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Genetic Algorithm Based on Operator Optimization in Illustration Art Design

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Abstract: - The current research explores the use of Genetic Algorithm (GA) Based on Operator Optimization in graphic art design, to improve the creative process using computational methods. By improving genetic operators such as crossover and mutation, the technique streamlines the creation of visually appealing artwork, allowing artists to efficiently express their distinctive vision. Through testing and research, the study reveals the effectiveness of this strategy in automating repetitive processes, exploring new creative pathways, and creating audience-resonant artwork. The combination of computational intelligence and creative intuition improves efficiency while also encouraging creativity and experimentation in the realm of graphic art design. The work sheds light on the revolutionary potential of Genetic algorithms (GA) based on Operator Optimization, highlighting areas for future research and development at the interface of technology and artistic effort. The results indicate that a better genetic algorithm (GA) provides efficacy and optimizes the operator in art design using a genetic algorithm.

Keywords: Genetic Algorithm (GA), Operator Optimization, Partly Mapped Crossover (PMX), Parameter Free Genetic Algorithm (PfGA), Stead State Genetic Algorithm (SSGA).

I. INTRODUCTION

The Genetic Algorithm (GA) is a strong computing approach based on natural selection and evolution. It has been widely applied in a variety of domains, including optimization, machine learning, and creative processes [1]. In recent years, the use of genetic algorithms in the art and design sectors has received increased interest due to its potential to improve the creative process and facilitate the creation of innovative and visually appealing artwork [2]. In this regard, Genetic Algorithm Based on Operator Optimization appears to be a promising strategy for maximizing the use of genetic algorithms in graphic art creation [3].

Colour selection, composition, texture, and style are among the many difficult and subjective considerations made during the illustration creation process. Historically, artists have relied on intuition, expertise, and manual effort to create artwork [4]. However, with the introduction of computational approaches, there is a growing interest in using algorithms to automate and enhance the creative process. Genetic algorithms, in particular, provide a promising framework for investigating the enormous solution space inherent in art and design problems [5][6].

The main idea behind Genetic Algorithm Based on Operator Optimization is to develop and optimize genetic operators like crossover and mutation to better meet the needs of illustration art design [7]. These operators play an important role in the evolution of solutions within a genetic algorithm by emulating the mechanisms of genetic recombination and mutation found in natural evolution [8]. By optimizing these operators, it is feasible to direct the search process toward creating artwork that fits specified aesthetic requirements while simultaneously encouraging diversity and the investigation of creative solutions [9]. In this study, they investigate approaches and a Genetic Algorithm Based on Operator Optimization in illustration art design [10][11]. The researcher examines the obstacles and opportunities inherent in this technique, as well as provides case examples and findings that indicate its effectiveness in producing high-quality artwork [12].

II. LITERATURE SURVEY

Hirvikorpi et al [13]. suggested a genetic algorithm to tackle task scheduling with the stochastic tool lifespan (JSSTL) problem, which outperformed the classic short processing time (SPT) method. A heuristic based on genetic algorithms is thus proposed for the dual problem of job scheduling and tool management. When tool management decisions are made by a removal rule, the algorithm seeks the most beneficial job sequence while keeping future anticipated tool usage in mind. The cost of each job sequence is evaluated by simulating job processing.

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Jing Liu et al [1]. this research provides an illustration art design model based on an operator clustering optimization genetic algorithm. The k-medoids algorithm is then used to improve the clustering of the genetic algorithm, and a cost function is employed to carry out and evaluate the quality of clustering to optimize the original algorithm's complexity. In addition, a multiobjective optimization genetic method with complex constraints based on group categorization is presented. This approach focuses on the problem of group diversity and solves it using the k-means clustering process. The algorithm separates the entire group into four subgroups and assigns fitness ratings that indicate the best preservation approach.

