MoEE: Mixture of Emotion Experts for Audio-Driven Portrait Animation

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Abstract

The generation of talking avatars has achieved significant advancements in precise audio synchronization. However, crafting lifelike talking head videos requires capturing a broad spectrum of emotions and subtle facial expressions. Current methods face fundamental challenges: ***a)*** *the absence of frameworks for modeling single basic emotional expressions, which restricts the generation of complex emotions such as compound emotions;* ***b)*** *the lack of comprehensive datasets rich in human emotional expressions, which limits the potential of models. To address these challenges, we propose the following innovations:* ***1)*** *the* ***M****ixture of* ***E****motion* ***E****xperts (****MoEE****) model, which decouples six fundamental emotions to enable the precise synthesis of both singular and compound emotional states;* ***2)*** *the DH-FaceEmoVid-150 dataset, specifically curated to include six prevalent human emotional expressions as well as four types of compound emotions, thereby expanding the training potential of emotion-driven models. Furthermore, to enhance the flexibility of emotion control, we propose an emotion-to-latents module that leverages multimodal inputs, aligning diverse control signals—such as audio, text, and labels—to ensure more varied control inputs as well as the ability to control emotions using audio alone. Through extensive quantitative and qualitative evaluations, we demonstrate that the MoEE framework, in conjunction with the DH-FaceEmoVid-150 dataset, excels in generating complex emotional expressions and nuanced facial details, setting a new benchmark in the field. These datasets will be publicly released.*

1. Introduction

In recent years, audio-driven avatar generation has achieved significant advancements in precise audio synchronization [3, 15, 17, 36, 40–42, 46]. However, creating realistic conversational videos requires more than just audio synchronization; it also demands the capture of a wide range of emotions and subtle facial expressions. Research in this area holds valuable applications not only in the entertainment industry but also in fields such as remote communication, virtual assistants, and mental health, showcasing considerable potential.

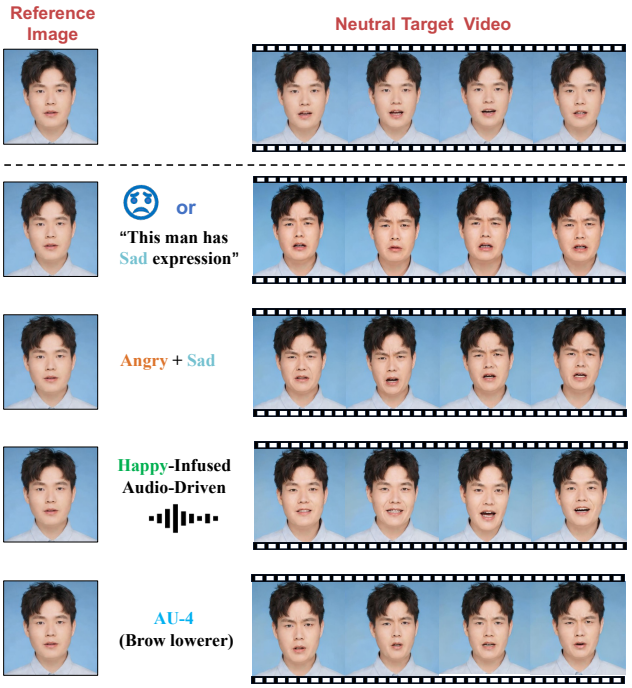

Figure 1. MoEE enables more natural and vivid basic emotion control and compound emotion control, via labels or text prompts in generated talking face. It also achieve emotion control based solely on audio with emotional cues. Beyond coarse-grained emotion control (*e.g.*, audio, label and text prompt), our method allows for fine-grained expression control through AU labels.

Previous studies attempt to integrate emotional and expressive information through labels, text, or videos [8, 20, 21, 33, 35, 39, 44]. While these approaches can control

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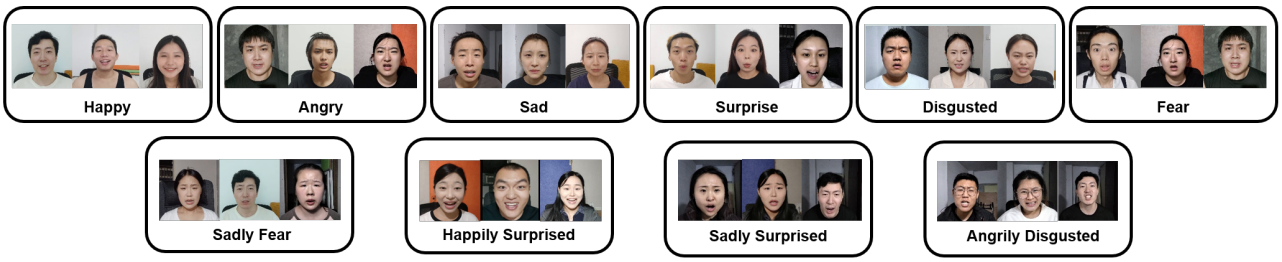
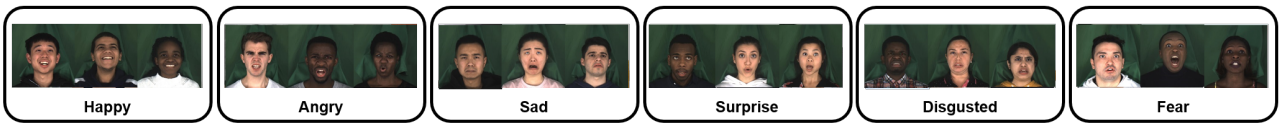


