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Research on Visual Semantic Reconstruction and Creative Generation Mechanism Based on Topological Computing Optimization in Digital Graphic Design in New Media Era

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Abstract In this paper, we propose a topology optimization method based on Generative Adversarial Networks (GANs), which considers a two-dimensional topology as an image generation problem. The quality of the generated image is improved by a weighted loss function of the adversarial loss and the mean square error. Analyze the parametric constraint solving method, describe the geometric elements and their constraint relationships through geometric constraint graph (GCG), define the concepts of degrees of freedom and constraints, classify the constraint problems, and clarify the evaluation criteria of the algorithms. Analyze the generative graphic design process and emphasize the central role of algorithms in graphic generation. Verify the visual quality and creative advantages of the generated graphics of this paper's method by means of digital graphic design practice and comparative evaluation of effects. The results show that the overall visual effect of the generated graphics of this paper's method has an aesthetic score between 2 and 5. The scores are higher than those of the comparison method in the seven indicators of the detailed layout performance of the generated graphics. When the embedded coded information reaches 205000 bits, the average values of PSNR, SSIM, and LPIPS are 26.20334, 0.98112, and 0.00424, respectively, with good quality of visual perception. And the generated graphs are more non-orderly and have excellent creative effect.

Index Terms generative adversarial networks, topology optimization, weighted loss function, geometric constraint graph, digital graph design

I. Introduction

In today's society, the new media show a vigorous development momentum, the communication media are constantly evolving, and the audience's access to information is increasingly rich. This change in communication media has not only changed the way people communicate with each other, but also shaped a communication environment of information digitization, diversification and personalization with the support of digital technology and the Internet [1]-[3]. In response to the current rapidly evolving communication environment, the traditional field of graphic design continues to explore new ways of expression [4]. Among them, digital graphic design has emerged as an emerging design trend by virtue of its combination of the dynamic effects of graphic art and the layout skills of graphic design [5], [6]. This design form not only integrates a rich visual language, but also shows innovative presentation skills and unique aesthetic tendencies [7], [8]. With the promotion of new media, digital graphic design has gradually entered the public domain and become one of the major design genres that are extremely popular in the new media environment [9]. With the continuous progress and innovation of technology, China's digital graphics industry is expected to continue to maintain the momentum of rapid development in the future.

Topology is not only widely used in many fields such as science and art, but also provides a new perspective for people to understand the transformation characteristics of geometric figures [10]. Topology focuses on the positional relationships among objects without considering their shapes and sizes, and has the rational quality of simplifying complexity, which is naturally coupled with the macroscopic form description of digital graphic design [11]-[13]. In addition, the graphic mapping transformation through topological forms can expand the visual semantics and spatial level of graphic expression, enabling graphics to be applied to a wider range of media to meet the information dissemination needs of the new era [14]-[16]. For this reason, it is of great significance to explore the digital graphic design based on topological computing optimization.

In the new media era, digital graphic design pays more and more attention to the visual effect and sense of creativity. In this paper, Adversarial Generative Networks are introduced to realize topology computation optimization. The GAN network model is constructed using U-Net, U-Net++, U-Net-based encoder-decoder structure, and three-layer discriminator Pixel Discriminator. Set the loss function to reduce the error between the generated and original graphs. Explore the basic concepts of parameter-based constraint solving, categorize constraint problems into over-constrained, under-constrained and complete constraints, and improve the quality of generated graphs. Analyze the basic process of generative graph design and the importance of algorithmic coding information. Demonstrate the value of this paper's method in digital graphic design through comparative experiments, quality assessment, and control analysis.

II. Analysis of technologies related to digital graphic design

This chapter builds a system of techniques related to digital graphic design through the steps of topological computation optimization, constraint theory modeling and generative process design.

II. A. Graphical design model construction based on topology optimization

II. A. 1) Introduction to the model structure and training process

In this paper, we propose a deep learning based approach for accelerating the topology optimization process. The problem we address is a distributed one. The main innovation of this work is to treat the 2D topology optimization structure as an image problem and use image generation algorithms to deal with it. We take advantage of deep learning for efficient image labeling on a per-pixel basis for topology optimization, effectively avoiding the problems associated with the discrete nature of finite element based solution methods. We introduce adversarial generative networks and solve the topology optimization problem with high quality.

