Principles of AIGC technology and its application in new media micro-video creation

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Abstract

AIGC, as a new generation of intelligent generation technology, provides new ideas for the progress and development of the new media field. This study constructs a communication model for new media micro-video creation based on the information communication model, analyzing the communication and development of new media micro-video creation. Combining the application characteristics of AIGC technology in new media micro-video creation and the needs of new media micro-video creation, it proposes the information hiding improvement method based on the GAN model and diffusion model. It constructs the AIGC optimization system based on new media micro-video creation. The model’s application effect in new media micro-video creation is explored after it passes the performance test. The results show that the average scores of all the indicators of the sense of using experience are above 3.5, the overall average score of micro-video creation is 4.12, and the peak traffic and cumulative traffic of the works created by utilizing this method have been improved by 17,000 and 1,910,000, respectively. The efficiency and quality of micro-video creation can be enhanced by using this study as a feasible reference.

Keywords: Information dissemination model; AIGC; GAN network; Diffusion model; Micro-video creation.

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1 Introduction

With the rapid development of mobile Internet, new media is becoming an important way for people to obtain information and spread ideas. In the field of new media, visual elements are one of the most important factors to attract audiences, and video has become an increasingly important part of new media communication. The use of AIGC video editing techniques can well enhance the effect of new media communication [1-2].

AIGC (i.e., Image Recognition, Artificial Intelligence, Speech Recognition, and Big Data) is an innovative approach that integrates technology and ideas, and the application of AIGC in the process of video editing and production can help to improve the quality and effect of new media communication. Video speech recognition can help editors better record text and increase the credibility of the video; image recognition can optimize the image quality of the video and improve the user’s viewing experience; and big data analysis can optimize the production process and improve production efficiency. Meanwhile, with the support of AIGC technology, AI can better understand users’ personalized needs and provide better new media content [3-5].

AIGC, as an important branch of the field of artificial intelligence, has risen rapidly in recent years, leading to a new trend of scientific and technological development. AIGC is not only a way of content classification but also a way of content production, as well as a collection of a class of technologies used for the automatic generation of content [6-8]. AIGC has shown great potential in all walks of life with its unique technological principles. In the process, the creation of micro-video for new media also ushered in new development opportunities. By training a large amount of video data, the model is able to learn the features and laws of the video content and then generate new video content. In addition, AIGC technology also combines computer vision technology, which can identify, analyze, and process the images in the video so as to achieve more intelligent video editing [9-10].

AIGC technology can automatically recognize the keyframes and scenes in the video and intelligently edit and synthesize them according to the user’s needs, which greatly improves the efficiency and quality of video production. Through deep learning models, AIGC technology can add a variety of special effects to the video, such as transition effects, filter effects, etc., which makes the video content richer and more vivid. AIGC technology can also be combined with natural language processing technology to automatically generate voice commentary and subtitles for the video, which further enhances the video’s viewability and audibility. AIGC technology can automate tedious video editing tasks, and AIGC technology can automate tedious video editing tasks, greatly saving production time and cost. Through deep learning models, AIGC technology can generate diversified video content to meet the needs of different users, and the popularization of AIGC technology makes it easier for more people to produce high-quality video content, which promotes the expression and dissemination of creativity [11-12].

With the continuous development of artificial intelligence technology, the application of AIGC technology in the field of video generation and editing will be more extensive and in-depth. With the constant improvement and optimization of deep learning algorithms, AIGC technology will be more effective in video generation and editing. By combining more creative elements and algorithmic models, AIGC technology will be able to generate more unique and interesting video content. With the continuous progress of natural language processing, computer vision, and other technologies, the intelligence of AIGC technology in video generation and editing will be further improved [13-14].

In summary, AIGC technology has revolutionized video generation and editing. It not only improves the efficiency and quality of video production but also enriches the form and style of video content. With the continuous development and optimization of the technology, we have reason to believe that
AIGC technology will play an even more important role in the future and bring more innovations and breakthroughs to the video field [15-16].

In this paper, we first analyze the demand and dissemination path of new media micro-video creation based on the information dissemination model and establish a dissemination effect model based on new media micro-video creation. Then, we analyze the application characteristics of AIGC technology in new media micro-video creation according to the needs of new media micro-video practitioners and optimize the AIGC technology by combining the improved GAN network and diffusion model. After examining the performance of the improved AIGC, the actual effect of the enhanced AIGC technology in new media micro-video creation is explored in terms of the sense of using experience, creation generation effect, and creation heat.

