Evolving Art: Past, Present and Future

Penousal Machado[a]
CISUC, Department of Informatics Engineering, University of Coimbra, 3030 Coimbra, Portugal

Keywords: Evolutionary Computation, Evolutionary Art, Machine Learning, Computational Creativity.

Abstract: Evolutionary Computation techniques have been applied in recent years to several fields in the Arts. This talk overviews how they have been used to create different types of artefacts, along with how past developments relate to current approaches, trends and challenges. The focus is one of the main challenge in the field: fitness assignment. We analyse this challenge from the perspective of the interplay between the evolutionary system and the user, and discuss how Machine Learning, Evolutionary Computation and Human-Computer Interaction techniques can be combined to create Computer-Aided Creativity systems that allow users to express their artistic and aesthetic intentions.

1 INTRODUCTION

At the very first Artificial Life conference, held in Los Alamos in September 1987, Richard Dawkins presented Biomorphs, a system that allowed users to act as selective breeders of artificial creatures, guiding the evolution of their morphology, and thus demonstrating the power of evolution (Dawkins, 1987).

Not long after, Karl Sims demonstrated how user-guided evolution could be used to evolve abstract images, 3D shapes, namely artificial plants, and animations (Sims, 1991). William Latham and Peter Todd were also instrumental for the popularisation of Evolutionary Art by commercialising Evolutionary Art software (Todd and Latham, 1992).

Eventually, the early work of these, and other, pioneers led to the birth of Evolutionary Art as an area of research. The core goal of Evolutionary Art as a discipline can be defined as the development and application of evolutionary techniques for the generation of computer graphics. An analysis of the research done throughout the years allows the identification of several core challenges, opportunities, and open issues (see, e.g., McCormack (2007)). These tend to follow on two main categories: representation and evaluation.

In what concerns representation, it is important to differentiate three main types of approaches: declarative, parametric, and procedural (Xiao et al., 2019). In declarative approaches, the genotype encodes or describes (i.e. declares) the characteristics of the individual, i.e. the phenotype. An example of a declarative approach is the work by Baker (1993) who uses a Genetic Algorithm where each genotype encodes the coordinates of a set of lines to evolve line drawings. In parametric approaches, one evolves a set of parameters that influences the behaviour of a generative art system. Notable examples of this approach include the works of Draves (2007), where the genotype is a set of parameters of a fractal formula, and the work of Machado et al. (2016), where the genotype is a set of parameters that defines the behaviour of artificial ants. Finally, in procedural approaches, the genotype is a program or procedure that, when executed, generates the phenotype. The most famous example of such approach is the seminal work of Sims (1991) who uses Genetic Programming to evolve symbolic expressions that, once interpreted, result in colour images. This expression-based procedural approach has become the most popular for the evolution of images. As such, its theoretical and practical expressive power becomes of importance. While Machado and Cardoso (2002) demonstrate that this sort of procedural representation has the theoretical power to generate any image, they also point out that in practice the type of image these systems tend to generate is intimately linked with the primitives they use. As such, representation has a major impact on the nature and quality of the results, making it a hot topic of research since the inception of Evolutionary Art.

We introduce several alternative representation schemes and analyse the impact of representation in the outcome of the systems. In particular, we explore the use of a multi-chromosome Genetic Programming

[a] https://orcid.org/0000-0002-6308-6484

Machado, P.
Evolving Art: Past, Present and Future.
DOI: 10.5220/0008345700050008
In *Proceedings of the 11th International Conference on Agents and Artificial Intelligence (ICAART 2019)*, pages 5-8
ISBN: 978-989-758-350-6

approach to evolve assemblages of objects (Graça and Machado, 2015), graphs to evolve non-deterministic context-free design grammars able to create a family of images from a single genotype (Machado et al., 2015a), behavioural parameters to evolve Non-Photorealistic Renderings (Machado et al., 2014), and digital stencil templates (Martins et al., 2018) to evolve typefaces.

