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Analysis of the Integration Mode of Visual Communication Design and Interaction Design Education for the Intelligent Era

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Abstract This paper takes CDGAN as the core technology framework, combines the data-user collaboration model with the reconstruction of the curriculum resource system, and explores the collaborative innovation path of visual communication design and interaction design education in the intelligent era. By introducing DO-Conv and CA, we optimize the number of parameters and feature extraction ability of CycleGAN image generation model, and realize the significant improvement in detail performance and semantic consistency of the generated images. Compared with the original model CycleGAN, the Loss value of CDGAN model is reduced by 0.016, the BLEU score is improved by 5.9%, and the performance is optimal in both FID and 1-NNA in both category and company datasets. The CDGAN model image clarity, vividness, and harmony index scores are 3.297, 3.286, and 3.278, respectively, which all have significant advantages over other methods. In the teaching experiment, there is a significant difference between the pre-test data and post-test data of the experimental group in the three dimensions of design thinking, such as variability, uniqueness and delicacy, and the cultivation of design thinking ability ($P<0.05$), and the post-test scores of each dimension are about 2 points higher than the pre-test scores, and the design thinking ability reaches 87.42 ± 4.286 points. This paper constructs a technology-enabled teaching model to provide theoretical basis and practical reference for the transformation of visual communication design education.

Index Terms visual communication design, interaction design, CDGAN; image generation

I. Introduction

With the advent of the experience economy, the ever-changing technological inventions and the ever-changing experiential needs have revolutionized the design field. Among them, visual communication design is constantly expanding from traditional graphic paper design to multimedia, multidimensional and multisensory interactability design scope [1]. The society needs compound design talents in the new era, which requires that students should have a comprehensive mastery of new media technology, experiential awareness and interactive design ability [2]. For this reason, we analyze the direction of the educational reform of visual communication design in the new era, focus on the center point of social talent demand, and comprehensively penetrate new media technology and interactive design concepts into professional teaching to help the comprehensive upgrade of visual communication design [3]-[5].

Interactive visual communication design, as an important branch of modern design field, has its theoretical foundation deeply rooted in the traditional concepts of visual communication design, and integrates the theories and practices of interaction design, user experience design and multimedia technology and other emerging fields [6]-[8]. This kind of design not only requires designers to have good visual aesthetic ability, but also need to master the logic of user interaction and the use of multimedia technology [9], [10]. In conclusion, interactive design is playing an increasingly important role in the field of digital media, mobile applications, website design, etc. It provides intuitive, easy-to-use and attractive interfaces, greatly enhancing the interaction between users and digital products, and thus improving the accessibility and efficiency of information dissemination [11]-[14].

In this paper, firstly, based on CycleGAN network, the network parameter learning ability is enhanced by DO-Conv. The CA mechanism is utilized to strengthen the spatial feature focus, and an improved CDGAN model is designed. A “data-user collaboration” workflow is constructed to embed image generation technology into the whole cycle of visual communication design. Based on the research of technology suitability and hierarchical teaching needs, we explore the application path of AI-assisted design in visual communication professional scenarios. Combine quantitative experiments and subjective evaluation to verify the performance of the model, and track the differences in design thinking ability between the teaching experiment group and the control group.

II. Artificial Intelligence-driven Teaching Mode Design for Visual Communication Design Specialization

In the context of the deep reconstruction of the design field by artificial intelligence technology, the traditional teaching mode urgently needs to adapt to the paradigm change brought by intelligent tools. This study focuses on two core issues: first, how to improve the generation efficiency and quality of design resources by improving the generation model; and second, how to build a synergistic teaching mode of visual communication design and interaction design in order to cultivate design talents for the intelligent era.

II. A.CDGAN-based image generation model

In this paper, we propose a new image generation model based on CycleGAN network for model improvement and name it CDGAN.CDGAN introduces DO-Conv model on the basis of generator and discriminator of CycleGAN, which increases the number of learnable parameters of the model. The number of learnable parameters is a measure of the model's learning ability, and the increase in the number of parameters can improve the model's performance in terms of generalization ability, fitting ability, and convergence speed. In addition, the CDGAN model additionally introduces the coordinate attention mechanism CA in the generator, which makes the model pay more attention to the detailed features, thus enhancing the model's attention to the target region.

