Original scientific paper

GANS for realistic animation: A qualitative study using ATLAS.ti

ABSTRACT

This study aims to explore the effectiveness of GANs in generating animations that achieve high levels of realism, focusing on motion quality, texture detail, visual composition, and frame-to-frame coherence. A qualitative approach was employed using ATLAS.ti to analyze outputs from models such as MoCo-GAN and StyleGAN3. The dataset included 110 animations, from which key visual elements were coded and analyzed thematically. The findings reveal that 68% of the animations demonstrated smooth motion transitions, while 20% exhibited jerky movements and 12% contained motion artifacts. Similarly, 70% of the animations featured highly detailed textures, but 20% had flat backgrounds, and 10% showed lighting inconsistencies. Visual compositions with strategic framing and depth perception were observed in 55% and 30% of the animations, respectively, whereas only 15% maintained symmetrical layouts. These results underscore the strengths and limitations of GANs in achieving realism, particularly in complex scenarios. This study contributes to the growing body of literature on GAN applications in animation by identifying critical visual factors that enhance aesthetic and narrative coherence. Practical implications include guiding designers and developers in leveraging GANs for high-quality animation production. Future research is recommended to address existing technical challenges and evaluate audience responses to GAN-generated animations, paving the way for more dynamic and engaging visual content.

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Introduction

In the digital era, advancements in artificial intelligence (AI) have transformed the creation and perception of visual content. Among these advancements, Generative Adversarial Networks (GANs) have emerged as a groundbreaking technology for generating realistic animations and visuals. GANs leverage deep learning to synthesize highly detailed and coherent images, videos, and animations by learning from extensive datasets (Goodfellow et al., 2014).

This innovation has opened new opportunities in animation production, particularly in generating realistic movement, textures, and environmental dynamics. Animation traditionally relies on human artistry and manual techniques to craft realism and aesthetic appeal. However, GANs challenge this paradigm by automating the generation of animations that often rival or even surpass traditional methods in terms of realism and efficiency (Sedkaoui & Benaichouba, 2024). Despite this progress, evaluating the aesthetic and realistic quality of GAN-generated animations remains a significant challenge, as existing standards for animation realism and aesthetics have been largely developed for human-created content (Chakraborty et al., 2024; Sangapu et al., 2024; Singh et al., 2024).

Moreover, while GANs have shown immense potential in creating static visuals, their application to realistic animation introduces unique complexities. These include ensuring smooth transitions between frames, maintaining consistency in texture and lighting, and accurately mimicking natural motion (Chakraborty et al., 2024;

Islam et al., 2024; Jain, 2024). Existing studies often focus on technical improvements in GAN architecture, such as video GANs or motion-aware GANs (Liang et al., 2025; Zhuo et al., 2024), but few have systematically examined whether these generated animations adhere to established principles of realism and visual coherence.

This study aims to address this gap by analyzing the visual and aesthetic trends in animations generated by GANs. Using qualitative methods with ATLAS.ti, the research explores dominant patterns in animation realism, focusing on elements such as motion quality, texture consistency, and visual composition. The analysis also evaluates how GAN-generated animations align with standards of visual realism, providing insights into their potential application in creative industries.

By situating GANs within the context of animation production, this research contributes to the growing body of knowledge on AI-generated visual content. The findings are expected to offer practical guidance for animators, designers, and technologists seeking to leverage GANs for realistic animation. Therefore, the research question this study seeks to answer is: How do GAN-generated animations adhere to established principles of realism and visual coherence? This question will be explored through a qualitative analysis conducted using ATLAS.ti, aiming to bridge the gap between technical innovation and artistic evaluation in animation.

Literature Review

Generative Adversarial Networks (GANs) and Animation

Generative Adversarial Networks (GANs), introduced by (Goodfellow et al., 2014), are a machine learning framework consisting of two competing neural networks: a generator and a discriminator. In the context of animation, GANs are utilized to produce realistic motion and dynamic visual elements (Mathew, 2024). This innovation has significantly advanced the creation of data-driven videos and animations that closely approximate human realism (Chakraborty et al., 2024).

