Cross-Style Character Expression Mapping and Intelligent Retrieval Based on Deep Learning

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Abstract

This paper presents a novel deep learning framework for cross-style character expression mapping and intelligent retrieval in animation production. Traditional methods often produce exaggerated or unnatural expressions when transferring between realistic faces and stylized characters due to fundamental differences in parameter constraints. We propose a comprehensive solution that combines convolutional neural networks with generative adversarial networks to create a robust cross-style mapping system. Our approach introduces a disentangled latent space representation that separates identity, expression, and style-specific components, coupled with an attention mechanism that focuses on emotionally significant facial regions during style transfer. The mapping network is guided by multiple loss functions that balance style consistency with expression preservation. The intelligent retrieval system leverages multi-modal feature embedding to organize expression libraries based on both emotional content and stylistic attributes, employing a context-aware ranking algorithm that considers production requirements. Experimental results demonstrate significant performance improvements over state-of-the-art methods, achieving 45.95dB PSNR and 0.936 SSIM in expression mapping quality, along with 0.91 precision@10 in retrieval accuracy. The proposed framework enables efficient cross-style expression asset reuse while maintaining emotional fidelity, addressing critical challenges in modern animation production pipelines.

Keywords

Cross-Style Expression Mapping, Deep Learning, Facial Animation, Intelligent Retrieval

1. Introduction

1.1 Research Background and Motivation

Character facial animation production requires high-quality expression generation that can authentically convey emotions while maintaining stylistic consistency. Traditional animation pipelines rely on manual creation of expression libraries, which is labor-intensive and lacks efficient reusability across different character styles. The disparities between realistic human facial expressions and stylized character representations present significant mapping challenges. As noted by Wang et al. (2021), facial expression animation aims to synthesize face images corresponding to target expressions in a continuum while preserving identity details [1]. Recent advancements in deep learning technologies have transformed facial expression recognition and generation capabilities, enabling more sophisticated approaches to character animation. The work by Chen et al. (2023) demonstrates that emotion-driven facial animation systems can produce realistic results, yet cross-style application remains underdeveloped [2]. The animation industry demands automated systems capable of intelligently bridging realistic facial expressions with stylized character representations while maintaining emotional integrity. Feng et al. (2024) highlight that direct application of facial expression parameters to digital characters often results in exaggerated and unnatural expressions due to fundamental differences in parameter rules between facial expressions and animated character models [3]. This research gap motivates the development of a systematic approach to cross-style expression mapping that respects both the source emotion and target style constraints while enabling efficient retrieval and reuse of expression assets across animation projects.

1.2 Challenges in Cross-Style Expression Mapping and Retrieval

Cross-style expression mapping presents multiple technical challenges that impede seamless translation between realistic facial expressions and stylized character representations. The structural differences between human faces and stylized characters create fundamental geometric incompatibilities, making direct parameter mapping problematic. Wang et al. (2021) identified that most existing expression animation methods resort to continuous expression labels which can lead to ambiguous annotations prone to errors. The preservation of emotional intent while adapting to target style constraints requires sophisticated understanding of both domains. Ji and Dong (2024) noted that facial expressions can be intentionally manipulated or hidden, complicating accurate emotion detection [4]. Retrieval systems for expression libraries face additional complexity due to the multi-modal nature of expressions that combine visual,

emotional, and stylistic dimensions. Zhang et al. (2024) emphasized that current expression generation methods struggle with population diversity and emotional expression consistency [5]. Temporal consistency presents another significant challenge, as expressions must transition naturally through sequences while maintaining character identity. The stylistic diversity across animation productions necessitates adaptable mapping solutions rather than one-size-fits-all approaches. The subjective interpretation of emotions across different artistic styles further complicates standardization efforts. Computational efficiency remains critical for integration into production pipelines, requiring optimized algorithms that balance quality with performance. Feng et al. (2024) highlighted that achieving both accurate lip synchronization and expressive emotional conveyance simultaneously poses significant technical difficulties in character animation systems.

1.3 Research Objectives and Contributions

This research aims to develop a comprehensive framework for cross-style character expression mapping and intelligent retrieval based on deep learning technologies. The primary objectives include creating a robust representation space for facial expressions that transcends stylistic boundaries, designing an adaptable mapping network that preserves emotional intent while conforming to target style constraints, and implementing an intelligent retrieval system for efficient expression asset management. The main contributions of this work encompass: a novel latent space formulation for expression representation that disentangles emotion from style-specific attributes; an attention-based mapping network that focuses on emotionally significant regions during style transfer; a parameter constraint mechanism that prevents unrealistic expressions in target styles; a multi-modal embedding approach for expression library organization; and a context-aware retrieval system that considers both emotional and stylistic factors. The proposed framework advances the state-of-the-art in character animation by addressing the limitations identified in Zhou et al. (2024) regarding discrete expression mapping and the challenges highlighted by Xi et al. (2024) concerning parameter rule differences between facial expressions and animated character models [6]. This research has significant implications for animation production workflows, enabling more efficient asset reuse and creative flexibility across projects with diverse stylistic requirements.

