
EchoShot: Multi-Shot Portrait Video Generation

Jiahao Wang¹ Hualian Sheng² Sijia Cai^{2,†} Weizhan Zhang^{1,*} Caixia Yan¹
Yachuang Feng² Bing Deng² Jieping Ye²

¹School of Computer Science and Technology, MOEKLINNS, Xi'an Jiaotong University

²Alibaba Cloud Computing

jiahaowang@stu.xjtu.edu.cn stephen.csj@alibaba-inc.com
zhangwzh@xjtu.edu.cn

Abstract

Video diffusion models substantially boost the productivity of artistic workflows with high-quality portrait video generative capacity. However, prevailing pipelines are primarily constrained to single-shot creation, while real-world applications urge multiple shots with identity consistency and flexible content controllability. In this work, we propose EchoShot, a native and scalable multi-shot framework for portrait customization built upon a foundation video diffusion model. To start with, we propose shot-aware position embedding mechanisms within the video diffusion transformer architecture to model inter-shot variations and establish intricate correspondence between multi-shot visual content and their textual descriptions. This simple yet effective design enables direct training on multi-shot video data without introducing additional computational overhead. To facilitate model training within multi-shot scenarios, we construct PortraitGala, a large-scale and high-fidelity human-centric video dataset featuring cross-shot identity consistency and fine-grained captions such as facial attributes, outfits, and dynamic motions. To further enhance applicability, we extend EchoShot to perform reference image-based personalized multi-shot generation and long video synthesis with infinite shot counts. Extensive evaluations demonstrate that EchoShot achieves superior identity consistency as well as attribute-level controllability in multi-shot portrait video generation. Notably, the proposed framework demonstrates potential as a foundational paradigm for general multi-shot video modeling. Project page: <https://johnneywang.github.io/EchoShot-webpage>.

1 Introduction

Recent advancements in Diffusion Transformer-based (DiT) model [34] have catalyzed transformative progress in text-to-video (T2V) generation, enabling the synthesis of visually realistic single-shot videos [10, 6, 4, 7, 3, 43]. In real-world content creation workflows, users frequently demand multi-shot video generation with persistent subject consistency, particularly in human-centric applications such as narrative storytelling, virtual try-on with background variations, and appearance attribute editing. However, prevailing T2V models exhibit limitations in achieving identity consistency when generating multiple human-centric videos, attributable to pre-training on independently fragmented single-shot data and a lack of effective cross-shot post-training strategies.

To tackle this challenge, we present a novel multi-shot portrait video generation (MT2V) task. As straightforward solutions, existing studies can be organized to perform this task through two

[†] Project Lead

^{*} Corresponding Author

This work was completed during the internship at Alibaba Cloud Computing.



Figure 1: Given multiple formatted prompts of the same character, EchoShot generates multi-shot portrait videos showing the same appearance with superior fine-grained controllability.

paradigms: (1) Iterative personalized generation. This approach achieves cross-shot consistency through recurrent applications of personalized text-to-video (PT2V) models [7, 53, 4, 3] but faces challenges in terms of textual controllability and full-body consistency. To specify, the facial feature guidance mechanism in PT2V models often leads to adversarial competition between identity preservation and prompt adherence, reducing the controllability in aspects such as hairstyle, expressions, and apparel. Moreover, these models, tailored for facial preservation, fail to maintain the whole body consistency across generated videos. (2) Keyframe-to-video synthesis. This approach first generates multiple keyframes using consistent text-to-image (CT2I) models [56, 42, 20, 44, 45] and transforms them into multiple shots utilizing sophisticated image-to-video (I2V) models [4, 3, 43]. Although this decoupled strategy partially mitigates the multi-shot consistency challenge, it fundamentally suffers from the bottleneck effect and highly depends on the performance of CT2I models. The flaws of keyframes, such as blur, distortion, and inconsistency, will severely degrade the quality of generated videos. Besides, the absence of explicit identity conditioning in I2V models leads to progressive degradation of facial consistency during temporal expansion, causing dynamic identity drift.