In this paper, the cumbersome training process of et al. work is discarded in favor of an end-to-end training approach, modeled as a GAN network. The conditional tensor is fed into the generator, the generator predicts the image, this image and the true value image are fed into the discriminator respectively, after which the discriminator makes a judgment on the truth of the input image. The loss function of the discriminator for the true value image is denoted as $Loss_{real}$, and the loss function for the false image is denoted as $Loss_{fake}$, the sum of the two is the sum of the loss function of the discriminator, and the gradient of the sum of the two is passed back at each iteration. And the generator's loss function is the sum of several losses that contain the discriminator's loss term.

The whole of the model is a GAN network model, the network structure is divided into two parts, the generator and discriminator structure, and the two are trained alternately, and they are briefly introduced here:

Generator part: in this paper, we use the existing generator network structure, because different networks have different performance, so we use U-Net, U-Net++, and the U-Net-based encoder-decoder structure proposed in.

Discriminator part: we use a three-layer discriminator Pixel Discriminator, the input to the discriminator is the fake image generated by the generator or the true value image solved by SIMP, i.e., a matrix of size 40*80. The entire discriminator network contains three convolutional layers. The first convolutional layer is accompanied by a Leaky ReLU layer that computes the activation function on the convolutional result. After the second convolutional layer, in addition to the Leaky ReLU layer, an instance regularization layer is added to normalize the individual images in each batchsize after the convolutional layer. If the discriminator judges the picture to be true, it outputs a 40*80 matrix of all 1s, and vice versa, it outputs a matrix of all 0s.

II. A. 2) Model Loss Functions and Principles in Detail

From an optimization perspective, the training process of a neural network is equivalent to an optimization problem - maximizing or minimizing an objective function with respect to the input tensor as well as other parameters during training. The objective of the problem optimized in this paper is to explore the probability distribution of each element in the region.

The foreground of the image is a two-dimensional topology, which indicates that there is a material distribution within the region, i.e., the pixels within the region have a probability of occurrence of 1. The background of the image is empty, there is no material distribution, and the pixels have a probability of occurrence of 0.

The loss function of the model proposed in this paper is obtained by weighting the 2-term loss function and is described as follows:

Since the model uses a generative adversarial network to generate topology optimization results, the first term of the loss function L_{GAN} is shown in Equation (1), which is the loss function of a GAN network in the form of a very large and very small:

$$L_{GAN}=\min_{\omega}\max_{\theta}\frac{1}{N}\sum_{i=1}^{N}\log D_{\theta}\left(y_i\right)+\log\left(1-D_{\theta}\left(G_{\omega}\left(x_i\right)\right)\right) \tag{1}$$

where N is the number of samples per batch, G is the generator network and ω is the parameter of G, and D is the discriminator network and θ is the parameter of D. D and G are alternately updated during training.

In order to make the images generated by the generator as similar as possible to the true values, we also introduce a mean square error (MSE) term L_{MSE} in the loss function. It is used to count the average of the sum of squares of the errors of the corresponding pixel points of the predicted and true value images, and since L_{MSE} compares the difference between the predicted image and the true value image, the closer it converges to 0, the better, and is calculated as follows:

$$L_{MSE} = \frac{\sum_{j=1}^{N}(y_j - y_j^{gt})^2}{N} \tag{2}$$

where y_j^{gt} is the true value at the j th pixel and y_j is the value of the predicted image at the j th pixel.

In summary, the loss function for the training of the model in this paper is the sum of the three loss functions as follows:

$$L = \lambda_1 L_{GAN} + \lambda_2 L_{MSE} \tag{3}$$

where $\{\lambda_k, k = 1,2\}$ is a hyperparameter that is manually adjusted according to the learning effect of the network in the experiments, where we will explore the effect of different values of λ_k on the accuracy of the generated data.

