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AIGC helps traditional cultural and creative industries with their digital transformation risks and challenges

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Abstract Artificial intelligence-generated content (AICG) is increasingly being applied in the cultural and creative industries. This paper focuses on the application of AICG in enhancing the diversity of generated content and reducing the risk of plagiarism. To control image generation attributes, a generative adversarial network (StyleGAN) with a style transfer module was designed to improve the training effectiveness of the model. Modules such as improved modulation and demodulation, and a jump-based structure were incorporated to construct the StyleGAN2 network, optimizing the detail of generated images. The K-means algorithm is used to perform optimal style clustering of the generated images. Research shows that when the truncation point number of the StyleGAN2 network is set to 10, the FID value ranges from 4.312 to 4.653. The highest score for generated images reaches 9.027, with a modification rate not exceeding 1%. The generated images are clustered into five categories, with contour coefficients ranging from [0.0, 1.0].

Index Terms AICG, style transfer, StyleGAN2, K-means clustering, cultural and creative industry

I. Introduction

As the Fourth Industrial Revolution advances rapidly, the exponential growth of information is driving the transition from informatization to intelligence [1], [2]. Artificial Intelligence Generated Content (AIGC) has become an increasingly important field, closely integrated with art design and creative industries, showcasing trends toward diversified creative themes and mass participation, and offering new possibilities for the inheritance and innovation of traditional culture [3]-[6].

Traditional cultural and creative products, as a unique form of commodity and cultural creativity, carry rich commercial, cultural, and artistic value [7], [8]. Traditional cultural and creative design methods suffer from issues such as limited subject diversity, insufficient depth of content, inadequate participation of stakeholders, and unclear understanding of user needs [9], [10]. The emergence of AIGC technology has not only introduced new tools and methodologies to the traditional cultural creative sector but has also driven the reconstruction of traditional design processes, thereby leading the field through an unprecedented digital transformation and innovative iteration [11]-[13]. AIGC not only serves as a generative tool for traditional cultural content but also as an auxiliary method to enhance the creative capabilities of the cultural and creative industry, significantly improving design production efficiency while reducing design production costs [14]-[16]. In the digital transformation of the cultural and creative industry, the core objective is to utilize high-tech means to undertake or enhance traditional manual and cognitive tasks [17], [18]. In the digital design process of traditional culture, it is not only necessary to achieve precise data mapping and the construction of digital twins but also to stimulate and preserve creative thinking [19], [20]. AIGC plays a crucial role in this process, not only as an auxiliary tool to help designers expand their thinking but also to enhance designers' creativity to some extent, bringing new opportunities for iteration and optimization to design works [21]-[23]. However, in the digital transformation of the traditional cultural and creative industry with the help of AIGC, there are many risks and challenges, mainly in terms of copyright disputes, weakening of creative subjectivity, cultural value and ethical risks, technical and implementation barriers, and insufficient system compatibility [24]-[27].

Literature [28] outlines the changes brought about by the digital transformation of the cultural and creative industries, noting that these changes are gradually becoming the industry norm, thereby prompting cultural and creative organizations to re-evaluate traditional business models. Literature [29] examines how the cultural and creative industries (CCIs) innovate by combining digital technology, creative input, and labor diversity, emphasizing that enhancing diversity faces significant challenges in the context of developing countries. Literature [30] discusses the impact of digitalization on the cultural and creative industries, emphasizing that cultural managers need to address and manage digital transformation issues as they enter a more vibrant era of artistic and creative production and consumption. Literature [31] describes the definition, evolution, and key attributes of digital transformation in the creative and cultural industries, analyzing the impact of digital platforms, data analysis, and personalized experiences on optimizing operations and enhancing customer engagement. It highlights the potential and complexity of digital technology in reshaping the cultural and creative industries. Literature [32] aims to establish a comprehensive model for the sustainable development of Iran's creative industries through digital transformation and an explanatory structural model, revealing that the prerequisite for the sustainable development of creative industries is the development of digital infrastructure, including digital communication and information security. Literature [33] aims to provide discussions on the role of new technologies and innovation for the cultural and creative sector. The first objective is to understand the new dynamics brought about by digital transformation and its impact on the cultural and creative industries and institutions. The second objective is to identify the challenges faced in developing cultural and creative industries in the digital age. Literature [34] aims to identify the issues raised by scholars in tracking the digital transformation of traditional cultural and creative industries, focusing on key points such as power dynamics and ownership discourse, and proposes the impact of this topic on industry stakeholders. Literature [35] discusses the transformation of cultural and creative industry work related to generative artificial intelligence, providing an empirical method to analyze direct and indirect exposure to generative artificial intelligence and its associated risks, revealing that the use of generative artificial intelligence in work requires a certain level of risk management capability.