For these issues, we explore a novel paradigm for native multi-shot consistent video generation in this work. Our motivation lies in the investigation of whether constructing a temporally coherent portrait dataset and implementing domain-specific post-training strategies can enable the DiT architecture to intrinsically model appearance-motion consistency across multi-shot videos. To this end, we introduce EchoShot, an advanced multi-shot portrait video generation framework built upon the state-of-the-art video DiT model Wan2.1-T2V [43], with our work contributing three core innovations: (1) We propose PortraitGala, a large-scale portrait dataset comprising 250k one-to-one single-shot video

clips and 400k many-to-one multi-shot video clips. Each video undergoes rigorous identity clustering via facial embeddings and is annotated with granular captions covering facial attributes, dynamic expressions, and scene conditions, ensuring strict consistency and fine-grained controllability in the final generated videos. (2) To enable efficient multi-shot post-training based on the pretrained T2V model, we integrate a new position embedding mechanism termed Temporal-Cut RoPE (TcRoPE) into the DiT-based visual token self-attention module to resolve challenges in variable shot counts, flexible shot durations, and inter-shot token discontinuities. In the video-text cross-attention module, a Temporal-Align RoPE (TaRoPE) with a mismatch suppression mechanism is further introduced to establish strict alignment between text descriptions and their corresponding video contents within each shot. (3) Based on our trained EchoShot model, we further extend its capabilities by incorporating an external facial encoder for reference image-based personalized multi-shot video generation (PMT2V), and designing a disentangled RefAttn mechanism for infinite shots video generation (InfT2V). These extensions highlight our model’s flexibility and generalization in real-world content creation.

Our experiments demonstrate that EchoShot excels in generating multi-shot portrait videos with consistent cross-shot identity preservation, while supporting fine-grained attribute control and scene manipulation. Comprehensive evaluations confirm its superiority over existing methods in quantitative metrics and user studies, particularly in maintaining identity coherence under complex motions and content variations, all within a native multi-shot video generation architecture.

2 Related Work

Video diffusion models. The video generation field has witnessed remarkable progress over the past year, marked by Sora [10]’s pioneering adoption of a scalable DiT architecture. Subsequently, both closed-source models like Kling [4], MovieGen [35], Hailuo [3], Veo2 [6] and Gen-4 [2], along with open-source alternatives such as Open-Sora-Plan [27], CogVideoX [51], HunyuanVideo [24], StepVideo [31], and Wan [43], have achieved remarkable and rapid advancements in video generation quality. Key technical strides stem from architectural shifts from U-Net [36, 9] to DiT/MMDiT [34, 15], the evolution from spatio-temporal [38, 16] to 3D full attention in video token interactions, model optimization from DDPM [36] to flow matching [15], advanced Video-VAE [51, 43] and enhanced text encoders [35, 24]. Despite advancements, existing methods are limited to single-shot videos, and extending pretrained T2V models for multi-shot scenarios poses a critical challenge.

Consistent generation. Maintaining subject consistency across scenes has broad real-world applications, with early efforts focusing on image consistency for story visualization and comics. Techniques include iterative use of personalized text-to-image models [26, 47, 18] for similarity preservation, or leveraging self-attention mechanisms [56, 42] and in-context capabilities [20] for multi-image alignment. With advances in video generation, these approaches could be applied to keyframe generation, combined with I2V models for multi-shot video synthesis. For example, VideoStudio [30] integrates entity embeddings for appearance preservation, MovieDreamer [54] predicts coherent visual tokens that are then decoded into keyframes, and VGoT [55] employs identity-preserving embeddings for cross-shot consistency. However, challenges persist in achieving high-fidelity dynamic identity consistency and controllability. Recent work explores fine-tuning T2V models for multi-event and multi-shot generation. HunyuanVideo [24] supports two-shot generation through caption concatenation. TALC [8] enhances temporal alignment with improved text conditioning, MinT [48] introduces time-aware interactions and positional encoding, and LCT [17] extends single-shot models using scene-level attention, interleaved 3D embeddings, and asynchronous noise strategies. While LCT emphasizes cross-shot coherence via scripted entity descriptions, our method focuses on identity consistency and text-guided control in multi-shot portrait generation.

Human video datasets. Diverse, large-scale human-centric video datasets are crucial for advancing portrait video generation. While existing high-quality portrait datasets like CelebV-HQ [57], CelebV-Text [52], and VFHQ [49] primarily feature close-up heads or upper bodies, other action datasets such as UCF101 [39], ActivityNet [11], Kinetics700 [12] suffer from inadequate visual quality and inconsistent face visibility. Recently, OpenHumanVid [25] introduces a large-scale and visually realistic dataset sourced from films, TV series, and documentaries for single-shot video pretraining/fine-tuning. However, both specialized portrait datasets and general pre-training datasets [13, 46] currently only offer single-shot video clips, leaving a critical gap in high-quality multi-shot identity-consistent portrait video datasets.

