UniTalker: Scaling up Audio-Driven 3D Facial Animation through A Unified Model

Xiangyu Fan, Jiaqi Li, Zhiqian Lin, Weiye Xiao, and Lei Yang✉

SenseTime Research, China
{fanxiangyu, lijiaqi2, linzhiqian, xiaoweiye1, yanglei}@sensetime.com

Abstract. Audio-driven 3D facial animation aims to map input audio to realistic facial motion. Despite significant progress, limitations arise from inconsistent 3D annotations, restricting previous models to training on specific annotations and thereby constraining the training scale. In this work, we present **UniTalker**, a unified model featuring a multi-head architecture designed to effectively leverage datasets with varied annotations. To enhance training stability and ensure consistency among multi-head outputs, we employ three training strategies, namely, PCA, model warm-up, and pivot identity embedding. To expand the training scale and diversity, we assemble **A2F-Bench**, comprising five publicly available datasets and three newly curated datasets. These datasets contain a wide range of audio domains, covering multilingual speech voices and songs, thereby scaling the training data from commonly employed datasets, typically less than 1 hour, to 18.5 hours. With a single trained UniTalker model, we achieve substantial lip vertex error reductions of 9.2% for BIWI dataset and 13.7% for Vocaset. Additionally, the pre-trained UniTalker exhibits promise as the foundation model for audio-driven facial animation tasks. Fine-tuning the pre-trained UniTalker on seen datasets further enhances performance on each dataset, with an average error reduction of 6.3% on A2F-Bench. Moreover, fine-tuning UniTalker on an unseen dataset with only half the data surpasses prior state-of-the-art models trained on the full dataset. The code and dataset are available at the project page[1].

Keywords: Audio-driven · Facial animation · Unified Model

1 Introduction

Realistic facial animation synchronized with voice is crucial in human-related animation [2, 7, 33, 38] and simulation [6, 14, 48]. Traditional methods involve vision-based facial performance capture or labor-intensive handcrafted work by artists. Recent neural network advancements enable expressive 3D facial animation based on vocal audio, categorized as vertex-based and parameter-based models. Bao *et al*. [5] showcased that a personalized model, *i.e.*, a model tailored to an individual and trained with approximately 3,000 utterances, can

[1] Homepage: `https://github.com/X-niper/UniTalker`

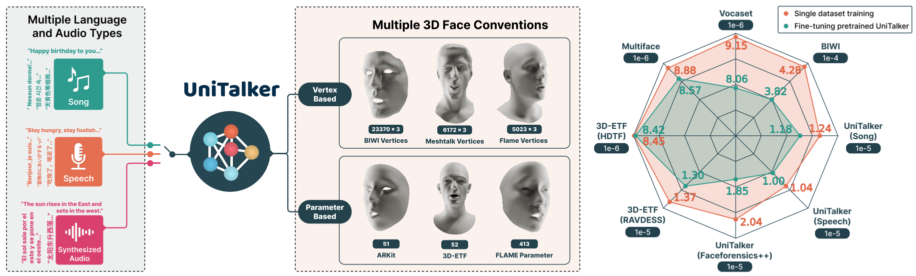


Fig. 1: Left: UniTalker aims to learn from diverse datasets in a unified manner. It takes multilingual, multi-vocal-type audios as input and outputs various 3D facial annotation conventions simultaneously. **Right**: Finetuning UniTalker on each dataset consistently shows lower lip vertex error (LVE) than training the model on the dataset, leading to an average LVE drop of 6.3%. Refer to Tab. 5 for comprehensive numerical results.

yield reasonably good results when using the pre-trained speech model [4,13]. A larger dataset of 10,000 utterances further improved performance [5]. It implies that non-personalized models would require an even larger dataset to attain optimal performance. However, existing datasets like BIWI [17] or Vocaset [15] typically contain less than 1,000 utterances. To train a robust and generailizable audio-to-face model, an appealing solution is to scale up to a larger dataset by assembling existing datasets, similar to recent studies [8,50]. Yet, there are two main challenges: *inconsistent data annotation* and *insufficient data variety*.

To effectively exploit multiple datasets with inconsistent data annotation, we propose UniTalker, a multi-head model that learns from multiple datasets in a unified manner. However, a straightforward multi-head design faces two primary challenges, notably *training instability* and *dataset bias*. (1) As shown in Fig. 1 and Tab. 1, diverse datasets adhere to distinct annotations. Vertex-based methods handle thousands of 3D coordinates, while parameter-based methods deal with only a few hundred parameters, leading to different training difficulty. To address this, we employ Principal Component Analysis for vertex-based annotations to reduce the representation dimension, thus balancing the trainable parameters of different motion decoder heads. (2) Existing audio-to-face methods often embed speaker identity during training, directly applying it to multiple datasets introduces annotation bias. As there are no shared speakers across datasets with different annotations, dataset bias will leak to the identity embedding module. Inspired by classifier-free guidance [19], we devise Pivot Identity Embedding to mitigate the biases between different motion decoder heads, where a pseudo identity is created and probable to be chosen during training.

With the designed unified model, increasing the scale of training necessitates both the quantity and diversity of datasets. Although there are some publicly available audio-to-face datasets, current datasets predominantly focus on English content and primarily feature a small number of speakers. When dealing with cross-language scenarios, pronunciation and mouth shapes may lack direct

Table 1: Overview of audio-driven 3D facial datasets. ID refers to dataset identifiers. N denotes the annotation dimension. E, C, M stands for English, Chinese and Multilingual. #Seq. and #Subj. means the number of sequences and subjects.

Dataset	ID	N	GT Type	Acquisition	Language	Audio	#Seq.	Duration	FPS	#Subj.	Accessible
BIWI [17]	D0	23,370×3	Vertices	4D Scan	E	Speech	238	0.33h	25	6	✓
Vocaset [15]	D1	5,023×3	Vertices	4D Scan	E	Speech	473	0.56h	60	12	✓
Multiface(Meshtalk) [45]	D2	6,172×3	Vertices	4D Scan	E	Speech	612	0.67h	30	13	✓
3D-ETF (HDTF) [32]	D3	52	BS	3D fitting	E	Speech	2,039	5.49h	30	141	✓
3D-ETF (RAVDESS) [32]	D4	52	BS	3D fitting	E	Speech	1,440	1.48h	30	24	✓
Talkshow [49]	D8	413	FLAME	3D fitting	E	Speech	17,110	38.6h	30	4	✓
BEAT [27]	D9	52	BS	ARKit	M	Speech	2,508	76h	60	30	✓
RenderMe-360 [30]	-	52	FLAME	4D Scan	C, E	Speech	18,000	25h	30	500	✗
MMFace4D [43]	-	35,709×3	Vertices	4D Scan	C	Speech	35,904	36h	30	431	✗
Song2face [22]	-	51	BS	ARKit	M	Song	-	1.93h	-	7	✗
Ours(Faceforensics++)	D5	413	FLAME	3D fitting	M	Speech	1,714	3.65h	30	719	✓
Ours(Speech)	D6	51	BS	ARKit	C	Speech	789	1.24h	60	8	✓
Ours(Song)	D7	51	BS	ARKit	M	Song	1,349	5.11h	60	11	✓

counterparts in English (*e.g.*, jiāo in Chinese phonetics). Furthermore, certain sounds, especially in musical content like American TV shows, require exaggerated mouth movements not commonly found in regular speech. The lack of such data challenges trained models to accurately reproduce corresponding mouth shapes. To enrich both sound types and mouth shapes, we curated a multilingual and multi-vocal-type dataset. The dataset comprises 1.4 hours of Chinese speech and 5.1 hours of multilingual songs. To increase the diversity of speakers, we annotated the 2D face video dataset FaceForensics++ [36], contributing additional 3.6 hours of multilingual speech from over 700 individuals. Combining five existing datasets with three newly curated ones, we assembled **A2F-Bench**. It contains 934 speakers and 8,654 sequences, with a total duration of 18.53 hours.

