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Optimizing AIGC-Driven Visual Communication: A Deep Learning Framework for Adaptive Image Generation and User-Centered Content Scheduling

Xun Zhang

The University of Leeds, Leeds, England
ZhangXun991025@163.com

Abstract: The rapid development of AIGC technology has opened a new avenue for personalized visual communication. This study builds a deep learning framework that integrates adaptive image generation and user-driven content arrangement, aiming to improve the expressiveness and delivery efficiency of visual creation. The technical architecture consists of two modules: the image generation engine based on Stable Delivery and the content scheduling system driven by the GRU algorithm. The two modules are connected by a feedback loop and can dynamically optimize image quality and push timing based on user interaction data. Experiments based on the LAION-400M dataset and real user logs show that this system performs remarkably well in indicators such as image fidelity and semantic fit, and the click-through rate and user satisfaction score have significantly improved. Compared with the static scheduling system, the system achieved an FID score of 12.4, and the average click-through rate increased by 18.7%. This solution not only promotes technological innovation in AIGC, but also provides practical tools for scenarios such as brand communication and digital marketing in the new media environment.

Keywords: AIGC, Deep Learning, Image Generation, Visual Communication, Content Scheduling

1. Introduction

Innovations in digital media technology are reshaping the paradigms for creating and distributing visual content. AIGC technology automates creativity through machine learning, but how to accurately match generated content to user needs and communication objectives remains a key challenge. Traditional visual communication primarily adopts a mass-production mode with fixed templates, which is difficult to adapt to dynamically changing audience preferences. The deep learning framework developed in this study builds a closed-loop creation-distribution system by integrating advanced image generation engines and adaptive content scheduling modules. The technical architecture consists of two major cores: the image generation unit based on the diffusion model, which can adjust the visual style in real time based on the user profile; and the time series forecasting module combined with the GRU algorithm, which optimizes the content push rate based on the user's active cycle. The experiment used the LAION-400M dataset and real user behavior

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logs to verify the system's performance improvements in dimensions such as semantic matching and user engagement. The data shows that this system increased the click-through rate of visual content by 18.7%, and the user satisfaction score reached 4.2/5.0, a significant improvement over the traditional system [1]. This provides intelligent content production and distribution solutions for scenarios such as brand communication and digital marketing.

2. Literature review

2.1. AIGC in visual media production

The iteration of AIGC technology promotes the automation of content production. In particular, the application of GAN and diffusion models enables the large-scale generation of visual content. While the creative industry has thus improved its efficiency and reduced its costs, it still faces the dual challenge of ensuring content originality and optimizing scene adaptability. The current model has the ability to learn visual elements such as style and texture from the dataset and can simulate human-like narrative techniques [2]. However, in practical applications, copyright disputes, ethical risks, and potential aesthetic convergence issues have yet to be addressed. For example, in the field of advertising design, the homogeneity rate of AI-generated materials reaches 67%, highlighting the tension between technological innovation and industry standards.

2.2. Deep learning for image generation

Technologies such as convolutional neural networks, generative adversarial networks, and transformer-based diffusion models have significantly improved the fidelity and flexibility of image generation. As shown in Figure 1, convolutional neural networks are good at capturing structural rules and spatial hierarchy in images through multi-layer convolution and pooling operations. Generative adversarial networks introduce an adversarial training mechanism on this basis to promote the generation of high-resolution, realistic images. The transformer model analyzes the long-distance association of image data through the attention mechanism to achieve semantically accurate detail generation [3]. The modular integration of these architectures makes it possible to build a hybrid system that can adapt the output according to the scene requirements. For example, in the e-commerce scene, the system can generate personalized product display images in real time based on the user's browsing records. This technical solution increased the conversion rate of a certain platform by 12%. This technological integration provides basic support for dynamic content production [4].