II. B.Basic concepts of parameter-based constraint solving

For parametric design systems, the user is given a number of dimensions and topological or attribute constraints on the design sketch, the software system can automatically generate the corresponding design drawings, this process is called constraint solving. The types of constraints are mainly categorized into geometric constraints, topological constraints and attribute constraints. For the set of geometric entities in the sketch and the set of constraints about the set, constraint solving will make one or all geometric shapes that satisfy the set of constraints according to a certain algorithm.

In order to structurally categorize constraint problems, a few related concepts are first introduced.

Definition 1: Graph representation of geometrically constrained problems. Usually we represent a geometrically constrained problem by the graph $G = (V, E)$, where V stands for the set of geometries of the geometrically constrained problem; E stands for the set of geometrical constraints of the geometrically constrained problem; and G is called the constraint graph (GCG) of the geometrically constrained problem. A more general approach is to represent a geometrically constrained problem by an even graph $G = (V^+, V, E)$, where V^* denotes the geometry; V denotes the geometric constraints; and E denotes that the corresponding geometry is associated with the geometric constraints.

Definition 2: Degrees of freedom of a geometry. Refers to the number of independent parameters required to determine the position of this geometry, and we use $DOF(O)$ to notate the degrees of freedom of the geometry O. For example, the degree of freedom of a point in two dimensions is 3, the degree of freedom of a circle is 4, and the degree of freedom of a line segment is 5; the degree of freedom of a point in three dimensions is 4, and the degree of freedom of a line is 5. For a graphical representation of a geometrically constrained problem, $G = (V, E)$, it is clear that $DOF(V) = \sum_{v \in V} DOF(v)$.

Definition 3: Degree of constraint of a geometric constraint. Refers to the number of numerical equations required in order to describe a geometric constraint, we use $DOC(O)$ to notate the degree of constraint of a geometric constraint C. For example, the constraint on the distance between points has a constraint degree of 1, and the ternary constraint on the point M being the midpoint of the line segment AB has a constraint degree of 2. For the graphical representation of a geometrically constrained problem $G = (V, E)$, it is clear that $DOC(E) = \sum_{e \in E} DOC(e)$.

From the above definition, we claim that a geometrically constrained problem $G = (V, E)$ is:

(1) Structurally overconstrained: if there exists a derived subgraph $H = (V_H, E_H)$ such that $DOC(E_H) > DOF(V_H) - D$.

(2) Structurally underconstrained: if G is not structurally overconstrained and has $DOC(E) < DOF(V) - D$.

(3) Structurally complete constrained: if the geometrically constrained problem corresponding to G is neither structurally underconstrained nor structurally overconstrained.

(4) Strictly complete constrained: if $DOC(G) = DOF(G)$ and each subgraph H of G satisfies the condition $DOC(H) \leq DOF(H) - D$.

where $D = 4$ in the two-dimensional case and $D = 7$ in the three-dimensional case.

Constraint solving problems can be categorized into three types;

(1) Constraint solving problems with complete constraints: there are a finite number of shapes of the geometry corresponding to the constraint problem.

(2) Under-constrained constraint solving problems: there are an infinite number of shapes of the geometry corresponding to the constraint problem.

(3) Over-constrained constraint solving problem: The constraint solving problem has no solution.

The structural constraint properties (structurally complete, structurally underconstrained, and structurally overconstrained) of geometric shapes are often used to characterize the geometrically constrained properties of geometric shapes (fully constrained, underconstrained, and overconstrained). This is true in most cases, but it is not always possible to infer the actual constraint properties of the geometry from the structural constraint properties of the geometry, e.g., a structurally complete constrained problem may be a complete constrained problem in most cases, but it may be over-constrained and under-constrained as well. Based on the problem requirements, we usually use the following criteria to evaluate a new method for geometric constraint solving: (1) Scope of the solution. The types of geometric constraints and geometries that the algorithm can solve. (2) Speed of the algorithm. The complexity of the algorithm and the actual testing speed, especially whether it can handle large constraint problems. (3) Completeness of the solution. Whether all solutions can be found and whether it can handle under-constrained and over-constrained problems. (4) Stability of the algorithm. The stability of the algorithm to sketch modifications.