This paper leverages the intelligent and digital advantages of AICG technology in traditional cultural and creative industries, utilizing the StyleGAN2 network and K-means clustering algorithm to reconstruct traditional aesthetic expression methods. Conditional constraint information is introduced into the generator and discriminator to construct a generative adversarial network architecture (cGAN) and continuously iterate and update it. To achieve diverse image styles and reduce risks such as copyright infringement and ethical misconduct, multiple mappings and syntheses are performed to enhance the style transfer capabilities of the StyleGAN network. To address the limitations of the StyleGAN network in handling detailed deformations, components such as the normalization module and progressive growth structure are replaced to reduce image overfitting. By combining K-means clustering to quantify content homogenization risks and naming image styles, this approach provides a classification reference for creating digital IP in the traditional cultural and creative industry.

II. Analysis of the principles and application concepts of AICG technology

II. A. Application of AICG in content creation in the cultural and creative industries

II. A. 1) Intelligent Creative Design

The intelligent design of creative content is the most direct manifestation of AICG technology in the creation of cultural and creative content. Intelligent design tools are emerging rapidly, leveraging advanced AI algorithms to automatically analyze design trends, color schemes, and graphic compositions, providing users with intelligent design recommendations. AI can also assist in creative ideation and inspiration through deep learning, analyzing vast amounts of design cases and creative materials to provide creators with creative insights, making the creation process more efficient and innovative.

II. A. 2) Digitalization of Content Production

AICG technology also plays a crucial role in the content production process. The introduction of digital workflows has enabled high levels of automation and integration across the entire production process, from concept development, scriptwriting, filming, and post-production editing. By establishing a unified digital platform, project teams can share resources in real time and collaborate seamlessly, significantly enhancing production efficiency and teamwork capabilities. Additionally, the widespread adoption of efficient collaborative creation platforms, such as online collaboration tools and project management software, enables cross-regional and cross-time zone creative teams to seamlessly coordinate and jointly advance the smooth progression of projects. These digital tools not only streamline production processes but also ensure the stability and high quality of outputs.

II. B. StyleGAN-related technologies

II. B. 1) Generative Adversarial Networks

Generative adversarial networks utilize the zero-sum game concept from game theory. The network model consists of two major modules: a generator and a discriminator. The generator is responsible for forging data, while the discriminator is responsible for distinguishing between real data and forged data. The goal of the generator is to generate data that the discriminator cannot distinguish as real or fake, while the goal of the discriminator is to accurately distinguish between real data and data forged by the generator. During training, the generator and discriminator are alternately optimized to achieve the optimal state of the entire model. The objective function of the generative adversarial network is shown in Equation (1):

$$\min_G \max_D V(D,G) = E_{x\sim p_{data}(x)}\left[\log D(x)\right] + E_{z\sim p_z}\left[\log\left(1-D(G(z))\right)\right] \tag{1}$$

Among these, x represents the real image, $p_{data}(x)$ represents the distribution of the real image, $D(x)$ represents the discriminator's prediction score for the real image, z represents the random noise input to the generator, p_z represents the distribution of the noise, and $G(z)$ represents the image generated by the generator from the noise. Traditional generative adversarial networks (GANs) use only random noise as input, making it impossible to control the attributes of the generated images. To overcome this limitation, many methods have been developed to improve upon this approach.