The application of GANs in animation often involves algorithm modifications to accommodate motion and frame-to-frame transitions. For instance, MoCoGAN (Motion and Content GAN) (Tran, Bach & Doan, 2020; Ursegov, Zakharian & Miklina, 2022) separates motion elements from static content, enabling the creation of more consistent and realistic videos. Additionally, models like vid2vid and StyleGAN3 have demonstrated remarkable capabilities in adapting visual aesthetics to complex animations (Alaluf et al., 2023; Che Azemin et al., 2024; Kumar & Singh, 2023; Mallya et al., 2020; Zhuo et al., 2022).

However, applying GANs to animation is not without challenges. One major issue is ensuring frame-to-frame coherence, particularly when dealing with dynamic scenarios or complex movements. Furthermore, controlling visual elements such as lighting and texture remains a persistent problem that requires innovative solutions (El-Nasr et al., 2009; Kubiak, 2024; Vecchio et al., 2024). These challenges drive further research to optimize GAN structures for generating more realistic animations. With the advancement of GAN technology, the need to evaluate the quality of animations from an aesthetic and realism perspective has emerged. This research aims to fill a gap in the literature by analyzing the visual elements in GAN-generated animations, contributing to a better understanding of how this technology can be utilized in creative industries.

Realism in Animation

Realism in animation refers to the concept of replicating the real world visually, whether through motion, textures, or lighting. In the context of GANs, realism is not only about creating visuals that resemble the real world but also about how these elements interact harmoniously within the animation (Rakshitha et al., 2024). Key elements in achieving animation realism include motion quality, frame-to-frame consistency, and texture integrity. For example, research by (El-Nasr et al., 2009; Kubiak, 2024; Vecchio et al., 2024) highlights that long-term motion prediction in GAN-based animation requires a hierarchical approach to maintain frame-to-frame coherence. Additionally, aspects such as adaptive lighting and dynamic shadows are critical focal points for enhancing realism (Hamza, 2024; Rakshitha et al., 2024; Zhang, 2023).

However, realism often clashes with the technical limitations of GANs. Visual artifacts, such as texture distortion or color inconsistencies across frames, frequently arise due to constraints in model training or inadequate datasets (Gao et al., 2024). Therefore, further research is needed to understand how these elements can be optimized through improved GAN architectures. This study seeks to explore the extent to which GAN-generated animations meet standards of visual realism. By using ATLAS.ti, a qualitative analysis of these elements will provide new insights into the strengths and weaknesses of GAN technology in creating realistic animations

Evaluating GAN-Generated Content

Evaluating GAN-generated content has become an increasingly important topic, particularly in the context of animation. Traditional evaluation methods, such as Frechet Inception Distance (FID) and Structural Similarity Index (SSIM), are commonly used to quantitatively measure visual quality (Kancharla & Channappayya, 2018; Lee & Leeghim, 2022).

However, these approaches often fail to capture the nuanced aesthetics and human perception of animated content. Qualitative approaches offer a deeper alternative for evaluating GAN-generated animations. For example, thematic analysis of visual elements such as texture, lighting, and composition can provide insights not covered by quantitative metrics. Previous studies by (Li et al., 2021; Rakshitha et al., 2024; Re et al., 2022) have shown that aesthetic qualities, such as color harmony and visual dynamics, significantly contribute to the perception of realism.

Moreover, narrative-based analysis is also crucial for evaluating GAN-generated animation content. Animation is not only judged based on its visual elements but also on how these elements support the overall story or visual narrative (El-Nasr et al., 2009; Kubiak, 2024; Vecchio et al., 2024). Therefore, this study will utilize ATLAS.ti to identify patterns and themes in GAN-generated animations' visual and narrative elements. This research aims to provide a more comprehensive evaluation framework for GAN-generated animation content by combining qualitative and thematic approaches. These findings are expected to further expand the applications of GAN technology in creative design and animation production.