2 Performance of AIGC technology in new media micro-video

2.1 Information dissemination based on new media micro-video creation

Information communication theory is a theory that covers how information is created, transmitted, and understood. The model was originally designed to solve communication problems in telecommunication systems and has since been widely applied to the social sciences and information communication. The information dissemination model based on new media micro-video creation is shown in Figure 1. The source of information is the micro-video creation worker, which is where the information starts, and it may be an individual or an organization. Generating and transforming information into a specific form is the responsibility of the information source in the process of micro-video dissemination. It is then vetted and promoted by the new media platform and thus disseminated. The platform user, as the receiver, responds to the information received either by giving explicit information back to the sender or by changing the receiver’s behavior. Information communication theory provides an important tool for understanding and analyzing these changes in order to better understand the production of micro-videos in the new media era and how it affects the public and society.

![Figure 1. Information dissemination model based on new media micro video creation](image)

2.2 Characterization of micro-video creation with AIGC support

With the continuous growth of data scale in the Internet era, new media micro-video practitioners need to process and analyze a large amount of data in order to extract news value and insights from it. The emergence of AIGC technology provides practitioners with a more efficient, accurate, and comprehensive way to process and analyze the data. AIGC technology has a very wide range of applications in creative production, and it can bring new media micro-video industry a. AIGC technology has a wide range of applications in creation and production and can bring great changes and improvements to the new press micro-video industry. With the continuous development and popularization of AIGC technology, micro-video production will be further digitized and
intelligentized, providing more accurate, comprehensive, and in-depth content creation for viewers and platform users. The characteristics of the application of AIGC technology in new media micro-videos are shown in Figure 2. AIGC technology, represented by artificial intelligence, exhibits the characteristics of self-learning in the new stage. Artificial intelligence will realize the real-time positive cycle of “perception - cognition - autonomous decision-making - self-learning.” The data transmission speed will realize a qualitative leap, the cloud will be seamlessly integrated, new forms of hardware such as interventional chips will appear, and even human-machine integration will be realized so that knowledge can be learned and managed more flexibly and autonomously. The systematic management of “generation-storage-application-optimization” will be supported, and the systematic management of “generation-storage-application-optimization” will be supported. It can learn and manage knowledge more flexibly and autonomously, support the systematic management of knowledge “generation-storage-application-optimization,” perceive the dynamic changes of the external environment more accurately in advance, understand the user’s needs, and make judgments and decisions.

![Figure 2](image-url)

**Figure 2.** The application of AIGC technology in new media micro video

3 Optimization of AIGC technology based on new media micro-video

Artificial Intelligence Content Generation (AIGC) involves the use of artificial intelligence and machine learning algorithms to generate various types of digital content, such as images, videos, audio, text, and 3D models. The technology trains neural networks and generative models on large datasets containing real content, allowing the algorithms and models to learn patterns and features from the real data and then use this learning to generate new content similar in style, subject matter, and quality to the original content. AIGC focuses on creativity and artistic expression, and needs to take into account more humanistic considerations. AIGC contains many types of generative algorithms, such as Generative Adversarial Networks (GANs), Variational Autoencoders (VAEs), Diffusion Models (DMs), Streaming Models, Autoregressive Models, and so on. To enhance the AIGC technique, this paper utilizes GAN and DM, two of the most commonly used models.
3.1 GAN-based generative information hiding methods

GAN is a class of generative models that are currently used to generate high-quality synthetic data. Two neural networks work together to improve sample generation quality by playing and iterating with each other.

Mathematically, the training of GAN is a very small and very large optimization problem; if the generator distribution can perfectly match the statistical distribution of the real data, then the discriminator will maximally confuse the input samples, predicting that all the inputs are 0.5. In line with other deep learning models, the training of the GAN also needs to have a well-defined objective function, which can be expressed as:

$$L(G, D) = E_{x \sim p_{data}(x)} \log D(x) + E_{z \sim p_z(z)} \log(1 - D(G(z)))$$  \hspace{1cm} (1)

The goal of the training is:

$$\arg \max_D \arg \min_G L(G, D)$$  \hspace{1cm} (2)

Traditional GAN generates images by inputting random noise; the generator is not controllable in the process of generating images, so traditional GAN cannot generate the eligible pictures according to the specified constraints; Mirza et al. proposed conditional Generative Adversarial Networks (cGAN). The loss function of cGAN is:

$$L_{cGAN}(G, D) = E_{x, y} [\log D(x, y)] + E_{x, z} [\log(1 - D(x, G(x, z)))]$$  \hspace{1cm} (3)

Where $y$ represents the real image distribution and $z$ represents the distribution of random noise. On the basis of cGAN, the researchers proposed the pix2pix framework. The pix2pix framework structure is shown in Fig. 3. This model takes an image (such as a contour map) as a constraint, and the generator generates an image with that contour information according to the constraint, and then pairs of the generated image and the image as a constraint are input to the discriminator, which determines the truthfulness of the pairs of images.