Leveraging the proposed unified model alongside datasets, a single trained UniTalker achieves lower lip vertex error (LVE) than previous state-of-the-art [31], demonstrating reductions from 4.25 $\times 10^{-4}$ to 3.86 $\times 10^{-4}$ for BIWI and 9.63 $\times 10^{-6}$ m^2 to 8.30 $\times 10^{-6}$ m^2 for Vocaset. Dataset-specific fine-tuning further enhances the performance and results in an average error reduction of 6.3% on A2F-Bench. To demonstrate the generalizability of pre-trained UniTalker, we introduce a practical yet under-explored task, *Annotation Transfer*, which involves transferring to an unseen annotation convention with limited data. Compared with fine-tuning the commonly adopted audio encoder [13], fine-tuning UniTalker requires less than half the data to achieve comparable performance.

Our contributions are three-folds: (1) We introduce a multi-head model that integrates diverse datasets and annotation types within a unified framework for 3D facial animation. Our model surpasses existing state-of-the-art with higher accuracy and faster inference speeds. (2) We demonstrate that pre-trained UniTalker can serve as a foundation model for audio-to-face tasks. Fine-tuning on pre-trained UniTalker enhances performance on both seen and unseen annotations, especially when the data scale is limited. (3) We curate A2F-Bench, a large-scale dataset comprising five released high-quality datasets and three newly assembled ones. A2F-Bench enriches the diversity of audio-to-face data and offers a more comprehensive benchmark for audio-to-face methods.

2 Related Work

Audio-Driven 3D Facial Animation. Early works utilise non-parametric audio features like linear predictive coding (LPC) [23] and Mel Frequency Cepstrum Coefficient (MFCC) [15, 37, 42] and regress facial motion from these features with CNN [23], LSTM [37] and RNN [40]. Recent works [16, 31, 39, 46] adopt self-supervised pre-trained speech models like Wav2vec 2.0 [4, 13], Hubert [21] and Wavlm [11] to extract audio features, greatly enhancing performance and reducing the data requirements. Faceformer [16] and Codetalker [46] model audio-driven facial animation as an auto-regressive problem while Emotalk [32] and Selftalk [31] model it as regressive. More recently, diffusion models are incorporated for speech-driven 3D facial animation [39, 52] and improve the diversity of the generated animation. Despite achieving realistic facial animation in recent advances, one single model usually focuses on audios of a single domain, *e.g.*, English speech, and outputs one facial animation representation, *e.g.*, vertices of one topology. A unified model is desired that has robust performance in various audio domains, *e.g.*, multilingual speeches and songs, and outputs various 3D representation types, *e.g.*, blendshapes and vertices.

Audio-Driven 3D Facial Datasets. Existing publicly available audio-visual datasets focus on English speeches and conversations. As listed in Tab. 1, vertex-based datasets that are registered from 4D scans feature short duration and few subjects like BIWI, Vocaset and Multiface. 3D-ETF [32] is annotated with pseudo ground truth 52 ARkit blendshape weights from 2D videos [28, 51]. It enlarges the available data scale for the audio-to-face generation task. However, 3D-ETF focuses on English content. The two large-scale datasets, Talkshow and BEAT exhibit audio-annotation misalignment and inaccurate annotation, not suitable for audio-to-face generation. RenderMe-360 [30], MMFace4D [43] and Song2face [22] are not publicly accessible. In summary, there is a lack of non-English audio-visual data and song-to-face data for academic study.

3 Methods

3.1 Formulation

Let $\mathbf{M}^i_{1:T} = (\mathbf{m}^i_1, ..., \mathbf{m}^i_T)$ be a sequence of face motion, where $\mathbf{m}^i_t$ denotes the face motion at t-th frame following the i-th annotation convention. For vertex-based annotations, $\mathbf{m}^i_t \in \mathbb{R}^{3V}$ denotes the displacement of V vertices at t-th frame over a neutral-face template. For parameter-based annotations, $\mathbf{m}^i_t \in \mathbb{R}^P$ denotes the P parameters at t-th frame. Let $\mathbf{A}_{1:T\cdot d}$ be the input audio, where d is the audio samples aligned with one frame. The goal in this paper can be expressed as follows: Given an input audio $\mathbf{A}_{1:T\cdot d}$, the model needs to map it into face motion denoted by every desired annotation, *i.e.*, $\mathbf{M}^i_{1:T}$, $\forall i \leq N$, where N is the number of face annotation types involved in the training process.

3.2 Unified Multi-Head Model

As shown in Fig. 2, our unified multi-head audio-to-face model, namely UniTalker, follows an encoder-decoder architecture. Given an input audio, the audio encoder initially transforms it into contextualized audio features. Subsequently, the frequency adaptor adapts these audio features via temporal linear interpolation to match the frequency of output face motion. The motion decoder maps the interpolated audio features into motion hidden states. Finally, the motion hidden states are decoded onto each annotation through the respective decoder head.

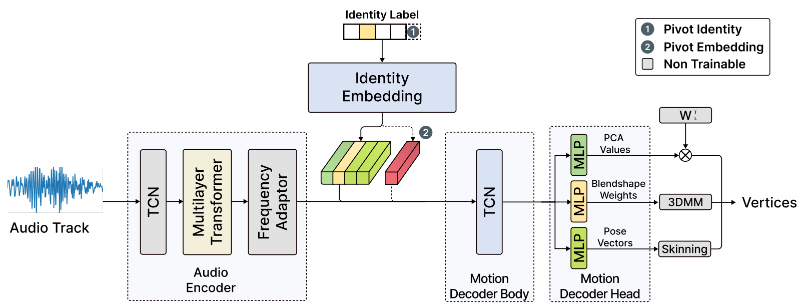


Fig. 2: UniTalker architecture. UniTalker adopts vertices PCA to balance the annotation dimension across datasets, uses decoder warm-up to stablize training, and develops a pivot identity embedding to mitigate dataset bias.

Audio Encoder. We adopt the state-of-the-art pre-trained speech model [11,13] for the audio encoder. Pre-trained audio encoders have been extensively proved to be effective in audio-driven 3D facial animation [5,16,31,32,39,46]. The audio encoder consists of a temporal convolution network (TCN) and a multi-layer transformer encoder. TCN converts the raw audio waveform $\mathbf{A}_{1:T \cdot d}$ into feature vectors with frequency of 50 Hz and the transformer encodes the feature vectors into contextualized audio representations.