(a) DH-FaceEmoVid-150



(b) MEAD

Figure 2. Showcase of publicly available datasets and our proposed datasets: We refer to datasets like (a) DH-FaceEmoVid-150 and (b) MEAD as emotion datasets.

basic emotions, they lack naturalness in generating single emotions and diversity in generating complex compound emotions. The fundamental limitations are twofold: first, the absence of precise frameworks for modeling basic emotions hinders accurate synthesis of complex emotional states. Second, the lack of comprehensive datasets rich in diverse human emotional expressions significantly limits the potential of these models to produce varied emotional outputs.

To address these issues, we draw inspiration from mixture of experts and propose the Mixture of Emotion Experts (MoEE) model. This model decouples six basic emotions, enabling precise synthesis of both singular and compound emotional states. To push the performance boundaries of MoEE, we curate the DH-FaceEmoVid-150 dataset, comprising 150 hours of video content featuring six basic and four compound emotions. Initially, we fine-tune a referenceNet [13, 41] and a denoising unet [12, 28] on the entire dataset. We then train six emotion expert networks with single emotion data for precise modeling, and a gating network with compound emotion data to synthesize complex expressions. This approach significantly boosts the generative quality and generalization ability of the MoEE model.

Furthermore, we design an emotion-to-latents module that aligns multimodal inputs (*i.e.*, audio, text, labels, as illustrated in Figure 1) into a latent space using adaptive attention. Extensive quantitative and qualitative evaluations demonstrate that the MoEE framework, in conjunction with the DH-FaceEmoVid-150 dataset, excels in generating both singular and complex emotional expressions with nuanced facial details. Our contributions are as follows:

- We present the Mixture of Emotion Experts (MoEE) model focused on facial emotional expression in audio-driven portrait animation. MoEE achieves lifelike generation quality for both singular and compound emotions with strong generalization ability.
- We introduce the DH-FaceEmoVid-150 dataset, a high-resolution (1080p) collection specifically for human facial emotional expressions. It comprises six basic and four compound emotions, providing multimodal information such as AU labels, text descriptions, and emotion categories for each video.
- We develop a module that aligns multimodal inputs to unify coarse and fine-grained control signals, allowing flexible and controllable generation of detailed expressions in conjunction with MoEE.
- Extensive experiments validate the superiority of our dataset and MoEE model architecture, achieving state-of-the-art emotional expression in portrait animation.

2. Related Work

Audio-driven Talking Head Generation. Significant progress has been made in audio-driven talking head generation and portrait image animation, emphasizing realism and synchronization with audio inputs [3, 5, 10, 30, 32, 33, 36]. Notably, Wav2Lip [26] excels at overlaying synthesized lip movements onto existing video content, though its outputs can sometimes show realism issues, such as blurring or distortion in the lower facial region. Recent advancements have pivoted towards image-based methodologies, undergirded by diffusion models, to mitigate the limitations of video-centric approaches and enhance the realism and expressiveness of synthesized animations. Subsequent methods like SadTalker [46] and VividTalk [33] incorporated 3D motion modeling and head pose generation to enhance expressiveness and temporal synchronization. AniPortrait [40], EchoMimic [3], Hallo [41] and Loopy [15] have contributed to enhanced capabilities, focusing on expressiveness, realism, and identity preservation.