II. A. 1) DO-Conv

The nature of both neural networks and machine learning is to fit an equation with a large number of parameters, therefore, the number of learnable parameters in a neural network has a large impact on the accuracy of the model. Therefore, the number of learnable parameters in a neural network is important. Traditionally, if you want to use a parametric model to interpolate data, you need to ensure that the number of parameters is greater than the number of equations. The convolutional layer, as a core module of the neural network, extracts the desired image features based on the objective function through the convolution operation.The network structure of DO-Conv is shown in Fig. 1.Instead of the traditional convolutional layer, DO-Conv uses a new type of over-parameterized convolutional layer. The normal convolutional layer is essentially a linear operation and DO-Conv is a linear operation combining two convolutions. DO-Conv collapses the depth convolution in the inference phase, which requires only one linear operation like the traditional convolution, so the number of parameters at runtime is essentially the same. In other words, using DO-Conv does not add any computational cost to the original neural network.

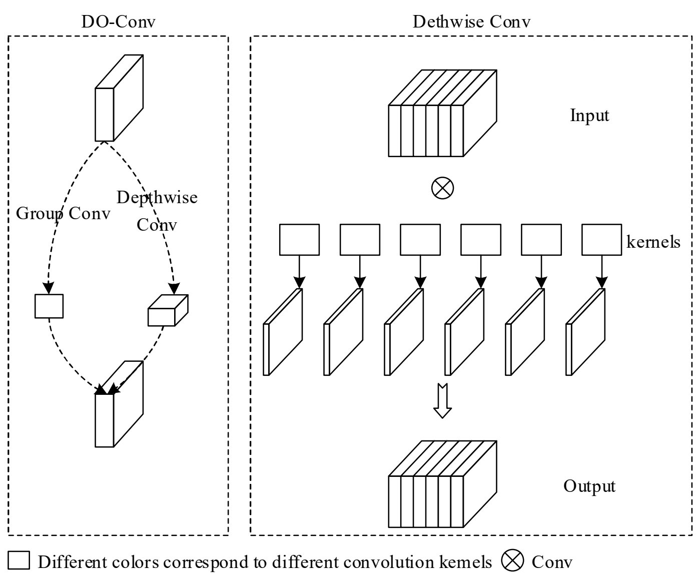

Figure 1: The network structure of DO-Conv

Since DO-Conv is a linear operation that combines two convolutional operations, the number of learnable parameters is higher than the traditional convolution, allowing the DO-Conv network to better fit the data distribution of the training data. DO-Conv is added to CycleGAN to increase the number of parameters that can be learned by the model, thus improving the quality of the generated images. For ease of description, assume that the input feature map is $x \in \mathrm{R}^{C\times H\times W}$, where C is the number of channels, and H and W are the height and width, respectively. The $x_{c,:,:}$ denotes the feature map of the c th channel of x.

In the deep convolution section, DO-Conv reduces the number of convolution kernels to the number of input channels by convolving each input channel separately. Specifically, let the size of the convolution kernel be $k \times k$ and the number of output channels be D, then the deep convolution is shown in Equation (1):

$$DepthConv(x) = \begin{bmatrix} Conv(x_{1,:,:}) \\ Conv(x_{2,:,:}) \\ \cdots \\ Conv(x_{c,:,:}) \end{bmatrix} \in R^{D \times H \times W} \tag{1}$$

where $Conv\left(x_{c,:,:}\right)$ denotes a convolution operation on $x_{c,:,:}$. The parametric quantity for deep convolution is $C \times K \times K \times D$.

In the general convolution part, DO-Conv divides each input channel into multiple groups, and each group is convolved independently, thus realizing the shared weights of the convolution kernel. Specifically, let the input channels be divided into G groups, and each group contains C/G channels, then the general convolution is shown in Equation (2):

$$GroupConv(x) = \begin{bmatrix} Conv\left(x_{\frac{C}{G}+1:\frac{2C}{G},:,:}\right) \\ Conv\left(x_{\frac{2C}{G}+1:\frac{3C}{G},:,:}\right) \\ \cdots \\ Conv\left(x_{\frac{(G-1)C}{G}+1:G\times\frac{C}{G},:,:}\right) \end{bmatrix} \in R^{D \times H \times W} \tag{2}$$

where $Conv(x_{1,k,:,:,:})$ denotes a convolution operation on $Xx_{1,k,:,:}$. The number of parameters for a general convolution is $K \times K \times C / G \times D$.