Erol Egrioglu et al [14]. This paper proposes a new genetic technique that involves an artificial chromosome substitution technique to enhance optimization processes. The proposed genetic algorithm is then utilized to train a multiple-neuron approach, artificial neural networks. The evolutionary algorithm's goal function's result is the root squared error of the exponential neuron model prediction in an artificial neural network. This set of strategies is presented for a specific sort of problem: time series forecast. They test various types of the three stock exchange time series and the proposed method's efficacy by contrasting it with identical methods. The results show that the proposed genetic algorithm for the multiplicative neuron model of the artificial neural network outperforms various other AI optimization approaches.

John McCall [15]. This study examines the use of genetic algorithms in modeling and optimization, emphasizing their success in many domains. This study is designed to provide an introduction to GAs for immunologists and mathematicians interested in immunology. They outline how to build a GA and the basic strands of GA theory before speculating on potential GA uses in immunology research.

III. METHODOLOGY

A. Illustrate Art Design Based on Genetic Operator Optimization

Art Design Based on Genetic Operator Optimization entails using genetic algorithms (GAs) to improve the creative process of producing artwork by optimizing genetic operators such as crossover and mutation. These genetic operators, influenced by natural selection and evolution, are fine-tuned to better suit the complexities of artistic production. By optimizing these operators, artists and designers may automate and optimize many areas of the art design process, such as colour selection, composition, style emulation, and character design. Genetic Operator Optimization uses iterative refining and experimentation to create artwork that not only meets aesthetic criteria but also expresses the artist's vision and intent. This technique blends computational tools with artistic sensibilities, providing a novel framework for investigating new possibilities of creativity and expression in the field of visual and design.

B. Crossover operator

The crossover operator is an important genetic operation in genetic algorithms (GAs) because it models the reproduction and genetic recombination processes seen in natural evolution. It entails merging genetic material from two parent individuals to produce kids with novel genetic traits. The crossover operator is often used to choose a specific point or set of locations along an individual's chromosome representation (commonly referred to as parents) and exchange genetic information between these places. The result is two new kids, both with a mix of genetic material from their parents. The selection of crossing points and the mechanism of transferring genetic information can differ based on the issue domain and individual representation. Common crossover approaches include single-point crossover, which selects a single crossing location at random along the chromosome, and multi-point crossover, which selects many crossover points. The crossover operator is critical for preserving diversity in the solution population and permitting solution space exploration. It allows the evolutionary algorithm to mix advantageous genetic features from diverse individuals, potentially producing children with higher fitness and better solutions to the optimization problem at hand.

The current research used the partly mapped crossover (PMX) approach to create the kid chromosome. This approach preserves chromosome order and linkages, ensuring that offspring follow permutation laws.

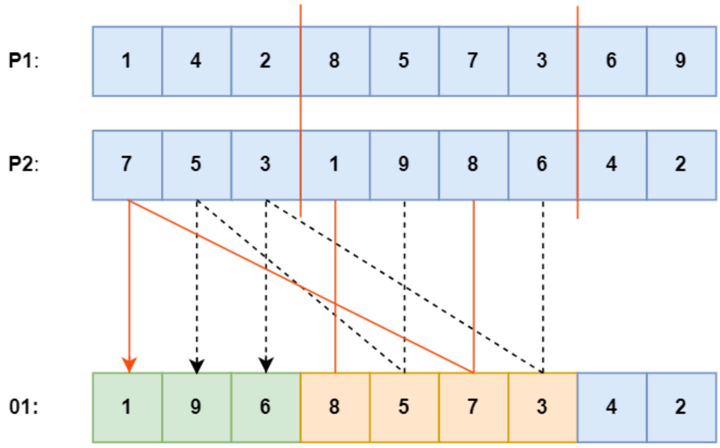

Fig 1: Illustration of a partially mapped crossover (PMX) operation.