![Figure 3. Framework of pix2pix](image)

Sequence generation has always been an important problem in the field of unsupervised learning; this paper understands the image as a contour plus content and proposes a contour-generative information-hiding method based on a generative adversarial network. The contour-generative information-hiding framework of GAN is shown in Fig. 4, and the framework mainly includes two parts: information hiding and information extraction. In the information hiding stage, this paper redesigns a contour generative model (CtrGAN) based on SeqGAN.
3.2 Generative Information Hiding Method Based on Diffusion Modeling

The diffusion model-based generative information hiding framework is depicted in Fig. 5, which consists of two main parts, i.e., the part of secret information hiding and extraction. The main purpose of the secret information hiding function is to encode the secret information into text via DMHC and then use the text as a generative condition to guide the diffusion model in creating the secret-carrying image.

Based on the structure of the Diffusion Language Model (DM) and Vector Quantization Diffusion Model, as well as the training process, the DMHC secret message encoding scheme, i.e., the process of converting a secret message into text, is introduced as follows.

In this paper, we first construct a lexicon \( D \) containing all the words appearing in the training set, i.e:

\[
D = \{\text{word}_{D_1}, \text{word}_{D_2}, \text{word}_{D_3}, \ldots, \text{word}_{D_k}\}
\]  

Figure 4. Gan’s contour generated information hiding framework

Figure 5. The generated information hidden framework based on the diffusion model
Where \( D_i \) denotes the \( i \)nd word in the dictionary and \( N \) denotes the number of words in the dictionary, in the same way, a complete text can be represented as:

\[
S = \{ \text{word}_1, \text{word}_2, \text{word}_3, \ldots, \text{word}_n \}, \forall \text{word}_i \in D
\]  

Where \( s_i \) denotes the \( i \)nd word in the text and \( l \) denotes the length of the text.

Diffusion language model belongs to a kind of conditional diffusion model; in the process of training Diffusion-LM, in addition to learning the model parameters, will also learn an embedding function \( \text{emb}(w_i) \); the function of this function is to map each discrete word into a continuous hidden space vector \( v \in \mathbb{R}^d \), then for a sequence of text of length \( n \) is:

\[
S = \{ w_1, w_2, \ldots, w_n \}, \text{emb}(S) = [\text{emb}(w_1), \text{emb}(w_2), \ldots, \text{emb}(w_n)] = [v_1, v_2, \ldots, v_n] \in \mathbb{R}^{nd}
\]  

In the forward diffusion process, pure noise \( s_T \) is finally obtained by continuously denoising \( s_0 \). In the reverse diffusion process, in addition to denoising \( s_T \), the hidden space vectors need to be reduced to discrete words, so the model adds a trainable approximation operation to the reverse diffusion, which can be parameterized as \( q_\theta(S \mid s_i) = \prod_{i=1}^n q_\theta(w_i \mid s_i) \), where \( q_\theta(w_i \mid s_i) \) is a softmax distribution, i.e., a loss function that classifies the continuous spatial features obtained from each step in the reverse diffusion process. Of continuous space features to do the classification, the loss function to train this model is:

\[
L_{\text{simple}}^{\text{L2E}}(S) = E_{p_\theta(s_0 \mid S)} \left[ L_{\text{simple}}(s_0) + \log p_\theta(s_0 \mid S) - \log q_\theta(S \mid s_0) \right]
\]  

\[
L_{\text{simple}}^{\text{L2E}} = E_{p_\theta(s_0 \mid S)} \left[ L_{\text{simple}}(s_0) + \|\text{emb}(S) - \mu_\theta(v_1, 1)\|^2 - \log q_\theta(S \mid s_0) \right]
\]  

Where \( L_{\text{simple}}^{\text{L2E}}(S) \) is the ordinary diffusion model loss function formula and \( L_{\text{simple}}^{\text{L2E}}(S) \) is derived from \( L_{\text{simple}}^{\text{L2E}}(S) \). The trainable approximation operation is actually selecting the most appropriate word at each moment, which is computed as \( q_\theta(S \mid s_i) = \prod_{i=1}^n q_\theta(s_i \mid v_i) \). Therefore, Diffusion-LM can obtain the probability distribution of the words generated at each moment on the lexicon \( D \) during the inverse diffusion generation process.