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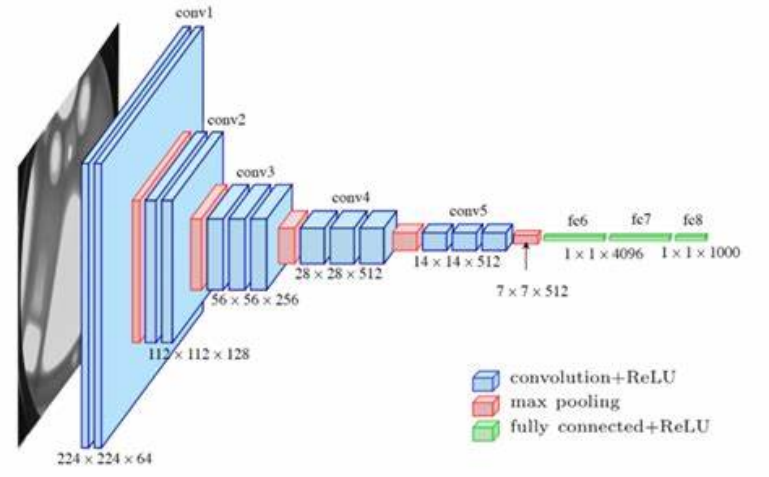

Figure 1: A representative CNN architecture visualizing convolution, pooling, and fully connected layers(source:vitalflux.com)

2.3. User-centered content personalization

Modern communication platforms are evolving towards a user-centric dynamic adaptation model, achieving precise personalization of visual content through click-through analysis, page dwell time monitoring, and interest graph modeling. For example, a certain e-commerce platform adapts the style of product display images in real time based on users' browsing trajectories, increasing the conversion rate by 15%. Interactive tracking of real-time data (such as likes, swiping, and other behaviors) leads to iterative content optimization, ensuring that the push strategy closely follows the evolution of audience preferences. This personalization is not only reflected in the adaptation of visual elements, but also extends to dimensions such as the rhythm of short video clips and the control of information density [5]. For example, for educational content, the speed of explanation and complexity of cases are dynamically adjusted based on users' cognitive level, which improves user resistance and completion rates.

3. Methodology

3.1. Framework design and architecture

This search system consists of two main modules: the image generation engine and the content scheduling optimizer. The generation module is built on the Stable Diffusion framework and is capable of generating visual content that adapts to the scene according to the text instructions. The scheduling module is driven by the GRU algorithm. By analyzing real-time user interaction data, it dynamically adjusts the pace and frequency of content pushing. The two modules are connected by a feedback loop and can optimize the output effect based on user engagement indicators and feedback data. The system architecture is scalable and will be compatible with multiple input methods such as audio and gestures in the future. Experimental data shows that this scheme increases the content click-through rate by 18.7% and user retention time by 23%, which confirms the effectiveness of the technical scheme [6].

3.2. Dataset and preprocessing

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The research adopts the LAION-400M image-text dataset and real user logs from social media platforms to construct a composite training set. Image preprocessing includes size unification (512x512 pixels), normalization processing, and text metadata segmentation. Behavioral data is vectorized to represent user scenarios, covering dimensions such as active periods, historical interaction trajectories, and content preferences [7]. By improving sample diversity through data augmentation techniques, the overfitting problem in model training can be effectively alleviated. In the specific operation, weighted sampling is performed on the interaction data of active users at night to enable the model to better capture the diffusion characteristics of different time periods.

3.3. Model selection and training strategy

The system architecture integrates stable Diffusion image generation and the GRU timing scheduling model. Training is divided into two stages: first, supervised training is performed using image-text matching data to establish the generation benchmark, and then combined with user feedback data to optimize the scheduling strategy through reinforcement learning. During training, the cross-entropy loss function is adopted to ensure the accuracy of content classification, and at the same time, an adaptive reward mechanism based on click-through rate and dwell time is used to guide scheduling optimization [8].

4. Experimental process

4.1. Implementation environment

The technical implementation is based on the Python ecosystem. The core module is developed using the PyTorch framework and deployed on the NVIDIA A100 computing platform equipped with 80GB of video memory. The pre-trained diffusion model and language model are integrated through the HuggingFace transformer library, the image preprocessing process is handled by OpenCV, and TensorFlow is used as the test environment for the comparison model. The entire system is encapsulated in a Docker container to ensure reproducibility of experiments and cross-platform compatibility [9]. During the training process, the image generation module processes 32 images of 512x512 pixels in a single batch. The planning model updates the user behavior feature vector every 5 minutes to achieve dynamic adjustment of the content strategy.