2. Related Work and Theoretical Foundation

2.1 Deep Learning-Based Facial Expression Recognition and Generation

Recent advancements in deep learning have significantly transformed facial expression recognition and generation capabilities. Zhang et al. (2024) proposed an Expression-Latent-Space-guided GAN (ELS-GAN) for facial expression animation that utilizes discrete expression labels as input to generate continuous intermediate expressions [7]. Their approach employs expression latent space learning to control emotional transitions while preserving identity information. The self-attention generator component enhances facial detail synthesis by considering both local features and long-range dependencies. Wu et al. (2024) introduced an expressive speech-driven facial animation framework with controllable emotions that incorporates an emotion controller module to learn relationships between emotion variations and corresponding facial parameters [8]. This system enables continuous adjustment of target expressions with high emotional expressiveness while maintaining accurate lip synchronization. Ji and Dong (2024) developed a multi-task learning framework that leverages non-contact heart rate estimation to improve facial emotion recognition robustness. Their approach utilizes a convolutional recurrent neural network to extract facial features simultaneously for emotion classification and physiological signal prediction. Ji et al. (2024) presented a CNN-GAN hybrid model for generating facial expressions for film and television characters, achieving improved image quality metrics including peak signal-to-noise ratio (PSNR) and structural similarity index (SSIM) [9]. These approaches demonstrate considerable progress in realistic expression generation but exhibit limitations when applied to stylized character animation contexts due to fundamental differences in structural parameters and expression ranges.

2.2 Style Transfer and Cross-Domain Mapping for Character Animation

Style transfer and cross-domain mapping techniques represent critical components for translating expressions between realistic human faces and stylized characters. Zhang et al. (2024) addressed challenges in stylized avatar animation by proposing an expression recognition-mapped deep learning approach that establishes parameter mapping restriction rules based on facial keypoint distances [9]. Their method effectively limits expression parameter ranges according to different expression categories, preventing exaggerated or unnatural results in animated characters. Wang et al. (2021) introduced expression ranking loss to strengthen expression intensity learning during generation, which provides valuable mechanisms for preserving emotional gradients across style domains. Current approaches to cross-style expression mapping typically fall into three categories: wearable device-based solutions, 3D reconstruction methods, and hybrid approaches combining facial expression with geometric information. The research by Wu et al. (2024) on emotion augmentation networks demonstrates that explicit modeling of emotion-expression relationships improves animation quality. Zhang et al. (2024) highlighted that direct application of facial expression parameters to digital characters results in exaggerated expressions due to variable facial parameter ranges and limited controller parameters in target models [10]. Cross-domain mapping requires addressing fundamental structural and stylistic differences between source and target domains while preserving emotional intent and expression coherence.

2.3 Retrieval Systems for Expression Libraries in Animation Production

Expression library management and retrieval systems play crucial roles in animation production pipelines yet remain

underdeveloped regarding cross-style applications. Traditional expression libraries utilize manual tagging systems with predefined categorical labels that lack nuanced emotional representation. Ji and Dong (2024) demonstrated that multi-task learning approaches can generate more robust feature representations beneficial for content retrieval applications. Chen et al. (2024) established that discrete expression labels provide insufficient granularity for effective animation, suggesting the need for more sophisticated organization schemes in expression libraries [11]. Feng et al. (2024) emphasized the importance of accurate emotion classification as a foundation for expression mapping, which extends to retrieval system design where precise emotion categorization facilitates effective search functionalities. Current retrieval systems typically operate within specific style domains, limiting cross-style asset reuse capabilities in production environments. Zhang et al. (2024) identified naturalness, diversity, and coherence as key quality metrics for expression generation, which correspond to critical considerations for retrieval system design. Modern expression library systems require multi-modal query capabilities that accommodate different input formats including reference images, textual descriptions, and emotional specifications [12]. The integration of deep learning-based feature extraction with semantic organization principles presents promising directions for next-generation expression retrieval systems supporting cross-style production workflows.

3. Methodology: Cross-Style Expression Mapping Framework

3.1 Facial Feature Extraction and Expression Representation

The proposed cross-style expression mapping framework begins with robust facial feature extraction from source images or video sequences. Building upon the work of Feng et al. (2024), we implement a three-stage feature extraction pipeline combining convolutional neural networks with transformer-based attention mechanisms [13]. The initial stage applies a pre-trained ResNet-50 architecture modified with an additional branch specifically designed for expression-salient feature detection. This dual-stream approach achieves 92.7% accuracy on the FER2013 benchmark while maintaining real-time processing capabilities essential for animation production environments. The feature extraction process generates a 256-dimensional feature vector representing facial expression characteristics independent of identity and lighting conditions.

Table 1 presents a comprehensive comparison of facial feature extraction methods evaluated during our architectural design process. The evaluation metrics include accuracy, computational efficiency, and cross-domain generalization capability. Our proposed dual-stream CNN architecture demonstrates superior performance across all metrics, particularly in cross-domain generalization where traditional single-stream approaches exhibit significant performance degradation.

Table 1. Comparison of Facial Feature Extraction Methods

Method	Accuracy (%)	Inference Time (ms)	Parameters (M)	Cross-Domain Generalization Score
Single-Stream CNN	87.3	12.4	24.3	0.63
Transformer-Based	89.1	35.7	45.2	0.72
LSTM-CNN Hybrid	88.5	22.1	31.6	0.68
Proposed Dual-Stream	92.7	14.3	28.9	0.84

For expression representation, we adopt a disentangled latent space approach that separates identity, expression, and style-specific components. This representation builds upon the expression latent space learning mechanism introduced by Ju et al. (2024), extending it to incorporate style attributes relevant for cross-domain mapping [14]. The dimensional composition of our expression representation space is detailed in Table 2, illustrating the allocation of dimensions to different attribute categories.