Conditional Generative Adversarial Networks (cGAN) introduce conditional information into the generator and discriminator of the generative adversarial network to guide model training. Figure 1 shows the model structure. In cGAN, the discriminator not only needs to determine whether an image is real but also whether the generated image matches the additional input constraints. The objective function of cGAN is shown in Equation (2):

$$\min_G \max_D V(D,G) = E_{x\sim p_{data}(x|y)}\left[\log D(x)\right] + E_{z\sim p_z}\left[\log\left(1-D(G(z\mid y))\right)\right] \tag{2}$$

Compared with the objective function of traditional generative adversarial networks, condition y is added. The trained cGAN can generate images that meet the condition information according to the input condition.

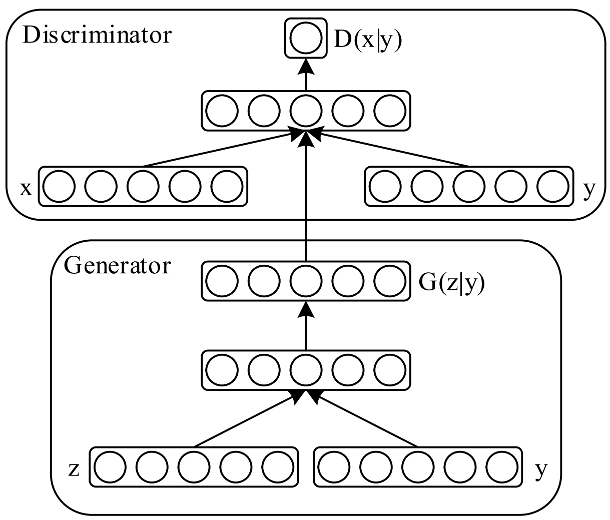

Figure 1: cGAN network structure

Building upon cGAN, this method utilizes paired image data to train the generative network based on pixel similarity and adversarial loss. CycleGAN overcomes the former's rigid requirement for paired data by employing a cycle consistency loss to maintain key attribute consistency between input and output images. However, these methods can only achieve transformation between the source domain and target domain, making it difficult to control multiple attributes. StarGAN introduces an auxiliary classifier on top of the discriminator and adds a domain classification loss, overcoming the dual-domain limitation and allowing multiple datasets from different domains to be trained simultaneously within a single network. Its generator uses domain labels as additional inputs and maps images to the corresponding domains. However, this model learns deterministic mappings from the source domain to each target domain, resulting in a lack of diversity in the generated outputs. Building on StarGAN, domain-adapted style latent codes replace domain labels, and a mapping network and style encoder are introduced to achieve diverse generated images. However, this method can only control generation at the domain level, resulting in severe attribute entanglement and difficulty in precisely controlling finer attributes.

II. B. 2) StyleGAN Network Architecture

StyleGAN builds upon the concept of style transfer in generative adversarial networks (GANs) to design a new generator architecture. Figure 2 illustrates the StyleGAN network architecture. The StyleGAN generator consists of two components: a mapping network and a synthesis network. Unlike traditional GANs, which directly feed noise into the first layer of the generator, StyleGAN first maps the noise into a latent space via the mapping network, then inputs the resulting latent vectors into the synthesis network. The synthesis network consists of multiple synthesis modules. In each synthesis module, the latent vector is transformed into a style vector via an affine transformation layer, followed by scaling and bias addition on the feature map using adaptive instance normalization (AdaIN). This network model not only generates highly realistic images but also possesses latent vectors in its latent space with excellent property disentanglement potential, enabling intuitive property control through interpolation or concatenation of latent vectors.