PMX involves randomly selecting 2 parent chromosomes (P1 and P2) and 2 crossover sites. Fig 1 shows how the initial parent (P1) segment between two sites is replicated to the identical place as the other child (O1). The parts in the centre section of the other parent (P2) but not in P1 (elements 1, 9, and 6 in the picture) are moved to their respective places on the child's chromosomes. For example, item 9 in P2 is at position 5 in O1, hence the following phase is to move item 9 to the position that is vacant from the preceding 5 in P2. The approach for items 6 and 1 is the same. The balance components of parent P2 are transferred to their respective places on the child's chromosome. This strategy assures the child's chromosomes acquire inherited qualities from each parent keeping the solution's directive and interconnectivity. The PMX approach preserves population variability and enhances the likelihood of achieving optimal results.

C. Mutation operator

In genetic algorithms (GAs), the mutation operator is a fundamental genetic operation that causes random alterations to individual chromosomes in the population. Inspired by a genetic mutation in natural evolution, this operator is critical for diversifying genetic material and exploring new regions of the solution space. Mutation allows the GA to escape local optima and explore possibly better solutions by randomly modifying genes on individual chromosomes. The extent and frequency of mutation are often influenced by criteria such as mutation rate, which determines the likelihood of a mutation in each gene. Mutation may appear paradoxical to the optimization process since it provides randomness, yet it is an important mechanism for maintaining genetic diversity and preventing premature convergence.

D. Improved Genetic Algorithm

In visual art design, a genetic algorithm (GA) based on operator optimization combines computer optimization approaches with artistic creativity to improve the artwork generation process. In this technique, genetic algorithms are tailored to the specific needs of graphic art design, drawing on natural selection and evolution concepts. The emphasis is on enhancing genetic operators like crossover and mutation, which are essential to GAs, to better correspond with the complexities of creative creativity. The optimization procedure entails fine-tuning these genetic operators to produce more diverse and high-quality solutions that match the aesthetic preferences of artists and designers. By experimenting with different operator tactics, artists can automate numerous components of the art creation process, including colour selection, composition, style replication, and character design. Through iterative refinement and analysis, the genetic algorithm adapts and evolves to make artwork that matches the artist's vision and intent. This approach has various benefits in graphic art design. For starters, it accelerates the creative process by automating repetitive processes and opening up new paths for artists to explore. Second, it enables artists to create a diverse spectrum of artwork with minimal manual intervention, resulting in improved efficiency and production. Finally, by combining computational optimization techniques and artistic sensibilities, it creates new avenues for creative expression and innovation in the digital age.

IV. RESULTS

In this section, they employ operator optimization problems to evaluate the effectiveness of the proposed enhanced GA. It introduced multimodal functions for evaluating a procedure's global convergence behaviour. The ideal solution for each of the five functions is 0. These operations have varying degrees of difficulty. The fifth function is particularly challenging, with 25 very native optimums. The space within the two nearby maxima is smooth, whereas every local optimal has a pointed edge. The study introduced a parameter-free genetic algorithm (PfGA) and imitation of its operations. The results of the enhanced GA were compared to those of the PfGA due to the previously reported excellent results.

Table 1: Simulated outcomes of various GAs on five operations.

Methods	**Solution**	**Average**	**SD**
F1			
SSGA method	8.26148e−10	3.4425e−7	3.8669e−7
PfGA method	2.79497e−12	7.0721e−12	3.1041e−11
Improve genetic algorithm	1.79497e−12	1.6831e−12	0
F2			
SSGA method	2.46481e−9	1.4670e−2	6.5278e−2
PfGA method	4.67071e−10	6.5134e−3	1.7286e−2
Improve genetic algorithm	4.20446e−11	2.1670e−3	3.1364e−3
F3			
SSGA method	0	0	0
PfGA method	0	0	0
Improve genetic algorithm	0	0	0
F4			
SSGA method	5.83467e−11	2.6363e−2	2.5355e−2
PfGA method	1.66667e−12	5.4346e−2	4.2492e−2
Improve genetic algorithm	1.66445e−12	8.3508e−2	1.7120e−1
F5			
SSGA method	2.75578e−2	2.4325e−1	8.7051e−2
PfGA method	7.07846e−3	2.6506e−1	4.0253e−1
Improve genetic algorithm	7.30713e−3	7.3171e−3	0

The findings of stead-state GA (SSGA) are compared to conventional GA, as SSGA has shown superior performance over several years. Table 1 summarizes the simulation findings for the stead-state genetic algorithm, parameter-free genetic algorithm, and the current improved genetic algorithm, including best, average, and standard deviation values. Table 1 shows that the suggested modifiedGA outperforms the other 2 genetic algorithms in the sense of standard deviation, best, and average results.