If Evolutionary Art lives up to its name, then fitness assignment becomes the biggest challenge, since evolving art requires assessing the artistic quality of candidate images, which, arguably, requires Artificial General Intelligence. Early efforts in the field circumvented this difficulty by resorting to user-guided evolution, i.e. the user selected the images to breed, guiding the evolutionary process. While this approach has many merits, allowing the generation of remarkable images that match the preferences of the user, it also has severe limitations. By definition, this type of user-guided systems lacks autonomy and ability to judge their production, which is a major limitation from an Artificial Intelligence perspective. Additionally, from a practical perspective, these systems require constant intervention by the user, which becomes extremely time-consuming, leads to user fatigue and jeopardises the quality of the results.

Over the years, researchers made several contributions to the automation of fitness assignment. These can be classified in two major categories: the use of hardwired fitness functions and the use of Machine Learning techniques.

In the first case, the authors create a static function or program that assesses the quality of the evolved images. However, it has been proven extremely hard to formally define aesthetic criteria and, in most cases, it is trivial to demonstrate by counterexamples that the conditions considered by the authors are neither sufficient nor necessary to capture a general notion of aesthetics. Notwithstanding, several examples exist that indicate that some aesthetical principles can be partially formalised, explored and exploited, allowing the autonomous evolution of images. Among such research efforts we highlight the works of Machado and Cardoso (2002), who use complexity estimates to assign fitness; Greenfield (2003), who proposes a multi-objective optimisation approach to evolve images that satisfy several criteria; Ross et al. (2006), who promotes the evolution of images that show a "natura" distribution of colour gradients; Romero et al. (2012), demonstrate how complexity measure can be used in aesthetic appreciation tasks, later showing how they relate to humans perception of complexity (Machado et al., 2015b); and Reed (2013), who revisit Birkhoffs work, using aesthetic measures to evolve vase designs.

In what concerns the use of Machine Learning for fitness assignment purposes, the seminal work of Baluja et al. (1994) is the first effort in the field of Evolutionary Art. Interestingly, they propose the use of a Deep Neural Network to learn user preferences, and although their results do not live to their own expectations, this work paves the way for future research in this area. Romero et al. (2003) realise that learning user preferences is a demanding task and suggest combining a general purpose Evolutionary Art system with a Machine Learning classifier, trained to detect human faces. Roughly ten years later, Machado et al. (2012) implement this idea, showing that a conventional expression-based Evolutionary Art system guided by Machine Learning classifiers is able to evolve recognisable faces, flowers, leaves, lips, etc. In later works, they combine several classifiers to evolve ambiguous images, i.e. images that induce multistable perception, a phenomenon that occurs when the brain (or the computer) is confronted with visual stimulus that can be interpreted in multiple ways (Machado et al., 2015c). Furthermore, by changing the representation, they are able to evolve typefaces (Martins et al., 2018), photorealistic faces (Correia et al., 2016), as well as other types of imagery (Assunção et al., 2015), showing the impact of representation on the outcomes of the evolutionary process.

This type of works highlight the power of Machine Learning, but also its current limitations. As Baluja et al. (1994) already indicated, the evolutionary engine tends to find ways of exploiting the limitations of the Neural Networks and this way fool them. For instance, when trying to evolve faces, the evolutionary engine routinely finds and converges to images that, albeit detected as faces by the Machine Learning classifier, do not resemble faces to the human eye. The use of false positives generated throughout the evolutionary runs to enrich training datasets has been explored by Correia (2018), who shows that significant improvements of performance can be obtained.

In a different line of research, Machado et al. (2007) present an adversarial system that promotes the competition between a Neural Network discriminator and an Evolutionary Computation generator. This approach, which precedes Generative Adversarial Networks (Goodfellow et al., 2014), results in a continuous pursuit of novelty, style change and reinvention.

Although the automation of fitness assignment poses many relevant scientific challenges and questions, full automation has a cost: users are no longer able to express themselves through such systems. This realisation led us to propose an approach, meta-level interactive evolution, that overcomes these limitations. The core idea is to allow users to become designers of the fitness function, by allowing them to specify their preferences and goals through the use of a responsive user interface, which implicitly defines fitness. This approach frees users from the need of evaluating thousands of images, as is the case of user-guided evolution, while still engaging the users, allowing them to influence the result of the system and, above all, giving them a sense of authorship. Following this line of research, Photogrowth (Machado et al., 2016), a system that relies on the simulation of artificial ant species to produce Non-Photorealistic Renderings, allows the user to design fitness functions by specifying features pertaining the desired behaviour of the ants, as well as features related with the output image.