The common constraints in the geometric constraint system are binary constraints, and thus the geometric elements in this model and their constraint relationships with each other can be canonically expressed in the structure of a geometric constraint graph (GCG). In $GCG = (V, E)$ the fixed point geometry V represents the basic geometric elements and the edge geometry E represents the constraints between geometric elements. The initially created graph is undirected because the vertices are equal in status and role, and no dependencies have been established between neighboring points. Figure 1 shows the planar graph and its GCG representation. The planar graph is transformed to form a GCG, which clearly indicates the geometric elements and their interrelationships within the geometric constraint system.The vertices in the GCG record the type of geometric elements, degrees of freedom DOF and other relevant parameter information; the edges record the type of geometric constraints, degree of constraint DOC and other information. The definition of the weights of the edges depends on the needs of a particular problem solution. For example, the constraint degree DOC, constraint value and constraint priority of a geometric constraint can be considered as the weights of GCG edges, and thus GCG is a geometric constraint network.

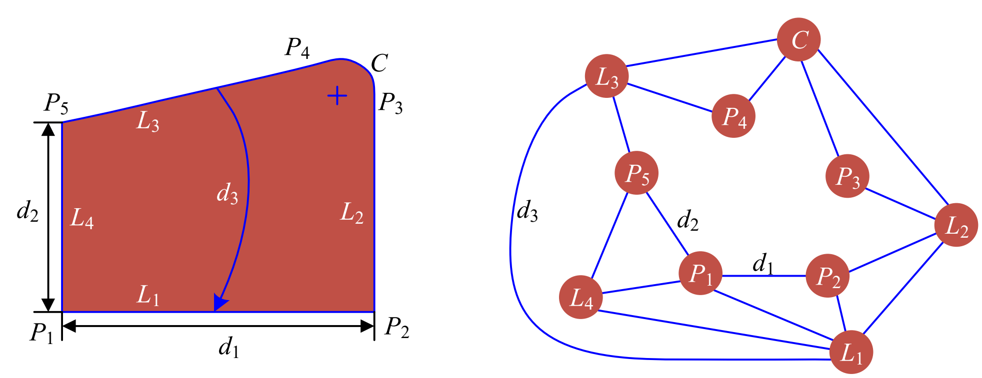


Figure 1: Plan and its GCG representation

II. C.Basic flow of generative graphic design

The overall action process of generative graphic design and traditional graphic design in the design strategy phase is basically the same, mainly divided into three steps: background analysis, audience modeling, and defining requirements. Figure 2 shows the specific process. Generative graphic design from the technical, functional and other perspectives and software interaction design has a great deal of similarity, part of the generative graphics in the current technology and other conditions and software design also has certain requirements on the audience's ability to operate, hardware tools, etc., and therefore need to be more detailed audience modeling this step of the analysis of the behavior, ability, equipment and so on. The definition of requirements for generative graphic design is also somewhat different from traditional graphic design, which can realize a variety of types and functions of graphics.

