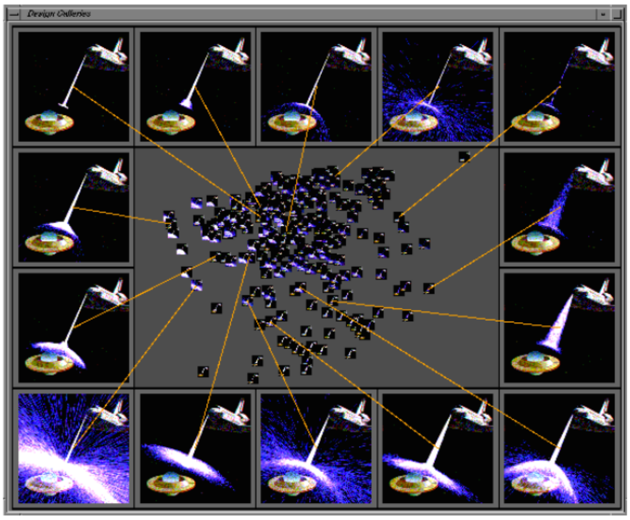

Fig. 2 A design gallery for particle systems (figure taken from [25] with permission). Design alternatives surround a depiction of the design space being explored.

be understood in their intuitive meaning. Our coverage and discussion in this paper will expand from inspired modeling tools to modeling paradigms that could possibly lead to creative shapes or designs. Generally speaking, inspiring modeling tools or methods are expected to help a user or modeler to come up with creative ideas for modeling shapes or other visual products.

We start by discussing *explorative modeling* which necessarily involves human user interactions to explore certain design spaces. A primary example is design galleries [25], where the user explores a parametric design space with mappings from the design space to concrete design alternatives for the user to view. In this context, modeling inspirations are drawn from visual examination of the design alternatives with the machine facilitating the user's exploration process (see Fig. 2).

In a modeling paradigm which can be intuitively referred to as "*more of the same*" [1], the user starts the modeling by offering a set of examples, often objects belonging to the same category, e.g., cars, chairs, leaves, etc. Then, inspired by the provided examples, the machine generates more instances of the same type (e.g., see Fig. 3) guided by some rules extracted or learned from the examples. An alternative name for such a modeling paradigm is *example-driven synthesis*. A closely related modeling technique is *suggestive modeling* [8], where the system analyzes a given set of models offline and learn their structure and/or semantics. Then during the online, interactive modeling phase, a modeler is suggested with parts or elements to compose and alter products arising from these suggestions.

To turn inspired modeling to creative modeling, the questions of what *is* creativity and how creativity arises are unavoidable. There have been numerous studies and published works on creativity, mainly from the fields of cognitive sciences and artificial intellegence, e.g., see Boden [6], Sternberg [37], Jennings [22], as well as Colton and Wiggins [9], as starting points to explore this vast and complex topic. A common view is that creativity is innately linked with *unpredictability* or the elements of *surprise* [5]. Specific to computer graphics, creative inspirations to modelers are often in the form of new models that were not envisioned and contain certain elements of surprise or unexpectedness.

Encouragingly, unpredictability is something that a machine or program can model, e.g., by simulating a stochastic process. At the same time however, such a process must be sufficiently well controlled so that the presented models remain sensible and follow the rationale of the modeling task. Realizing this approach is challenging since it requires an understanding and computational expression of that rationale. Furthermore, the two goals of unpredictability and controllability conflict each other and a balance must be achieved.

We discuss two modeling paradigms which provide the element of surprise in different ways. The more classical approach utilizes *evolutionary algorithms* which are intrinsically stochastic to mimic the evoluation process in nature. Combined with exploratory modeling, the stochasticity may lead the users to new and unexpected modeling results [45]; see Fig. 1. The final option presented involves *co-creation* [41], where multiple parties collaborate to create contents. Surprises may arise when the parties *independently* perform targeted tasks, leading to what is referred to as "*co-creativity*"[10,18]. In both cases, human interaction with the modeling system is typically required.

Before going into more details about the various modeling paradigms outlined above, we emphasize that our paper is not a survey and we do not thoroughly cover all, or even most, relevant existing works. Rather, we intend to write a position paper on the subject matter, providing a first in-depth look at possible approaches to inspired and creative modeling.