A final word goes to recent advancements in the field of Machine Learning. Considering the success of Generative Adversarial Networks and Style Transfer approaches, which set new expectations for the application of Artificial Intelligence to artistic domains, we analyse their strengths and limitations, identifying opportunities for research.

REFERENCES

Assunção, F., Correia, J., Martins, P., and Machado, P. (2015). Evolving families of shapes. In Yang, Q. and Wooldridge, M., editors, *Proceedings of the Twenty-Fourth International Joint Conference on Artificial Intelligence, IJCAI 2015, Buenos Aires, Argentina, July 25-31, 2015*, pages 4134–4135. AAAI Press.

Baker, E. (1993). Evolving line drawings. Technical Report TR-21-93, Harvard University Center for Research in Computing Technology.

Baluja, S., Pomerlau, D., and Todd, J. (1994). Towards automated artificial evolution for computer-generated images. *Connection Science*, 6(2):325–354.

Correia, J., Martins, T., Martins, P., and Machado, P. (2016). X-faces: The exploit is out there. In Pachet, F., Cardoso, A., Corruble, V., and Ghedini, F., editors, *Proceedings of the Seventh International Conference on Computational Creativity (ICCC 2016)*, pages 164–182. Sony CSL Paris, France.

Correia, J. a. (2018). *Evolutionary Computation for Classifier Assessment and Improvement*. PhD thesis, University of Coimbra.

Dawkins, R. (1987). *The blind watchmaker: why the evidence of evolution reveals a universe without design*. W.W. Norton and Company, Inc., New York.

Draves, S. (2007). Evolution and collective intelligence of the electric sheep. In Romero, J. and Machado, P., editors, *The Art of Artificial Evolution: A Handbook on Evolutionary Art and Music*, pages 63–78. Springer Berlin Heidelberg.

Goodfellow, I., Pouget-Abadie, J., Mirza, M., Xu, B., Warde-Farley, D., Ozair, S., Courville, A., and Bengio, Y. (2014). Generative adversarial nets. In Ghahramani, Z., Welling, M., Cortes, C., Lawrence, N. D., and Weinberger, K. Q., editors, *Advances in Neural Information Processing Systems 27*, pages 2672–2680. Curran Associates, Inc.

Graça, F. and Machado, P. (2015). Evolving assemblages. *IJART*, 8(2):167–184.

Greenfield, G. R. (2003). Evolving aesthetic images using multiobjective optimization. In Sarker, R., Reynolds, R., Abbass, H., Tan, K. C., McKay, B., Essam, D., and Gedeon, T., editors, *Proceedings of the 2003 Congress on Evolutionary Computation CEC2003*, pages 1903–1909, Canberra. IEEE Press.

Machado, P. and Cardoso, A. (2002). All the truth about NEvAr. *Applied Intelligence, Special Issue on Creative Systems*, 16(2):101–119.

Machado, P., Correia, J., and Assunção, F. (2015a). Graph-based evolutionary art. In Gandomi, A. H., Alavi, A. H., and Ryan, C., editors, *Handbook of Genetic Programming Applications*, pages 3–36. Springer International Publishing, Cham.

Machado, P., Correia, J., and Romero, J. (2012). Expression-based evolution of faces. In *Evolutionary and Biologically Inspired Music, Sound, Art and Design - First International Conference, EvoMUSART 2012, Málaga, Spain, April 11-13, 2012. Proceedings*, volume 7247 of *Lecture Notes in Computer Science*, pages 187–198. Springer.

Machado, P., Martins, T., Amaro, H., and Abreu, P. H. (2014). An interface for fitness function design. In Romero, J., McDermott, J., and Correia, J., editors, *Evolutionary and Biologically Inspired Music, Sound, Art and Design - Third International Conference, EvoMUSART 2014, Granada, Spain, April 23-25, 2014. Proceedings*, volume 8601 of *Lecture Notes in Computer Science*. Springer.

Machado, P., Martins, T., Amaro, H., and Abreu, P. H. (2016). Beyond interactive evolution: Expressing intentions through fitness functions. *Leonardo*, 49(3):251 – 256.