Frequency Adaptor. To address varying annotation frequencies across multiple datasets, we incorporate a frequency adaptor into our model. This adaptor performs linear interpolation, aligning audio features from 50 Hz to the frequency of output face motion. In contrast to prior methods [16, 46], we reposition the frequency adaptor behind the transformer encoder. This adjustment ensures the frequency of the transformer input in training stage is aligned with that in pre-training stage. Hence, the pre-trained weights of the audio encoder are better utilised. The result is enhanced convergence and improved model precision, as evidenced in Supplementary Materials.

Non-autoregressive Motion Decoder. Faceformer [16] and CodeTalker [46] have formulated audio-to-face generation as an auto-regression task. It involves a motion encoder to project the preceding predicted motion into motion embeddings. The decoder uses both the motion embeddings and contextualized

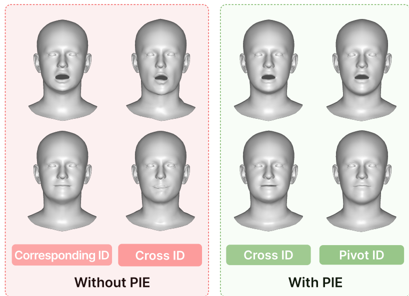


Fig. 3: Effect of PIE. Without PIE, the model generates unnatural face motion when input identity and output annotation mismatch.

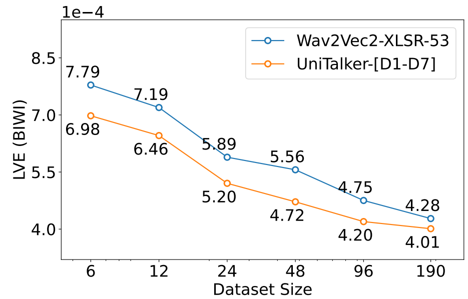


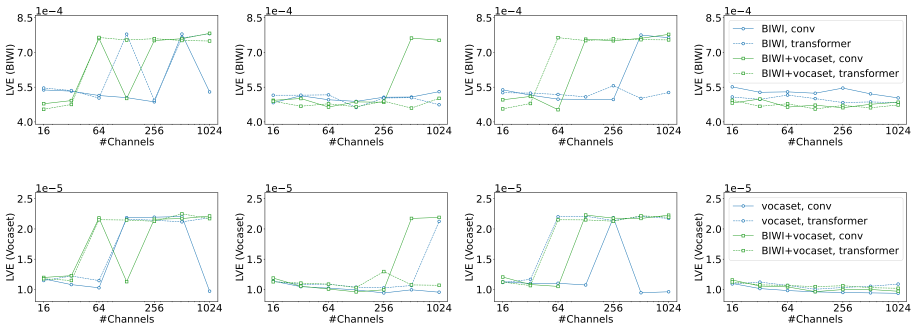
Fig. 4: Comparison between finetuning Wav2vec2-xlsr-53 [12] and UniTalker-L-[D1-D7] on D0. The x-axis is in *log-scale*.

audio representations to predict the face motion at the next frame. Other works adopt non-autoregressive models, employing transformer [5,31] and TCN [49] for the motion decoder. We observe that removing autoregression from FaceFormer brings 30 times faster inference speed and does not adversely affect precision for either BIWI or Vocaset. UniTalker adopts TCN for the motion decoder as it exhibits better precision for multi-head training. Please refer to Supplementary Materials for detailed results.

Identity Embedding. To model the speaking styles of different individuals, face motion generation is conditioned on the input identity label, as shown in Fig. 2. The speakers in different datasets are exclusive to each other, implying that each motion decoder head is trained within a specific subset of speakers and audios. As a result, the decoder head of one annotation does not necessarily output natural face motion when the input identity label and audio belong to another annotation. Fig. 3 shows that the model generates satisfactory face motion only when conditioned on an identity label from the corresponding annotation. Unnatural face motion, *e.g.*, weird mouth shape and self-intersection may be generated when input identity and motion decoder head mismatch (Cross ID inference). Inspired by classifier-free diffusion guidance [19], we propose Pivot Identity Embedding (PIE) to mitigate the annotation biases. Specifically, we introduce an additional pivot identity that does not belong to any datasets, as shown in Fig. 2. During training, we replace the ground truth (GT) identity label with this pivot identity label with a probability of 10%. Fig. 3 shows that UniTalker exhibits the ability to generate satisfactory face motion regardless of the identity label used for conditioning.

3.3 Unified Multi-Head Training

Improving Training Stability. A vanilla multi-head model (shown in Supplementary Materials) associates each annotation convention with one output head. However, the vanilla multi-head model fails to gain advantages from increased



(a) w.o. PCA, w.o. DW **(b)** w.o. DW **(c)** w.o. PCA **(d)** w. PCA, w. DW

Fig. 5: The effect of PCA and DW. LVE values are evaluated on test set at 100th epoch. Training with both PCA and DW ensures training stability across various settings. Removing either strategy harms training robustness.

data size. We hypothesize that the difference in annotation dimensions results in different difficulties of training convergence. For example, BIWI and Vocaset possess 23,370 and 5,023 vertices, respectively. Previous studies [16, 46] have chosen distinct hyperparameters for these datasets. We conducted systematical experiments for the two datasets, across different decoder channels and decoder architectures, using the same audio encoder adopted in FaceFormer [16]. As shown in Fig. 5a, the model precision is highly related to the hyperparameters and the optimal hyperparameters for the two datasets are different.

To train the multi-head model stably, we employ *Principal Component Analysis (PCA)* for each vertex-based annotation. This process reduces the output dimension and maintain consistent output head dimensions for each vertex-based annotation. Restricted by memory limit, we employ Incremental Principal Components Analysis (I-PCA) [35] as an approximation of PCA. It reduces the dimension of motion representation from $3V$ to $L = 512$, where V denotes the vertex number and L denotes the number of the preserved principle components. Each decoder head for vertices is then replaced with a decoder head for PCA values. The PCA values $\hat{\mathbf{y}}_{PCA}$ and vertices $\hat{\mathbf{y}}_v$ are linked through the PCA components $\mathbf{W}_L^T$, according to Eq. (1).

$$\hat{\mathbf{y}}_v = \hat{\mathbf{y}}_{PCA} \times \mathbf{W}_L^T \tag{1}$$

We further stabilize the multi-head training by adopting a two-stage training scheme [44]. In the first stage, we freeze the weights of the pre-trained audio encoder and only update the weights of the decoder. This stage, named *Decoder Warm-up (DW)*, gradually aligns the convergence state of the randomly initialized decoder to that of the pre-trained audio encoder. In the second stage, both the audio encoder and the motion decoder are updated simultaneously.

Fig. 5 illustrates the effect of PCA and DW. With both strategies, the model converges across various scenarios, including training on single and multiple datasets, employing either TCN or transformer architectures for motion decoder, and covering a wide range of decoder channel options. Fig. 5a shows that the vanilla model collapses in many settings and the optimal setting for BIWI and Vocaset is different. Removing either PCA or DW will deteriorate training stability, especially for multi-dataset training, as shown in Fig. 5b and Fig. 5c.