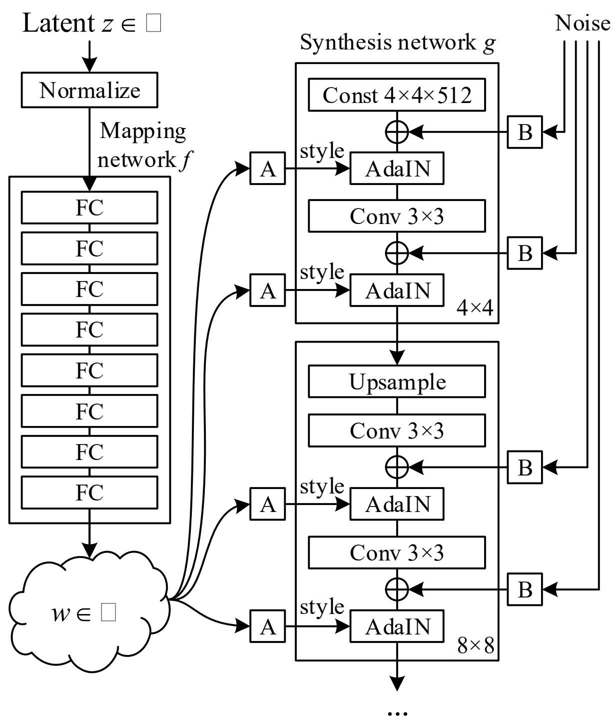

Figure 2: StyleGAN Network Architecture

StyleGAN2 pointed out that StyleGAN generates images with teardrop-shaped defects and facial features that do not change direction with the face. To solve these problems, StyleGAN2 first modified the AdaIN part of StyleGAN, replacing normalization with modulation and demodulation modules. It then compared and analyzed the effects of different network architectures on the generator and discriminator on the generation results. Based on the results of the comparative experiments, StyleGAN2 changed the network structure of the generator from a progressive growth structure to a jump structure, and changed the network structure of the discriminator from a progressive growth structure to a residual structure.

Based on the bCR method, adaptive overfitting image enhancement was added to StyleGAN2. The expected value of the discriminator's output when using training set images as input was used as an indicator of the degree of overfitting. Based on this indicator, the probability p for data enhancement was determined, overcoming the need for a large-scale dataset and enabling the generation of high-quality facial images even when trained with a smaller dataset.

II. C.K-means clustering analysis method

Cluster analysis (CA), in simple terms, involves dividing a group of unordered samples into different categories based on certain rules, such that the samples within each category are as similar as possible, while the samples between different categories are as dissimilar as possible. The K-means clustering method is used to divide data based on the intrinsic similarity of the data. The creation of style group profiles is based on cluster analysis methods, which group individual samples with similar consumption behavior characteristics into the same cluster. This ensures that the similarity among data objects within a cluster is high, while the distance between each data object and the cluster's center (the mean of all sample points in the cluster) is minimized, and the similarity between clusters is kept as low as possible.

For the data object set $A=\{x_1,x_2,...,x_m\}$ containing m data entry, first divide the data objects in A into k groups, denoted as $G=\{G_1,G_2,...,G_p,...,G_k\}$, with their cluster centers denoted as $\lambda=\{\lambda_1,\lambda_2,...,\lambda_p,...,\lambda_k\}$; the number of data objects in each cluster is denoted as $n=\{n_1,n_2,...,n_p,...,n_k\}$ and $p\in[1,k]$. Use Euclidean distance to calculate the distance between each data object and the center of its initial cluster $d(x_k,\lambda_k)$, then reclassify the data objects into groups by assigning them to the cluster with the smallest distance. Repeat this process of recalculating and reclassifying until the value of k reaches an optimal level. K-means clustering typically uses methods such as the elbow method or the silhouette coefficient from clustering evaluation metrics to assess the effectiveness of cluster partitioning. The partitioning process for A concludes when the cluster centers no longer change and the classification status of each data object stabilizes, at which point k achieves its optimal value. Specific tools for evaluating clustering effectiveness include the silhouette coefficient (SC), sum of squared errors (SSE), and DB index (DBI), among others.