Machado, P., Romero, J., and Manaris, B. (2007). Experiments in computational aesthetics: An iterative approach to stylistic change in evolutionary art. In Romero, J. and Machado, P., editors, *The Art of Artificial Evolution: A Handbook on Evolutionary Art and Music*, pages 381–415. Springer Berlin Heidelberg.

Machado, P., Romero, J., Nadal, M., Santos, A., ao Correia, J., and Carballal, A. (2015b). Computerized measures of visual complexity. *Acta Psychologica*, 160(1):43 – 57.

Machado, P., Vinhas, A., Correia, J., and Ekárt, A. (2015c). Evolving ambiguous images. In Yang, Q. and Wooldridge, M., editors, *Proceedings of the Twenty-Fourth International Joint Conference on Artificial Intelligence, IJCAI 2015, Buenos Aires, Argentina, July 25-31, 2015*, pages 2473–2479. AAAI Press.

Martins, T., Correia, J., Costa, E., and Machado, P. (2018). Evotype: Towards the evolution of type stencils. In Romero, J. and Liapis, A., editors, *Evolutionary and*

Biologically Inspired Music, Sound, Art and Design. Springer International Publishing. *(To Appear)*.

McCormack, J. (2007). Facing the future: Evolutionary possibilities for human-machine creativity. In Romero, J. and Machado, P., editors, *The Art of Artificial Evolution: A Handbook on Evolutionary Art and Music*, pages 417–451. Springer Berlin Heidelberg.

Reed, K. (2013). Aesthetic measures for evolutionary vase design. In Machado, P., McDermott, J., and Carballal, A., editors, *Evolutionary and Biologically Inspired Music, Sound, Art and Design - Second International Conference, EvoMUSART 2013, Vienna, Austria, April 3-5, 2013. Proceedings*, volume 7834 of *Lecture Notes in Computer Science*, pages 59–71. Springer.

Romero, J., Machado, P., Carballal, A., and Santos, A. (2012). Using complexity estimates in aesthetic image classification. *Journal of Mathematics and the Arts*, 6(2-3):125–136.

Romero, J., Machado, P., Santos, A., and Cardoso, A. (2003). On the development of critics in evolutionary computation artists. In Günther, R. et al., editors, *Applications of Evolutionary Computing, EvoWorkshops 2003: EvoBIO, EvoCOMNET, EvoHOT, EvoIASP, EvoMUSART, EvoSTOC*, volume 2611 of *LNCS*, Essex, UK. Springer.

Ross, B. J., Ralph, W., and Hai, Z. (2006). Evolutionary image synthesis using a model of aesthetics. In Yen, G. G., Lucas, S. M., Fogel, G., Kendall, G., Salomon, R., Zhang, B.-T., Coello, C. A. C., and Runarsson, T. P., editors, *Proceedings of the 2006 IEEE Congress on Evolutionary Computation*, pages 1087–1094, Vancouver, BC, Canada. IEEE Press.

Sims, K. (1991). Artificial evolution for computer graphics. *ACM Computer Graphics*, 25:319–328.

Todd, S. and Latham, W. (1992). *Evolutionary Art and Computers*. Academic Press, Winchester, UK.

Xiao, P., Toivonen, H., Gross, O., Cardoso, A., Correia, J., Machado, P., Martins, P., Oliveira, H. G., Sharma, R., Pinto, A. M., Díaz, A., Francisco, V., Gervás, P., Hervás, R., León, C., Forth, J., Purver, M., Wiggins, G. A., Miljković, D., Podpečan, V., Pollak, S., Kralj, J., Žnidaršič, M., Bohanec, M., Lavrač, N., Urbančič, T., van der Velde, F., and Battersby, S. (2019). Conceptual representations for concept creation. *ACM Computing Surveys*.

BRIEF BIOGRAPHY

Penousal Machado leads the Cognitive and Media Systems at the University of Coimbra. His research interests include Evolutionary Computation, Computational Creativity, and Evolutionary Machine Learning. In addition to the numerous scientific papers in these areas, he is the recipient of scientific awards, including the EvoStar Award for Outstanding Contribution to Evolutionary Computation in Europe and the award for Excellence and Merit in Artificial Intelligence granted by the Portuguese Association for Artificial Intelligence. His works have been presented in venues such as the National Museum of Contemporary Art (Portugal) and the Talk to me exhibition of the Museum of Modern Art, NY (MoMA).