Training Loss. As shown in Fig. 2, the model predicts PCA values $\hat{\mathbf{y}}_{PCA}$ for vertex-based annotations, blendshape weights and pose vectors $\hat{\mathbf{y}}_\theta$ for parameter-based annotations. We can derive vertices $\hat{\mathbf{y}}_v$ for every annotation through differentiable computation. We apply mean squared error (MSE) on both the model output and the derived vertices, as indicated by Eq. (2),

$$\mathcal{L} = l(\hat{\mathbf{y}}_v, \mathbf{y}_v) + \alpha \cdot l(\hat{\mathbf{y}}_{PCA}, \mathbf{y}_{PCA}) + \beta \cdot l(\hat{\mathbf{y}}_\theta, \mathbf{y}_\theta), \tag{2}$$

where $\alpha = 0.01$ and $\beta = 0.0001$ in our training.

3.4 UniTalker as a Foundation Model

Our UniTalker model could output different types of face annotations. In real-wold scenarios, new annotation conventions often arise, and the available data is typically limited. In such cases, the UniTalker model needs to be transferred onto the new annotations. Previous works [16, 39, 46] adopts pre-trained audio encoders to decrease the data requirement. In this work, we replace the weights of audio encoder with the weights of pre-trained UniTalker, and find that UniTalker can further decrease half of the data requirement on unseen datasets, as evidenced in Fig. 4 and discussed in Sec. 4.6. Additionally, we randomly select only one sequence from Vocaset, which is less than 10 seconds. We fine-tune UniTalker with limited trainable parameters on this single sequence and find that the tuned model can still output satisfactory results (see Supplementary Materials). Note that Vocaset is excluded from the pre-training datasets in this experiment.

4 Experiments and Results

4.1 Datasets: A2F-Bench

Tab. 1 presents a summary of the datasets. To assemble **A2F-Bench**, we first select five widely used 3D audio-visual datasets, namely BIWI [17], Vocaset [15], Multiface [45], 3D-ETF-HDTF [32] and 3D-ETF-RAVDESS [32]. Additionally, to increase the number of speakers, we clean the multilingual 2D faceforensics++ dataset [36] and label speaker's faces with FLAME [24] parameters using 3D face reconstruction [25,29]. To enhance the model's proficiency with non-English speech and songs, we collect a dataset consisting of speeches from eight native Chinese speakers and a dataset comprising multilingual songs from eleven professional singers and label them with ARKit blendshape weights. We have made experiments on larger datasets like BEAT [27] and TalkShow [49], and find they exhibit audio-annotation misalignment and inaccurate annotation. Hence, they are not included in UniTalker training. For the sake of simplicity, we refer to each dataset as D0, D1, and so on as in Tab. 1. Consistent with previous studies [16, 32, 46], we downsample annotations originally collected at 60 fps to 30 fps. BIWI is maintained at 25 fps. The assembled **A2F-Bench** consists of 934 speakers and 8,654 sequences, with a total duration of 18.53 hours, featuring diverse sound types and mouth shapes. Refer to Supplementary Materials for detailed dataset description.

4.2 Implementation Details

We adopt two multilingual pre-trained audio encoders for UniTalker, *i.e.*, Wavlm-base-plus [10] for UniTalker-Base model and Wav2vec2-xlsr-53 [12] for UniTalker-Large model. The effect of the audio encoder is detailed in Sec. 5. UniTalker refers to UniTalker-Large by default, unless explicitly stated. We train each version of the model on both individual datasets and A2F-Bench. For instance, UniTalker-B-[D0] refers to UniTalker-Base trained on BIWI dataset. UniTalker-B-[D0-D7] and UniTalker-L-[D0-D7] refers to Unitalker-Base and UniTalker-Large trained on the entire A2F-Bench, respectively. We use Adam optimizer with a constant learning rate of 0.0001. We train 100 epochs for each model. It takes 2 days to train UniTalker-L-[D0-D7] on a single NVIDIA V100.

4.3 Comparison with Prior Works

Quantitative Evaluation. We compare UniTalker with four methods: FaceFormer [16], CodeTalker [46], SelfTalk [31] and FaceDiffuser [39]. FaceFormer and CodeTalker adopt Wav2vec2-base-960h [3] as their audio encoder. Both methods employ autoregressive decoder and exhibit slow inference. SelfTalk adopts Wav2vec2-large-xlsr-53-English [18] as the audio encoder. FaceDiffuser adopts Hubert-base-ls960 [20] as the audio encoder. The inference on FaceDiffuser is extremely slow since it adopts the diffusion mechanism and its inference scheduler has 500 steps. In case of BIWI, we directly evaluate their released models. For Vocaset, we retrain and test these methods using their official codebases, as they did not report the quantitative results.

We adopt lip vertex error (LVE) to measure lip synchronization, which is commonly used in prior works [16,39,46]. LVE is computed as the average over all frames of maximal L2 error of the lip vertices to the ground truth. Following [39], we measure mean vertex error by computing the mean Euclidean distance w.r.t. the ground truth across all vertices (MVE) and across the upper face (UFVE). Following [46], we adopt upper-face dynamics deviation (FDD) to measure the variation of upper facial dynamics for a motion sequence in comparison with that of the ground truth. We also list the trainable parameters and inference time of a 10-seconds audio on a single NVIDIA V100.

According to Tab. 2, UniTalker-B-[D0] and UniTalker-B-[D1] shows lower LVE, than FaceFormer and CodeTalker on BIWI and Vocaset, respectively. With the addition of more training data, UniTalker-B-[D0-D7] get a performance bonus for both datasets and beats all prior works on both datasets in

Table 2: Quantitative results on BIWI-Test-A and VOCA-Test. Best values are bolded.

Dataset	Method	LVE ↓ $\times 10^{-4}$	MVE ↓ $\times 10^{-3}$	UFVE ↓ $\times 10^{-3}$	FDD ↓ $\times 10^{-5}$	Params M	Time s
BIWI	FaceFormer	4.9836	7.2750	6.9081	4.0062	109	0.705
	CodeTalker	4.7914	7.3784	7.0050	4.2147	561	4.4
	SelfTalk	4.2485	6.9152	6.5428	**3.5851**	539	0.071
	FaceDiffuser	4.2985	6.8088	6.6220	3.9101	189	16.50
	UniTalker-B-[D0]	4.3681	6.8948	6.6277	4.6789	92	0.024
	UniTalker-B-[D0-D7]	4.0804	6.6458	6.3774	5.0438	92	0.024
	UniTalker-L-[D0-D7]	**3.8587**	**6.4166**	**6.1483**	5.2307	313	0.054
		LVE ↓ $\times 10^{-5}\ m^2$	MVE ↓ $\times 10^{-3} m$	UFVE ↓ $\times 10^{-3} m$	FDD ↓ $\times 10^{-7} m^2$	Params M	Time s
Vocaset	FaceFormer	1.1696	0.6364	0.4972	2.4812	92	0.624
	CodeTalker	1.1182	0.5750	0.4708	1.2594	315	3.464
	SelfTalk	0.9626	0.5665	0.4805	**1.0511**	450	0.053
	FaceDiffuser	0.9684	0.5768	0.4772	1.7335	89	13.08
	UniTalker-B-[D1]	0.9381	0.5695	0.4829	1.2115	92	0.022
	UniTalker-B-[D0-D7]	**0.8136**	**0.5338**	**0.4494**	1.3962	92	0.022
	UniTalker-L-[D0-D7]	0.8303	0.5524	0.4756	1.5206	313	0.053