DO-Conv improves the network performance by employing convolution kernels of different sizes, thus increasing the network width without increasing the network depth. The performance and expressiveness of the DO-Conv network is improved by adding a deep convolution on top of the normal convolution to achieve the effect of speeding up the network training and convergence with more parameters, and the deep convolution does not change the number of channels in the feature map. Since DO-Conv uses irregular sampling, the size of the convolution kernel can be smaller, which reduces the model parameters and model size, speeds up model training, and also avoids model overfitting. Assuming that the input of the convolutional layer is x, the output is y, the size of the convolutional kernel is $k \times k$, the number of output channels is c_{out}, and the number of input channels is c_{in}, the depth over-parameterized convolution is as shown in Eq. (3):

$$DOConv(x, w) = \mathrm{Re}LU\left(BN\left(DepthConv\left(x, W_d\right)\right) \square\ W_g\right) \tag{3}$$

where W is the convolution kernel parameter in DO-Conv, W_d is the convolution kernel parameter in the depth convolution part, W_g is the convolution kernel parameter in the general convolution part, $\square$ denotes element-by-element multiplication, ReLU denotes ReLU activation function, BN denotes batch normalization operation, and $DepthConv$ denotes depth convolution operation , whose convolution kernel size is $k \times k$, the number of output channels is c_{out}, and the number of input channels is c_{in}.

Specifically, the convolution kernel size of the deep convolution part is 1×1, the convolution kernel size of the general convolution part is $k \times k$, and the general convolution part divides the input channels c_{in} into d groups, with the number of channels in each group being c_{in} / d, and a total of c_{out} output channels. In this way, DO-Conv can not only effectively improve the computational efficiency of the model through the combination of deep convolution and general convolution, but also ensure the expressive ability of the model.

II. A. 2) CA

In order to better capture the spatial features of the image, CA is additionally used in the generator network of CycleGAN, which aims to improve the ability of image generation, and the core idea is to use the coordinate information to model the feature map, and accordingly assign different weights to the features in different regions in order to enhance the model's focus on the target region, and the structure of the network after adopting CA is shown in Fig. 2.

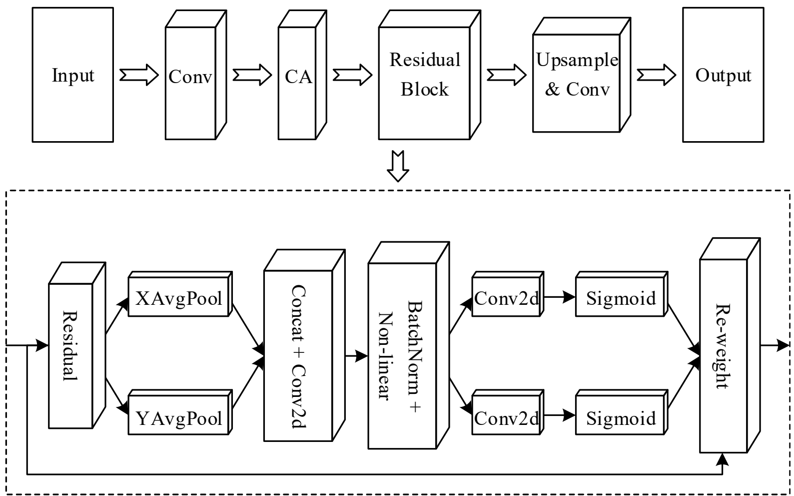

Figure 2: The network structure after adopting CA

Suppose the input features are $x \in \mathrm{R}^{H \times W \times C}$, where H, W, and C denote the height, width, and number of channels of the input feature map, respectively. Then the specific operation of CA attention mechanism network can be divided into the following two steps:

(1) Feature importance evaluation and weighting. First, for the input feature x, the average value in the horizontal and vertical directions is obtained by averaging the pooling operation in the direction of axis X and the direction of axis Y, respectively, to obtain two feature maps f_x and f_y of size $1 \times 1 \times C$. Then, these two feature maps are pooled to obtain a feature map f_{xy} of size $1 \times 1 \times 2C$ as shown in Equation (4):

$$f_{xy} = \left[f_x ; f_y \right] \in R^{1 \times 1 \times 2C} \tag{4}$$

Next, the feature map f_{xy} is mapped to a feature map f_s of size $1 \times 1 \times C / r$ by a convolution operation of 1×1, where r is a tunable parameter to control the degree of dimensionality reduction of feature importance. Then, the feature map f_s is passed through a $Sigmoid$ function that normalizes its value to the range $[0,1]$ to obtain a feature map f_a of size $1 \times 1 \times C / r$, as shown in Eq. (5):

$$f_a = Sigmoid\left(Conv_{1 \times 1}\left(f_{xy} \right) \right) \in R^{1 \times 1 \times \frac{C}{r}} \tag{5}$$