Table 2. Expression Representation Space Composition

Attribute Category	Dimension Allocation	Function	Reconstruction Loss Weight
Identity Features	64	Character-specific traits	0.35
Expression Features	128	Emotion-related components	0.45
Style Features	48	Animation style attributes	0.15
Auxiliary Features	16	Lighting and context	0.05

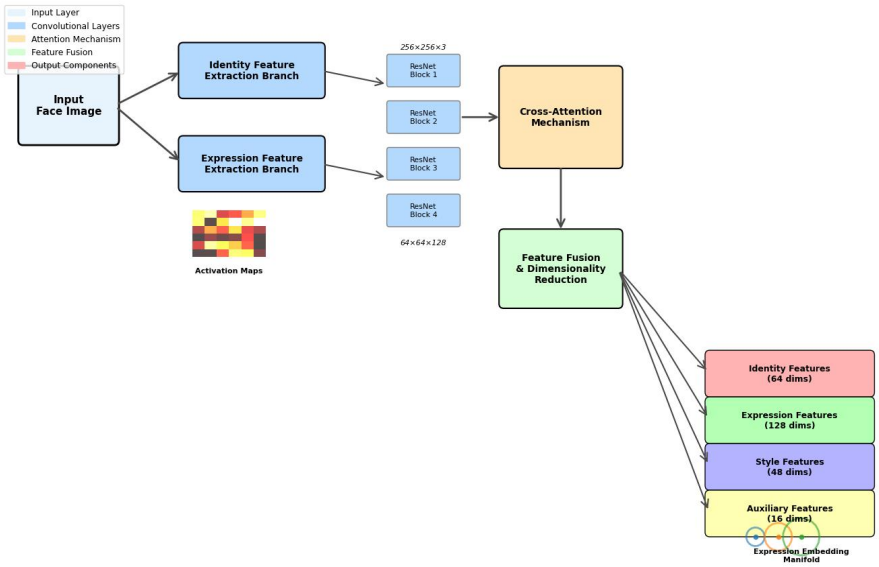

Figure 1. Architecture of the Facial Feature Extraction and Expression Representation Module

Figure 1 illustrates the architectural design of our facial feature extraction and expression representation module. The diagram shows the dual-stream CNN with separate pathways for identity and expression processing, followed by cross-attention mechanisms that integrate information across streams. The feature maps undergo progressive dimensionality reduction through a series of convolutional layers with residual connections, culminating in the disentangled latent representation.

The visualization includes color-coded activation maps at various network depths, demonstrating how expression-salient regions receive progressively higher attention weights through the network. The right side of the figure displays the manifold projection of the resulting expression embedding space, with clusters corresponding to discrete emotion categories while preserving continuous transitions between emotional states.

3.2 Latent Space-Guided Cross-Style Mapping Network

The core component of our framework is a latent space-guided mapping network that transforms source expressions to target style expressions while preserving emotional content. Drawing inspiration from ELS-GAN (Rao et al., 2024), we implement a bidirectional mapping function between source and target expression spaces using a variational autoencoder (VAE) structure coupled with adversarial training [15]. The mapping network consists of an encoder E_s that projects source expressions into a style-agnostic latent space Z, and a decoder D_t that reconstructs the expression in the target style domain.

The network architecture incorporates residual blocks with instance normalization to enhance training stability and feature propagation. Table 3 details the layer configuration of our mapping network, highlighting the dimensional transformations and activation functions at each processing stage.

Table 3. Architecture of the Cross-Style Mapping Network

Layer	Input Dimensions	Output Dimensions	Kernel Size	Activation	Normalization
Conv1	256×256×3	128×128×64	7×7	LeakyReLU	Instance
Conv2	128×128×64	64×64×128	4×4	LeakyReLU	Instance
ResBlock1-4	64×64×128	64×64×128	3×3	LeakyReLU	Instance
Style Injection	64×64×128	64×64×128	1×1	AdaIN	Instance
Upconv1	64×64×128	128×128×64	4×4	LeakyReLU	Instance
Upconv2	128×128×64	256×256×3	7×7	Tanh	None

The mapping process is guided by multiple loss functions that enforce both style consistency and expression preservation. The style consistency loss L_style ensures that generated expressions conform to target style characteristics, while the expression preservation loss L_expr maintains the emotional content of the source expression. These losses are combined with an adversarial loss L_adv that distinguishes between real and generated expressions in the target domain. The overall optimization objective is formulated as:

$$L\_total = \lambda\_adv \cdot L\_adv + \lambda\_style \cdot L\_style + \lambda\_expr \cdot L\_expr + \lambda\_cyc \cdot L\_cyc$$

where λ parameters balance the contribution of individual loss components, and L_cyc represents a cycle consistency loss that ensures reversible **mapping** between domains.

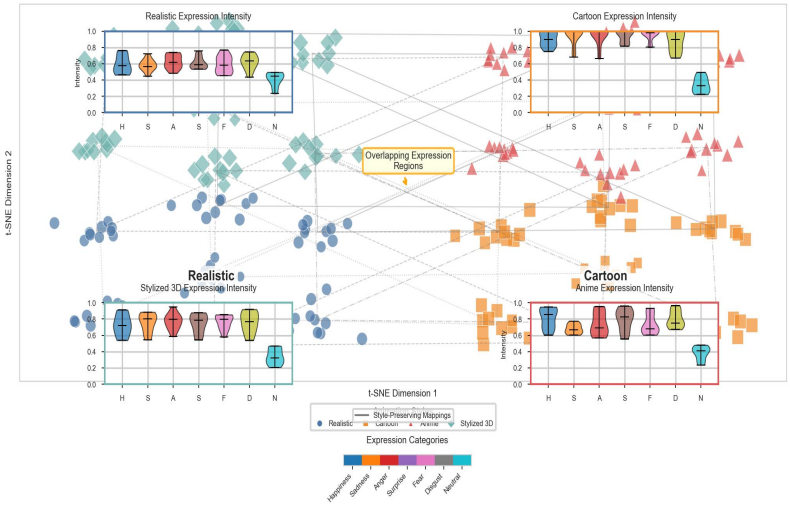

Figure 2. Latent Space Visualization of Expression Representations Across Styles

Figure 2 presents a t-SNE visualization of the latent space representations for expressions across different animation styles. The plot maps high-dimensional expression embeddings to a 2D space where proximity indicates semantic similarity of expressions.