The silhouette coefficient is generally used to evaluate the quality of clustering results in scenarios where the category information of the classification is unknown. The silhouette coefficient SC is defined as shown in Equation (3).

$$SC(x_p)=\frac{b(x_p)-a(x_p)}{\max\left(a(x_p),b(x_p)\right)} \tag{3}$$

$a(x_p)$ represents the data object. x_p is the average distance from the data object to other data objects within its cluster. If $a(x_p)$ is high, it indicates that the similarity of samples within the cluster is low. Calculate x_p as the average distance from the data object to all data objects in the nearest cluster, and set it as $b(x_p)$ to measure the dissimilarity between samples in different clusters, i.e., the separation degree. $d(x_p,x_q)$ represents the distance between data objects x_p and x_q. The formulas for calculating $a(x_p)$ and $b(x_p)$ are shown in Equations (4) and (5), respectively. Together, they yield the silhouette coefficient SC.

$$a(x_p)=\frac{1}{|n_p|-1}\sum\nolimits_{x_q,x_p\in G_p,q\neq p} d\left(x_p,x_q\right) \tag{4}$$

$$b(x_p)=\min_{q\neq p}\frac{1}{|n_q|}\sum\nolimits_{x_p\in G_p,x_q\in G_q} d\left(x_p,x_q\right) \tag{5}$$

The value of the contour coefficient falls between 1 and $[-1.0,1.0]$. The closer the value is to 1.0, the higher the similarity within clusters, the greater the distance between clusters, and the clearer and better the clustering effect. If the contour coefficient equals 0.0, it indicates cluster overlap; a value below 0.0 indicates poor clustering performance.

The sum of squared errors (SSE) and the silhouette coefficient (SC) are both methods used to evaluate clustering effectiveness. They are expressed as the sum of the squares of the distances between each data sample and the center of its assigned cluster in the clustering results. The sum of squared errors is the core metric for evaluating clustering effectiveness using the elbow rule. As the k-value increases, the fineness of data sample partitioning and the level of intra-cluster aggregation increase, while the sum of squared errors decreases. When the current k value is less than the optimal number of clusters, each unit increase in the k value significantly increases the internal aggregation level of the clusters and reduces the level of the sum of squared errors; conversely, the effect of increased aggregation diminishes rapidly, and the decrease in the sum of squared errors also significantly reduces. The smaller the value of the sum of squared errors, the better the clustering performance. Its calculation formula is shown in Equation (6).

$$SSE=\sum\nolimits_{i=1}^{k}\sum\nolimits_{x_i\in G_i}\left|d(x_i,\lambda_i)\right|^2 \tag{6}$$

III. Application of AICG in the digital transformation of cultural and creative industries

III. A. StyleGAN2 Network Parameter Settings and Performance Evaluation

III. A. 1) Determining the optimal number of truncation points

Taking the example of creating a purple sand IP in the traditional cultural and creative industry, AI-generated graphics (AIG) technology is used to convert the traditional purple sand production process into digital images, and various types of cultural products are designed based on these purple sand images. A dataset containing images and text of the original traditional purple sand production process is constructed, and the StyleGAN2 network described in this paper is used for feature learning and image generation. Table 1 shows the performance results of the StyleGAN2 network in feature learning and image generation when different cutoff points are set. Overall, as the number of cutoff points increases, the StyleGAN2 network achieves higher accuracy and recall rates, shorter path lengths, better image quality, and greater diversity (FID), indicating improved model training performance. Since the StyleGAN2 network achieves an accuracy of 0.824, a recall rate of 0.725, an FID of 2.096, and a path length of 118.020 when the number of truncation points is set to 10, resulting in the optimal performance, this paper sets the number of truncation points for the StyleGAN2 network during feature learning and image generation to 10.

Table 1: Experimental results of StyleGAN2 at different cut-off points

Number of truncation points	Precision	Recall	FID	Path length
2	0.698	0.606	3.094	119.463
4	0.713	0.647	3.002	119.018
6	0.746	0.693	2.951	118.942
8	0.795	0.701	2.344	118.431
10	0.824	0.725	2.096	118.020

III. A. 2) Performance Comparison of Different Models

To determine the advantages of the optimized StyleGAN2 network in generating images with text, we selected different numbers of training samples and trained and compared the performance of the generative adversarial networks before and after optimization. Table 2 shows the comparison results between StyleGAN2 and different image generation models. Among different numbers of training samples, the FID values of the StyleGAN2 network ranged from [4.312, 4.653], always being the lowest. Unlike the pre-optimized model, whose FID values fluctuated with the number of samples, the StyleGAN2 network's FID values remained consistently around 4, with fluctuations not exceeding 0.7, indicating more stable image quality and diversity. In terms of training time, the StyleGAN2 network took between 128 and 162 seconds, significantly less than the pre-optimized model, demonstrating faster text-based image generation speed.