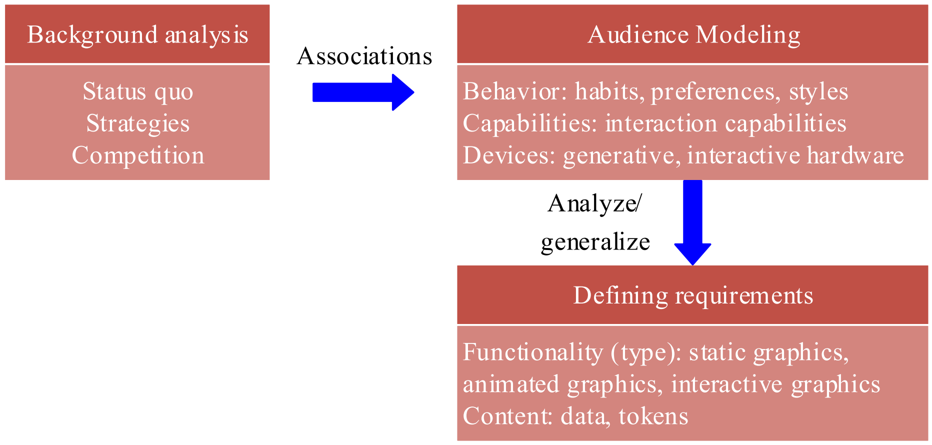


Figure 2: Specific process

Code is the core technology that makes generative art possible, and algorithms are the core part of code. In the field of computer engineering, there is a well-known formula “program equals data structure plus algorithm”, where algorithm simply means a method that leads to a certain calculation result.

In generative design, graphics are generated by inputting coded formula logic that can be analyzed by the computer. Even the most basic square requires manual input of its coordinate system, aspect ratio, RGB value, Alpha value, and other parameters, which is the most basic mathematical analysis. When creators need to generate a dynamic graphic, they need to stand in the physics point of view to think about the movement of the graphic is linear or non-linear motion, is uniform motion or accelerated motion, if you choose to gravity acceleration of the movement needs to be transformed in the physics of the acceleration of gravity formula, to create a computer programming language suitable for the acceleration algorithm, which is from the formula to the algorithm of the transformation, is the transformation of creativity into code, graphics, and algorithms. It is the core step in transforming ideas into code and graphics.

III. Digital graphic design technology application and effect analysis

In this chapter, several sets of experiments are conducted to verify the effectiveness of the proposed method in practical digital graphic design generation, as well as the quality of the generated graphics.

III. A. Algorithm comparison experiment

III. A. 1) Comparison of the running time of several algorithms

The running speed of the algorithm determines whether the graphical design model based on topology optimization can handle large constraint problems. In order to verify the advantage of the constraint problem processing effect of the algorithms in this paper, under the premise that the k value of λ_k takes the variation of 1-6, the traditional Newton iteration method (TNI), the fast display algorithm (FD), and the P-DQDA algorithm (P-DQDA) are selected as the comparison algorithms. A dataset containing 2000 non-ordered images with background is constructed, of which 70% is used as a training set to train the four algorithms, and 30% is used as a test set to test and record the running time of the four algorithms.

Table 1 shows the results of the comparison of the running time of several algorithms. Comparing the running time of each algorithm in Table 1, it is found that as λ_k increases from 1 to 6, the running time of this paper's algorithm decreases from 3116ms to 1495ms, with a decrease of 1621ms, and the running speed is much faster than that of the other three comparison algorithms. It indicates that as the value of hyperparameter increases, the speed of this paper's algorithm in determining the data related to the graphic position in the input image is getting faster and faster, and then it can be preliminarily judged that this paper's algorithm is able to deal with the large-scale constraints in the extraction of image information and image generation.

Table 1: Comparison of running time of four algorithms(ms)

Algorithm \ λ_k	λ_k =1	λ_k =2	λ_k =3	λ_k =4	λ_k =5	λ_k =6
TNI	11139	11357	11658	12066	12207	12221
FD	6711	5173	5069	4827	4691	4552
P-DQDA	5526	5517	5498	5483	5416	5400
Textual algorithm	3116	2424	2030	1779	1566	1495

III. A. 2) Comparison of the gap between the predicted image and the true image of different algorithms

Further compare and analyze the gap between the predicted image generated using different algorithms and the input true value image, the closer the gap is to 0, it means that the algorithms are more effective in visual feature extraction and the quality of visual semantic reconstruction is higher. Figure 3 shows the results of the comparison of the gap between the predicted image and the true value image of the four different algorithms. From the comparison in Figure 3, it can be found that as the value of λ_k increases from 1 to 6, the gap between the predicted image generated by the algorithm of this paper and the input image of the true value decreases from 14.79 to 4.52, the gap is gradually reduced, and finally close to 0. It shows that with the increase of the hyperparameter, the value of the loss function of the algorithm of this paper decreases, and the generated predicted image and the true value of the image are closer to each other. And the gap value of this paper's algorithm shows a trend of sequential reduction. Compared with other algorithms, such as the TNI algorithm, the gap value is 91.23 when k is taken as 1, 84.62 when k is taken as 3, and 91.69 when k is taken as 6, which shows that the gap value decreases and then increases, and the stability is poor. This also shows that the algorithm in this paper can generate the predicted image based on the true value image more smoothly and has the advantage of stability.