Emotion Editing in Talking Head Videos. Acknowledging the limitations of previous efforts, which often produce

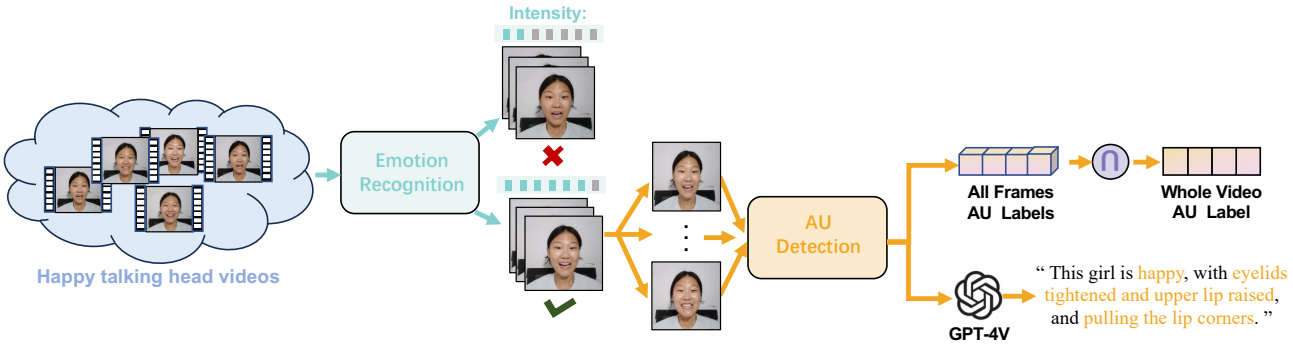


Figure 3. First, we filter the emotion dataset based on emotion intensity. Then, to achieve fine-grained control, we extract the AUs and prompt GPT-4V to paraphrase them into a sentence.

emotionless avatars, there is a growing interest in integrating emotions into talking face generation [16, 25, 34, 43]. For example, EAT [8] employs a mapping network to derive emotional guidance from latent codes, where EAMM [14] characterizes the facial dynamics of reference emotional videos as displacements in motion representations. Similarly, StyleTalk [20] develops a style encoder to capture the style of a reference video. However, these methods either support a limited range of individual emotion types or require other videos with the desired style, thereby restricting the flexibility and controllability. Recently, some efforts have focused on using text as an emotion control signal, such as InstructAvatar [39]. Nevertheless, these methods rely solely on text descriptions for emotion control, which limits the diversity of control conditions. In contrast, our approach combines advancements in model architecture and dataset design to enable vivid and natural emotion and expression control under multimodal conditions, achieving greater flexibility and expressiveness.

3. Data Collection and Filteration

Talking head generation model is naturally scalable for large datasets, but it also requires high-quality data as it learns from data distribution. We constructed our dataset from multiple sources. Some open-source emotion datasets, like MEAD [37], exhibit limitations including small size and a restricted range of emotion categories. To fill the gaps in existing datasets, we have additionally collected a new emotional dataset: DH-FaceEmoVid-150, which focuses on basic emotions and compound emotions. As shown in the Figure 2, the entire dataset comprises six basic emotions: angry, disgusted, fear, happy, sad, surprised. In addition, the dataset includes four compound emotions: angrily disgusted, sadly surprised, sadly fear, happily surprised. The total duration of the dataset is 150 hours, featuring 80 actors, with a resolution of no less than 1080×1080. The overview of all the dataset statistics this model used is demonstrated in Tab. 1. Additional visualizations of the dataset can be found in supplementary material.

On this basis, to improve the quality of the dataset, we filtered the dataset based on emotion intensity, extracted the corresponding AU (Action Unit) labels for each video, and generated fine-grained text instructions for each video. As shown in Figure 3, we used LibreFace [2] for emotion recognition to filter out videos with ambiguous emotions. We found that existing emotional talking head datasets typically provide only tag-level annotations with limited emotion categories (*e.g.*, "happy" or "sad") for talking videos, so we obtained fine-grained AU labels and natural text instructions through Action Unit Extraction and VLM Paraphrase. Action Units (AUs) are defined by Facial Action Coding System (FACS) [7] and are used to describe facial muscle movements. We extracted AU labels for each frame and the corresponding action descriptions using the ME-GraphAU model [19]. Then, we randomly selected 5 frames from a video, input the action descriptions and frames images into the GPT-4V [24], and obtained text instructions for the entire video.

Table 1. Statistics of the collected dataset

Datasets	IDs	Hours	Single Emotion	Compound Emotion	Text	AU Label
HDTF	362	16	×	×	×	×
DH-FaceVid-1K	500	200	×	×	×	×
Mead	60	40	✓	×	×	×
DH-FaceEmoVid-150	80	150	✓	✓	✓	✓

4. Methodology

In this section, we introduce our MoEE model. In Sec. 4.1, we provide an overview of the architecture of MoEE. Subsequently, Sec. 4.2 describes the Mixture of Emotion Expert to achieve diverse emotions control, while Sec. 4.3 introduce the detail of Emotion-to-latents Module. Finally, in Sec. 4.4, we demonstrate the training and inference details.