Methodology

Design Research

This research employs a qualitative approach with a case study design to analyze visual elements in realistic animations generated by Generative Adversarial Networks (GANs). A qualitative approach was chosen because the study focuses on exploring how visual elements such as motion, texture, and composition are utilized to create realistic animations.

The case study design allows for a detailed examination of complex visual phenomena within a specific context, namely GAN-based animation (Chen, Liu & Chen, 2020; Li et al., 2021; Purwanto et al., 2024; Re et al., 2022; Tian & Li, 2023). In this study, GANs are the primary focus for evaluating how this technology can produce animations that approximate visual realism. The analysis involves both technical and aesthetic elements to understand the extent to which GAN-generated animations meet standards of realism and aesthetics.

Data Source

The data for this research was collected from GAN models that generate realistic animations, including MoCoGAN (Tran, Bach & Doan, 2020), StyleGAN3 (Alaluf et al., 2023), and other video-based models. The datasets used to generate animations include:

1. HumanML3D Dataset: This dataset contains descriptions of human motion to produce realistic GAN-based animations.
2. AMASS Dataset: This dataset was used to train GAN models to create accurate and realistic human body movements.
3. Pretrained Models: Pretrained models like StyleGAN3 were utilized to generate realistic textures and lighting for animation elements.

The selection of models and datasets was based on their ability to produce animations that incorporate complex movements, detailed textures, and dynamic lighting.

Data Collection

The data collection process involved the following steps:

- Animation Generation: Animations were created using GAN models with preconfigured parameters to produce realistic motion and textures.
- Metadata Collection: Technical information was gathered, including model parameters, the number of frames, resolution, and input scenarios.
- Dataset Structuring: The dataset consisted of animation files (videos or frame sequences) accompanied by relevant metadata.

The data was collected in standard formats (e.g., MP4 or image sequences) and organized for qualitative analysis using ATLAS.ti.

Data Analysis

The Use of ATLAS.ti for Qualitative Analysis

The generated animation data was imported into ATLAS.ti for analysis using coding techniques and thematic analysis.

The analysis focused on the following aspects:

- Motion Quality: The smoothness and consistency of movement within the animations.
- Visual Composition: Framing, perspective, and balance of visual elements in the animation.
- Texture Realism: The level of detail in textures, lighting, and shadows.
- Frame-to-Frame Coherence: Visual consistency across animation frames.

Coding Process

The animations were analyzed frame-by-frame to identify key visual elements. The codes applied include:

- Smooth Movement: Evaluates the fluidity of motion in objects or characters within the animation.
- Symmetrical Composition: Assesses the balance of visual elements.
- Lighting Effects: Examines the impact of light and shadow on visual realism.
- Visual Artifacts: Identifies distortions or technical shortcomings in the GAN-generated animations.

Table 1 shows the code and sub-code use for Analysis. The coding results were then organized into thematic networks to uncover patterns and relationships among the visual elements. This approach provided structured insights into the strengths and weaknesses of the animations analyzed.

Thematic Analysis

Following the completion of the coding process, a thematic analysis was performed to uncover the primary themes emerging from the data. This approach is widely used in qualitative research to identify recurring patterns or themes within the dataset (Castleberry & Nolen, 2018; Vaismoradi & Snelgrove, 2019). Thematic analysis was conducted to uncover the main themes emerging from the data. This process involved grouping codes into the following categories:

- Trends in Visual Realism in Animation: Visual elements frequently utilized in GAN-generated animations, such as smooth motion, detailed textures, and balanced compositions
- Technical Weaknesses: Identification of artifacts or shortcomings in animations, including issues with texture fidelity, inconsistent lighting, or jerky movements.
- Visual Strengths: Elements that consistently enhance the perception of realism, such as cohesive frame-to-frame transitions, accurate shadowing, and well-executed lighting effects.

This thematic grouping allowed for a structured understanding of both the opportunities and limitations in the application of GANs for creating realistic animations. It also provided actionable insights for improving GAN architectures and their outputs in creative industries.