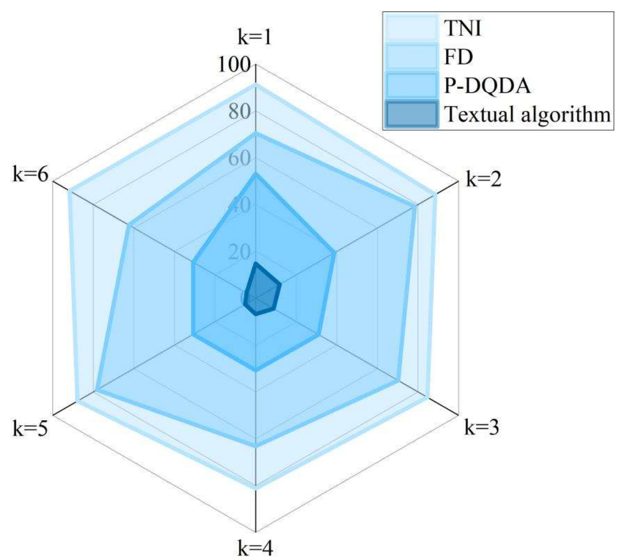


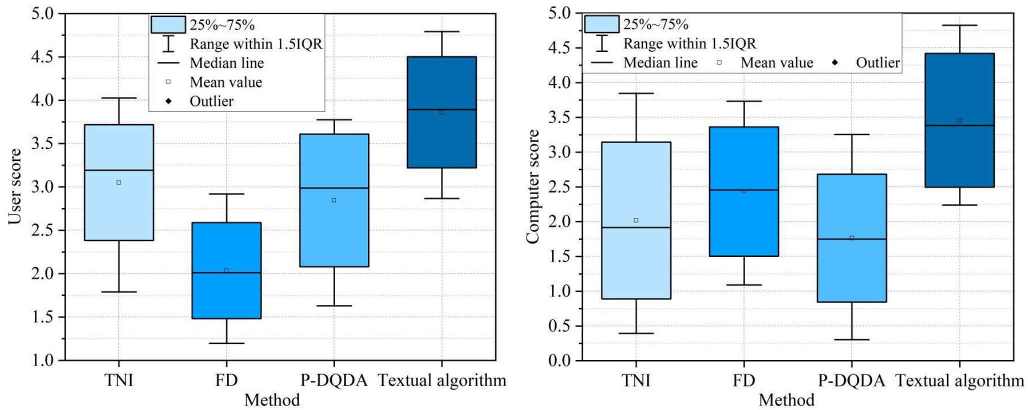
Figure 3 Difference between the predicted image and the true image

III. B. Evaluation of the quality of generated graphics

III. B. 1) Comparison of overall visual effect aesthetic scores

Evaluating the overall visual effect of the predicted images generated by this paper's method allows us to judge the quality of the visual semantic reconstruction and idea generation of this paper's method. One hundred images were selected from the test set, and the corresponding predicted images were generated using the previously mentioned image generation methods of Traditional Newton Iteration (TNI), Fast Display Algorithm (FD), and P-DQDA Algorithm (P-DQDA) as comparative methods, respectively. Fifty volunteers were recruited to aesthetically score these generated images with scores ranging from 1 (worst visual effect) ~ 5 (best visual effect) to obtain the results of the subjective user aesthetics scores. At the same time, a computerized image aesthetics assessment method was combined to aesthetically score these generated images as a computerized objective score complementary to the subjective user score, with the same score range of 1 (worst visual effect) ~ 5 (best visual effect).

