HUMAN TECHNOLOGY

ISSN: 1795-6889

https://ht.csr-pub.eu

Volume 17(2), October 2021, 118–125

From the Editors

CAN ARTIFICIAL INTELLIGENCE BECOME AN ARTIST?

Adam Wojciechowski
Lodz University of Technology,
Łódź, Poland

Kristiina Korjonen-Kuusipuro
University of Jyväskylä,
Jyväskylä, Finland

Abstract: *Modern visionaries claim supernatural abilities to artificial intelligence. Artificial intelligence has been attributed artistic skills, including those related to the visual arts. Is artificial intelligence a creator, or maybe it is the creators of algorithms who have to be creative, whose imagination is then transformed into works-of-art by a computer program? How are the rules that create aesthetic compositions created? Can we measure aesthetics? This article addresses the above questions by illustrating them with examples of visual arts created by intelligent algorithms.*

Keywords: *artificial intelligence, computational creativity, visual art.*

DOI: https://doi.org/10.14254/1795-6889.2021.17-2.2

INTRODUCTION

Let us consider whether a work of art made by a human and a computer are comparable? Do they have the same value? If one says no, this is direct evidence that the piece itself and the creation process affect the work's artistic value. Since nothing arises ex nihilo, it is essential to remember that most creative ideas originate from a historical-cultural background or some experience. If we have a creative idea ourselves, we very often attribute it to our ingenious invention or inspiration, thus rejecting a scientific explanation of the process by which the idea arose. Obviously, new ideas are not entirely new. We can say that our creative capabilities grow with experience and knowledge. The deeper it is, the greater the likelihood of discovering an original relationship underlying a new creative idea. Analogical to the laws of physics and theorems, musical pieces can be defined by a finite set of basic elements, suggesting creativity is an original way of solving problems based on memory records, looking for analogies, learning and inference. In this context, the process can be replicated by computers if both components and creation procedures are provided. It should be remembered that we have progressively improved artificial intelligence techniques that allow us to replicate such activities with increasing perfection. However, it is worth considering how Artificial Intelligence (AI) models the process of creativity, what components it uses, and how it describes the process itself.

Relations between computers and creativity are constantly being redefined with the rapid development of technologies. Artificial Intelligence has an especially significant influence on the creative process. Computers are no longer just a tool helping human creators but have become independent creative entities. In consequence, Computer Creativity has emerged as a new subfield of Artificial Intelligence. The mechanisms of computer creativity are still evolving, but logical systematics can be determined in it. At the same time, the question arises: Is computer creativity an attempt to imitate specific artistic patterns or exemplify the implicit rules that make up creative compositions? How to train Artificial Intelligence to exhibit behaviour that would be deemed creative in humans? What are the main challenges for computer creativity today?

Even though creative programs have proved their application in many fascinating areas, (like poetry (Lamb et al., 2017), storytelling (Gervás, 2009), humour (Ritchie, 2009)), this elaboration concentrates on visual art. The reason for discussing this artistic field lies in selected domain activity, and, by far, it is the one where the obtained results are the most impressive. The elaboration aims to understand the more in-depth methods involved in the "intelligent digital revolution of visual art".

COMPUTATIONAL CREATIVITY OF VISUAL ARTS

Artificial intelligence (AI) has moved on from an academic research topic to a global scientific and business incentive in recent decades. AI is not an exception, as many rapidly developing technologies are profoundly changing the prevailing paradigms in creative domains, attempting to fulfil the selected requirements of creative industries (Amato et al., 2019). AI has evolved from explicitly defined mathematical formulas (symbolic or logic-based) into implicit methods able to identify complex structures and patterns from datasets describing our environment and exploit them to make creative decisions or predictions. It relies on statistical learning from data and generalizing to unseen data.

It is important to note that the generation of aesthetic patterns dates to a period well before the recent rise of deep neural networks. Historically explored methods encompass Perlin noise-based concepts (Perlin, 2002) and L-systems' inspired biological patterns (Lindenmayer, 1974) to many others, (formalized stochastic or grammar-related routines). An inspiring complementarily studied methodology to generate plausible images and visual concepts are fractals (Barnsley et al., 1988). This practical, recently more widely used methodology for pattern generation is derived from mathematics. It uses algorithms for finding the roots of polynomials or algorithms in solving nonlinear equations. The field has even earned the name polynomialography. Its creator is considered to be Bahman Kalantari (Kalantari, 2005), who proposed methods for visualizing the zero places of complex polynomials in the form of fractal and non-fractal images, using the mathematical properties of the convergence of a sequence of function iterations. Picard, Mann, Ishikawa, Khan, Suantai, Karakaya and many other iterations are used among the popular functions for iterating approximate roots of a polynomial. Analogously, the formulas obtained from discrete dynamical systems theory are visually interesting. Gdawiec (2017), using various transformation functions to visualize the orbits of dynamical systems, has created a number of aesthetic patterns.

