Modern Evolution Strategies for Creativity: Fitting Concrete Images and Abstract Concepts

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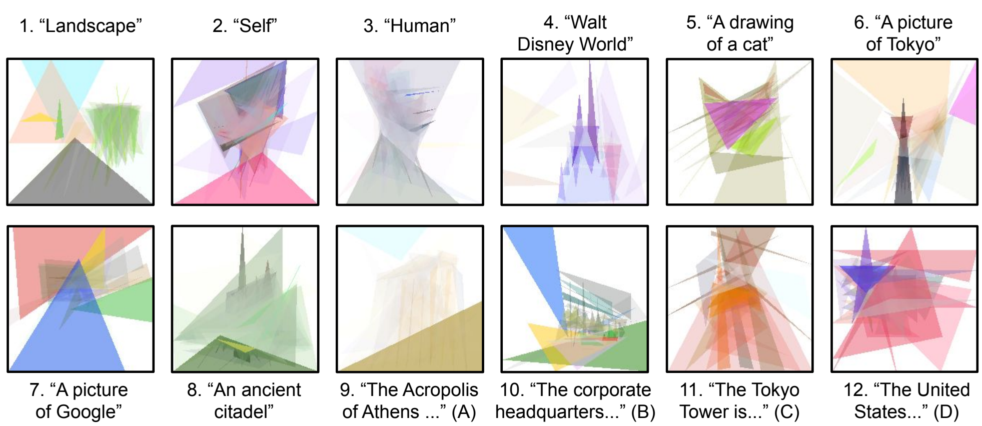
Abstract

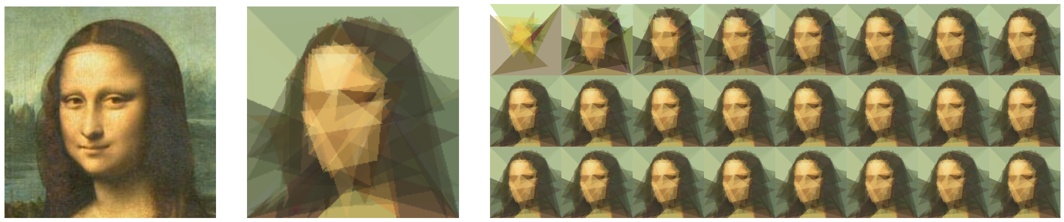
Evolutionary algorithms have been used in the digital art scene since the 1970s. A popular application of genetic algorithms is to optimize the procedural placement of vector graphic primitives to resemble a given painting. In recent years, deep learning-based approaches have also been proposed to generate procedural drawings, which can be optimized using gradient descent. In this work, we revisit the use of evolutionary algorithms for computational creativity. We find that modern evolution strategies (ES) algorithms, when tasked with the placement of shapes, offer large improvements in both quality and efficiency compared to traditional genetic algorithms, and even comparable to gradient-based methods. We demonstrate that ES is also well suited at optimizing the placement of shapes to fit the CLIP model, and can produce diverse, distinct geometric abstractions that are aligned with human interpretation of language. Videos and demo: https://es-clip.github.io/.

Staring from early 20th-century in the wider context of Modernism [29], a series of avant-garde art abandoned the depiction of objects from tradition rules of perspective and instead picking revolutionary, abstract point of views. Along this line were the Cubism art movement [41], where objects are analyzed by the artist, broken up, and reassembled in an abstract form consisting of geometric representations, and its successor, the geometric abstraction [8], which composed primitives that are either purely geometric and elementary. The impact is far-reaching: The use of simple geometry can be seen as one of styles found in the abstract expressionism [39] where artists expressed their subconscious or impulsive feelings. It also helped shaped the minimalist art [37] and architecture [42] movements, in which everything is stripped down to its essential quality to achieve simplicity [3].



A. “The Acropolis of Athens is an ancient citadel located on a rocky outcrop above the city of Athens and contains the remains of several ancient buildings including the Parthenon.”
B. “The corporate headquarters complex of Google located at 1600 Amphitheatre Parkway in Mountain View, California.The corporate headquarters complex of Google located at 1600 Amphitheatre Parkway in Mountain View, California.”
C. “The Tokyo Tower is a communications and observation tower in the Shiba-koen district of Minato Tokyo Japan.”
D. “The United States of America commonly known as the United States or America is a country primarily located in North America.”