regards to LVE, MVE and UFVE, with less parameters and much faster inference speed. UniTalker-L-[D0-D7] push LVE, MVE and UFVE even lower on BIWI. Compared with prior state-of-the-art model, *i.e.*, SelfTalk [31], UniTalker-B-[D0-D7] leads to LVE reductions of 4.0% for BIWI and 15.5% for Vocaset. UniTalker-L-[D0-D7] leads to reductions of 9.2% for BIWI and 13.7% for Vocaset. SelfTalk shows the best FDD on both datasets, indicating the best prediction of statistics of facial motion velocity. Note that although FDD and UFVE are computed over the same upper face region, they show inconsistent results. We argue that UFVE better reflects the temporal consistency with the ground truth. *e.g.*, for $t \in [0, 2\pi]$, $std(cos(t)) - std(sin(t)) = 0$, implies FDD $= 0$ and $\int_0^{2\pi} \|cos(t) - sin(t)\|_2 dt = 4\sqrt{2}$ indicates large UFVE. Notably, diverse data leads to worse FDD, possibly due to the increased diversity of facial motion statistics as shown in Fig. 6a. For instance, D1 (Vocaset) shows little motion variation in the upper face region while D4 (3DETF-RAVDESS) and D7 (Multilingual Songs) exhibit rich motion variation. At inference, the model trained on diverse datasets tends to predict average motion variation due to the weak correlation between audio and the motion of upper face.

Qualitative Evaluation. Corroborating the quantitative results above, we plot the mean and standard deviation of the motion velocity, and the mean of the Euclidean distance between the generated sequences and the reference sequence. According to Fig. 6b, SelfTalk predicts closest velocity mean and standard deviation maps to the ground truth, which is consistent with the FDD order in Tab. 2. The error map indicates UniTalker gain the best precision, which is consistent with the LVE, MVE and UFVE results. Interestingly, prior works show much larger error in the neck part than UniTalker.

User Study. We conducted user study to qualitativly compare UniTalker with prior works, FaceFormer, CodeTalker and SelfTalk. FaceDiffuser [39] reported worse qualitative results than FaceFormer and CodeTalker, so it is not selected

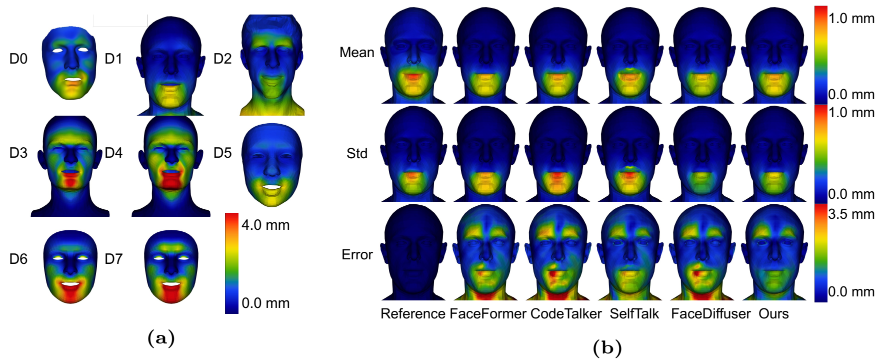


Fig. 6: (a) The standard deviation of facial motion within each training set. The upper face of D1(Vocaset) shows little motion variation and is close to static. **(b)** The temporal statistics (mean and standard deviation) of adjacent-frame motion variation and the mean of per-frame predicted-to-GT Euclidean distance within a sequence.

Table 3: The support rate for UniTalker over its competitors.

Method	**Realistic**	**Lip Sync**	**Emotion**
Ours *vs*. FaceFormer	74.7%	76.6%	78.2%
Ours *vs*. CodeTalker	71.8%	77.1%	80.7%
Ours *vs*. SelfTalker	72.5%	75.0%	82.1%

for comparison. Our selected audios for user study cover a wide range of scenarios, including different languages, audio types, emotional expressions, and audio sources (human voices and generated audios from text-to-speech models). In our Supplementary Materials, we provide a demo video to illustrate the performance of UniTalker under these scenarios. For each comparison pair, the output from UniTalker and its competitors were randomly placed at left or right. Users participating in the study were asked to answer three questions for every comparison pair: (1) which side appears more realistic, (2) which side demonstrates better lip synchronization with the audio, and (3) which side more effectively conveys the emotion in the audio. We collected 868 answers, with 308, 280 and 280 responses compared with Faceformer, CodeTalker and SelfTalk, respectively. Tab. 3 indicates that UniTalker achieves higher support rate across all three questions.

4.4 Comparison With Data Preprocessing

To train on multiple datasets, one straightforward approach is to preprocess different annotations in the datasets into one unified annotation through either 3D morphable model [24] fitting or mesh retopology [1]. While both methods require pre-selected corresponding facial keypoints, UniTalker does not. Moreover, the preprocessing approach limits future data expansion. When a new released

Table 4: We compare LVE of UniTalker and that of data preprocessing approach, under different training dataset settings. The LVE values are evaluated on D1(VOCA-Test) and expressed in $10^{-6}\ m^2$. The first row indicates the training datasets.

Method	D1	D0-D1	D0-D2	D0-D3	D0-D4	D0-D5	D0-D6	D0-D7
Preprocessing	9.1528	9.4856	8.2400	**8.0779**	8.4730	8.7049	8.4748	8.7532
UniTalker	9.1528	**8.7353**	**7.9243**	8.4495	**8.2336**	**8.0785**	**8.4192**	**8.3035**

dataset adheres to a different annotation, preprocessing approach needs to convert the new annotation into the required format. While for UniTalker, one can simply plug new decoder heads into UniTalker and train it with existing datasets or solely with new ones, avoiding retopology or fitting process.

To quantitatively compare the preprocessing approach with UniTalker, we preprocess all the annotations in [D0-D7] into FLAME vertices, namely [D0-D7]-FLAME, and train a one-head model on this dataset. Specifically, for vertex-based datasets like D0 (BIWI) and D2 (Multiface), we convert the vertices into FLAME topology through standard retopology method. The error between the original vertices and converted vertices is evaluated with chamfer distance and has an average value of 0.2 mm. For D3, D4, D6 and D7, we convert the ARkit blendshape weights into FLAME vertices with the aid of the released blendshape [26] with ARkit semantics and FLAME topology. For D5, we convert FLAME parameters into vertices using FLAME model [24].