Finally, the input features are weighted by performing channel-by-channel multiplication of input feature x and feature map f_a to obtain the weighted x_{ca} as shown in Equation (6):

$$x_{ca} = x \otimes f_a \in \mathrm{R}^{H \times W \times C} \tag{6}$$

(2) Feature passing after weighting the importance of features. Importance-weighted feature passing is achieved by passing the weighted feature x_{ca} to the next module. This process is similar to feature passing in ordinary convolutional neural networks, using convolutional layers for feature transformation and nonlinear mapping by activation functions. Specifically, the weighted feature x_{ca} passes through a convolutional layer to obtain the output feature y, as shown in Equation (7):

$$y = Conv(x_{ca}) \in R^{H \times W \times C'} \tag{7}$$

where $Conv$ denotes the convolution operation and C' denotes the number of channels in the output of the convolution layer. The final output feature y is obtained after the CA operation.

The CA module enables the model to focus more on localized regions in the image and can weight specific regions based on the information of pixel positions, thus increasing the model's focus on different regions in the image. Doing so helps to extract detailed information about the image and enhance the model's representational capabilities.

II. B.High-frequency generation model with data-user collaboration

In this section, we bring these generative patterns into the regular visual design workflow, using the “data-user-driven” approach to build the workflow framework shown in Figure 3.

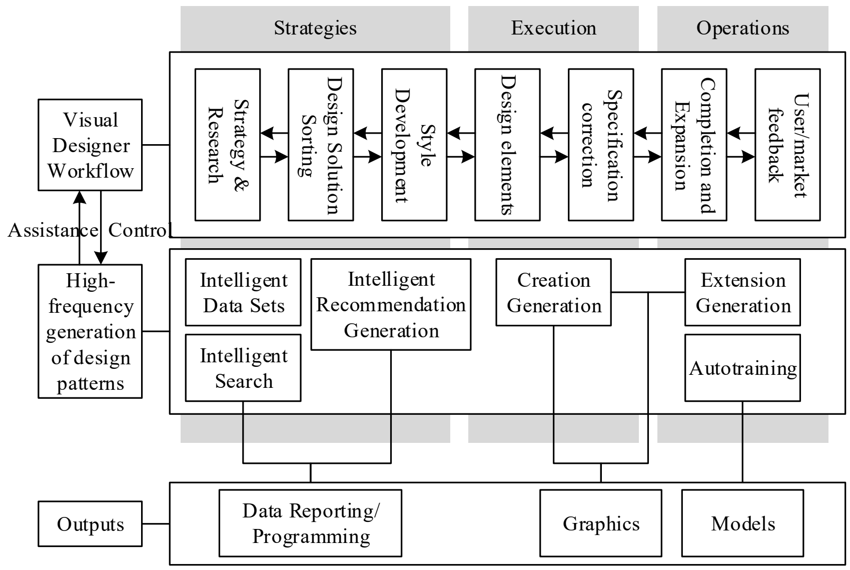

Figure 3: Data - Workflow under user collaboration

In this process, when visual communication students start the preliminary work, the generation mode can help students intelligently with data sets and data retrieval in the research session, and students can either rely entirely on the algorithm to collect data or manually conduct further screening. Upon entering the design solution combing session, the algorithm can recommend solutions through the retrieved data. In the middle of the process, during the design and creation session, the creation generation mode can perform intelligent image generation to support students with inspiration. In the latter part of the process, the extension generation mode can also output images to help students expand their mechanization, while students who need it can also use the autonomous training mode to conduct secondary training on existing models or customize training for their design needs, and output generated models.

In this process, students are still the main part of the design work, and the generative algorithms are involved in part of the visual design process in a controlled way to optimize the design process. Such a data-user collaborative visual identity design process is a complete systematic cyclical process, the screening of high-frequency generative models distributed in the conventional visual design process before, during and after the output of different forms of results, so if we need to improve the status quo of the visual identity design to achieve faster and higher-quality requirements, the use of one of the single intelligent production model to build a design platform is Far from enough, we need to integrate the entire design process, systematically improve every problematic link.