It includes comparisons between parallel genetic algorithm (PGA) and standard genetic algorithm (SGA). In the table, Ps represents the populace proportions, and the "error%" column represents the average percentage error of results derived from various runs, as described in “(1)”.

$$Error(\%) = \frac{\sum_i^N (Solution(i) - Optimal)}{N} \times \frac{1}{Optimal} \times 100 \quad \text{……. (1)}$$

The ideal solution to a problem is referred to as the "solution." Choosing GA settings can be challenging due to the lack of a general rule. In PGA and SGA, the optimal population size is determined using a "trial-and-error" process. The suggested improved GA does not employ "trial-and-error" to determine population size, instead using a fixed population size of 20 for each problem. Despite this, the enhanced GA outperforms the parallel GA and standard GA in the sense of optimal results and regular mistakes. The suggested upgraded GA is easier to apply to SCP compared to the PGA and SGA.

Table 2: Compare with different approaches.

	Improved GA		SA		TS	
	Effective	**Error**	**Effective**	**Error**	**Effective**	**Error**
SCP 41	431	3.73	525	23.31	480	12.31
SCP 42	525	8.42	732	44.33	N m	N m
SCP 44	513	7.71	691	41.46	599	21.46
SCP 51	267	7.15	2783	1036.29	N m	N m

Table 2 compares results from the SA and Tabu searches (TS) methods, indicating that the enhanced GA yields the highest quality solutions for both problems.

V. Discussion

The results provide useful insights into the diverse strategies and approaches used in the use of genetic algorithms. These techniques could serve as the basis for additional investigation and improvement to fulfil the special needs of the art and design sectors. Furthermore, genetic algorithms have been used successfully in a variety of disciplines, including optimization, modeling, and creative processes. Understanding how these algorithms are developed and used in other sectors can spur multidisciplinary partnerships and novel applications in art and design. However, it is critical to recognize the obstacles and limitations connected with genetic algorithms. Issues like as algorithm complexity, parameter adjustment, and scalability may offer significant barriers to their effective incorporation into art and design activities. Addressing these issues is critical for attaining genetic algorithms' full promise in improving creativity and innovation. Moving ahead, there are exciting opportunities for further research and development. Further investigation of genetic algorithm variants, the use of machine learning techniques, and integration with interactive tools may open up new avenues for creativity and expression in the art and design fields. Also, conversations on ethical issues such as algorithm bias, privacy, and ownership of generated artwork are critical for assuring the responsible and ethical use of these technologies.

VI. Conclusion

The usage of genetic algorithms Based on Operator Optimization, and illustrative art design provides a big step forward in the junction of computational approaches and artistic creativity. This approach streamlines the creative process, increases productivity, and makes it easier to create visually appealing artwork by refining genetic operators such as crossover and mutation. By blending computational intelligence with artistic intuition, this approach encourages artists to explore new creative channels and make artwork that expresses their unique vision and style. The incorporation of genetic algorithms Based on Operator Optimization, and illustrative art design not only improves the efficiency of the artistic process but also offers up new avenues for invention and experimentation. Additionally, it adds to the larger conversation about computational creativity and the role of algorithms in artistic expression. Continued study and development in this sector have the potential to transform how artwork is created and viewed, pushing the boundaries of both technology and artistic endeavour.

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References

[1] J. Liu, Q. Chen, and X. Tian, "Illustration Design Model with Clustering Optimization Genetic Algorithm," Complexity, vol. 2021, 2021, doi: 10.1155/2021/6668929.

[2] A. A. Ewees et al., "Boosting arithmetic optimization algorithm with genetic algorithm operators for feature selection: Case study on cox proportional hazards model," Mathematics, vol. 9, no. 18, 2021, doi: 10.3390/math9182321.