Figure 1. Aesthetic patterns obtained with polynominography (Gdawiec, 2017).

Further development of computer creativity, supported by deep neural networks, constituted a taxonomy of creativity. According to Boden (2004) there are three main types of creativity: combinational, exploratory and transformational.

Combinational creativity involves the deliberate or unconscious making of an unfamiliar combination of familiar ideas. Although this is technically one of the easiest methods (resulting in semantically abstract compositions), problems arise when evaluating the output - which should be valuable, have artistic value, and be human-relevant. Pure combinational rules seem to be insufficient to go beyond certain creativity limits.

Exploratory creativity is a type of creation that is structured by a conceptual space, specific style, genre or a scientific theory. In other words, the process of creation undergoes particular formation according to particular rules. Adopting a specific style, genre, or theory yields new and valuable results within determined rules. This approach can enable someone to see possibilities not perceived before. Machine learning plays a particularly important role in this field of creativity. The artificial intelligence methods accessing big sets of data learn from themselves and mimic previously processed patterns. AARON drawing system (Cohen, 1982) has become an example of this type of creativity. AARON is a robotic system, developed over many years by the artist and programmer Harold Cohen, which can pick up a paintbrush with its robotic arm and paint on canvas on its own. AARON draws human postures and plants, following previously learnt rules. Aaron's knowledge is acquired cumulatively. For example, when Aaron learns the concept of a plant, it can use it whenever it needs it, controlling principles of branching, aspects of thickness depending on size or the thickness of limbs.

One of Boden's remarkable sayings that "computers cannot do anything creative because they can only do what the program tells them to do is misleading since computers can do what its programs enable them to do" underlines the main bottleneck of computational creativity (Boden, 2009). In this context, it is essential to note that there are always algorithms whose creative effectiveness is at work in the background of programs.

Figure 2. *Two Friends with Potted Plant*, 1991. Oil on canvas by AARON, 60x84 inches. Photo: Becky Cohen. (source: *THE FURTHER EXPLOITS OF AARON, PAINTER,* Harold Cohen, 1994).

More recently, the potential of deep artificial networks has proved its usability in visual creativity acquired from a set of hand-made sketches. Ha et al. (2017) have proposed a Recurrent Neural Network to represent and reconstruct sketch drawings. Specifically, the authors managed to encode a vast set of hand-made sketches in the latent space of Sequence-to-Sequence Variational Autoencoder and decode them with autoregressive RNN. A crucial role in the sketch reconstruction process is played by the Gaussian Mixture Model, which encoded the distribution of ground truth data and helped semantically reconstruct the sketches.

Transformational creativity refers to the transformation of structured conceptual space. It is claimed to be the highest form of creativity, as it can generate new structures that could not have been observed before (Boden, 1998). While exploring unique aspects or new dimensions requires relatively small changes, transforming a more fundamental dimension or rule would result in possibly different and new structures within that space. Transformational creativity refers to radical changes. Thus, this high-level form of creativity is relatively difficult to implement in computer systems. Transformational creativity is difficult for computers to model as human associative memory and human values are difficult to express in computer forms. The result may not be interesting or valuable in human terms.

A well-grounded example of transformational creativity is DeepDream (Mordvitsev, 2015). It uses a Convolutional Neural Network (CNN) to find and enhance patterns in images via algorithmic pareidolia. The input images were deliberately over-processed through the convolutional pipeline, producing hallucinogenic visual art concepts. Initially, the DeepDream program was designed to understand how convolutional networks work, but its inherent ability to amplify certain features transformed it into an artistic tool. Sequential transformation of an image at different levels of abstraction amplifies elements seen by the network but not obvious in the original image.

Figure 3. Google DeepDream images (source: quora.com).

A resulting breakthrough in the visual arts is observed due to work on image style transfer using convolutional neural networks (Gatys et al., 2016). This work has inspired many new applications (i.e. Prisma[1], Artisto[2], Algorithmia[3]) of AI techniques for transferring styles between arbitrary images.

An interesting direction for transformative creativity is stimulated by the recently emerging Generative Adversarial Network (GAN) architectures (Goodfellow et al., 2014). The GAN network generates uniform distribution samples, and exploits discriminators, deciding whether they suitable for the real or generated image. Initially employed as a generator of images from a specific class, nowadays, they are used for many other applications. Notably, Elgammal et al. (2017) exploited GAN architecture to generate pastiches of selected images by introducing another style to the image. The solution's functionality is limited to style application but can also permute or combine image components to produce new pieces of art.