4.1. Model Overview

Given one portrait image $\boldsymbol{I}$, a sequence of audio clips $\boldsymbol{A} = [a_1, a_2, ..., a_N]$, and the Emotion Condition $\boldsymbol{C}$, our model is tasked with animating the portrait to utter the audio with the target style represented by the text, audio or label. Overall, we aim to learn a mapping to generate a video $\boldsymbol{V} = \boldsymbol{F}(\boldsymbol{I}, \boldsymbol{A}, \boldsymbol{C})$. As illustrated in Figure 4, the backbone of MoEE is a denoising U-Net [1], which denoises the input multi-frame noisy latent under the conditions. This

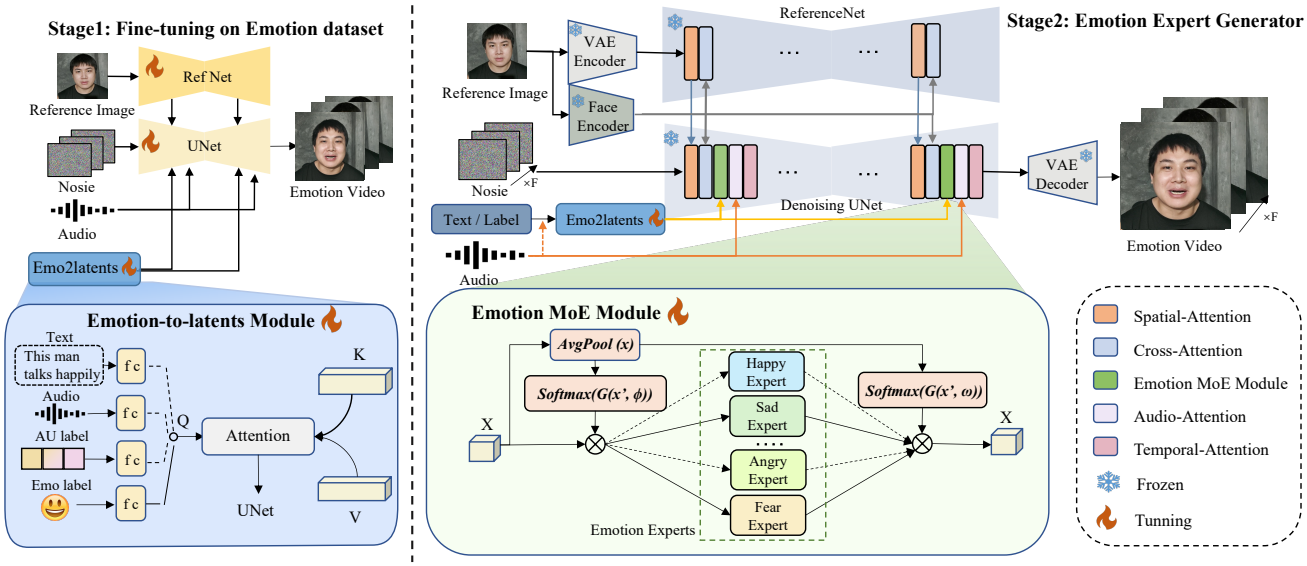


Figure 4. The overall framework of MoEE implements a two-stage training process. First, we fine-tune the Reference Net and denoising U-Net modules on emotion datasets to enable the model to learn as much prior knowledge about expressive faces as possible. Then, we achieve more natural and accurate emotion and expression control through the Mixture of Emotion Experts. Additionally, the Emotion-to-Latents module enables multi-modal emotion control.

architecture includes an additional Reference Net module, which is a Unet-based Stable Diffusion network with the same number of layers as the denoising model network, to capture the visual appearance of both the portrait and the associated background. The input audio embedding is derived from a 12-layer wav2vec [29] network and fed into the Audio Attention Layer to encode the relationship with the audio. The Temporal Attention layer [9] is a temporal-wise self-attention layer that captures the temporal relationships between the video frames. Additionally, the denoising U-Net incorporates an Emotion MoE Module, consisting of six emotion-specific expert modules, to encode relationships with specific emotional conditions. In the following sections, we will detail how to design a mixture of emotion experts module, as well as how to design a multimodal emotion condition module.

4.2. Mixture of Emotion Experts

To address the factors contributing to the poor performance of emotion generation, we propose constructing a Mixture of Experts (MoE) module. This module consists of emotion experts, each specializing in a single emotion. We focus on six basic emotions: happiness, sadness, anger, disgust, fear, and surprise, training an expert model for each. This is achieved by training six cross-attention modules on well-structured, single-emotion datasets. During the training of each expert, the latent noise bypasses the other modules, whose parameters remain fixed. The cross attention operation is formulated as:

$$CrossAttn(Z_t, C) = \text{softmax}(QK^T/\sqrt{d})V \quad (1)$$

where $Q = W_Q Z_t$, $K = W_K C$ and $V = W_V C$ are the queries; W_Q, W_K and W_V are learnable projection matrices; and d_k is the dimensionality of the keys.