II. C.Application of image generation technology in teaching visual communication design majors

II. C. 1) Building a system of curriculum resources

Using artificial intelligence image generation technology to build a curriculum resource system for visual communication design majors, the first thing to be clear is that this technology should be used as a design aid, aiming to broaden students' design thinking, creativity, and cultivate their design ability in the future digital world. Therefore, the curriculum resource system can be constructed through the following aspects: (1) study students' acceptance of AI image generation technology, learning interest, practical application and market demand, so as to design the curriculum resources more precisely; (2) include AI image generation technology into the scope of the general education curriculum, carry out the AI courses in conjunction with the professional characteristics, and, according to the curriculum objectives and the students' actual needs, select the AI image generation technology suitable for talent cultivation programs, and incorporate new concepts, new technologies, and new cases into the course teaching; (3) set up the AI image generation technology course practice, so that students can use the technology in practice to carry out creative design, such as generating brand promotion poster design, IP image design, logo design, text design, illustration design, graphic creativity, and so on, in combination with the real projects, AIGC tournaments, and test the teaching effect and students' design skills through practice; (4) continuous optimization and improvement of course resources, building continuous iterative updating of course resources, ensuring the practicality and advancement of the course content, paying close attention to the latest development and application trends of AI image generation technology, optimizing the course content and technology selection in a timely manner, and providing regular student Teachers and industry experts to feedback and adopt the views of students, teachers and industry experts.

II. C. 2) Teaching content

In the teaching content design of visual communication design, teachers should firstly master the skills and knowledge required for AI image generation technology, and incorporate AI into teaching cases, such as trying AI applications with new perspectives, different expressions and different design styles under the same design theme. Similar to sketching in advertising design courses, text-to-image conversion, hand-drawn sketch-to-image conversion, image style migration and other functions can be used to demonstrate compositional approaches and color schemes, enabling students to quickly generate countless sketches of alternative design solutions. For graphic images, visual elements, scene diagrams, font design, etc., which require high image quality, teachers guide students to train on the generation tools or platforms, so as to accurately generate the image materials required for design to assist design. Due to the fact that students majoring in visual communication design are usually stratified, some students with strong design software application ability often fail to achieve ideal visual effects because of the lack of design thinking and expression ability; in the case of some students with insufficient hand-drawing and software application ability, AI is more necessary to assist the design. At present, the visual communication design profession involves interdisciplinary integration, combining image, sound, motion, light and shadow, immersive and other forms, resulting in most students are unable to master each field skillfully, especially different design software application capabilities, students are bound to have some shortcomings, AI happens to make up for the shortcomings, to help students to quickly generate the first draft of the design, to save the students in the pre-sketch conception and exploration of the time. So students can focus more on the details of the design and creative expression. The teacher guides students to revise and adjust the AI-generated drafts, improve the details, and add their personal creativity and style in the homework exercises after the class. Assisting design instruction in this way enables students to improve their design level in a more efficient learning process. However, at the same time, the design faces a key challenge of counterfactually proving whether the images and videos generated by inputting text and descriptions can actually fulfill the inputter's requirements and can accurately convey the user's intent, emotion, and semantic requirements in order to satisfy the user's expectations.

III. Research on the Application Effect of the Teaching Integration Mode of Visual Communication Design and Interaction Design

III. A. Validation of model validity

III. A. 1) Experimental environment

In order to validate the effectiveness of the CDGAN model, multiple sets of experiments will be conducted on NVIDIA Tesla P100-PCIE-16GB, 1.3285GHzmemory Clock Rate GPU hardware facility. The development language chosen for programming the experiments is Python, version number 3.6, and the code is written with the help of keras and tensorflow frameworks. Based on the improvement of CycleGAN, CycleGAN, DO-Conv-based CycleGAN, CA-based CycleGAN models are selected, and then DualGAN and WGAN-GP, the mainstream advanced models in the field of image generation, including CDGAN model, are introduced for a total of six models to be analyzed in the controlled experiments.

III. A. 2) Accuracy analysis

The BLEU score was used to evaluate the model accuracy, and the results of the comparison of the BLEU score and Loss convergence ability of the six models are shown in Figure 4. Compared with the original model CycleGAN, the Loss value of CDGAN model is reduced by 0.016 and the BLEU score is improved by 5.9%, which is the best performance among the 6 models.

III. A. 3) Quantitative analysis

In order to better evaluate and validate the effectiveness of the GUI image generation model, this paper introduces FID and 1-NNA as the evaluation indexes.FID measures the diversity and quality of the generated images relative to the real images, and 1-NNA is used to analyze the distributional difference between the two sample sets.The performance of FID is inconsistent in the number of different generated or real datasets, and the value will be infinitely close to 0 if FID is compared with the same set of real images. comparison, the value will be infinitely close to 0. The performance evaluation of 1-NNA is based on the classification accuracy, and the lower the classification accuracy, the smaller the difference between the generated samples and the real samples, and the higher the quality of the generated model.