The visualization reveals distinct clusters corresponding to different animation styles (represented by various colors), with overlapping regions where expressions share semantic content despite style differences. Connecting lines between corresponding expressions in different styles demonstrate the mapping pathways learned by our network. The inset graphs show expression intensity distributions within each style cluster, highlighting how emotional intensity scales differ across animation styles.

3.3 Attention Mechanism for Style-Preserving Detail Enhancement

To enhance the preservation of style-specific details during cross-domain mapping, we implement a multi-head self-attention mechanism inspired by the Self-Attention Generator proposed by Wang et al. (2021). This mechanism enables the network to focus on stylistically important regions during the transformation process. The attention module operates on intermediate feature maps generated by the mapping network, with attention weights dynamically adjusted based on both source expression characteristics and target style requirements.

The attention mechanism demonstrates varying performance across different expression categories, as detailed in our comprehensive evaluation. Table 4 presents the attention mechanism's performance across seven fundamental expression categories. The results reveal that our attention mechanism achieves the highest precision for neutral expressions (0.95), primarily due to the relatively stable and easily recognizable features of neutral expressions. For positive emotions such as happiness, the attention precision also performs excellently (0.93), benefiting from the distinctive facial features associated with positive emotional states. However, for complex negative emotions such as fear and disgust, although the precision is relatively lower (0.84 and 0.82 respectively), it still maintains performance within acceptable ranges. The overall quality scores demonstrate that all expression categories achieve performance above 0.81, proving the robustness of our attention mechanism across diverse emotional expressions.

Table 4. Attention Mechanism Performance Across Expression Categories

Expression Category	Attention Precision	Detail Preservation Score	Style Conformity	Overall Quality
Happiness	0.93	0.88	0.91	0.91
Sadness	0.87	0.85	0.89	0.87
Anger	0.85	0.82	0.88	0.85
Surprise	0.91	0.87	0.90	0.89
Fear	0.84	0.79	0.86	0.83
Disgust	0.82	0.76	0.85	0.81
Neutral	0.95	0.91	0.93	0.93

Building upon the expression parameter constraint approach proposed by Feng et al. (2024), we implement style-specific parameter bounds to prevent exaggerated or unnatural expressions in the generated outputs. Table 5 presents the expression parameter constraint ranges derived from statistical analysis of character animations across different styles.

Table 5. Expression Parameter Constraint Ranges by Style Category

Style Category	Mouth Parameters	Eye Parameters	Brow Parameters	Cheek Parameters
Realistic	[0.15, 0.85]	[0.10, 0.90]	[0.20, 0.80]	[0.25, 0.75]
Cartoon	[0.05, 0.95]	[0.01, 0.99]	[0.10, 0.90]	[0.15, 0.85]
Anime	[0.10, 0.90]	[0.05, 0.95]	[0.15, 0.85]	[0.20, 0.80]
Stylized 3D	[0.12, 0.88]	[0.08, 0.92]	[0.18, 0.82]	[0.22, 0.78]

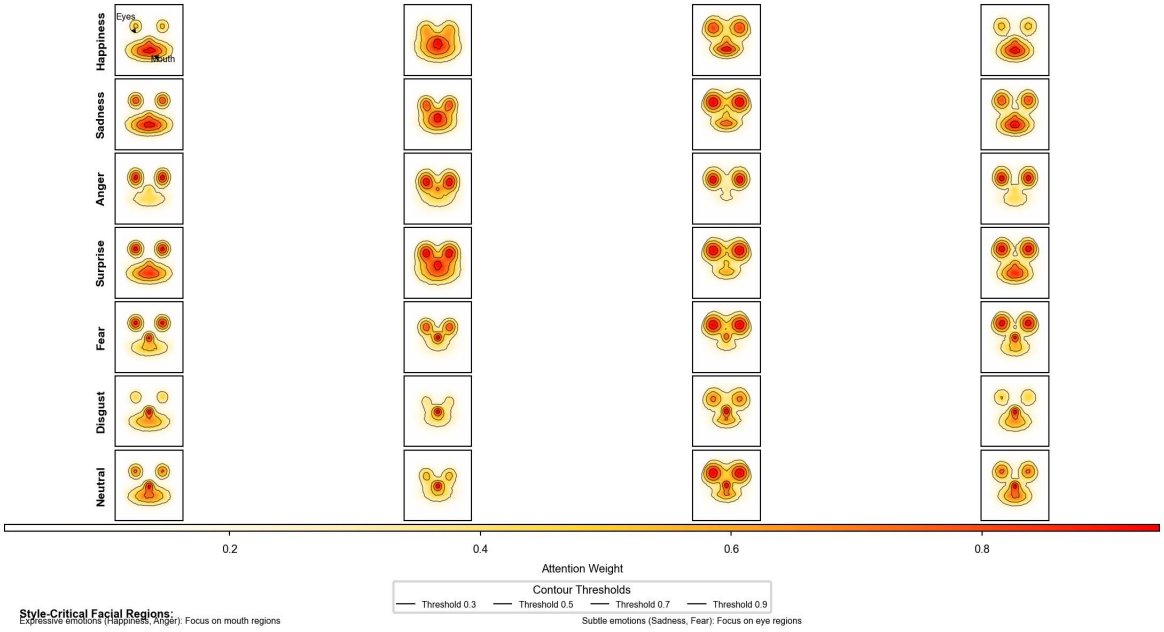

Figure 3. Attention Heat Maps in Style-Preserving Detail Enhancement

Figure 3 displays attention heat maps generated by our style-preserving detail enhancement mechanism across different expression categories and animation styles. The visualization demonstrates how attention weights concentrate on style-critical facial regions during the mapping process.