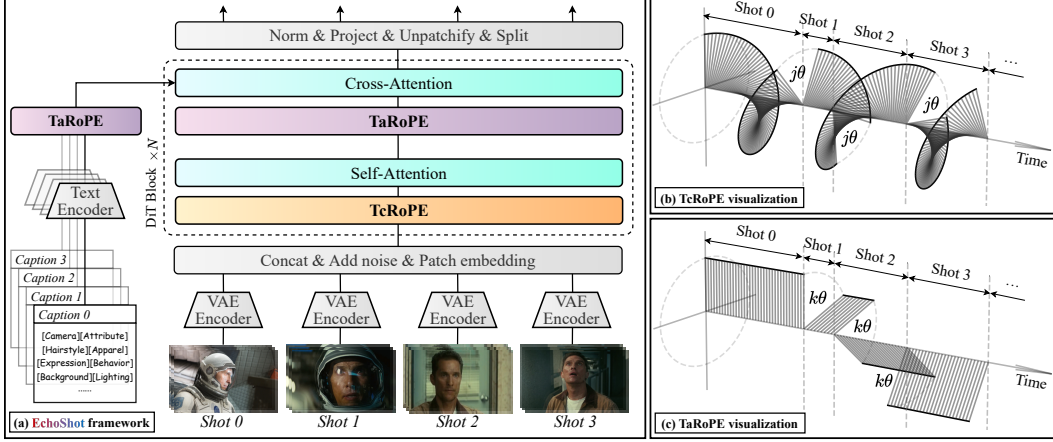


Figure 2: (a) The overall architecture of EchoShot, a multi-shot video generation paradigm, which features two intricate RoPE mechanisms. (b) TcRoPE, a 3D-RoPE that rotates an extra angular rotation at every inter-shot boundary along the time dimension. (c) TaRoPE, a 1D-RoPE that differentiates between matching and non-matching shot-caption pairs. Note that the visualization displays only one rotational component, with others excluded for simplicity.

3 Method

Overview. To accomplish multi-shot portrait video generation, we first review current single-shot models in Sec. 3.1. As a foundation, we devise and train a multi-shot text-to-video (MT2V) modeling paradigm in Sec. 3.2. We further tailor the personalized and infinite extensions in Sec. 3.3. All the training is driven by a meticulously curated dataset in Sec. 3.4.

3.1 Preliminary: Single-shot T2V Generation

Given a video segment x during training, prevailing T2V models first encode it into a latent feature: $z = \mathcal{E}(x)$, where \mathcal{E} is a pretrained video encoder. The latent feature is then mixed with Gaussian noise ϵ , becoming a noisy sample z_τ . The training is driven by a denoising process of rectified flow (RF) formulation [29, 15]: $\mathcal{L} = \mathbb{E}_{\epsilon, \tau, z} \|(\epsilon - z) - u_\phi(z_\tau, \tau, c)\|^2$, where $\tau \in [0, 1]$ is the denoising timestep, $u_\phi(\cdot)$ is a denoising network and c is the embeddings of the textual description. A typical implementation of $u_\phi(\cdot)$ is a DiT, combining self-attention and cross-attention layers. In the self-attention layers, given a 3D-position-indexed query or key vector $f_{t,h,w}^{sa} \in \mathbb{R}^d$, 3D Rotary Position Embedding (RoPE) [15] adds dimension-wise position information to it, forming $\tilde{f}_{t,h,w}^{sa}$:

$$\tilde{f}_{t,h,w}^{sa} = \text{3D-RoPE}(f_{t,h,w}^{sa}, t, h, w) = \mathbf{R}_{\Theta_{3D}, t, h, w}^d f_{t,h,w}^{sa}, \quad (1)$$

where $\mathbf{R}_{\Theta_{3D}, t, h, w}^d$ represents a 3D rotation matrix determined by the positional index and a set of base angles Θ_{3D} . Details are provided in the Appendix. Notably, RoPE is generally excluded from cross-attention layers. While single-shot T2V models can generate portrait videos, extending this capability to multi-shot T2V models while preserving consistent identity remains a significant challenge.

3.2 Modeling Multi-shot T2V Generation for Consistent Identity

This task focuses on generating coherent multi-shot portrait videos that exhibit consistent identity across all shots while allowing flexible, user-defined control over both content and appearance. During training, each instance consists of a multi-shot video paired with corresponding frame counts and textual descriptions for each shot: $\{x_s, n_s, p_s\}_{s=0}^{S-1}$, where S denotes the total number of shots. Here, n_s represents the frame count for the s -th shot, and p_s specifies its textual prompt. During inference, users are empowered to define the desired frame counts and prompts for S' shots: $\{n_s, p_s\}_{s=0}^{S'-1}$, enabling customized multi-shot video generation with consistent identity. This task presents three key challenges compared to single-shot video generation:

- **Variable Shot Lengths:** Each shot’s duration (i.e., frame count) can be flexibly defined by the user, accommodating diverse temporal requirements without imposing rigid constraints.
- **Identity Consistency Across Shots:** The generated video must ensure that all shots depict the same individual identity, maintaining seamless visual coherence throughout the sequence.
- **Text-Driven Control of Each Shot:** Both the background and foreground in each shot are controlled via textual prompts, enabling precise customization of scenes and characters.