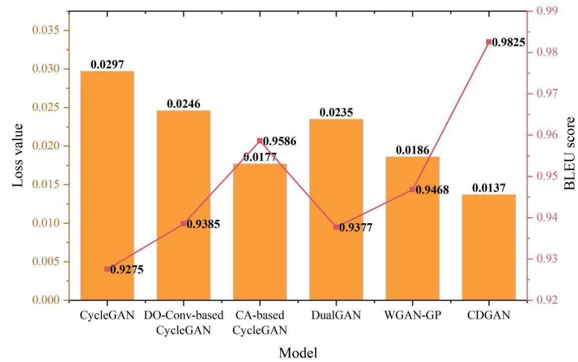

Figure 4: Comparison results of BLEU score and Loss convergence ability

Table 1: Model performance on different categorical datasets

		A1	A2	A3	A4	A5	Average
CycleGAN	FID	0.197	0.175	0.162	0.138	0.177	0.170
	1-NNA	0.993	0.975	0.982	0.918	0.964	0.966
DO-Conv-based CycleGAN	FID	0.167	0.108	0.115	0.126	0.113	0.126
	1-NNA	0.937	0.998	0.935	0.962	0.947	0.956
CA-based CycleGAN	FID	0.184	0.189	0.135	0.102	0.106	0.143
	1-NNA	0.922	0.914	0.928	0.921	0.933	0.924
DualGAN	FID	0.137	0.193	0.182	0.146	0.114	0.154
	1-NNA	0.927	0.935	0.928	0.931	0.912	0.927
WGAN-GP	FID	0.138	0.127	0.119	0.163	0.108	0.131
	1-NNA	0.932	0.893	0.906	0.925	0.934	0.918
CDGAN	FID	0.093	0.085	0.056	0.077	0.092	0.081
	1-NNA	0.818	0.827	0.795	0.772	0.836	0.810

Table 2: Model performance on different company datasets

		B1	B2	B3	B4	B5	Average
CycleGAN	FID	0.189	0.185	0.145	0.177	0.164	0.172
	1-NNA	0.963	0.975	0.997	0.993	0.966	0.979
DO-Conv-based CycleGAN	FID	0.126	0.164	0.125	0.118	0.105	0.128
	1-NNA	0.933	0.916	0.924	0.925	0.942	0.928
CA-based CycleGAN	FID	0.136	0.163	0.122	0.101	0.135	0.131
	1-NNA	0.929	0.934	0.938	0.914	0.945	0.932
DualGAN	FID	0.153	0.124	0.127	0.188	0.139	0.146
	1-NNA	0.936	0.975	0.951	0.935	0.966	0.953
WGAN-GP	FID	0.142	0.133	0.113	0.106	0.125	0.124
	1-NNA	0.974	0.826	0.945	0.853	0.918	0.903
CDGAN	FID	0.056	0.095	0.074	0.088	0.082	0.079
	1-NNA	0.856	0.824	0.808	0.821	0.785	0.819

Since students have a clear target category for visual communication design. As the categories of each field have their own characteristics, including news and information, book reading, e-commerce shopping, social communication, and travel and life (numbered A1~A5). This paper tests the modeling capability of this paper by preparing a separate dataset for the five most common application categories in the Rico dataset. In addition, it is considered that students will often refer to the design styles of large companies. Therefore, based on the Rico dataset, this paper collects graphic design images of the five most appearing company (numbered B1~B5) apps.

The performance of different models on the category dataset and company dataset are shown in Table 1 and Table 2, respectively. The results show that CDGAN model performs optimally on both FID and 1-NNA on category and company datasets. FID is reduced by 52.35% and 54.07% and 1-NNA is reduced by 16.15%, 16.34% over CycleGAN model on category and company datasets respectively.

III. A. 4) Subjective evaluation analysis

Human visual perception analysis was used for subjective evaluation, and in this experiment 25 generated images were selected from the data with the corresponding original images to compare the different performance of different models. Thirty graduate students in visual communication design were invited as professional evaluators to score these images under the comparison with the corresponding images. 6 methods were divided into 6 groups of images, and 30 subjects labeled 25 images in each group each time. In order to ensure the accuracy of the image quality, the subjects of the six groups of images by virtue of visual perception assessment, each group of image quality evaluation is divided into three indicators: image (color) clarity (analysis of the color distribution of color is uniform), color vividness (analysis of the saturation of color is not bright), the overall degree of harmony (analysis of the color and the graphic structure of the harmony of the collocation or not). The scoring is labeled using a five-point scale, and each index is able to obtain 750 scores to find its average, and finally compare the average of the three indexes of the six groups of images.