[3] M. T. Multazam, R. Dijaya, and N. M. S. Devi, "Index group optimization based on automatic clustering using K-Means genetic algorithm," in Journal of Physics: Conference Series, 2019. doi: 10.1088/1742-6596/1402/6/066028.

[4] F. M. Rodríguez-Bejarano, M. A. Vega-Rodríguez, and S. Santander-Jiménez, "GADPO: Genetic Algorithm based on Dominance for Primer Optimization," Expert Syst. Appl., vol. 238, 2024, doi: 10.1016/j.eswa.2023.122206.

[5] F. Peng, X. C.-I. T. on A. And, and U. 2024, “An Efficient Optimization Method for Antenna Arrays Using a Small Population Diploid Genetic Algorithm Based on Local RBF Networks,” ieeexplore.ieee.orgF Peng, X ChenIEEE Trans. Antennas Propagation, 2024•ieeexplore.ieee.org.

[6] R. Polo-Mendoza, G. Martinez-Arguelles, and R. Peñabaena-Niebles, “A multi-objective optimization based on genetic algorithms for the sustainable design of Warm Mix Asphalt (WMA),” Int. J. Pavement Eng., vol. 24, no. 2, 2022, doi: 10.1080/10298436.2022.2074417.

[7] X. Jin, “Application of machine vision based on genetic algorithm in image painting style method and image processing optimization,” Soft Comput., 2023, doi: 10.1007/s00500-023-08408-1.

[8] L. Jiang and W. Zhou, “Application of Interactive Genetic Algorithm in Fractal Art Pattern Design System,” in 2023 International Conference on Network, Multimedia and Information Technology, NMITCON 2023, 2023. doi: 10.1109/NMITCON58196.2023.10276254.

[9] M. Adamik, J. Goga, J. Pavlovicova, A. Babinec, and I. Sekaj, “Fast robotic pencil drawing based on image evolution by means of genetic algorithm,” Rob. Auton. Syst., vol. 148, 2022, doi: 10.1016/j.robot.2021.103912.

[10] V. Pal, Yogita, G. Singh, and R. P. Yadav, “Cluster Head Selection Optimization Based on Genetic Algorithm to Prolong Lifetime of Wireless Sensor Networks,” in Procedia Computer Science, 2015, pp. 1417–1423. doi: 10.1016/j.procs.2015.07.461.

[11] S. W. Kielarova and P. Pradujphongphet, “Genetic Algorithm for Product Design Optimization: An Industrial Case Study of Halo Setting for Jewelry Design,” in Lecture Notes in Computer Science (including subseries Lecture Notes in Artificial Intelligence and Lecture Notes in Bioinformatics), Springer Science and Business Media Deutschland GmbH, 2023, pp. 219–228. doi: 10.1007/978-3-031-36622-2_18.

[12] Sukono et al., “Analysis of stock investment selection based on CAPM using covariance and genetic algorithm approach,” in IOP Conference Series: Materials Science and Engineering, 2018. doi: 10.1088/1757-899X/332/1/012046.

[13] M. Hirvikorpi, T. Knuutila, T. Leipälä, and O. S. Nevalainen, “Job scheduling and management of wearing tools with stochastic tool lifetimes,” Int. J. Flex. Manuf. Syst., vol. 19, no. 4, pp. 443–462, Dec. 2007, doi: 10.1007/s10696-008-9043-y.

[14] E. Egrioglu, C. Grosan, and E. Bas, “A new genetic algorithm method based on the statistical-based replacement for the training of multiplicative neuron model artificial neural networks,” J. Supercomput., vol. 79, no. 7, pp. 7286–7304, May 2023, doi: 10.1007/s11227-022-04935-0.

[15] J. McCall, “Genetic algorithms for modelling and optimisation,” J. Comput. Appl. Math., vol. 184, no. 1, pp. 205–222, 2005, doi: 10.1016/j.cam.2004.07.034.