The codebook in the vector quantizer is a fixed set of vectors learned from the training data by a clustering algorithm; each vector corresponds to a class of similar input vectors, i.e.:

\[
\text{Quantize}(E_{\text{top}}(x_i)) = b_{\text{top}}
\]

\[
k = \min_j \|E(x_i) - b_{\text{top}, j}\|
\]
After obtaining the discrete vector $b_{top}$, it is fed into $E_{bottom}$ as a condition together with $x_i$. The discrete vector $b_{bottom}$ corresponding to the local information is computed by Eq. Finally, $b_{top}$ and $b_{bottom}$ are spliced along the channel dimension to obtain $b$, and $b$ is fed into the decoder.

The decoder is updated by backpropagation, and the reconstruction error is used as a loss function:

$$L(x, \hat{x}) = \|x - \hat{x}\|_2^2 + \|sg[E(x)] - b\|_2^2 + \beta \|sg[b] - E(x)\|_2^2$$

(11)

The training process of the model is also divided into forward diffusion and backward diffusion. Taking the $i$th discrete vector in $z_0$, as an example, in the process of forward diffusion, the VQ-Diffusion model is modeling the transfer probabilities of discrete vectors at different moments through the state transfer probability matrix $M_i$, i.e.:

$$[M_i]_{mn} = p(\hat{z}_t = m | z_{t-1} = n) \in R^{(K+1) \times (K+1)}$$

(12)

Where $m$ and $n$ are discrete vectors and $m \leq K, n \leq K$, denotes the index in the codebook corresponding to the discrete vector. The discrete vector indexed in the codebook from moment $t-1$ is $n$ is the discrete vector:

$$p(\hat{z}_t = m | \hat{z}_{t-1} = n)$$

(13)

to the probability that moment $t$ is transferred to a discrete vector of index $m$ in the codebook. The forward diffusion addition of noise is done by means of matrix $M_i$ for random substitution and random masking of elements in $z_{t-1}$, so that at moment $t$ the forward diffusion process is:

$$p(\hat{z}_t | \hat{z}_{t-1}) = h^T(\hat{z}_t)M_ih(\hat{z}_{t-1})$$

(14)

Where $h(z)$ denotes one-hot coding of $z$ and the role of $M_i$ is to realize the state transfer of the discrete vector from moment $t-1$ to moment $t$. It is computed by the following equation:

$$M_i = \begin{bmatrix}
\alpha_t + \beta_t & \beta_t & \beta_t & \cdots & 0 \\
\beta_t & \alpha_t + \beta_t & \beta_t & \cdots & 0 \\
\vdots & \vdots & \vdots & \ddots & \vdots \\
\gamma_t & \gamma_t & \gamma_t & \cdots & 1 
\end{bmatrix}$$

(15)

Where $\alpha_t \in [0,1], \beta_t = (1-\alpha_t) / K, p(\hat{z}_t | \hat{z}_{t-1})$ denotes the probability of state transfer of discrete vectors from moment $t-1$ to moment $t$. It can be seen from Eq. that the probability of discrete vectors not changing from moment $t-1$ to moment $t$ is $\alpha_t = 1 - K\beta_t - \gamma_t$, the probability of change, i.e., re-sampling of discrete vectors across all $K$ categories, is $K\beta_t$, and the probability of discrete vectors being masked is $\gamma_t$. 
4 Analysis of the application of AIGC in new media micro-video creation