The one-head model only outputs annotation of FLAME vertices. We compare the performance on D1 (VOCA-Test), which originally has FLAME topology. Tab. 4 shows that UniTalker achieves lower LVE in most dataset settings than the one-head model trained on [D0-D7]-FLAME. Interestingly, the lowest LVE occurs in different dataset settings for these two approaches. Tab. 4 reveals that the unified training framework does take advantages of the multi-head design. UniTalker is not only versatile due to its multi-annotation output, but also shows better precision than data preprocessing approach.

4.5 Effect of Scaled-up Datasets

We train UniTalker on each individual dataset and get eight models, denoted as L-[D*]. We evaluate LVE of each model on its corresponding test set. After that, we evaluate LVE of UniTalker-[D0-D7] on every test set. As shown in Tab. 5, the one UniTalker model beats the individual models on most dataset. For small-scale datasets like BIWI and Vocaset, UniTalker leads to over 9% decrease in LVE. However, the performance improvement is not achieved on all datasets. As the audio domains differ largely among A2F-Bench, UniTalker needs to balance the performance across datasets. For D3 (3D-ETF-HDTF), which already contains 5.49 hours of audios, UniTalker does not lead to better precision. For D6 (Chinese speech), UniTalker results in higher LVE because the proportion of Chinese speeches in A2F-Bench is small.

Table 5: Quantitative comparison between single dataset training and mixed dataset training. The metric is LVE. L-[D*] denotes the eight individual models trained on each dataset. L-[D0-D7] denotes UniTalker-Large trained on A2F-Bench. L-FT denotes the eight models finetuned from L-[D0-D7]. LVE is in 10^{-4} for D0, 10^{-6} m^2 for D1-D3 and 10^{-5} m^2 for D4-D7.

Method	**D0** 0.33h	**D1** 0.56h	**D2** 0.67h	**D3** 5.49h	**D4** 1.48h	**D5** 3.65h	**D6** 1.24h	**D7** 5.11h
L-[D*]	4.279	9.153	8.881	8.445	1.370	2.040	1.043	1.235
L-[D0-D7]	3.859$\downarrow_{9.8\%}$	8.303$\downarrow_{9.3\%}$	8.648$\downarrow_{2.6\%}$	8.991$\uparrow_{6.5\%}$	1.326$\downarrow_{3.2\%}$	2.056$\uparrow_{0.8\%}$	1.145$\uparrow_{9.7\%}$	1.211$\downarrow_{1.9\%}$
L-FT	3.816$\downarrow_{11\%}$	8.060$\downarrow_{12\%}$	8.56$\downarrow_{3.5\%}$	8.417$\downarrow_{0.3\%}$	1.30$\downarrow_{5.2\%}$	1.848$\downarrow_{9.4\%}$	0.998$\downarrow_{4.3\%}$	1.178$\downarrow_{4.6\%}$

4.6 Taking UniTalker as a Foundation Model

Fine-tuning UniTalker on Seen Annotations. UniTalker is motivated to improve the overall performance and needs to consider the trade-off in performance across different datasets. To get consistent improvement on every dataset, we fine-tune UniTalker on each individual dataset and get eight fine-tuned models, denoted as L-FT. As evidenced by Tab. 5, this fine-tuning process further enhances performance on every dataset. Compared with L-[D*], L-FT leads to better precision across all datasets, including the hard-case datasets like D4 with emotional speeches [28] and D7 with songs. The largest two LVE reductions are 11.9% on D1 and 10.8% on D0. The average LVE drop across datasets is 6.3%.

Fine-tuning UniTalker on Unseen Annotations. We train UniTalker-[D1-D7] and fine-tune it on D0 (BIWI). As a comparison, we directly fine-tune Wav2vec2-xlsr-53 [12] on D0. When fine-tuning UniTalker-[D1-D7], we only keep the weights of UniTalker encoder and reinitialize the weights of decoder, to ensure fair comparison. The original D0 training set contains 190 sequences, with 32 utterances for each speaker and 2 utterances missing. We iteratively discard half of the training set, leaving 96, 48, 24, 12 and 6 sequences. The smallest subset contains only one utterance per speaker, and the utterance content is identical across all speakers. We fine-tune UniTalker-[D1-D7] and Wav2vec2-xlsr-53 on D0 and each subset. Fig. 4 shows that fine-tuning UniTalker-[D1-D7] always yields better precision. It requires less than half of the data to get comparable performance. Moreover, fine-tuning UniTalker on D0-half, achieves lower LVE, *i.e.*, 4.197×10^{-4} than that of previous state-of-the-art model [31] trained on D0-full, *i.e.*, 4.249×10^{-4}.

5 Ablation Study

To analyse the effects of the different components of UniTalker, we conducted ablation studies in terms of audio encoder, motion decoder and the frequency adaptor. Please refer to Supplementary Materials for the latter two.

Effect of Pre-trained Audio Encoder. Bao *et al.* [5] shows that the self-supervised pre-trained audio features substantially boost the performance for audio-driven facial animation, compared with handcrafted features. Based on

Table 6: The effect of pre-trained audio encoders. The first row indicates the test dataset. LVE is in 10^{-4} for D0, 10^{-6} m^2 for D1-D3 and 10^{-5} m^2 for D4-D7.

Audio Encoder	D0	D1	D2	D3	D4	D5	D6	D7
Wav2Vec2-Base-960h [3]	4.491	9.916	9.887	9.812	1.585	2.217	1.351	1.409
WavLM-Base [11]	4.033	8.269	9.253	9.117	1.417	2.044	1.184	1.340
WavLM-Base-Plus [10]	4.080	**8.136**	9.776	9.053	1.392	**1.975**	1.158	1.264
Wav2Vec-XLSR-53 [12]	**3.859**	8.303	**8.648**	**8.991**	**1.326**	2.056	**1.145**	**1.211**

this observation, we investigate the effect of different pre-trained audio encoders. Wav2vec2-base-960h [3,4] is pre-trained on 960 hours of English speech. Wavlm-base [9] is pre-trained on the same dataset with different pre-training method. Wavlm-base-plus [10] has the same model size with Wav2vec2-base-960h and Wavlm-base, but is pre-trained on 94k hours of audios in 23 languages. Wav2vec2-xlsr-53 [12, 13] is a larger audio encoder and pre-trained on 56k hours of audios in 53 languages. We train UniTalker on A2F-Bench, based on these four audio encoders and report LVE on each test set. As shown in Tab. 6, UniTalker based on Wav2vec2-base-960h shows suboptimal performance. Wavlm-base shows significant improvement over Wav2vec2-base-960h due to better pre-training method. With scaled-up pre-training data, Wavlm-base-plus shows better performance over Wavlm-base. Benifit from the diversity of pre-training data and larger capacity, Wav2vec2-xlsr-53 leads to an overall performance improvement. Tab. 6 shows that the downstream UniTalker precision is largely affected by the pre-trained audio encoder from three aspects, including the pre-training method, the scale and diversity of pre-training dataset and the capacity of pre-training backbone.

6 Conclusion and Discussion

We propose UniTalker, which effectively exploits the existing datasets with inconsistent annotation format. The model precision benefits from the increased scale and diversity of A2F-Bench. The experiment shows that the pre-trained UniTalker has the potential to serve as a foundation model for more audio-to-face tasks, especially when the data is scarce.