Figure 4 is a demonstration of the aesthetic scores of the different methods for the aesthetic evaluation of computerized images and the aesthetic scores from the user survey. From the computer scoring results and user scoring results in Fig. 4, the highest score of the overall visual effect of the images generated by this paper's method is close to 5 and the lowest score is greater than 2, which is higher than that of the comparison methods, both in subjective scoring and objective scoring. Especially in computer scoring, the lowest score of this paper's method is 2.24, which is much higher than the 0.39 score of the TNI method and the 0.30 score of the P-DQDA method. In the aesthetic assessment of the overall visual effect, this paper's method performs better than the other methods. Because this paper's method considers the loss function between the true value image and the predicted image, and at the same time combines the degrees of freedom and constraints to constrain the generated image, it is able to generate a digital graphic with a more harmonious and beautiful overall visual effect, and more in line with the user's actual aesthetics, and gets a higher aesthetic score.



(a) User score results (b) Computer score results

Figure 4: Score result

III. B. 2) Comparison of Detailed Layout Performance of Different Models

From the overall visual effect aesthetic scoring results in 3.2.1, it is found that the digital graphics generated by this paper's method are more harmonious and beautiful. The dataset of this paper is further used to compare the detail layout performance of the images generated by different methods to judge the quality of the graphics generated by the method of this paper from a microscopic point of view. Table 2 shows the comparison results of the detailed layout performance of the graphics generated by different methods. From the comparison of the seven index values in Table 2, the detailed layout performance of the images generated by this paper's method are all optimal. In the Acc2/5 index, this paper's method achieves a score of 52.9 points, which is much higher than the score of 7.3 points of the TNI method. Similar comparison results are found in Acc4/5 metrics and Acc1/1 metrics. In the other four indicators, although there is no huge score gap, the scores of this paper's method are all the highest, with 0.528, 0.107, 0.889, and 0.866 scores, respectively. It indicates that this paper's method has a better detail layout performance effect in visual semantic reconstruction and creative generation of digital graphics.

Table 2: compares the detailed layout representation of the generated graph

Method	IoU	BDE	PCC	SRCC	$Acc_{4/5}$	$Acc_{2/5}$	$Acc_{1/1}$
TNI	0.105	0.257	0.001	0.004	3.0	7.3	0.08
FD	0.297	0.161	0.617	0.634	12.2	22.2	1.76
P-DQDA	0.475	0.120	0.882	0.854	20.6	36.2	4.07
Textual algorithm	**0.528**	**0.107**	**0.889**	**0.866**	**38.7**	**52.9**	**12.24**

III. B. 3) Visual quality assessment of coded images

The quality of the coded information also affects the quality of the generated predictive graphics. This section continues to analyze the quality of the graphs after the coded information is embedded as one of the bases for judging the visual effect of the graphs. For a fair comparison, the images of the tested dataset are resized to be consistent and the algorithmic coded data of the same size is embedded in the test pictures. Higher peak signal-to-noise ratio (PSNR), higher structural similarity (SSIM), and lower perceived image similarity (LPIPS) indicate better visual effect of the coded image after embedding the information.

The visual quality of the coded image decreases when more data is embedded, which is one of the difficulties in embedding a large amount of information in graphic design. Therefore, experiments were conducted to evaluate the visual quality of the generated images after embedding different lengths of encoded information using the method of this paper. The resolution of the carrier image used for testing was set to 1500 × 1500.Fig. 5 demonstrates the results of the visual quality assessment of the encoded graphics by this paper's method, where the X-axis represents the number of bits of input information and the Y-axis represents the average value of the corresponding graphic quality assessment metrics. When embedding 205000 bits of information, the average value of PSNR of this paper's method is 26.20334, the average value of SSIM is 0.98112, and the average value of LPIPS is 0.00424. When embedding such a large amount of information, the peak SNR of this paper's method still stays above 25, the structural similarity is close to 1, and the image perceptual similarity is close to 0. The data of these metrics show that this paper's method can guarantee good visual perception quality of the encoded graphic design even when embedding coded information on larger scale data.