The visualization results of the subjective evaluation indexes of the images generated by different methods are shown in Fig. 5, which clearly show the size of the three indexes of clarity, vividness and harmony, and the scores of the indexes of clarity, vividness and harmony of the images generated by the CDGAN model are 3.297, 3.286, and 3.278 respectively, which are obvious advantages compared with other methods, indicating that the images generated by using the CDGAN model are in line with the user's appreciation level, and are in line with the user's appreciation level in visual communication. It shows that the images generated by using CDGAN model meet the user's appreciation level and have feasibility and applicability in the field of visual communication design.

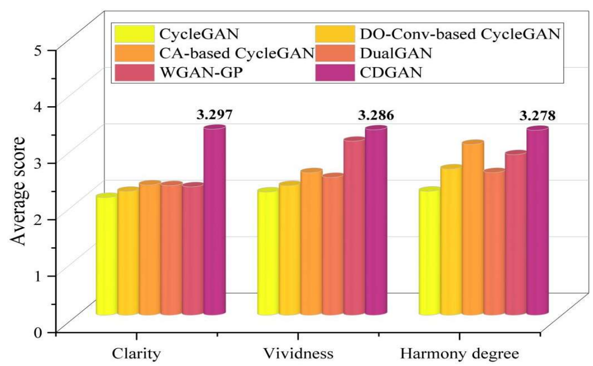

Figure 5: Subjective evaluation indicators of different models

III. B. Analysis of Teaching Effectiveness

III. B. 1) Experimental design

In order to test the teaching effect of the teaching integration mode of visual communication design and interaction design constructed in this paper, college students majoring in visual communication in college A were selected as the research subjects. In order to ensure that the test results of the experimental subjects are scientific, the students of each class of visual communication in college A were first tested through the design thinking test, and the visual communication design class 3 and visual communication design class 5, in which there is no difference in the results, were selected as experimental subjects, and the visual communication design class 3 was selected as the experimental group, with the number of 50 people in the class, and the visual communication design class 5 was selected as the control group, with the number of 49 people in the class. In order to exclude the interference of the teacher factor, the two selected classes were taught by the same teacher.

The Drawing Creative Thinking Test was chosen to test the experimental subjects, and the Design Thinking Test for College Students Majoring in Visual Communication was designed with the characteristics of visual communication. The quiz was designed in terms of constructing drawings, completing drawings, and parallel line strips, with each question taking 3 minutes, and scored in terms of fluency, variability, uniqueness, and delicacy.

The experimental group adopts the teaching mode constructed in this paper in visual communication teaching, and then conducts the design thinking test for visual communication college students after passing one semester of teaching. The control group adopts the conventional teaching training in visual communication teaching, and takes the design thinking test of visual communication college students after one semester of teaching. In order to ensure the representativeness of the scoring results, six teachers majoring in visual communication, six teachers majoring in psychology and three teachers majoring in other fields were selected to participate in scoring, and their average scores were taken as the scores of each dimension.

III. B. 2) Analysis of experimental results

(1) Differential analysis of the experimental pre-test between the control group and the experimental group

The experimental group and the control group were pre-tested on the innovative thinking test for college students majoring in visual communication, and SPSS19 was applied to analyze the test data in terms of the four dimensions of fluency, adaptability, uniqueness, and sophistication, as well as the overall situation of design thinking by t-test, and the difference analysis between the experimental group and the control group is shown in Table 3. There is no significant difference between the experimental group and the control group in the four dimensions of fluency, adaptability, uniqueness and sophistication of design thinking as well as the overall design thinking (P>0.05), which can be seen that there is no significant difference between the experimental group and the control group, and the conclusions of the experiment are of reference value under the exclusion of disturbing factors such as differences in teacher's teaching and students' individual differences.

Table 3: Pre-test difference analysis of the experiment

Dimension	Experimental group(M±SD)	Control group(M±SD)	t	Sig.(Double Tail)
Fluency	18.43±2.058	18.29±2.117	0.497	0.329
Variability	18.22±2.183	18.95±2.084	-0.832	0.276
Uniqueness	19.19±2.295	19.24±2.183	-0.388	0.197
Refinement	20.11±2.038	21.48±2.055	-1.086	0.288
Design thinking	75.95±6.033	77.96±5.927	-1.397	0.329

(2) Analysis of the differences between the experimental group's pre-test and post-test