Table 2: Comparison of image generation models

Serial number	Method	Number of training samples	Number of iterations	FID	Time (s)
1	GAN	800	1600	6.893	375
2	GAN	1600	3200	7.046	499
3	GAN	900	1600	6.941	381
4	GAN	1800	3200	7.925	502
5	StyleGAN	800	1600	5.872	276
6	StyleGAN	1600	3200	6.451	293
7	StyleGAN	900	1600	5.933	281
8	StyleGAN	1800	3200	6.095	300
9	StyleGAN2	800	1600	4.206	128
10	StyleGAN2	1600	3200	4.537	156
11	StyleGAN2	900	1600	4.312	130
12	StyleGAN2	1800	3200	4.653	162

III. B. Training the StyleGAN2 Network Based on Style Transfer

III. B. 1) First training of StyleGAN2 networks with different content types

The creation of a digital IP for purple clay cultural and creative products requires that related cultural and creative products be made as appealing as possible to a diverse audience. This means that when using AICG technology to generate text, images, and other content, the diversity of styles in the generated digital content must be ensured. Therefore, this paper selects volunteers representing different types of audiences from the traditional purple clay digital IP target audience and trains the StyleGAN2 network selectively according to their preferred cultural and creative styles to improve the model's stylistic diversity. Table 3 shows the first training data for volunteers with different styles. The 12 volunteers were divided into three groups based on age, preferred style, and number of cultural and creative product purchases, ensuring that each group had volunteers with complex aesthetic preferences. The final scores for the text-based images generated by training the StyleGAN2 network ranged from 6 to 8 points, with the lowest score being 6.095 and the highest being 7.352, all of which were below 7.5 points. In terms of image generation modification rates, each volunteer's modification rate exceeded the standard value of 1.000%, with the highest reaching 2.907%, indicating a relatively high modification rate. This suggests that volunteers of different types tended to use images of their preferred styles as training samples during the training of the StyleGAN2 network, resulting in a high degree of similarity among the generated images. Due to the high similarity, there is a risk of plagiarism, necessitating further improvements in the diversity of image styles.

Table 3: The first training data of volunteers of different styles

Age	Group	Like style	Number of purchases of cultural and creative products	Generate image scoring (out of 10 points)	Modification rate (%)
15	Group A	Simple and elegant	16	6.684	1.342
21		Elaborate and magnificent	28	6.095	1.653
25		Bright and exquisite	40	6.723	1.980
30		Luxurious and meticulously crafted	32	6.269	1.564
15	Group B	Elaborate and magnificent	19	7.106	2.093
21		Luxurious and meticulously crafted	31	7.237	2.167
25		Simple and elegant	46	7.352	1.353
30		Bright and exquisite	37	7.018	1.672
15	Group C	Bright and exquisite	16	6.934	1.385
21		Luxurious and meticulously crafted	27	7.252	1.582
25		Bright and exquisite	39	6.846	1.609
30		Simple and elegant	35	6.431	2.907

III. B. 2) Second training of StyleGAN2 networks with different content types

Based on the scoring results, a detailed analysis of the generated images was conducted, and feedback or suggestions from volunteers and experts were collected to adjust and improve the training model strategy, followed by a second round of training for the StyleGAN2 network. Figure 3 shows the scoring and modification rates of the generated images after the second round of training by 12 volunteers. After adjusting the training strategy, the scoring of the generated images improved to a range of 7.186–9.027 points, with the lowest score exceeding 7 points and the highest score exceeding 9 points. Compared to the first training, there was an improvement of approximately 1 point. The modification rate range decreased to [0.216, 0.933]%, with none exceeding 1%, representing a significant decrease. This indicates that in the second training, the quality and diversity of the generated images were significantly improved, largely meeting the preferences of the target audience for the purple clay cultural and creative IP.