Identifying the inter-shot boundary via TcRoPE. Starting with S training video segments, a video encoder is first utilized to separately encode them into compressed latent features z_s , as shown in Fig. 2(a). Then, the latent features are further projected into query, key, and value embeddings to prepare for the self-attention mechanism. To preserve relative positional and temporal information, in vanilla 3D-RoPE, query and key embeddings require being modulated by the indexes of time, height, and width. However, such temporal index modulation is based on the assumption of continuous video content, which is not suitable for multi-shot scenarios with discontinuous video content. For example, the final frame of the first shot should correlate strongly with its preceding frame and weakly with the subsequent frame (i.e., the initial frame of the second shot). To model such an intricate correlation, as shown in Fig. 2(b), we raise TcRoPE to modulate the query and key embeddings, which incorporates a rotary phase shift between every two shots. For the feature embedding $\mathbf{a}_{t,h,w,s}^{sa}$ at time t , height h , width w , and shot s , the processed feature can be denoted as:

$$\tilde{\mathbf{f}}_{t,h,w,s}^{sa} = \text{TcRoPE}(\mathbf{f}_{t,h,w,s}^{sa}, t, h, w, s) = \text{3D-RoPE}(\mathbf{f}_{t,h,w,s}^{sa}, t + s \cdot j, h, w), \quad (2)$$

where j is the phase shift scale. Intuitively, TcRoPE delineates the inter-shot boundary along the whole timeline concisely via an extra angular rotation. This method paves the way for precise control over the number of shots and the duration of each shot.

After the self-attention process, single-shot T2V models indiscriminately fuse semantic and visual modalities without incorporating positional information. In multi-shot scenarios, a straightforward approach is to concatenate all shot-wise captions into a single comprehensive caption. However, this method imposes limitations on the length of each shot-wise caption, given that the total caption must remain within the input window size of the text encoder.

Associating the semantic and visual modality via TaRoPE. Therefore, it is necessary to establish a shot-wise intricate correspondence when processing multi-shot videos and their associated captions. Specifically, the query of a specific shot should fully interact with the key of its corresponding caption, while maintaining a limited interaction with the keys of other captions, because simply ignoring interactions with other captions would risk discarding potentially useful supplementary details that could enhance the representation of the shot. To achieve such delicate interactions, we first input the captions separately into the text encoder to generate their respective embeddings. These embeddings are then concatenated to form the complete caption representation. Subsequently, as shown in Fig. 2(c), we propose TaRoPE to modulate the visual query embeddings and textual key embeddings. Given the i -th feature embedded in shot s , the processed feature can be expressed as:

$$\tilde{\mathbf{f}}_{i,s}^{ca} = \text{TaRoPE}(\mathbf{f}_{i,s}^{ca}, s) = \text{1D-RoPE}(\mathbf{f}_{i,s}^{ca}, s \cdot k), \quad (3)$$

where k is a hyperparameter that controls the mismatch suppression scale. Following feature modulation, attention calculation is performed, and the attention score between the query of s_1 -th shot and the key of s_2 -th shot is given by:

$$\tilde{A}_{s_1,s_2} = A_{s_1,s_2} \cdot \delta(k|s_1 - s_2|), \quad (4)$$

where A_{s_1,s_2} represents the standard vanilla attention, and $\delta(\cdot)$ is a monotonically decreasing function within a specific input interval, with $f(0) = 1$. Detailed derivation is provided in the Appendix. Consequently, the attention between the matched query and key (i.e., when $s_1 = s_2$) remains identical to that in vanilla models. In contrast, the attention between unmatched pairs is suppressed, controlled by k . Finally, the processed features are passed through an FFN to generate the output.

Our proposed TcRoPE supports variable shot lengths and counts, while TaRoPE enables text-driven control of each shot. The multi-shot training paradigm inherently ensures identity consistency across all shots. Notably, the two proposed RoPE mechanisms introduce no additional parameters.