Validity and Reliability

The validity and reliability of the data in this study are ensured through several strategies designed to guarantee the accuracy and consistency of results. First, triangulation was conducted by comparing the visual analysis results with relevant literature in the fields of animation and GAN technology. This approach aims to validate findings with evidence from credible sources.

Table 1

Codes and Sub-codes Used for Analysis in ATLAS.ti

No	Code	Sub-Code	Description
1	Motion Quality	Smooth Movement	Evaluates the fluidity and continuity of motion between frames.
		Jerky Movement	Identifies abrupt or unnatural transitions in movement.
		Motion Artifacts	Detects visual inconsistencies, such as motion blur or frame skipping.
2	Texture Realism	Detailed Texture	Assesses the level of detail in surface textures, such as fabric, skin, or object materials.
		Flat Texture	Identifies areas with low or unrealistic texture detail.
		Lighting Artifacts	Highlights issues with shadows, reflections, or inconsistent lighting across frames.
3	Visual Composition	Framing	Analyzes the placement of objects or characters within the scene to achieve visual balance.
		Depth Perception	Evaluates the use of perspective to create a sense of depth in the scene.
		Symmetry	Identifies balanced and harmonious arrangements within the frame.
4	Animation Realism	Frame-to-Frame Coherence	Assesses consistency in movement, lighting, and texture across frames.
		Natural Physics	Evaluates adherence to physical laws, such as gravity, inertia, and collision.
		Emotional Expression	Analyzes the expressiveness of characters or objects, such as facial movements or gestures.
5	Narrative Support	Visual Storytelling	Identifies how the animation supports the overall narrative or storytelling.
		Scene Continuity	Evaluates the logical progression and coherence of scenes within the animation.
		Artistic Intent	Explores the creative or artistic purpose behind visual choices in the animation.

Second, a peer review process was carried out by involving animation experts and GAN developers to assess the interpretation of the data. Input from these experts helped identify potential biases or errors in the analysis and ensured more objective and reliable results.

Third, re-analysis was performed by repeating the coding process on the dataset to verify the accuracy and consistency of the findings. This step ensures that every visual element identified in the study is based on strong and reliable evidence.

Limitations

This study has several limitations that should be noted. First, the data used comes from specific GAN models, such as MoCoGAN and StyleGAN3. While these models are widely recognized, the study's findings may not reflect the full spectrum of available GAN technology. Second, the qualitative analysis approach employed yields interpretative findings.

Therefore, these results cannot be widely generalized to all GAN applications, particularly outside the context of realistic animation. Third, the focus of this study is limited to the analysis of visual elements such as motion, texture, and composition. This research does not include audience responses or user perceptions of GAN-generated animations, which could be an important area for future exploration.

Result

Motion Quality

Motion quality is one of the key indicators of realism in animations generated by GANs. The analysis shows that most animations exhibit smooth motion and consistent frame-to-frame transitions. This is particularly evident in animations involving simple movements, such as facial expressions or slow body position changes. This smooth motion creates an effective illusion of realism, especially when supported by appropriate textures and lighting.

However, some animations were found to display jerky or unnatural movements, particularly during sudden position changes or complex actions such as jumps or rotations. These jerky movements create an artificial impression that can detract from the visual experience of the audience. Additionally, motion artifacts, such as shadows that shift abruptly or visual elements that disappear in certain frames, were also detected in a small portion of the animations. Table 2 shows the motion quality analysis. These findings indicate that, while GANs can generate realistic motion, there are technical limitations that need to be addressed for more complex motion scenarios.

Table 2

Motion Quality Analysis

No	Motion Quality	Freq. (%)	Observation
1	Smooth Movement	68	Smooth frame-to-frame transitions, especially in slow or simple movements such as walking.
2	Jerky Movement	20	Movements appear jerky, for example, during sudden position changes or extreme rotations.
3	Motion Artifacts	12	Visual artifacts are observed in unstable shadows or objects that suddenly disappear in certain frames.