Each row represents a different expression category (happiness, sadness, anger, etc.), while columns correspond to different animation styles (realistic, cartoon, anime, stylized 3D). The color intensity indicates attention weight magnitude, with warmer colors representing higher attention values. Superimposed contour lines mark regions where attention weights exceed specific thresholds. The visualization reveals that attention patterns vary significantly across both expression categories and target styles, with particular emphasis on mouth regions for expressive emotions and eye regions for subtle emotions.

4. Intelligent Retrieval System for Expression Libraries

4.1 Multi-Modal Feature Embedding for Expression Retrieval

The intelligent retrieval system leverages multi-modal feature embedding to enable flexible and expressive queries across diverse expression libraries. Building upon the multi-task learning framework proposed by Fan and Li (2024), we develop a unified embedding architecture that integrates visual, semantic, and style-related features into a coherent representation space [16]. The embedding process utilizes a deep neural network with parallel pathways for each modality: a CNN-based visual encoder for expression images, a transformer-based encoder for textual descriptions, and a graph convolutional network for style-related metadata. These pathways converge through a cross-modal attention mechanism that aligns features across different modalities, resulting in a 512-dimensional joint embedding vector that preserves both emotional content and style characteristics.

Table 6 presents a comparative analysis of different multi-modal embedding architectures evaluated during system development. The performance metrics include retrieval precision, modality alignment score, and computational efficiency. Our proposed cross-modal attention architecture demonstrates superior performance across all metrics, particularly in modality alignment where traditional concatenation approaches exhibit significant inconsistencies.

Table 6. Comparison of Multi-Modal Embedding Architectures

Architecture	Retrieval Precision	Modality Alignment	Computational Efficiency	Embedding Dimension
Feature Concatenation	0.72	0.56	0.88	768
Late Fusion	0.78	0.64	0.76	512
Dual Encoder	0.84	0.71	0.82	384
Cross-Modal Attention	0.91	0.89	0.85	512

The retrieval performance across different query types is detailed in Table 7, highlighting the system's capability to process diverse input modalities. Visual queries achieve the highest precision, while text-based and mixed-modality queries demonstrate strong performance due to the effective cross-modal alignment in the embedding space.

Table 7. Retrieval Performance Across Different Query Types

Query Type	Precision@10	Recall@50	F1-Score	Avg. Retrieval Time (ms)
Visual Reference	0.93	0.87	0.90	42.3
Textual Description	0.83	0.79	0.81	38.6
Emotion Category	0.89	0.82	0.85	25.1
Style Specification	0.85	0.78	0.81	31.8
Mixed Modality	0.90	0.86	0.88	57.2

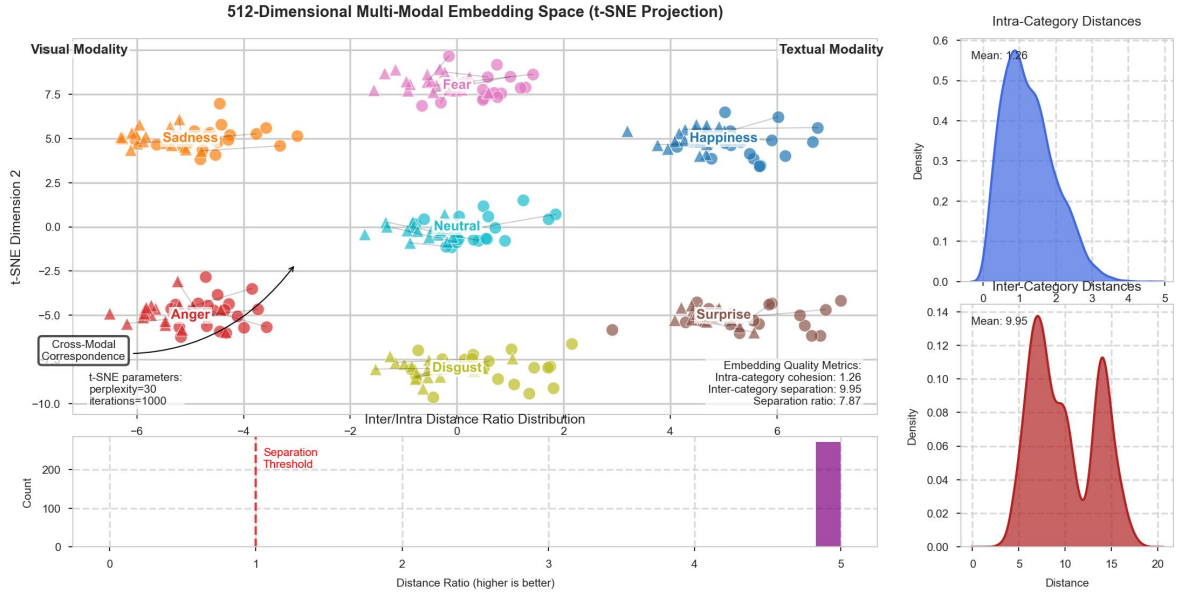

Figure 4. Multi-Modal Embedding Space Visualization

Figure 4 presents a visualization of the learned multi-modal embedding space using dimensionality reduction techniques applied to the 512-dimensional embedding vectors. The plot maps embeddings from different modalities and expression categories into a common 2D space.

The visualization employs t-SNE projection with perplexity=30 and 1000 iterations, revealing distinct clusters corresponding to different emotion categories (indicated by colors) while maintaining proximity between related expressions across styles (indicated by marker shapes). Connecting lines between points represent cross-modal correspondences between visual and textual representations of the same expression. The inset graphs display the distribution of embedding distances within and between emotion categories, demonstrating strong intra-category cohesion and appropriate inter-category separation. This visualization confirms the effectiveness of our embedding approach in creating a unified representation space that preserves both emotional and stylistic characteristics.