2 Explorative modeling

A basic means to inspire the user is the well-known Design Galleries of Marks and many other colleagues [25]. A design gallery is simply a visual interface to assist the user in selecting parameters through a visual display of random solutions. The design gallery work avoids manual tweaking of parameters, and displays several random solutions, where some of them can possibly be unexpected and liked by the user [39]. Yet, a fair question is whether sheer random sampling can be considered

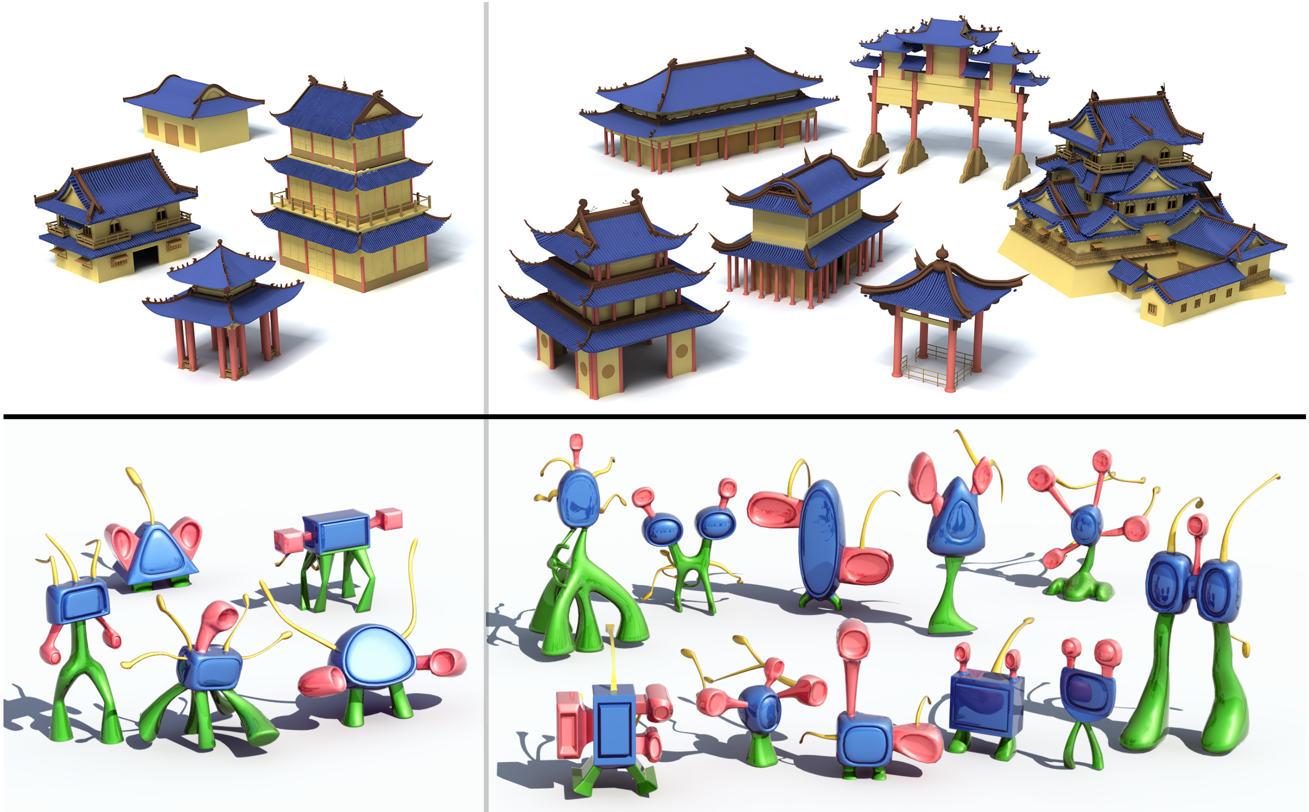

Fig. 3 "More of the same': two sets of example-driven modeling. The examples are shown on the left, and the generated instances are on the right. Courtesy of Jiacheng Ren.

creative or truly inspring. We argue that while a random result could be inspiring, we would like an inspiring tool to be smarter to offer more targeted inspirations and to allow the user a sufficient level of control.