Texture Realism

Realistic textures are a crucial element in creating convincing animations. The analysis results indicate that GANs can generate highly realistic texture details on primary elements, such as clothing or character skin surfaces. This is evident in the presence of fabric folds, light reflections on materials, and natural color gradients. These textures provide visual depth that enhances the overall impression of realism.

However, in background elements, textures often appear flat and lack detail. Areas such as walls, floors, or secondary objects tend to receive less attention during GAN model training. Additionally, lighting artifacts frequently occur in transition areas between shadows and light, creating visual inconsistencies.

Table 3 shows the texture realism analysis. These shortcomings indicate that, although GANs have successfully captured texture details for primary elements, further optimization is needed for background elements and complex lighting scenarios.

Table 3

Texture Realism Analysis

No	Texture Realism	Freq. (%)	Observations
1	Detailed Texture	70	Textures on primary elements, such as clothing or skin surfaces, appear realistic and detailed.
2	Flat Texture	20	Background elements, such as walls or floors, often look flat and lack sufficient detail.
3	Lighting Artifacts	10	Inconsistencies in lighting are detected, such as uneven shadow transitions or incorrect reflections.

Visual Composition

The visual composition in GAN-generated animations tends to utilize effective framing, where key elements are strategically placed to create visual harmony. Perspective is also frequently employed to convey a sense of depth, thus creating a convincing illusion of three-dimensional space. This is particularly evident in animations involving interactions between characters and their environment.

However, symmetry in the arrangement of visual elements is often lacking, especially in scenes with numerous objects or extreme perspective changes. This imbalance can reduce the aesthetic appeal of the visuals, although it does not significantly impact the sense of realism. Table 4 shows visual composition analysis. These findings indicate that GANs have significant potential for creating compelling visual compositions, but there is room for improvement in the arrangement of more complex layouts.

Table 4

Visual Composition Analysis

No	Visual Composition	Freq. (%)	Observations
1	Framing	55	Key visual elements are strategically placed to create good visual harmony.
2	Depth Perception	30	Perspective is used to provide the illusion of three-dimensional space, particularly in forward or backward movements.
3	Symmetry	15	An imbalance in the layout of elements is observed in some scenes, reducing visual harmony.

Frame-to-Frame Coherence

Frame-to-frame coherence is a critical aspect that ensures smooth and consistent transitions in animations. Most animations exhibit high visual coherence, especially in small movements such as facial expressions or hand gestures. Table 5 shows frame-to-frame coherence. These transitions create a natural visual flow and enhance the audience's perception of animation realism.

However, in major scenario changes, such as character movements or lighting transitions, some inconsistencies were observed. For example, lighting in one frame might differ significantly from the next frame, creating an unnatural impression. This indicates that GANs need to be trained with a broader variety of scenarios to improve frame-to-frame coherence in major changes.

Table 5

Frame-to-Frame Coherence

No	Frame-to-Frame Coherence	Freq. (%)	Observations
1	High Coherence	75	Frame-to-frame transitions appear consistent, especially in small movements such as changes in facial expressions.
2	Low Coherence	25	Inconsistencies are observed during major changes, such as lighting shifts or large-scale movements.

Narrative Support

The narrative elements in GAN-generated animations show varying results depending on the complexity of the story being presented. In simple scenarios, such as characters moving within a static environment, the animation effectively supports the narrative. Character movements, framing, and lighting contribute to visual storytelling.

However, in more complex scenarios, such as interactions between multiple characters or dynamic environmental changes, visual narratives sometimes lose continuity. This is due to inconsistencies in visual elements across scenes, such as differences in lighting or illogical changes in character positions. Despite these challenges, the potential of GANs to support visual narratives remains evident, particularly if model training is focused on specific story scenarios.

Discussion

Relationship Between Motion Quality and Texture Realism with Visual Realism

The findings of this study indicate that motion quality and texture realism play a crucial role in creating realistic animations. Smooth motion and consistent frame-to-frame transitions provide the fluidity illusion that is essential in GAN-based animations. Approximately 68% of the analyzed animations demonstrated smooth movement, while 20% exhibited jerky motion, and the remainder contained visual artifacts. These findings align with prior research by (Tran, Bach & Doan, 2020), which emphasized the importance of motion coherence in GAN-based animation.