Besides pure image generation, intelligent editing can also be treated as a method for visual art creation. At the core of effective editing lies intelligent transformations (Gharbi et al., 2017) or retouching (Yan et al., 2014). However, algorithms based on artificial intelligence in transformations or retouching have to strongly rely on semantic analysis of the content and many image transformation examples. Efficient separation of content and style information guarantee higher reliability of the algorithm output. Artificial intelligence focusing on image inpainting is able to reconstruct damaged or missing parts of an image so that the modifications cannot be perceived. Based on a deep convolutional GAN network, such a method was proposed by (Yeh et al., 2016) to replace missing parts of an image with meaningful content. A missing eye, for instance, can be generated and placed in the correct position. While the algorithms are perfectly acceptable at completing or retouching objects of known and typical appearance, such as the human face, perfection in this area is strongly desired and requires further development to generate generic scenes effectively.

[1] https://prisma-ai.com/
[2] https://artisto.my.com/
[3] https://demos.algorithmia.com/deep-style/

CHALLENGES

Despite the many spectacular successes in computer creation with artificial intelligence, some art recipients point out a number of shortcomings. While the generation of art images, sometimes abstract, seems possible and aesthetically interesting, the generation of photorealistic images using AI is still challenging. Just a between image style transfer seems to be relatively advanced and available as a technique for artists. Due to the infinite number of patterns and rules describing referential environments, photorealistic computer creativity has become an unachieved goal for generative art.

Some creators expect to be able to create visual art based on a semantic description. However, generating graphics from a description presents another challenge. Underpinning the solution to this problem is semantic analysis and transcription between many different forms of data description. While there are encouraging successes in individual domains (phrase analysis, ontologies, or dictionary-based description generation), a valuable and comprehensive solution in computer visual art with the potential for another breakthrough in computer creativity is still out of reach.

Although automatic recognition of image content is emerging (mainly due to the development of algorithms for semantic segmentation and classification of an increasing number of object classes), this task, in general, is still quite challenging. Techniques of automated image content analysis also influence possible creativity schemes. The effectiveness of component recomposition or hierarchical decomposition of inherent structures, describing the analyzed environment, defines further challenges and opportunities in developing artificial intelligence for the visual arts. Efficient retrieval of graph-based image structural decomposition will result in algorithms that build more reliable artistic creations.

The final issue, one which is, on the one hand, challenging but also an essential part of the creation process, is the evaluation of computer creativity. By evaluating the design, we can improve the algorithms and methods to address increasingly complex tasks. Assessment of creative quality is rarely reported in the literature, mainly due to their subjective nature. One group of authors postulating the determinants of creativity was Maher et al. (2012). These authors, supporting other researchers, claim that we can talk about the creativity of work when it has the characteristics of novelty, is valuable and arouses surprise. A more formal approach to measuring the level of creativity was presented by Fuge et al. (2013). By introducing submodular functions, the authors introduce measures of creativity in computer-based design synthesis systems with reference to models (if definable) or based on human judgement-based metrics.

However, current considerations in the literature indicate that the well-known Turing test, in which subjects are asked to judge whether a human or a computer has created selected designs, is perhaps the most widely used referential form of assessing the provenance of visual art and its quality. In contrast, other non-referential, objective measures have yet to be legitimized.

Reactions to visual art made by AI have varied from competitor to collaborator, from positive to more sceptical (Zeilinger, 2021). Both this and the above-mentioned need to know whether the artist is human or machine, is probably due to the idea that creativity is still considered something very human. This is also connected to the relational and diverse nature of the material world. We need to rethink our understanding of how the social and the physical have material effects in an ever-changing world that is in a continuous state of 'coming into being' (Barad, 2007; Haraway, 2004). When it comes to AI and visual arts, we need to rethink agency as being something more than just human subjectivities and intentionalities. Feminist scholar Karen Barad (2007) sees agency as intra-action, an entanglement of human and non-human forces. She stresses the way agency involves the refiguring of material-discursive possibilities and accountability of bodily production. Materialities, including digital materialities, take various forms, and because of the blurred nature of human-material relations, materiality is 'an ongoing discursive construct and material formation that is co-constituted about its material environment' (Höppner & Urban, 2018). Furthermore, this is also connected to our ideas of knowing. A shift from *knowing about* towards *knowing with* the world has emerged, which stresses that the relations we have and produce with our surroundings are not only modes of being but simultaneously of knowing (Barad, 2007; Rautio, 2014).

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Authors' Note

All correspondence should be addressed to
Adam Wojciechowski
Lodz University of Technology,
Łódź, Poland
adam.wojciechowski@p.lodz.pl
ORCID 0000-0003-3786-7225

Human Technology
ISSN 1795-6889
https://ht.csr-pub.eu