Soft Mixture Assignment. After training expert models for the six basic emotions, an assignment mechanism needs to be introduced to better coordinate each expert model during the generation process. Since the process of generating complex emotions requires combinations of multiple basic emotions, while the hard assignment mode in MoE only permits one expert to access the given input. Therefore, inspired by Soft MoE [27], we adopt a soft assignment, allowing multiple experts to handle input simultaneously. In addition to the need for emotion control over the global video frames, localized control is also essential, as different emotions are mainly expressed through specific facial expressions. Therefore, we use both global and local assignments. Local assignment, by independently assigning weights to each token, enables more precise control over the emotional expression of local features, facilitating the generation of more vivid expressions.

Specifically, considering the input $X \in \mathbb{R}^{b\times n\times d}$ where b is the number of batch size, n is the number of token and d is the feature dimension. For local assignment, we use a local gating network that contains a learnable gating layer $G(\,,\phi)$ ($\phi \in \mathbb{R}^{d\times e}$, e is the number of experts and here e is 6, below is the same) and a sigmoid function. The gating network is to produce six normalized score maps $s = [s_1, s_2, s_3, s_4, s_5, s_6]$ ($s \in \mathbb{R}^{n\times e}$) for six emotion experts as formulated:

$$s = \text{sigmoid}(G(X\,,\phi) \quad (2)$$

For global soft assignment, we use a global gating network including an AdaptiveAvePool, a learnable gating layer $G(\,,\omega)$ ($\omega \in \mathbb{R}^{d\times e}$), and a $\mathrm{softmax}$ function. This gating network is to produce six global scalars $g = [g_1,\ g_2,\ g_3,\ g_4,\ g_5,\ g_6](g \in \mathbb{R}^e)$ for six experts as formulated:

$$g = \mathrm{softmax}(G(\mathrm{Pool}(X)\,,\omega))\,. \tag{3}$$

The soft mechanism is built on the fact that the input X can adaptively determine how much (weight) should be sent to each expert by the $\mathrm{softmax}$ function. At the same time, the weights among the various emotion experts are interdependent. For single emotion control generation, only the corresponding expert model needs to be invoked. For compound emotion control generation, cooperation among different emotion expert modules is required. Specifically, we first send X to each emotion expert respectively, use s_i, where i is the number of emotion expert, to perform element-wise multiplication (local assignment), and also perform global control by scalars g_i. Then we add them back to the X, producing a new output $X^{'}$:

$$X^{'} = X + \sum_{i=1} g_i \cdot E_i(X \cdot s_i) \tag{4}$$

Futher network details about Mixture of Emotion Experts are provided in the supplementary material.

4.3. Emotion-to-latents Module

This module can accept a variety of different modality conditions, such as text, audio, and labels. As illustrated in Figure 4, it maps multimodal conditions, which have both strong and weak correlations with emotion, to a shared emotion latent space, ensuring that all these conditions have a good control effect. Specifically, the conditions from various modalities are first transformed into feature vectors using pretrained encoders. For textual information, we use the T5 text encoder [23] and for audio signals, we employ emotion2vec model [22]. For label signals, we train a custom two-layer MLP network as an encoder. Then, we map these feature vectors to the same dimension via fully connected layers (FC) to serve as query latent in the attention mechanism. Additionally, we maintain a set of learnable embeddings, which act as key and value features for attention computation to obtain new features. These new features, referred to as emotion latent, replace the input conditions in subsequent computations. These feature vectors are then fed into the Emotion MoE Module, serving as key and value features, injecting condition information into the U-Net. Futher network details about Emotion-to-latents Module are provided in the supplementary material.

4.4. Training and Inference

Masked Noisy Emotion Sampling. Due to the relatively small size of the segmented single-emotion datasets, the expert models trained on them often risk learning knowledge beyond the targeted emotion. To amplify the impact of emotion, we incorporate data of other emotions or neutral expressions with a certain probability for a particular emotion. As illustrated in Figure 4, this approach introduces noise into the emotion conditions while expanding the number of person IDs thus enabling the model to concentrate more effectively on the control of emotion conditions.

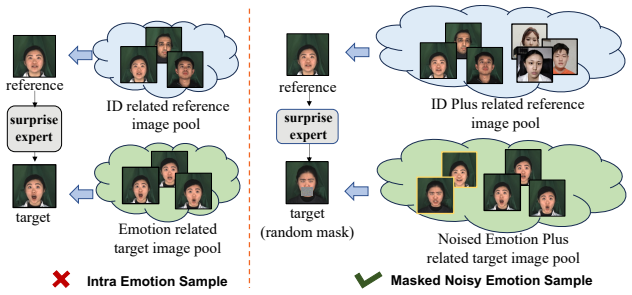


Figure 5. Visualization of different emotion sample strategy. Results demonstrate that the proposed masked noisy emotion sample strategy can ensure natural and vivid expression.