4.1 Performance analysis of the improved AIGC

To validate the performance of AIGC optimized based on GAN and diffusion models in this paper, this section uses a self-built dataset M for experimental evaluation. The proposed multi-style generative network is trained using 1205 micro-videos and their color images. This experimental method uses the Adam optimizer with multi-stage learning rate decay because it enables the network to converge faster and facilitates convergence. Therefore, the learning rate will decay to one-tenth of the original rate when the model is trained for 40 or 80 rounds. All videos require 100 rounds of training. For the input videos, random cropping data enhancement was first performed, then the videos were adjusted to a resolution of 252*252 and finally normalized and fed into the network. The experiments mainly analyzed different backbone networks based on CycleGAN. Finally the generated video quality of the network in this paper is examined by ablation study. The quality of the generated video is evaluated in terms of Peak Signal to Noise Ratio (PSNR) and FID metrics for five styles (PS1–5) of storytelling, contrast, entertainment, inspirational, and literary, and the results of Peak Signal to Noise Ratio of the videos of the different methods are shown in Table 1, as compared to the results of Pix2Pix, GAN(UNet), GAN(ResNet), GANw/SE and GAN+Aftercure five models of PUSR, the performance of this paper’s method is better. Its average value of peak SNR is 33.52. Compared with GAN+Aftercure, its average performance on PNSR metrics is improved by 4.09 compared to GAN and by 7.1 compared to GANw/SE. It shows that this paper’s method can better remove more noise and further improve the quality of the generated video.

<table>
<thead>
<tr>
<th>Method</th>
<th>PS1</th>
<th>PS2</th>
<th>PS3</th>
<th>PS4</th>
<th>PS5</th>
</tr>
</thead>
<tbody>
<tr>
<td>GAN(UNet)</td>
<td>23.29</td>
<td>22.25</td>
<td>22.07</td>
<td>24.52</td>
<td>22.91</td>
</tr>
<tr>
<td>GAN(ResNet)</td>
<td>24.52</td>
<td>23.09</td>
<td>22.86</td>
<td>25.64</td>
<td>23.64</td>
</tr>
<tr>
<td>GANw/SE</td>
<td>27.20</td>
<td>24.32</td>
<td>26.22</td>
<td>27.62</td>
<td>26.74</td>
</tr>
<tr>
<td>GAN+Aftercure</td>
<td>29.77</td>
<td>29.22</td>
<td>29.34</td>
<td>29.81</td>
<td>28.99</td>
</tr>
<tr>
<td>This method</td>
<td>34.47</td>
<td>32.94</td>
<td>33.06</td>
<td>34.50</td>
<td>32.63</td>
</tr>
</tbody>
</table>

The FID results of the generated videos using different methods are shown in Table 2, where the lower the score, the better the quality in terms of FID metrics. The average FID performance of this paper’s method is 138.96, which is reduced by 8.36 compared to the average of GAN+Aftercure, 10.92 compared to GANw/SE, and 33.91 compared to GAN(ResNet). The FID metrics indicate that this paper’s method generates videos closer to the original video with a smaller difference, the performance has gained a large improvement. This paper’s process is able to retain the content information of the original video.

<table>
<thead>
<tr>
<th>Method</th>
<th>PS1</th>
<th>PS2</th>
<th>PS3</th>
<th>PS4</th>
<th>PS5</th>
</tr>
</thead>
<tbody>
<tr>
<td>Pix2Pix</td>
<td>230.95</td>
<td>198.58</td>
<td>269.72</td>
<td>151.65</td>
<td>48.64</td>
</tr>
<tr>
<td>GAN(UNet)</td>
<td>231.01</td>
<td>199.58</td>
<td>291.42</td>
<td>129.94</td>
<td>48.02</td>
</tr>
<tr>
<td>GAN(ResNet)</td>
<td>232.66</td>
<td>188.33</td>
<td>297.72</td>
<td>113.17</td>
<td>32.46</td>
</tr>
<tr>
<td>GANw/SE</td>
<td>194.19</td>
<td>154.96</td>
<td>243.07</td>
<td>107.45</td>
<td>49.70</td>
</tr>
<tr>
<td>GAN+Aftercure</td>
<td>222.31</td>
<td>146.37</td>
<td>239.33</td>
<td>94.26</td>
<td>34.34</td>
</tr>
<tr>
<td>This method</td>
<td>198.67</td>
<td>143.21</td>
<td>231.87</td>
<td>92.01</td>
<td>29.03</td>
</tr>
</tbody>
</table>
4.2 Application Analysis of Micro Video Creation Based on Improved AIGC