The work of Shapira et al. [32] takes the design galleries to a creative means. Rather than being shown a static gallery of random parameters, the user navigates through a whole space of parameters, exploring a large number of results displayed to him in a gallery (Fig. 4). The exploration is open-ended, meaning that when the user starts his journey, he does not know where he is heading. During navigation, with the display of possible results, he may learn and move towards regions that he likes more. The navigation tool is inspiring since many of the results offered are ones that he probably did not envision. Inspired by the presented galleries, he narrows down towards regions that he likes more. The tool offers him inspiration and some degree of control of what is presented and offered. Clearly, developing such navigation tools to explore spaces of variations requires having a parameterization of the explored space.

Other means for interactively exploring a design space through galleries or collections of objects have been presented in [40, 24, 2, 16]. The gallaries should not necessarily present an entire object or a whole solution, but would suggest relevant object parts or partial solutions to the artist, to inspire him during an interactive modeling process [15, ?, 7]. These techniques analyze the current evolving model, and aim to suggest relevant parts using probablistic or other data-driven reasoning. While effective and inspiring, these techniques model the expected, in a probabilistic sense, rather than directly striving for the unexpected or the creative.

3 "More of the same"

Under the example-driven paradigm for inspired modeling, the process would start with a moderate number of examples, either designed or selected by the user. The tool then generates a gallery of new examples that follow the spirit of the input. Importantly, some of these novel synthesized new instances are unexpected, which the user did not envision, yet, they all make sense, and follow the inner logic of the input examples.

The notion of "more of the same" [1] refers to the following problem: given a set of examples, how to generate more of the same, in the positive sense, more instances that clearly appear to belong to the same class as the input set of examples. The work of Baxter and Anjy [3] generates more of same vector shapes. The

Fig. 4 A gallery of possible colorization of an input image. The artist can be inspired by the choices offered.

user draws few strokes to define few examples and the system can generate more in-betweens by interpolating corresponding strokes, creating more and more instances. Similarly, the work of Hun et al. [17] generates more of the same texture variations, with the geometries of the textured shapes remain intact.

The "more of the same" problem is more challenging than it may first appear. An effective solution must analyze the input set of examples, their shapes, textures, geometries, etc., and capture their essence to the point that they can be modified to generate more of the same that belong to the same class or category of data. This is a data *understanding* problem, first an understanding of the commonality and variation among the input examples, while the ultimate understanding is of the data *category* in question. This is a very hard problem in general, and all the above works dealt only with limited types of data. More importantly, the generated instances were not aimed to include unexpected results or be truly creative in any sense. Hence, the problem setting for "more of the same" only addresses one aspect of the example-driven paradigm for inspired modeling, it does not address the inspiration aspect.

4 Creativity by evolution

If one believes that nature is creative and evolution is nature's most fundamental and prominent "algorithm", then it should be easy to accept that evolutionary algorithms [**?**,12] have played the most dominant role in creative modeling so far. Evolutionary algorithms (EAs) are inspired by biological evolution in nature, which features *mutation* and *cross-over* of DNAs, as well as *selection*. The element of surprise or unpredictability, which is central to creative modeling, arises from the stochasticity embedded in the mutation, recombination (cross-over), and selection operators of an EA.

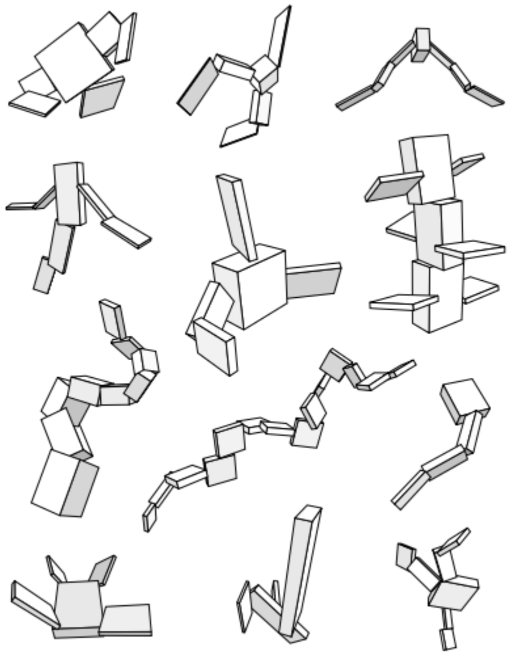

Fig. 5 Some virture creatures evolved for swimming by Karl Sims' algorithm (figure taken with permission from [35]).