However, since frames with different emotions come from different speech videos, there can be significant variations in mouth shapes, leading the model to focus more on mouth transformations rather than the emotions themselves. To mitigate this, we first locate the position of the mouth in portrait images by Mediapipe [18]. We then apply a mask to the mouth. This method ensures that the expert model maintains consistent person ID while achieving more accurate learning of facial expression transformations.

Loss function. Since the resolution of latent space (64×64 for 512×512 image) is relative too low to capture the subtle facial details, a timestep-aware spatial loss is proposed to learning the face expression directly in the pixel space. The loss function L is summarized as:

$$L = L_{latent} + \lambda L_{spatial} \tag{5}$$

Where L_{latent} is the objective function guiding the denoising process. With timestep t is uniformly sampled from $\{1, ..., T\}$. The objective is to minimize the error between the true noise ϵ and the model-predicted noise $\epsilon_\theta(z_t, t, c)$ based on the given timestep t, the noisy latent variable z_t, and c_{embed} denotes the conditional embeddings. The loss function during the training process is summarized as:

$$L_{latent} = \mathbb{E}_{t, c_{embed}, z_t, \epsilon}[||\epsilon - \epsilon_\theta(z_t, t, c_{embed})||^2] \tag{6}$$

For $L_{spatial}$, predicted latent z_t is first mapped to z_0 by sampler and the predicted image I_p is obtained via passing z_0 to the vae decoder. The L1 loss is computed on the predicted image and its corresponding ground truth. Additionally, we introduce a Perception loss, enhancing details and visual realism. The specific formula is shown below:

$$L_{spatial} = w(t)(||I_p, I_{GT}|| + ||V(I_p), V(I_{GT})||^2) \tag{7}$$

Figure 6. Qualitative comparison with baselines. It shows that MoEE achieves well lip-sync quality and emotion controllability. Additionally, MoEE enables emotion control without text prompt.

where V denotes the feature extractor of VGG19, and $w(t) = cosine(t * \pi/2T)$ serves as a timestep aware function to reduce the weight for large t.

Training. This study implements a two-stage training process to optimize distinct components of the overall framework. In the initial stage, considering the limited emotion priors due to the lack of high-quality emotion datasets, our work bridges this gap by providing carefully collected emotion datasets. We fine-tuning the Reference Net and denoising U-Net modules on these emotion datasets, and the well-trained model is then sent to the next stage.

In the second stage, the model is trained to generate video frames based on the reference image, driven audio, and emotion condition. During this phase, the spatial modules, cross modules, audio modules and temporal modules of Reference Net and denoising U-Net remain static. The optimization process focuses on the Emotion MoE modules, which are optimized to enhance the accuracy and diversity of emotion control generation capabilities.

Inference. During the inference stage, the network takes a single reference image, driving audio and emotion condition as input, producing a video sequence that animates the reference image based on the corresponding emotion and audio. To produce visually consistent long videos, we utilize the last 2 frames of the previous video clip as the initial k frames of the next clip, enabling incremental inference for video clip generation.

5. Experiment

5.1. Experiment setup

Datasets. As outlined earlier, this research utilizes the filtered HDTF [47], a segment of the DH-FaceVid-1K [6] dataset, as well as MEAD [37] and DH-FaceEmoVid-150 for training. During the testing phase, we choose 20 subjects from the HDTF, MEAD and DH-FaceEmoVid-150 datasets, selecting 10 video clips for each subject with each clip lasting about 5 to 10 seconds.

Evaluation Metrics. The evaluation metrics utilized in the portrait image animation approach include Learned Perceptual Image Patch Similarity (LPIPS) [45], Fréchet Inception Distance (FID) [11], Fréchet Video Distance (FVD) [38] , Average Keypoint Distance (AKD) [31] , Average Emotion coeffcient Distance (AED) and synchronization metrics Sync-C and Sync-D [4]. LPIPS measures perceptual similarity. FID and FVD evaluate realism. AKD and AED measures the alignment of facial keypoints. Sync-C and Sync-D evaluate lip synchronization. We use tailored combinations of evaluation metrics for each dataset.

Baseline. We compared our proposed method with publicly available implementations of AniPortrait [40], Hallo [41], EchoMimic [3], StyleTalk [20], EAT [8] on the HDTF, MEAD, and DH-FaceEmoVid-150 datasets. We also conducted a qualitative comparison to provide deeper insights into our method's performance and its ability to generate realistic, expressive talking head animations. More experiment details can be found in the supplementary material.