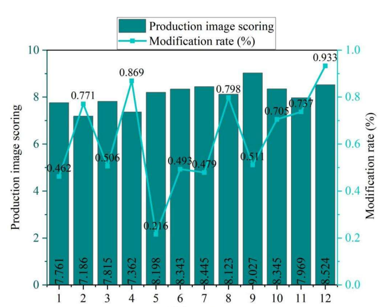

Figure 3: Score and modification rate of generated images aftery training 2

III. C. Generating image style clustering based on K-means

III. C. 1) Generating initial clustering results for images

Perform cluster analysis on the digital images of purple clay cultural and creative IP generated after the second model training by volunteers. Figure 4 shows the initial clustering results. The initial clustering divides the generated images into four categories, roughly aligned with the style preferences of the 12 volunteers. The contour coefficients are mostly below 0, with few images exceeding 0.5, indicating that the four-category clustering based on volunteer preferences is ineffective. The reason may be that after the second training, the training samples were subjected to multi-style fusion, resulting in more diverse styles in the generated images.

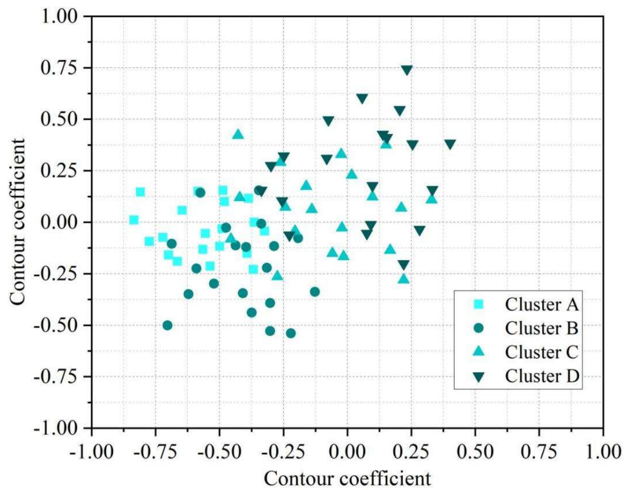

Figure 4: Initial clustering results

III. C. 2) Analysis of final clustering results

The K-means algorithm was used to perform 5-class and 6-class clustering on the generated images. Figure 5 shows the results of 5-class clustering. Figure 6 shows the results of 6-class clustering. When clustering into 5 categories, the contour coefficients of the generated images are all between 0.0 and 1.0, with small differences within clusters and large differences between clusters. When clustering into 6 categories, the contour coefficients of the generated images are between [-0.75, 0.75], and overall, the clustering results are not as good as when clustering into 5 categories. Therefore, the generated images are divided into 5 categories based on different styles.