To design an EA for creative modeling, one needs to properly encode the contents to be created and define appropriate mutation and cross-over operators to allow the contents to evolve and produce surprises. Controllability is defined by the selection process, where a *fitness* function determines whether a new creation is allowed to survive to further produce offsprings.

More than twenty years ago, the pioneering works of Karl Sims applied EAs to evolve textures [34] and virtue creatures made up of connected blocks [35], among other things. The virtue creatures were encoded as graphs and evolution operators were defined by certain graph editing and merging operations. The fitness function depends on the type of tasks at hand, e.g., for swimming, simulated creatures that can swim faster have a higher chance of survival. Amazing results were produced showing the creatures gradually "learned", as they evolve to walk, jump, and swim (see Fig. 5) better, or to grab food from competitors.

Many follow-up works have appeared since, e.g., the creature academy of Pilat and Jacob [28], object assemblies such as robots by Pollack et al. [29], and mechanical designs by Jakiela et al. [21]. The application domain of creative modeling via evolutionary design has spanned urban planning [36], architecture [14], visual arts [13], even music [30], among other things [4].

Most recently, the work by Xu et al. [45] reminds us the power of evolutionary or genetic algorithms for *creative* modeling. Their work combines EA-based stochastic object modeling and a design gallery [25] to allow human users to control the evolution. A distinguishing feature of their problem setup is that they evolve an *entire set*, rather than individual entities, simultaneously. As well, they focus on the *diversity* of the set, as a means to encourage creativity.

Specifically, starting with an initial population of 3D objects belonging to the same category, e.g., chairs, stochastic mutation (deformation) of object parts and cross-over between objects (exchanging one or more object parts based on a notion of fuzzy correspondence) drive the evolution and produce generations and generations of new objects; see Fig. 6.

During evolution, part of the evolving set is presented to the user as a shape gallery; see Fig. 7. User preferences define the fitness function for the evolution as he/she selects shapes from the gallery that are deemed to be *fit* (a chair needs to be "chair-like") and "liked" to breed the next generation. Over time, the shape population will mainly consist of fit individuals. However, for the creations to potentially inspire user creativity, the evolving set needs to be kept diverse. This is realized by explicitly allowing unfit objects, those accounting for only a small percentage of the evolving set, to survive and produce offsprings.

The idea of set evolution guided by the "fit *and* diverse" principle is biologically motivated. Nature has its own reason to keep the species diverse, and not only fit; it is more than just "survival of the fittest". Only maintaining fitness of a population over time tends to produce an *elite* population which can hardly survive a "virus" that attacks the common characteristics of the population. In the context of creative modeling, an elite population lacks diversity and creativity potential.

5 Creativitiy from co-creation

Co-creativity originates from co-creation, which has a generic definition from Wikipedia [41]: co-creation is

Fig. 6 The part crossover and mutation operators in [45] produce significant shape variations, even topology changes. The arrows show the evolution paths traced.

Fig. 8 Some results produced from an exquisite corpse game where a group of people draw a "person" cooperatively (courtesy of Ronit Reitshtein).

a management initiative, or form of economic strategy, that brings different parties together, in order to jointly produce a mutually valued outcome.

While multiple parties collaborate to create something, how could a creativity argument be made? Similarly, how does co-creation facilitate creative modeling for content creation in graphics? Both questions can be addressed, at least in part, if the element of surprise [6] can be introduced to the co-creation, while ensuring controllability of the modeling process.

A straightforward way to introduce surprises is for each creator to work indepdently from the others. If the creations were executed in a sequence, then one creator would not know what previous creators had produced, increasing the likelihood of unexpectedness in the current creation. Nevertheless, unexpectability does not equal total randomness. Each creator must be generally aware what the overall goal is and what role his/her creation plays in the full product. Furthermore, there must be more stringent control to ensure a sufficient level of coherence between the creations. In this case, while prior creations should be concealed, they should only be concealed partially, so that each creator sees a hint to constrain his/her own contribution.