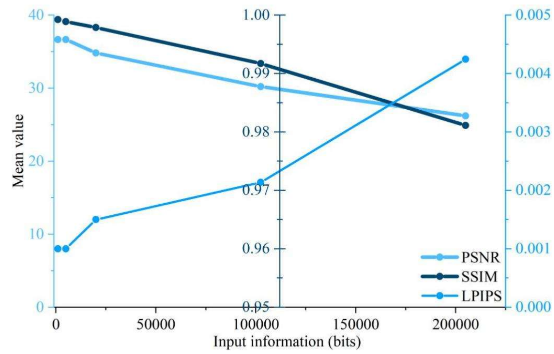


Figure 5: The results of visual quality evaluation of coded graphics are presented

Table 3: Validation of the non-ordered graphics evaluation system

Generation mode	Usage method	Picture name	M	H	E
Symmetric generation	Symmetry analysis	Symmetry generation contrast picture 1	0.98	-	-
		Symmetric generation 1	0.41	-	-
		Symmetric generation 2	0.65	-	-
		Symmetric generation 3	0.52	-	-
		Symmetric generation 4	0.48	-	-
		Symmetric generation 5	0.69	-	-
Translation and rotation are self-generated	Texture regularity	Translation and rotation self-generated comparison picture 1	-	0.93	0.76
		Translation and rotation self-generated comparison picture 2	-	0.84	0.54
		Translation and rotation generate 1	-	0.55	0.13
		Translation and rotation are self-generated 2	-	0.57	0.20
		Translation and rotation are self-generated 3	-	0.33	0.16
		Translation and rotation are self-generated 4	-	0.37	0.15
Repetitive self-generation	Repeatability analysis	Repeat the self-generated comparison picture 1	0.76	-	-
		Repeat the self-generated comparison picture 2	0.77	-	-
		Repeat to generate 1	0.25	-	-
		Repeat to generate 2	0.12	-	-
		Repeat to generate 3	0.37	-	-
		Repeat to generate 4	0.31	-	-

III. C. Generating Graph Control Experiments and Analyzing the Results

Referring to the evaluation system of non-ordered graphs, some of the generated graphs are selected and the control group of orderliness is added, which is imported into the computer for numerical analysis and validation to judge the creativity of the non-ordered graphs generated by the method of this paper. Table 3 is the validation results of the non-order graphic evaluation system. Among them, the structural similarity index (M), energy (E), uniformity (H) values range from 0 to 1, the closer to 1 represents the more regular and regular. Table 3 contains the validation parameters that constitute the three groups of generated graphs as well as their control groups. From the results, while visually ensuring non-order, the values of the parameters verify that the non-order of the generative graphs is significantly greater than that of the control group's orderly graphs. Taking symmetry analysis as an example, the symmetric generative comparison graph 1 is accomplished by mirror symmetry, and the symmetry analysis index value M is 0.98, which indicates that it is more symmetric and less non-orderly from the objective index. The symmetry values of the 5 non-ordered symmetric graphs generated by the generative approach in this paper are between 0.41-0.69, which are significantly lower than the symmetry values of the comparison graphs, and there is a clear improvement in non-order. The other 2 types of graphs also have similar numerical results. Therefore, the graphics generated by the method of this paper can break through the constraints of the traditional visual sense of order and improve the sense of creativity and innovation in digital graphic design.

IV. Conclusion

In this paper, we construct a digital graphic design model based on topological computation optimization to improve the quality and creative innovativeness of digital graphic generation. The running time of this paper's method decreases from 3116ms to 1495ms with the increase of hyperparameters, and the gap between the generated graphic and the original graphic also decreases from 14.79 to 4.52.In the computer aesthetic scoring and the user aesthetic scoring, the scores of the overall visual effect of the generated image of this paper's method are between 2-5, which are higher than those of the comparison methods. In the detail layout performance comparison, the scores of the seven indicators are higher than the comparison methods. After embedding 205000 bits of coded information, the average PSNR of the generated graphics of this paper's method is still greater than 25, the average SSIM is close to 1, and the average LPIPS is close to 0. While having good visual effects, it has better non-order and creative effects.

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