Through the pre-test and one-semester post-test of the innovative thinking test for visual communication college students in the experimental group, SPSS19 was applied to analyze the test data from the four dimensions of fluency, adaptability, uniqueness and sophistication, as well as the overall situation of design thinking by T-test, and the difference analysis between the pre-test and post-test of the experimental group is shown in Table 4. There is no significant difference between the pre-test data and post-test data of the experimental group in terms of fluency of design thinking (P>0.05), and there is a significant difference in the three dimensions of adaptability, uniqueness and delicacy of design thinking and the cultivation of design thinking ability (P<0.05), and the post-test scores of each dimension have increased by about 2 points compared with the pre-test scores, and the design thinking ability has reached 87.42±4.286 points. It can be seen that the use of the teaching model constructed in this paper has a significant effect on the cultivation of college students' design thinking ability.

Table 4: Difference analysis of pre-test and post-test in the experimental group

Dimension	Experimental group pretest(M±SD)	Experimental group Posttest(M±SD)	t	Sig.(Double Tail)
Fluency	18.43±2.058	20.85±1.264	-1.396	0.093
Variability	18.22±2.183	20.93±2.137	-1.527	0.004
Uniqueness	19.19±2.295	22.58±1.973	-2.496	0.012
Refinement	20.11±2.038	23.06±1.389	-1.063	0.015
Design thinking	75.95±6.033	87.42±4.286	-4.664	0.003

(3) Analysis of differences between the pre-test and post-test of the control group experiment

By taking the pre-test and one semester post-test of the design thinking test of the visual communication college students in the control group, and applying SPSS19 to analyze the test data from the four dimensions of fluency, adaptability, uniqueness, and delicacy as well as the overall situation of design thinking with T-test, the analysis of differences between the pre-test and post-test of the control group is shown in Table 5. There is no significant difference between the control group in the four dimensions of fluency, adaptability, uniqueness and delicacy of innovative thinking and the cultivation of design thinking ability (P>0.05), which shows that it is difficult to effectively improve the design thinking ability of the students in the practice of visual communication education for the intelligent era by adopting the traditional mode for teaching.

Table 5: Difference analysis of pre-test and post-test in the control group

Dimension	Control group pretest(M±SD)	Control group Posttest(M±SD)	t	Sig.(Double Tail)
Fluency	18.29±2.117	18.63±2.535	-0.635	0.246
Variability	18.95±2.084	19.58±2.232	-1.022	0.725
Uniqueness	19.24±2.183	18.62±2.047	0.644	0.567
Refinement	21.48±2.055	20.96±2.183	0.386	0.422
Design thinking	77.96±5.927	77.79±4.645	0.227	0.853

To summarize, the conventional visual communication teaching method has been unable to meet the needs of college students' design thinking ability cultivation, and the teaching mode constructed in this paper has feasibility and practical value in cultivating college students' innovative thinking.

IV. Conclusion

This paper validates the effectiveness of the CDGAN image generation model and the data-user collaboration model in visual communication education through a two-way linkage between technological innovation and teaching practice.

Compared with the original model CycleGAN, the CDGAN model Loss value is reduced by 0.016, the BLEU score is improved by 5.9%, and it has the best performance among six models.The CDGAN model has the best performance in both FID and 1-NNA in both category and company datasets, and the FID in the category and company datasets is reduced than the CycleGAN model by 52.35% and 54.07% and 1-NNA by 16.15% and 16.34%, respectively. On subjective evaluation, the scores of image clarity, vividness and harmony indexes of CDGAN model are 3.297, 3.286 and 3.278, respectively, which have obvious advantages compared with other methods, indicating that the images generated by using CDGAN model are in line with the user's appreciation level, and have feasibility and applicability in the field of visual communication design.

The results of the pre-test and post-test of the teaching experiment show that there is no significant difference between the pre-test data and post-test data of the experimental group in the fluency of design thinking ($P>0.05$), and there is a significant difference between the three dimensions of adaptability, uniqueness and sophistication of design thinking and the cultivation of the ability of design thinking ($P<0.05$), and the performance of the post-test of each dimension is improved by about 2 points compared with the pre-test, and the ability of design thinking reaches 87.42±4.286 points. It can be seen that the use of the teaching mode constructed in this paper has a significant effect on the cultivation of college students' design thinking ability. There is no significant difference between the control group in the four dimensions of fluency, adaptability, uniqueness and delicacy of innovative thinking and the cultivation of design thinking ability ($P>0.05$), which shows that it is difficult to effectively improve the design thinking ability of students in the practice of visual communication education for the intelligent era by adopting the traditional mode of teaching.

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