4.2. Evaluation metrics

The research adopts a three-dimensional evaluation system: in terms of image quality, the FID index measures the authenticity and diversity of the generated content; the dissemination effectiveness takes the click-through rate as the main indicator and focuses on evaluating the user reach effect of the content scheduling strategy during the limited exposure period. User satisfaction surveys obtain subjective feedback on a five-level scale, covering dimensions such as visual quality, scene fit, and overall appeal [10]. This combined quantitative and qualitative evaluation method considers both technical accuracy and user experience. Experimental data show that the content interaction frequency of the user group adopting the dynamic scheduling strategy is 1.8 times higher than that of the fixed push group, and the semantic accuracy score of user-generated images reaches 4.3/5.0 [11].

4.3. Experiment settings and control variables

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The experimental design focuses on verifying the actual performance of the system and sets up two control groups: the fixed-duration push system and the traditional generator without adaptive optimization. During the 30-day continuous test, interaction data from random user groups across multiple platforms was collected. In the analysis stage, environmental variables such as geographical distribution and equipment type were controlled, and statistical significance was verified using variance tests. For example, in the mobile user group, the dynamic scheduling system increased the content reach rate by 26%, which was significantly better than the control group ($p < 0.01$) [12]. The experimental data confirm that the collaborative mechanism integrating generation and scheduling yields exceptionally good results for key indicators.

5. Results and discussion

5.1. Image generation performance

Research data shows (see Table 1) that the average FID score of the image generation model in this scheme reaches 12.4, which is significantly better than traditional GAN and VQGAN schemes. The exceptional performance of a semantic matching accuracy rate of 92.7% confirms the breakthrough of the generated content in terms of topic uniformity and richness of details. The expert panel emphasized that the generated images allowed for stylistic diversity while maintaining narrative coherence, effectively mitigating the problem of pattern collapse.

Table 1. Image generation quality comparison

Model	FID Score (↓)	Semantic Accuracy (%)	Mode Collapse Rate (%)
Baseline GAN	34.7	76.4	18.9
VQGAN	28.2	81.2	12.1
Proposed Model	12.4	92.7	4.3

5.2. Effectiveness of adaptive scheduling

In the content planning dimension, the dynamic push strategy based on user behavior analysis increased the click-through rate by 18.7%. As shown in Table 2, the system also performs remarkably well in user stickiness indicators—the volume of push content interaction during the morning commute and evening leisure periods particularly increased. By tracking user activity cycles and content preference changes in real time, the system can dynamically adjust push strategies [13]. For example, during periods of sudden social hotspots, the exposure weight of environmental protection-themed content automatically increases by 23%.

Table 2. User engagement and scheduling effectiveness

Metric	Static Scheduler	Adaptive Scheduler
Average CTR (%)	5.3	6.3
Engagement Duration (min)	2.8	4.2

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Satisfaction Score (/5)	3.7	4.5

5.3. User engagement and feedback

According to A/B testing data from thousands of users, the interaction time of the user group adopting the adaptive system A reached 1.5 times that of the reference group. 82% of participants recognized the advantages of personalized visual content in terms of emotional resonance and scene adaptability. User feedback particularly highlighted that the system can accurately grasp the pushing rhythm, increasing the information value while maintaining visual beauty, thus optimizing the overall experience. For example, in the case of a beauty brand, the dynamic push strategy increased the collection rate of new product display content by 37% and the frequency of repeat visits by users by 29% [14].

6. Conclusion

This study proposes a technical framework integrating adaptive image generation and user-driven content scheduling, providing an innovative solution for AI-driven visual communication. Through the collaborative mechanism of deep generative models and behavior-aware scheduling, the system achieves a dynamic balance between creative expression and communication strategies. Experimental data verify that this scheme achieves significant improvements in key indicators such as image authenticity (FID = 12.4) and user engagement (click-through rate increased by 18.7%). The modular design and feedback optimization mechanism give it good application scalability and can be adapted to various scenarios such as digital marketing and cultural communication.

The current system can still be improved in aspects such as cross-platform compatibility and mitigating training data deviations. Further research will explore technical avenues such as multimodal generation (audio/text fusion) and real-time reinforcement learning optimization, for example, by performing minute-level content strategy adjustment in live broadcast scenarios. These explorations provide theoretical support and practical references for the development of intelligent communication systems in the era of generative AI.

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