Limitations and Future Works. Tab. 5 indicates that UniTalker shows better precision on most datasets than the corresponding individual models. However, achieving consistent improvement over every dataset requires dataset-specific fine-tuning. The potential for enhancing model capacity to alleviate performance trade-offs across diverse datasets remains an open problem. Meanwhile, Fig. 4 indicates that the pre-trained UniTalker exhibits promise as the foundation model for audio-driven facial animation tasks. Nonetheless, the data scale used for UniTalker, *i.e.*, 18.53 hours, is still considerably smaller than that used for training the audio encoder, *i.e.*, 56k hours. Exploring the utilization of large-scale datasets with suboptimal data quality, such as BEAT and Talkshow, represents a promising future direction. Applying UniTalker to 2D facial animation [34,41,47] to enhance consistency under large head poses is also a worthwhile pursuit.

References

1. Amberg, B., Romdhani, S., Vetter, T.: Optimal step nonrigid icp algorithms for surface registration. In: 2007 IEEE conference on computer vision and pattern recognition. pp. 1–8. IEEE (2007)
2. Anyi, R., Xuekun, J., Yuwei, G., Linning, X., Lei, Y., Libiao, J., Dahua, L., Bo, D.: Dynamic storyboard generation in an engine-based virtual environment for video production. arXiv preprint arXiv:2301.12688 (2023)
3. Baevski, A., Zhou, Y., Mohamed, A., Auli, M.: Wav2Vec2-Base-960h. `https://huggingface.co/facebook/wav2vec2-base-960h`
4. Baevski, A., Zhou, Y., Mohamed, A., Auli, M.: wav2vec 2.0: A framework for self-supervised learning of speech representations. Advances in neural information processing systems **33**, 12449–12460 (2020)
5. Bao, L., Zhang, H., Qian, Y., Xue, T., Chen, C., Zhe, X., Kang, D.: Learning audio-driven viseme dynamics for 3d face animation. arXiv preprint arXiv:2301.06059 (2023)
6. Black, M.J., Patel, P., Tesch, J., Yang, J.: Bedlam: A synthetic dataset of bodies exhibiting detailed lifelike animated motion. In: Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition. pp. 8726–8737 (2023)
7. Cai, Z., Jiang, J., Qing, Z., Guo, X., Zhang, M., Lin, Z., Mei, H., Wei, C., Wang, R., Yin, W., et al.: Digital life project: Autonomous 3d characters with social intelligence. arXiv preprint arXiv:2312.04547 (2023)
8. Cai, Z., Yin, W., Zeng, A., Wei, C., Sun, Q., Yanjun, W., Pang, H.E., Mei, H., Zhang, M., Zhang, L., Loy, C.C., Yang, L., Liu, Z.: Smpler-x: Scaling up expressive human pose and shape estimation. In: Oh, A., Neumann, T., Globerson, A., Saenko, K., Hardt, M., Levine, S. (eds.) Advances in Neural Information Processing Systems. vol. 36, pp. 11454–11468. Curran Associates, Inc. (2023)
9. Chen, S., Wang, C., Chen, Z., Wu, Y., Liu, S., Chen, Z., Li, J., Kanda, N., Yoshioka, T., Xiao, X., et al.: WavLM-Base. `https://huggingface.co/microsoft/wavlm-base`
10. Chen, S., Wang, C., Chen, Z., Wu, Y., Liu, S., Chen, Z., Li, J., Kanda, N., Yoshioka, T., Xiao, X., et al.: WavLM-Base-Plus. `https://huggingface.co/microsoft/wavlm-base-plus`
11. Chen, S., Wang, C., Chen, Z., Wu, Y., Liu, S., Chen, Z., Li, J., Kanda, N., Yoshioka, T., Xiao, X., et al.: Wavlm: Large-scale self-supervised pre-training for full stack speech processing. IEEE Journal of Selected Topics in Signal Processing **16**(6), 1505–1518 (2022)
12. Conneau, A., Baevski, A., Collobert, R., Mohamed, A., Auli, M.: Wav2Vec2-XLSR-53. `https://huggingface.co/facebook/wav2vec2-large-xlsr-53`
13. Conneau, A., Baevski, A., Collobert, R., Mohamed, A., Auli, M.: Unsupervised cross-lingual representation learning for speech recognition. arXiv preprint arXiv:2006.13979 (2020)
14. Contributors, X.: Openxrlab synthetic data rendering toolbox. `https://github.com/openxrlab/xrfeitoria` (2023)
15. Cudeiro, D., Bolkart, T., Laidlaw, C., Ranjan, A., Black, M.J.: Capture, learning, and synthesis of 3d speaking styles. In: Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition. pp. 10101–10111 (2019)
16. Fan, Y., Lin, Z., Saito, J., Wang, W., Komura, T.: Faceformer: Speech-driven 3d facial animation with transformers. In: Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition. pp. 18770–18780 (2022)

17. Fanelli, G., Gall, J., Romsdorfer, H., Weise, T., Van Gool, L.: A 3-d audio-visual corpus of affective communication. IEEE Transactions on Multimedia **12**(6), 591–598 (2010)
18. Grosman, J.: Fine-tuned XLSR-53 large model for speech recognition in English. `https://huggingface.co/jonatasgrosman/wav2vec2-large-xlsr-53-english` (2021)
19. Ho, J., Salimans, T.: Classifier-free diffusion guidance. arXiv preprint arXiv:2207.12598 (2022)
20. Hsu, W.N., Bolte, B., Tsai, Y.H.H., Lakhotia, K., Salakhutdinov, R., Mohamed, A.: facebook/hubert-base-ls960. `https://huggingface.co/facebook/hubert-base-ls960`
21. Hsu, W.N., Bolte, B., Tsai, Y.H.H., Lakhotia, K., Salakhutdinov, R., Mohamed, A.: Hubert: Self-supervised speech representation learning by masked prediction of hidden units. IEEE/ACM Transactions on Audio, Speech, and Language Processing **29**, 3451–3460 (2021)
22. Iwase, S., Kato, T., Yamaguchi, S., Yukitaka, T., Morishima, S.: Song2face: Synthesizing singing facial animation from audio. In: SIGGRAPH Asia 2020 Technical Communications, pp. 1–4 (2020)
23. Karras, T., Aila, T., Laine, S., Herva, A., Lehtinen, J.: Audio-driven facial animation by joint end-to-end learning of pose and emotion. ACM Transactions on Graphics (TOG) **36**(4), 1–12 (2017)
24. Li, T., Bolkart, T., Black, M.J., Li, H., Romero, J.: Learning a model of facial shape and expression from 4d scans. ACM Trans. Graph. **36**(6), 194–1 (2017)
25. Lin, Z., Lin, J., Li, L., Yuan, Y., Zou, Z.: High-quality 3d face reconstruction with affine convolutional networks. In: Proceedings of the 30th ACM International Conference on Multimedia. pp. 2495–2503 (2022)
26. Liu, H., Zhu, Z., Becherini, G., Peng, Y., Su, M., Zhou, Y., Iwamoto, N., Zheng, B., Black, M.J.: Emage: Towards unified holistic co-speech gesture generation via masked audio gesture modeling. arXiv preprint arXiv:2401.00374 (2023)
27. Liu, H., Zhu, Z., Iwamoto, N., Peng, Y., Li, Z., Zhou, Y., Bozkurt, E., Zheng, B.: Beat: A large-scale semantic and emotional multi-modal dataset for conversational gestures synthesis. In: European Conference on Computer Vision. pp. 612–630. Springer (2022)
28. Livingstone, S.R., Russo, F.A.: The ryerson audio-visual database of emotional speech and song (ravdess): A dynamic, multimodal set of facial and vocal expressions in north american english. PloS one **13**(5), e0196391 (2018)
29. Martyniuk, T., Kupyn, O., Kurlyak, Y., Krashenyi, I., Matas, J., Sharmanska, V.: Dad-3dheads: A large-scale dense, accurate and diverse dataset for 3d head alignment from a single image. In: Proc. IEEE Conf. on Computer Vision and Pattern Recognition (CVPR) (2022)
30. Pan, D., Zhuo, L., Piao, J., Luo, H., Cheng, W., Yuxin, W., Fan, S., Liu, S., Yang, L., Dai, B., et al.: Renderme-360: A large digital asset library and benchmarks towards high-fidelity head avatars. In: Thirty-seventh Conference on Neural Information Processing Systems Datasets and Benchmarks Track (2023)
31. Peng, Z., Luo, Y., Shi, Y., Xu, H., Zhu, X., Liu, H., He, J., Fan, Z.: Selftalk: A self-supervised commutative training diagram to comprehend 3d talking faces. arXiv preprint arXiv:2306.10799 (2023)
32. Peng, Z., Wu, H., Song, Z., Xu, H., Zhu, X., He, J., Liu, H., Fan, Z.: Emotalk: Speech-driven emotional disentanglement for 3d face animation. In: Proceedings of the IEEE/CVF International Conference on Computer Vision. pp. 20687–20697 (2023)