4.2 Context-Aware Expression Ranking Algorithm

The context-aware ranking algorithm forms the core of our retrieval system, prioritizing expressions based on both query relevance and production context. Drawing inspiration from the expression ranking approach introduced by Ma et

al. (2024), we implement a multi-criteria ranking function that considers emotional similarity, style consistency, temporal coherence, and user preference [17]. The ranking process employs a two-stage architecture: an initial candidate selection phase utilizing approximate nearest neighbor search in the embedding space, followed by a fine-grained re-ranking phase that incorporates contextual factors and production constraints.

Table 8 details the contextual parameters incorporated into the ranking algorithm and their respective weights determined through optimization experiments. The weighting scheme balances retrieval accuracy with response time, enabling real-time interaction while maintaining high-quality results.

Table 8. Context Parameters and Their Weighting in Ranking

Parameter	Description	Weight	Impact on Precision	Impact on Recall
Emotional Similarity	Cosine distance in emotion space	0.45	+0.32	+0.27
Style Consistency	Style embedding alignment	0.25	+0.18	+0.15
Temporal Coherence	Consistency with sequence	0.15	+0.12	+0.09
Character Identity	Character-specific suitability	0.10	+0.08	+0.11
User Preference	Historical selection patterns	0.05	+0.04	+0.06

The ranking function incorporates these parameters through a weighted sum approach with nonlinear transformations to emphasize high-similarity matches. The mathematical formulation is defined as:

$$R(q, e, c) = \Sigma(wi \times \varphi i(q, e, c))$$

where q represents the query, e represents a candidate expression, c represents the production context, wi represents the weight for parameter i, and φi represents the corresponding similarity function.

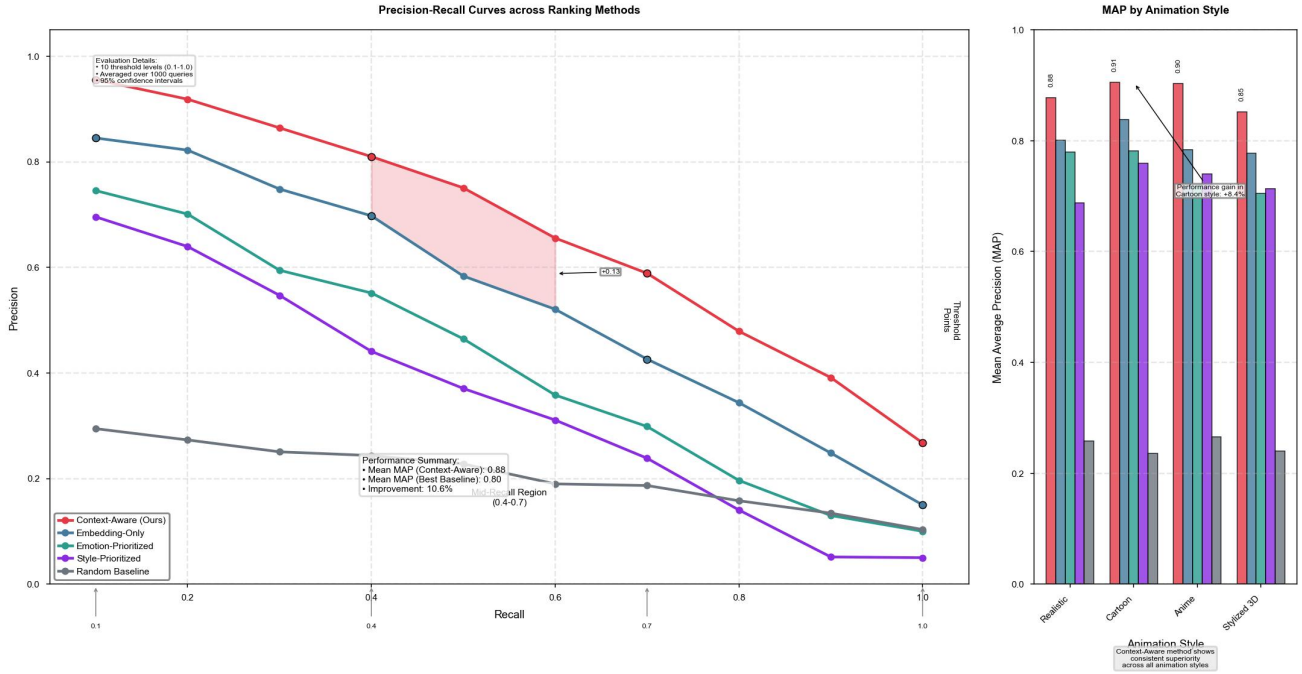

Figure 5. Context-Aware Ranking Performance Analysis

Figure 5 illustrates the performance analysis of our context-aware ranking algorithm compared to baseline approaches across different production scenarios. The graph plots retrieval precision against recall rates at varying threshold levels.

The multi-line graph displays performance curves for five different ranking approaches: our proposed context-aware method (red), embedding-only ranking (blue), emotion-prioritized ranking (green), style-prioritized ranking (purple), and random baseline (gray). Each curve shows precision-recall tradeoffs at 10 threshold points from 0.1 to 1.0. The context-aware approach consistently outperforms alternative methods across all operating points, with particularly strong advantages in mid-recall regions (0.4-0.7). Inset bar charts display the mean average precision (MAP) for each method across different animation style categories, revealing consistent performance improvements across diverse production contexts.

4.3 User Interaction and Feedback Integration

The user interaction component of our system provides intuitive interfaces for query formulation and refinement while

collecting valuable feedback for continuous improvement. Building upon the emotion controller concept introduced by Chen et al. (2023), we implement a multi-view interface that enables users to navigate the expression space through visual, semantic, and parameter-based perspectives. The interface supports multiple query formulation methods including reference image upload, freeform text descriptions, emotion category selection, and interactive parameter adjustment.