4.2.1 Improved measurement and analysis of the use of AIGC technology

In order to understand users’ real evaluation and feedback on the implementation of AIGC functions and user experience in this paper and to obtain references for product iteration and optimization, this paper invited 100 workers with expertise in new media micro-video creation to participate in the design evaluation study. According to the strategy and positioning of new media micro-video creation, 30 participants were asked to evaluate the system in 8 aspects, including ease of use A1, professionalism A2, experience A3, pleasantness A4, creative extensibility A5, inspiration A6, program recommendation A7, and intention to use A8, etc. In the scoring questions, a scoring system of 1-5 was used, with 1 indicating very dissatisfied and 5 indicating very satisfied. The evaluation results of micro-video creation workers are shown in Figure 6. The evaluation results show that, in terms of functional application, micro-video creation workers are more satisfied with the overall application effect of this paper’s micro-video-based intelligent generation scheme, the average rating of each index is above 3.5 points, and the majority of the micro-video creation workers affirmed the positive effect of this paper’s optimized intelligent generation technology in terms of ease-of-use. Its average score is the highest of 4.21 points. The vast majority of micro-video creation workers believe that this paper is based on the intelligent generation of excellent experience, with an average score of 4.15 points. The average score for creative extensibility is 4.10, which helps inspire micro-video creation. This paper’s optimized AIGC for micro-video creation can better meet the functional requirements of micro-video creation workers.

![Figure 6. Micro video creation worker evaluation results](image)

4.2.2 Analysis of the effect of new media micro-video generation

To assess the effectiveness of this paper in improving the application of AIGC technology in micro-video creation, we use a multi-criteria evaluation method to measure the quality of the generated videos. Seven aspects of micro-video are evaluated, including video details B1, diversity B2, expressiveness B3, innovativeness B4, content structure B5, viewability B6, and artistry B7, and in the scoring questions, the scoring system of 1-5 points is still used: 1 point indicates very dissatisfied, and 5 points represent very satisfied. Figure 7 displays the evaluation of micro-video generation effects, with the box plots representing the range of scores, the red line representing the average value, and the green dots representing the scoring situation. Observations show that micro-video creation is
most recognized by workers in terms of video diversity and artistry, with scores of 4.22 and 4.26, respectively. In contrast, the evaluation score of video expressiveness was 3.87, the lowest rating, indicating that the vast majority of micro-video creation workers believe that the expressiveness of the generated micro-video is relatively average and the video images lack a certain degree of attractiveness. On the whole, it seems that, except for expressiveness, the average scores of other indicators are above 4. The overall average score is 4.12, which indicates that micro-video creation workers are relatively satisfied with the quality and effect of the generated video and verifies that the optimized AIGC in this paper has an excellent effect on video generation.

![Figure 7. Micro video generated effect evaluation](image)

4.2.3 Heat analysis of micro-video creation based on AIGC

New media micro-video creation of traffic heat is an important indicator of the quality of micro-video creation, using this paper’s AIGC-generated micro-video creation and traditional micro-video creation methods for comparison, generated video content positioning and parameter design, etc., to maintain the same, to analyze the changes in the flow of data in 72 hours, micro-video creation of the heat of the comparison is shown in Figure 8, it can be seen that this paper’s method of generating micro-videos in the 50 hours or so reaches the highest traffic value of 69,000, while the highest traffic of traditional AIGC-generated micro-video is 52,000. The micro-video traffic of this paper’s method at the peak is improved by 17,000. The cumulative traffic of micro-videos in this paper is about 4.93 million, which is an improvement of about 1.91 million, indicating that the content created by micro-videos based on the improved AIGC in this paper has a higher attraction to the viewers and better meets the viewing needs.
5 Conclusion

In this paper, the research is oriented to the new media micro-video creation needs through the improvement of the GAN network and diffusion model to optimize the AIGC technology and its application in the micro-video creation of the example through the relevant workers’ scores to explore its application effect.

1) The average peak signal-to-noise ratio of the algorithm in this study is 33.52, and the average performance of FID is 138.96. Compared with other method models, the performance of the improved AIGC in this paper is significantly enhanced, which illustrates that the method in this paper can better improve the quality of the generated video while retaining the original content information for creation.

2) From the experience of micro-video creators in use, the average rating of each index is above 3.5 points. In the micro-video generation effect, except for the expressive power of 3.87 points, the average score of other indexes is above 4 points, which illustrates that this paper’s method can meet the needs of micro-video creators and effectively improve the quality and effect of micro-video creation.

3) The peak traffic of micro-video creation utilizing the method of this paper is 17,000 higher than that of the traditional method. The cumulative traffic is about 1,910,000 higher, which further illustrates that the improved AIGC of this paper has a better effect on micro-video creation, meets the needs of the viewers, and has a greater attraction and traffic value.

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