However, the results also reveal weaknesses in some animations, particularly during rapid position changes or complex lighting scenarios. Realistic textures were found on primary elements, such as characters and foreground objects, but flat textures in the background often diminished the overall effect.

This observation is consistent with the findings of (El-Nasr et al., 2009; Kubiak, 2024; Vecchio et al., 2024), which identified that background textures are often overlooked in GAN training. These challenges can be addressed by incorporating more diverse datasets and more advanced GAN models.

Influence of Visual Composition on Aesthetic Perception

Visual composition, such as framing and depth perspective, also significantly contribute to the aesthetics of the generated animations. Approximately 55% of the analyzed animations utilized strategic framing, while depth perspective appeared in 30% of the total data. However, only 15% of the animations demonstrated symmetrical layouts, reducing visual harmony in some scenes.

These findings align with (Rakshitha et al., 2024), who stated that depth perspective and framing can significantly enhance visual perception. However, the results differ from (Kanuri et al., 2024), who argued that symmetry tends to be more effective in capturing the audience's attention. In the context of GANs, the challenge of maintaining symmetry and visual harmony highlights the need for further optimization in model architecture.

Narrative Support Through Frame-to-Frame Coherence

Frame-to-frame coherence is a key element in supporting visual narratives. Animations with smooth frame-to-frame transitions can create a coherent and easily followed storyline. In this study, 75% of the analyzed animations had high levels of frame-to-frame coherence, but 25% showed inconsistencies, particularly in lighting changes or large movements. These findings support the visual narrative theory proposed by (Hussain et al., 2024; Manovich, 2016), which highlights the importance of frame-to-frame transitions in creating a seamless visual experience.

Contribution

This research makes significant contributions to understanding how GANs can be used to create realistic animations. The study highlights the relationship between visual elements—such as motion quality, realistic textures, and visual composition—and aesthetic and narrative perception in animations. Thus, this research extends previous literature by demonstrating how these elements can be applied in GAN-based animation production. Practically, these findings can serve as a guide for animators, designers, and technology developers seeking to leverage GANs to create more compelling and convincing animations. The combination of smooth motion, detailed textures, and balanced visual composition has proven to be an effective tool in enhancing animation quality.

Limitations and Future Research

While this research provides valuable insights, several limitations must be acknowledged. First, the data used originates from specific GAN models (MoCoGAN and StyleGAN3), which may not represent the capabilities of all available GAN models. Second, the analysis is limited to visual elements without considering audience perceptions of the generated animations. Future research can expand the scope by involving audience perception analysis to understand how they respond to GAN-based animations. Additionally, future studies can use more diverse datasets to explore the potential of GANs in more complex animation scenarios, including character and environment interactions.

Conclusion

This study reveals that Generative Adversarial Networks (GANs) hold significant potential in producing realistic animations with smooth motion quality, detailed textures, and aesthetically pleasing visual compositions. By analyzing outputs from models such as MoCoGAN and StyleGAN3 using a qualitative approach, it was found that elements like frame-to-frame motion smoothness, depth perspective, and realistic textures contribute to the perception of animation realism.

However, the study also identified weaknesses, such as visual artifacts and lighting inconsistencies, which frequently appear in scenarios involving complex movements or significant changes within animations. These findings underscore that while GANs are promising, further optimization is needed to meet the high standards of visual realism.

The results of this research provide an important contribution to the literature on GAN-based animation by exploring visual elements that influence aesthetic and narrative perception. This study not only fills a knowledge gap but also offers practical guidance for designers, animators, and technology developers in utilizing GANs for animation production. However, the limited focus on visual elements without considering audience perceptions indicates room for further research, which could include analyzing audience responses or exploring GAN applications in more dynamic and complex animation scenarios.

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