Figure 1: Our proposed painting synthesization places transparent triangles using an Evolution Strategy (ES). Each concept represented as a text prompt is accompanied by its corresponding synthesized image. Here, the fitness is defined as the cosine distance between rendered canvas and text, both embedded by CLIP [40], and we optimize the position and the color of triangles using ES, which produces diverse and distinct geometric abstractions.



“Mona Lisa” Evolved Results Evolution Process

Figure 2: We use modern ES (PGPE with ClipUp), with 50 triangles and running evolution for $10,000$ steps to fit the target image “Mona Lisa”.

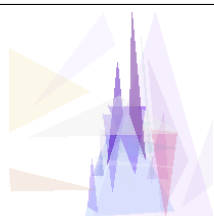
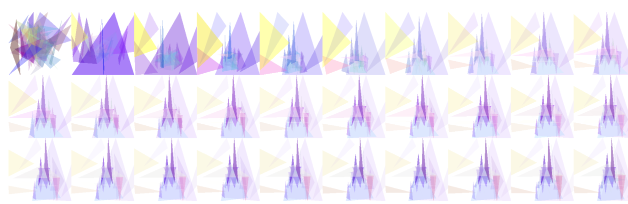
Prompt	**Evolved Results**	**Evolution Process**
“Self”		
“Walt Disney World”		

Figure 3: Our method fits the concept represented in text prompt, using 50 triangles and running evolution for $2,000$ steps.

The idea of minimalist art has also been explored in computer art with a root in mathematical art [35]. Schmidhuber [45] proposed low-complexity art, as a minimal art form that attempts to depict the essence of an object by making use of ideas from algorithmic complexity [28]. Similarly, algorithmic art [52], and in a broad sense genetic algorithm, proposed to generate arts using the algorithm and/or rules designed by the artist. As one example, a basic genetic algorithm using evolution has been proposed [2, 25] to represent a target image using semi-transparent, overlapping triangles and has gained popularity over the years with the creative coding community, resulting in a number of sophisticated extensions [6, 11, 47]. Interestingly, since these methods are iterative, they also echo Process art [49] which emphasizes the process of making. More discussion regarding the related works can be found in Appendix A.

With the recent resurgence of interest in evolution strategies (ES) in the machine learning community [17, 43], in this work, we revisit the use of ES for creativity applications as an alternative to gradient-based methods (details in Appendix B). For the image-approximation with shapes task, illustrated in Figure 2, we find that modern ES algorithms offer large improvements in both quality and efficiency when compared to traditional genetic algorithms, and as we will also demonstrate, even comparable to state-of-the-art differentiable rendering methods [30] (details in Appendix C). We show that ES is also well suited at optimizing the placement of shapes to fit the CLIP [40] model targeting concepts in the form of text, as illustrated in Figure 3, and can produce diverse, distinct geometric abstractions that are aligned with human interpretation of language (details in Appendix D). In both tasks, we study the effect of a wide range of target images and concepts to choose from, the number of triangles as an computational and artistic budget, and the behavior of other method compared to differentiable method optimized with gradient descent. We also explore differences from multiple runs which may be helpful for artists in the loop. Interestingly, the results produced by our method resemble Abstract expressionism [39] and Minimalist art [37, 42], and opens the door for the further studying into computer generated art (discussion in Appendix E). We provide a reference code implementation of our approach so that it can be a useful tool in the computational artist’s toolbox.

Ethical Implications. This project itself does not pose ethical concerns *per se*. Using the framework provided in this project, a user could let the method produce art works fitting on the provided target image or text prompt, both under the sole control of the user. However since we use CLIP to interpret the meaning of text provided by the user, the intrinsic bias in CLIP itself, as identified by its very developers [1], may impact the generated art. Although such impact is hard to anticipate, partially due to the abstract and indirect nature of the generated art, we still believe it is worthy of consideration.

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