The best example to illustrate the above mechanism is *exquisite corpse* [43], a method by which a collection of words or images is collectively assembled. The most representative instance of the latter is the well-known game of picture consequences, where a group of people cooperatively draw a person, or more generally, a human-like creature. Each group member knows which part of the person, e.g., the head or the torso, is to be drawn, and was not aware of the other parts that were drawn or to be draw. The only visual hint given is through a thin slice from the adjacent drawings to reveal their boundaries. With such a small hint, one can be quite imaginative about how to draw his/her own part; see Fig. 8 for a few examples.

Fig. 7 The evolving population (left) consists of a diverse background set (in gray) and a fit foreground set (in gold). A shape gallery presented to the user is shown on the right, which consists of shapes taken from the foreground set.

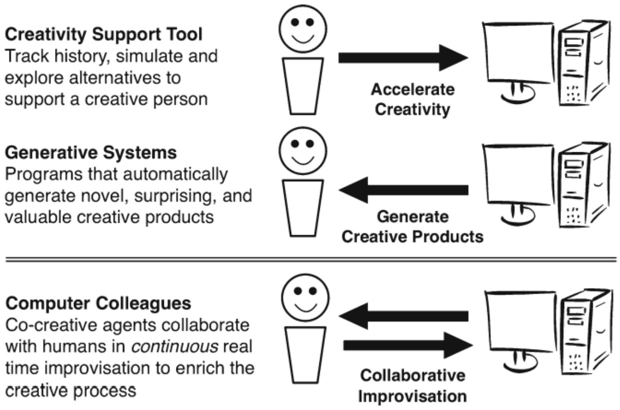

Fig. 9 Three possible approaches in the field of computational creativity (figure taken from [11] with permission).

In the realm of co-creation, we are most interested in *human-computer co-creation*, since it is intimately linked to the fundamental question posed at the beginning of this paper: can computers and humans collaborate to improve human creativity? The HCI community, in particular researchers specializing in computer-supported cooperative work, have developed tools to *support* creativity [33]. Differences between creativity-support tools and co-creation tools are highlighted in Fig. 9. Examples of the former include Picbreeder, a collaborative image evolution platform [31], and the work in computer graphics by Talton et al. [38] on exploratory modeling in collaborative design spaces. In both cases, the tools play support roles in offering design alternatives in an exploratory interface; the machines do not co-create with human users.

Some efforts on co-creativity-driven content creation have been geared towards the more artistic and open-ended tasks, e.g., in creating 2D abstract art work [11] and movement-based performances [20]. How to design and develop an exquisite-corpse-like tool for *realistic* yet creative 3D object design and modeling is certainly an interesting pursuit. A key difference in this pursuit from producing purely artistic expressions is the need to create usable or *functional* designs to possibly serve real-world applications. The challenges are two-fold. First, functionality-oriented 3D shape analysis and design is only making a start in the computer graphics community [19,23]. Second, a delicate balance has to be struck between controllability, based on functional as well as physical design criteria, and creativity arising from the co-creation paradigm.

6 Concluding remarks

As the field of geometric modeling is fast evolving [27] and expanding its boundaries, it is natural to ask the question whether machines can truly inspire and assist humans in a creative endeavor. On the one hand, the question is intriguing simply because creativity, like intelligence, is such a fundamental and characteritic human trait. At the same time, the modeling challenge seems to be taking center stage in computer graphics, driven by the increasing demand for big visual data and wide adoption of data-driven techniques [44]. Recent research on geometric modeling is shifting its focus beyond geometric validity and robustness to serve emerging applications in design and production. The new criteria that are key to design applications include aesthetics, functionality, and inevitably, creativity.

We hope our short paper can help drive the study of creative modeling forward in the field of computer graphics. Gaps between graphics and other fields such as computational creativity, AI, and HCI on the subject matter need to be narrowed. More artistically appealing problems should be encouraged in the field and attempted by graphics researchers. We should all believe that computer graphics is far beyond image synthesis. It is capable, and should be driven, to supplement humans at a much earlier stage in the synthesis pipeline, as early as creative design and conceptualization.

As a final remark, we woud like to point out that creativity is sometimes personal: different individuals exhibit and resonnate with different types of creativity thinking. As an example, to maximize creative outputs in the context of explorative modeling, the presented examples should ideally be personalized to adapt to the design taste of the individual artist. The tool that generates the examples may need to learn the preference of a specific individual. This requirement reflects yet another challenging aspect of operationalizing creativity.

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