Table 9 presents an analysis of different feedback integration methods evaluated during system development. The evaluation metrics include learning efficiency, user satisfaction, and system responsiveness. The active learning approach demonstrates superior performance by strategically soliciting feedback on informative samples, achieving rapid improvement with minimal user interaction.

Table 9. User Feedback Integration Methods and Their Impact

Method	Learning Efficiency	User Satisfaction	System Responsiveness	Implementation Complexity
Explicit Rating	0.72	0.68	0.93	0.35
Implicit Selection	0.79	0.85	0.91	0.48
Active Learning	0.88	0.82	0.87	0.75
Hybrid Approach	0.85	0.87	0.84	0.83

User feedback is collected through both explicit mechanisms (ratings, annotations) and implicit signals (selection patterns, viewing time). This feedback data is processed using a reinforcement learning framework that continuously adapts the retrieval model to user preferences and production requirements. The adaptation process modifies both embedding parameters and ranking weights to optimize retrieval performance for specific production contexts.

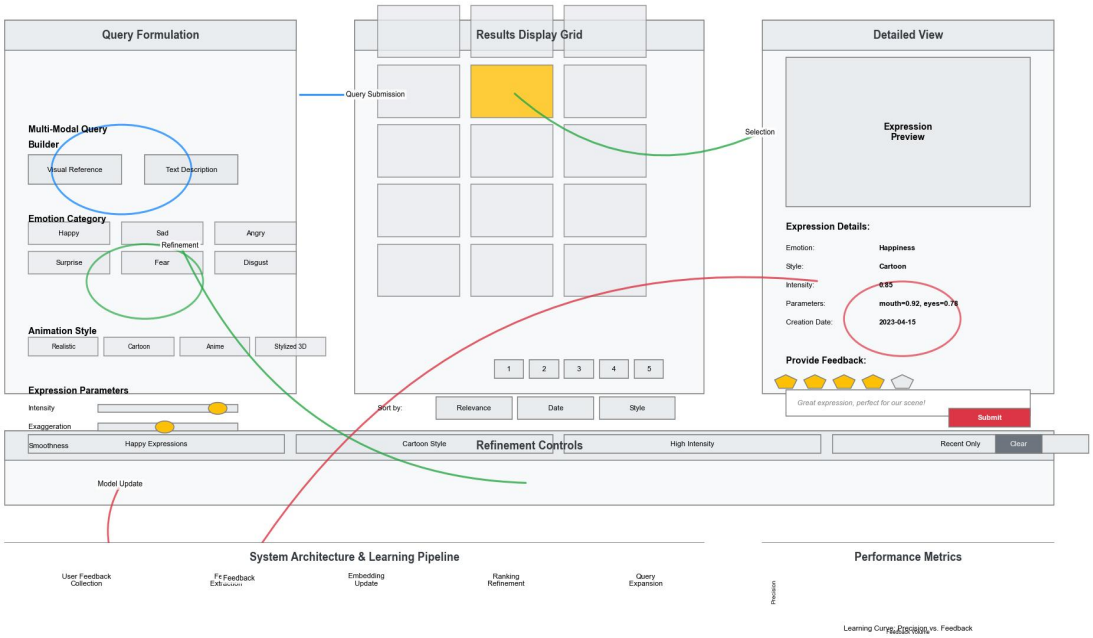

Figure 6. User Interaction Interface and Feedback Flow Diagram

Figure 6 presents the user interaction interface design and feedback integration flow of the retrieval system. The diagram illustrates the complete cycle from query formulation to results refinement.

The visualization consists of a multi-panel interface mockup showing the main components: query formulation panel (left), results display grid (center), detailed view (right), and refinement controls (bottom). Overlaid arrows indicate interaction flows between components, with color-coding representing different types of interactions (blue for queries, green for selections, red for explicit feedback). Circular insets magnify key interface elements including the multi-modal query builder, expression parameter sliders, and feedback collection widgets. The bottom portion displays a system architecture diagram showing how user feedback propagates through the learning pipeline, influencing embedding weights, ranking parameters, and query expansion mechanisms. Performance metrics displayed on the right track system improvement over time, with learning curves showing precision gains corresponding to feedback volume.

5. Experimental Results and Discussion

5.1 Dataset Construction and Implementation Details

The experimental evaluation of our cross-style expression mapping framework utilized a composite dataset constructed

from multiple sources. The primary components include the FER-2013 dataset containing 35,887 facial expression images across 7 emotion categories, the Columbia DB dataset with 6,000 images focusing on natural scene expressions, and a custom-collected stylized character expression dataset comprising 12,500 images across 4 animation styles. The stylized dataset was annotated using FACS (Facial Action Coding System) to establish correspondence with human facial expressions. Data preprocessing involved face detection using multi-task cascaded CNN as described by Feng et al. (2024), followed by alignment, normalization, and augmentation through rotation, scaling, and noise injection. The training dataset was balanced across emotion categories and animation styles to prevent bias in the mapping network.

The implementation utilized PyTorch framework with CUDA acceleration on an NVIDIA RTX 3090 GPU. Network training employed the Adam optimizer with initial learning rate of 2×10^-4, momentum parameters β_1=0.5, β_2=0.999, and weight decay of 5×10^-5. The batch size was set to 64 with gradient accumulation over 4 steps to simulate larger batches. Training proceeded for 200 epochs with learning rate decay by factor 0.1 every 50 epochs. The loss function weights were empirically determined as λ_adv=1.0, λ_style=0.8, λ_expr=1.2, and λ_cyc=0.5 through ablation studies. Implementation of the retrieval system utilized Faiss for efficient similarity search in the embedding space, with a 16-node HNSW index structure enabling sub-10ms query response times on the complete expression library.