Table 2. Comparison of various methods on the HDTF dataset.

Method	HDTF				
	FID↓	FVD↓	LPIPS↓	Sync-C↑	Sync-D↓
AniPortrait[40]	36.826	476.818	0.211	5.977	9.898
Hallo[41]	**28.605**	343.023	0.167	**6.254**	**8.735**
Echomimic[3]	48.323	526.125	0.312	6.073	9.157
StyleTalk[20]	76.564	502.334	0.326	3.885	10.644
EAT[8]	81.254	545.266	0.357	5.012	9.885
MoEE (Ours)	28.834	**322.625**	**0.152**	6.114	9.101

Table 3. Comparison of various methods on the MEAD dataset.

Method	MEAD				
	FID↓	FVD↓	LPIPS↓	AED↓	AKD↓
AniPortrait[40]	64.582	735.691	0.379	0.241	19.455
Hallo[41]	72.384	715.119	0.356	0.183	13.913
Echomimic[3]	75.678	699.322	0.413	0.185	7.355
StyleTalk[20]	49.399	577.657	0.295	0.202	3.555
EAT[8]	**32.696**	412.709	0.394	0.179	12.262
MoEE (Ours)	39.420	**403.416**	**0.288**	**0.159**	**3.121**

Figure 7. Portrait image animation results on Emotion Control and AU Control with different portrait styles.

5.2. Quantitative Results

We conducted an exhaustive comparative analysis of existing diffusion-based methods driven by audio. This study underscored the efficacy of MoEE in achieving vivid and accurate control over emotions and expressions. To ensure rigorous evaluation across datasets, we selected appropriate metrics to showcase each method's unique strengths.

Comparison on the HDTF dataset. Table 2 indicates that MoEE outperforms other methods across multiple metrics. The Sync-C and Sync-D metrics show a slight decline due to the Chinese talking head dataset we used.

Comparison on the MEAD dataset. Table 3 indicates that MoEE can achieve the best performance in most metrics, demonstrates superior and stable performance across image and video quality, as well as motion synchronization.

Comparison on the DH-FaceEmoVid-150 dataset. DH-FaceEmoVid-150 dataset contains a large set of facial videos with various emotions, enabling MoEE to generate more stable results. As shown in Table 4, MoEE significantly outperforms all other methods across all metrics.

Table 4. Comparison of various methods on the DH-FaceEmoVid-150 dataset.

Method	DH-FaceEmoVid-150				
	FID↓	FVD↓	LPIPS↓	AED↓	AKD↓
AniPortrait[40]	66.034	712.291	0.323	0.225	20.654
Hallo[41]	72.354	702.841	0.329	0.174	16.444
Echomimic[3]	71.288	653.927	0.366	0.181	8.332
StyleTalk[20]	51.038	534.217	0.242	0.189	4.234
EAT[8]	48.011	467.739	0.260	0.172	14.109
MoEE (Ours)	**39.619**	**402.803**	**0.182**	**0.153**	**4.028**

Table 5. More ablation studies. The first row shows the results without using Mixture of Emotion Experts (MoEE). The second row presents the results without Global Soft Assignment (GS Assignment). The third row displays the results without Masked Noisy Emotion Sample (MNS Sample). The forth row displays the results without DH-FaceEmoVid-150 dataset.

Methods	FID↓	FVD↓	LPIPS↓	AKD↓
(a) w/o MoEE	58.411	655.329	0.325	14.959
(b) w/o GS Assigment	46.334	447.814	0.194	10.652
(c) w/o MNS Sample	51.788	489.241	0.211	4.591
(d) w/o DH-FaceEmoVid-150	52.412	511.928	0.275	7.885
MoEE (Ours)	**39.619**	**402.803**	**0.182**	**4.028**

5.3. Qualitative Results

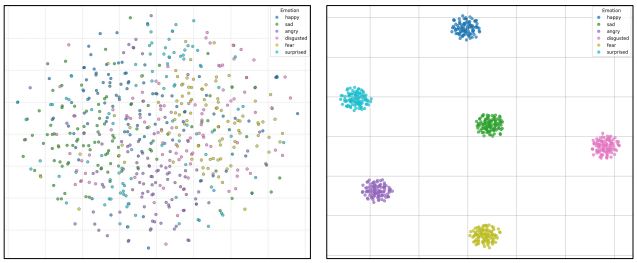
Visual comparison with baselines Figure 6 presents a visual comparison of MoEE against other methods across different emotion control, demonstrating superior performance under different conditions. Notably, AniPortrait, Hallo and EchoMimic often exhibit background noise issues, while EAT and StyleTalk often produce incorrect and unnatural expressions. Our model achieves strong lip-sync accuracy, enhanced naturalness and clarity, while effectively preserving identity characteristics and background stability.