33. Qing, Z., Cai, Z., Yang, Z., Yang, L.: Story-to-motion: Synthesizing infinite and controllable character animation from long text. In: SIGGRAPH Asia 2023 Technical Communications, pp. 1–4 (2023)
34. Qiu, H., Chen, Z., Jiang, Y., Zhou, H., Fan, X., Yang, L., Wu, W., Liu, Z.: Relitalk: Relightable talking portrait generation from a single video. International Journal of Computer Vision pp. 1–16 (2024)
35. Ross, D.A., Lim, J., Lin, R.S., Yang, M.H.: Incremental learning for robust visual tracking. International journal of computer vision **77**, 125–141 (2008)
36. Rossler, A., Cozzolino, D., Verdoliva, L., Verdoliva, L., Riess, C., Thies, J., Nießner, M.F.: Learning to detect manipulated facial images. arxiv 2019. arXiv preprint arXiv:1901.08971
37. Shimba, T., Sakurai, R., Yamazoe, H., Lee, J.H.: Talking heads synthesis from audio with deep neural networks. In: 2015 IEEE/SICE International Symposium on System Integration (SII). pp. 100–105. IEEE (2015)
38. Siyao, L., Gu, T., Yang, Z., Lin, Z., Liu, Z., Ding, H., Yang, L., Loy, C.C.: Duolando: Follower gpt with off-policy reinforcement learning for dance accompaniment. In: The Twelfth International Conference on Learning Representations (2023)
39. Stan, S., Haque, K.I., Yumak, Z.: Facediffuser: Speech-driven 3d facial animation synthesis using diffusion. In: Proceedings of the 16th ACM SIGGRAPH Conference on Motion, Interaction and Games. pp. 1–11 (2023)
40. Suwajanakorn, S., Seitz, S.M., Kemelmacher-Shlizerman, I.: Synthesizing obama: learning lip sync from audio. ACM Transactions on Graphics (ToG) **36**(4), 1–13 (2017)
41. Tian, L., Wang, Q., Zhang, B., Bo, L.: Emo: Emote portrait alive-generating expressive portrait videos with audio2video diffusion model under weak conditions. arXiv preprint arXiv:2402.17485 (2024)
42. Wang, L., Han, W., Soong, F.K., Huo, Q.: Text driven 3d photo-realistic talking head. In: Twelfth Annual Conference of the International Speech Communication Association (2011)
43. Wu, H., Jia, J., Xing, J., Xu, H., Wang, X., Wang, J.: Mmface4d: A large-scale multi-modal 4d face dataset for audio-driven 3d face animation. arXiv preprint arXiv:2303.09797 (2023)
44. Wu, H., Zhou, S., Jia, J., Xing, J., Wen, Q., Wen, X.: Speech-driven 3d face animation with composite and regional facial movements. In: Proceedings of the 31st ACM International Conference on Multimedia. pp. 6822–6830 (2023)
45. Wuu, C.h., Zheng, N., Ardisson, S., Bali, R., Belko, D., Brockmeyer, E., Evans, L., Godisart, T., Ha, H., Huang, X., et al.: Multiface: A dataset for neural face rendering. arXiv preprint arXiv:2207.11243 (2022)
46. Xing, J., Xia, M., Zhang, Y., Cun, X., Wang, J., Wong, T.T.: Codetalker: Speech-driven 3d facial animation with discrete motion prior. In: Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition. pp. 12780–12790 (2023)
47. Xu, S., Chen, G., Guo, Y.X., Yang, J., Li, C., Zang, Z., Zhang, Y., Tong, X., Guo, B.: Vasa-1: Lifelike audio-driven talking faces generated in real time. arXiv preprint arXiv:2404.10667 (2024)
48. Yang, Z., Cai, Z., Mei, H., Liu, S., Chen, Z., Xiao, W., Wei, Y., Qing, Z., Wei, C., Dai, B., Wu, W., Qian, C., Lin, D., Liu, Z., Yang, L.: Synbody: Synthetic dataset with layered human models for 3d human perception and modeling. In: Proceedings of the IEEE/CVF International Conference on Computer Vision (ICCV). pp. 20282–20292 (October 2023)

49. Yi, H., Liang, H., Liu, Y., Cao, Q., Wen, Y., Bolkart, T., Tao, D., Black, M.J.: Generating holistic 3d human motion from speech. In: Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition. pp. 469–480 (2023)
50. Zhang, M., Jin, D., Gu, C., Hong, F., Cai, Z., Huang, J., Zhang, C., Guo, X., Yang, L., He, Y., et al.: Large motion model for unified multi-modal motion generation. arXiv preprint arXiv:2404.01284 (2024)
51. Zhang, Z., Li, L., Ding, Y., Fan, C.: Flow-guided one-shot talking face generation with a high-resolution audio-visual dataset. In: Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition. pp. 3661–3670 (2021)
52. Zhao, Q., Long, P., Zhang, Q., Qin, D., Liang, H., Zhang, L., Zhang, Y., Yu, J., Xu, L.: Media2face: Co-speech facial animation generation with multi-modality guidance. arXiv preprint arXiv:2401.15687 (2024)