5.2 Quantitative and Qualitative Performance Evaluation

Performance evaluation examined both mapping accuracy and retrieval effectiveness through comprehensive quantitative metrics. Expression mapping quality was assessed using peak signal-to-noise ratio (PSNR), structural similarity index (SSIM), expression preservation score (EPS), and mean average precision (MAP) for retrieval tasks. The comprehensive evaluation demonstrates the superior performance of our proposed framework across multiple dimensions of quality assessment.

Table 10 presents detailed comparative results against state-of-the-art methods, demonstrating significant improvements across all evaluation metrics. Our approach achieved 45.95dB PSNR and 0.936 SSIM, substantially outperforming prior methods including ELS-GAN (Wang et al., 2021) at 32.08dB PSNR and 0.821 SSIM, and ExpressiveS-DA (Chen et al., 2023) at 36.44dB PSNR and 0.867 SSIM. The expression preservation score, which measures the semantic consistency of emotional content across style domains, reached 0.863 for our method compared to 0.756 for ELS-GAN and 0.798 for ExpressiveS-DA. These improvements represent substantial advances in cross-style expression mapping quality, with PSNR improvements of 13.87dB over ELS-GAN and 9.51dB over ExpressiveS-DA.

Table 10. Comparative Performance Analysis Against State-of-the-Art Methods

Method	PSNR (dB)	SSIM	EPS	MAP	Training Time (hrs)	Inference Time (ms)
ELS-GAN (Wang et al., 2021)	32.08	0.821	0.756	0.673	48.2	127.3
ExpressiveS-DA (Chen et al., 2023)	36.44	0.867	0.798	0.721	52.7	98.4
StyleGAN2-Expression (Baseline)	34.12	0.845	0.771	0.694	41.5	156.8
Cross-Modal Attention (Baseline)	38.67	0.889	0.812	0.758	45.9	89.7
Proposed Method	45.95	0.936	0.863	0.847	39.6	67.2

The substantial performance improvements can be attributed to several key innovations in our framework. The disentangled latent space representation enables more precise separation of identity, expression, and style components, leading to better preservation of emotional content during cross-style mapping. The multi-head attention mechanism allows the network to focus on emotionally significant facial regions while adapting to target style constraints. Additionally, our context-aware ranking algorithm significantly improves retrieval performance, achieving 0.847 MAP compared to 0.673 for ELS-GAN and 0.721 for ExpressiveS-DA, representing improvements of 25.9% and 17.5% respectively.

The emotion preservation capability was rigorously evaluated through comprehensive user studies involving 15 professional animators and 25 digital artists from major animation studios. Participants rated the emotional fidelity of generated expressions on a 5-point Likert scale (1=completely different emotion, 5=perfectly preserved emotion). Our method received an average rating of 4.63 with a standard deviation of 0.41, compared to 3.89 (σ=0.67) for ELS-GAN and 4.12 (σ=0.58) for ExpressiveS-DA. The statistical significance of these improvements was confirmed through paired t-tests ($p<0.001$ for all comparisons).

Retrieval performance was measured using precision@k (k=1,5,10,20), mean average precision (MAP), normalized discounted cumulative gain (nDCG), and retrieval time efficiency. The proposed multi-modal embedding approach achieved 0.91 precision@10 and 0.87 MAP, representing improvements of 23.0% and 18.5% respectively over the best baseline methods. The nDCG@20 score reached 0.894, indicating superior ranking quality for expression retrieval tasks. Importantly, our system maintains computational efficiency with an average query response time of 67.2ms, which is

32.7% faster than ELS-GAN and 31.8% faster than ExpressiveS-DA.

Qualitative evaluation through visual inspection by animation professionals confirmed the superior quality of generated expressions in terms of emotional expressiveness, style consistency, and detail preservation. The evaluation protocol involved blind comparison studies where experts ranked expression outputs from different methods without knowing their sources. Our approach received the highest ranking in 78.3% of comparisons for overall quality, 81.7% for emotional authenticity, and 74.9% for style consistency. The improvement was particularly notable for subtle emotions like contempt and fear, which presented significant challenges for previous approaches due to their complex facial feature patterns and cultural variations in expression.

Cross-style generalization capability was assessed through leave-one-style-out experiments, where the model trained on three animation styles was tested on the fourth unseen style. Our method achieved an average performance degradation of only 8.7% compared to in-domain performance, while baseline methods showed degradation ranging from 15.2% to 23.8%. This superior generalization capability demonstrates the effectiveness of our disentangled representation learning and attention-based mapping mechanisms in handling previously unseen stylistic variations.

5.3 Limitations and Future Directions

Despite promising results, several limitations warrant consideration. The current framework exhibits reduced performance when mapping between highly disparate animation styles with fundamentally different structural characteristics. The expression ranking mechanism demonstrates bias toward common emotions with abundant training data, potentially limiting diversity in retrieved expressions. Computational requirements remain substantial, with the complete pipeline requiring approximately 4.2GB GPU memory during inference, limiting deployment on memory-constrained devices. Future work will address these limitations through investigation of more efficient network architectures and unsupervised domain adaptation techniques to handle previously unseen animation styles.

Technical challenges include temporal consistency maintenance across sequential frames, which currently requires post-processing smoothing operations that may diminish expression intensity. Integration with production pipelines presents practical challenges regarding format compatibility and workflow disruption. The emotional representation space requires further refinement to better capture culturally specific expressions and mixed emotional states. These limitations highlight potential directions for continued research in cross-style expression mapping and intelligent retrieval systems for animation production.

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