Visualization on Emotion Control and AU Control. Figure 7 illustrates that our method can achieve single-emotion control, compound emotion control, and fine-grained expression control based on AU labels. Additionally, our method is capable of processing a wide range of input types, including paintings, portraits from generative models and more. These findings highlight the versatility and effectiveness of our approach in emotion control and accommodating different artistic styles. More experiment details can be found in the supplementary material.

5.4. Ablation Study

Mixture of Emotion Experts Method. We analyze the impact of different emotion control methods. As shown in Figure 8, we compare three approaches: without mixture of experts models, without global assignment, and with both

Figure 8. Visualization of different emotion control methods. Results demonstrate that the proposed mixture of experts methods can ensure natural and vivid expression.



(a) w/o MoEE (b) w MoEE

Figure 9. Visualization of the latent space.

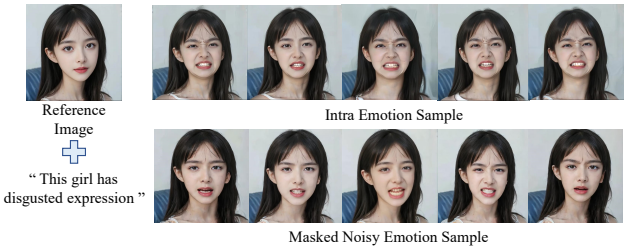


Figure 10. Visualization of different emotion sample strategy. Results demonstrate that the proposed masked noisy emotion sample strategy can ensure natural and vivid expression.

mixture of experts models and global assignment. The experiments demonstrate that our method effectively capture fine-grained expression details. Table 5 illustrates the effects of Mixture of Emotion Experts. Notably, using Global Soft Assignment enhances visual quality and emotion control, as reflected by improvements in FID, FVD, and AKD.

We also analyzed the effect of employing the Mixture of Emotion Experts module on the latent space. Figure 9 presents a visualization of the latent space: with the application of this module, the latent distributions across different emotional conditions exhibit greater separation, ensuring accurate and stable generation with specific emotions.

Masked Noisy Emotion Sample Strategy. We introduced a masked noisy emotion sample strategy to enhance emotion accuracy and character ID consistency. As illustrated in

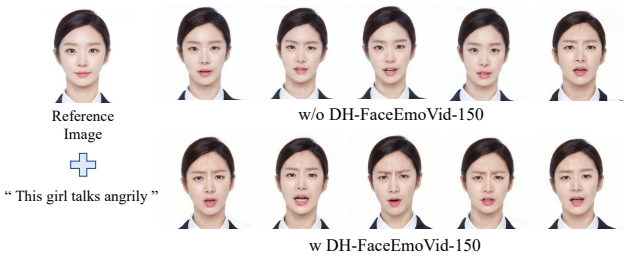


Figure 11. Visualization of emotion control based on different datasets. Results demonstrate that DH-FaceEmoVid-150 can enhance emotion control ability.

Figure 10, we compared two sampling methods: (a) intra-emotion sampling and (b) masked noisy emotion sampling and the experimental results demonstrate that our proposed approach effectively generates accurate and natural expressions. Table 5 further validates the effectiveness of the masked noisy emotion sampling strategy.

Dataset Efficiency. To evaluate the effectiveness of the dataset, we conducted both quantitative and qualitative comparison experiments. As illustrated in Figure 11 and Table 5, the results verified that DH-FaceEmoVid-150 significantly enhances the ability of emotional Audio-Driven Portrait Animation.

6. Limitations

Our method still has certain limitations in the following areas: (1) Due to the limited compound emotion categories in the DH-FaceEmoVid-150 dataset, some compound emotions are poorly represented. For example, the "sadly disgusted" emotion emphasizes "disgusted" rather than blending both emotions effectively. (2) In terms of fine-grained expression control, our model is trained solely on a combination of action units extracted from real talking videos. This dependency between action units may limit its ability to precisely control a disentangled single action unit. Our future efforts will aim to address these issues.

7. Conclusion and Future Work

In this paper, we introduce MoEE, a novel multimodal-guided framework for coarse-grained emotion control and fine-grained expression control in avatar generation. By utilizing end-to-end diffusion models, our approach significantly enhances controllability and expressiveness compared to previous models. Specifically, we develop a mixture of emotion expert module and an emotional talking head dataset to achieve precise control over expressions. Additionally, our Emotion-to-Latents module supports multi-modal emotion control and enhances emotion regulation beyond audio signals alone. Experimental results demonstrate MoEE's exceptional lip-sync quality, fine-grained emotion controllability, and the naturalness of the generated videos. We hope that our work will inspire further research into emotional talking heads.

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