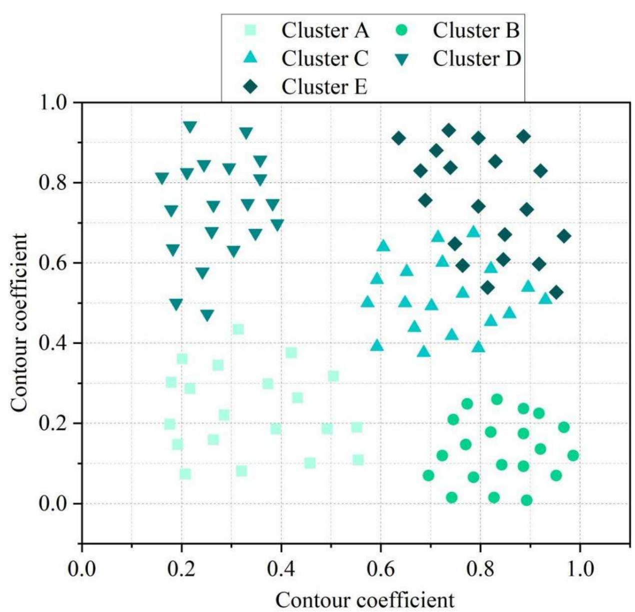

Figure 5: The contour coefficient results clustered into 5 categories

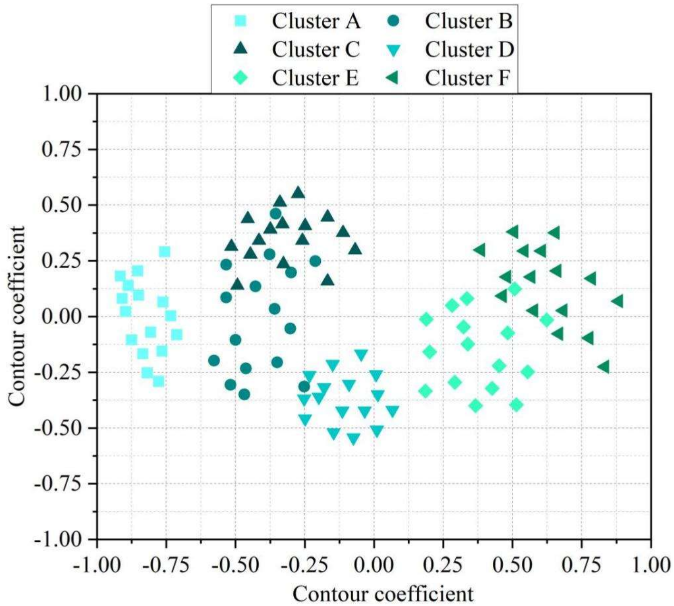

Figure 6: The contour coefficient results clustered into 6 categories

III. C. 3) Cultural and creative consumer needs met by different clusters

Table 4 shows the style preferences of cultural and creative consumers met by the five categories of images. Based on the level of satisfaction with each preference, the categories of images were named accordingly. The five categories of generated images meet different style preferences of cultural and creative consumers. Category A images focus on simple styles (85.34%), Category B images focus on detailed depictions (87.91%), Category C images emphasize vibrant colors (83.98%), Category D images emphasize exquisite visuals (73.21%), and Category E images emphasize retro textures (82.09%). Based on the satisfaction levels for each category, Category A is named “Classic Elegance,” Category B is named “Luxurious Detail,” Category C is named “Vivid Precision,” Category D is named “Elaborate Opulence,” and Category E is named “Retro Minimalism.” When developing purple clay cultural and creative digital IP, products can be designed according to these styles to make traditional cultural and creative digital IP more widely accepted and avoid potential plagiarism risks.

Table 4: 5 types of images meet style demands of cultural and creative consumers

Clustering		Proportion (%)				
		A	B	C	D	E
Demand	Simple style	85.34	0.00	0.00	0.0	17.91
	Detailed depiction	4.43	87.91	0.00	0.0	0.00
	Exquisited picture	0.00	10.09	16.02	73.21	0.00
	Texture retro	10.23	0.00	0.00	16.79	82.09
	Bright and colorful	0.00	2.00	83.98	10.00	0.00

IV. Conclusion

This paper uses the StyleGAN2 network and K-means clustering algorithm to enhance the diversity of traditional cultural and creative image generation and reduce risks such as copyright disputes. The FID values of the StyleGAN2 network range from [4.312, 4.653], with training times between 128 and 162 seconds, enabling the rapid generation of high-quality and diverse images. After two training sessions, the image scores improved from the original 6.095–7.352 to 7.186–9.027. The modification rate was reduced to a minimum of 0.216%. When the generated images were clustered into five categories, the highest contour coefficient was obtained, indicating the best classification results. The five categories of images were named: Classic Elegance, Luxury and Intricacy, Vibrant and Delicate, Elaborate and Lavish, and Retro Minimalism. In the future, a deep hybrid learning mechanism can be introduced into the StyleGAN2 network to enhance the integration of different traditional cultural crafts and minimize the risk of plagiarism.

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