3.3 Towards Personalized and Infinite Multi-shot T2V Generation

PMT2V. The aforementioned method enables the model to generate video segments while preserving consistent identity. However, a key application involves extending the model’s capability to generate

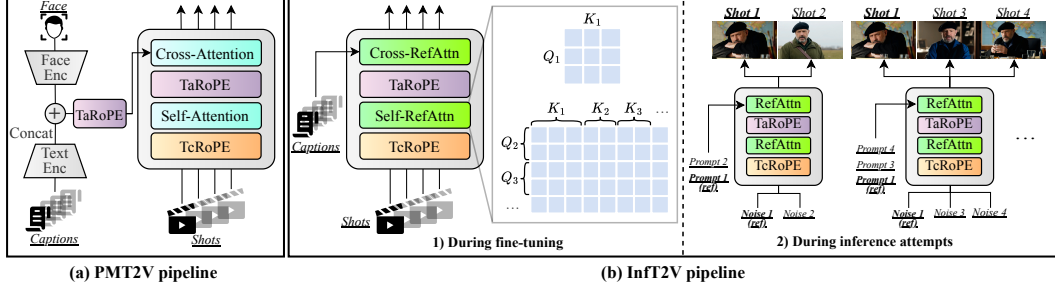


Figure 3: Two enhanced pipelines based on MT2V model. (a) PMT2V pipeline, with an integrated conditioner branch, generates multi-shot portrait videos of a given face input. (b) InfT2V pipeline creates infinite shots of the same person across multiple generation attempts, enabled by RefAttn, which disentangles the first shot as a constant reference.

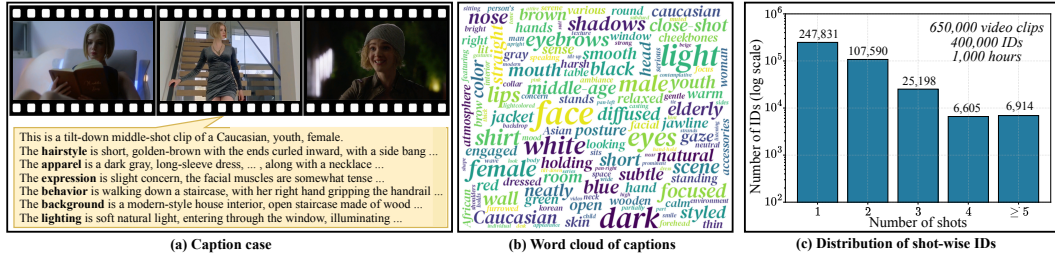


Figure 4: (a) A caption case of PortraitGala. Each clip is thoroughly captioned in the fine-grained format. (b) The word cloud reflects the comprehensiveness of the captions. (c) PortraitGala consists of 650,000 clips with 400,000 IDs, totaling a video duration of 1,000 hours.

video segments corresponding to a user-specified image. To achieve this goal, as illustrated in Fig. 3(a), we incorporate a conditioning branch to encode the face input using a face encoder, which consists of ArcFace [14] and CLIP-G [41]. The resulting face embeddings are concatenated with the semantic embeddings of each text prompt, modulated by TaRoPE, and subsequently fed into the cross-attention layers. The denoising network is fine-tuned from the MT2V weights, guided by the standard RF loss.

InfT2V. In real-world applications, life-long video generation with an infinite number of shots for the same individual is required. A natural approach is to fix the first shot as a reference across multiple generation attempts while varying the remaining shots. The inherent dynamics of the full-attention mechanism update the denoising path of each shot based on the fixed noise input from the first shot and the random noise inputs from remaining shots, resulting in variations in the first shot across different generation attempts. To address this issue, we disentangle the first shot using RefAttn, as illustrated in Fig. 3, which computes two attention weight matrices:

$$A_1 = Q_1 \times K_1, \quad A_2 = [Q_2, \dots] \times [K_1, \dots], \quad (5)$$

where $[\cdot]$ is concatenation operation. Here, A_1 is employed to update the first shot, while A_2 is utilized to update the remaining shots. Integrating RefAttn, the model undergoes a quick fine-tuning to learn this new pattern. During inference, we maintain the noise, length, and prompt of the first shot unchanged across different generations, providing a fixed reference. As we change the prompts of the remaining shots, our method generates infinite shots while preserving the identity of the first.

3.4 PortraitGala: The First Multi-shot Portrait Video Dataset

Data processing. To support training, we meticulously construct a high-quality and large-scale human portrait dataset through an incremental process: 1) collect a raw data pool from diverse sources, including movies, episodes, open-source dataset, etc.; 2) filter by aspect ratio, resolution, and other criteria; 3) slice into single-shot clips using PySceneDetect [5]; 4) detect human face [23] and retain single-person clips; 5) identify many-to-one clips showing the same person using in-house

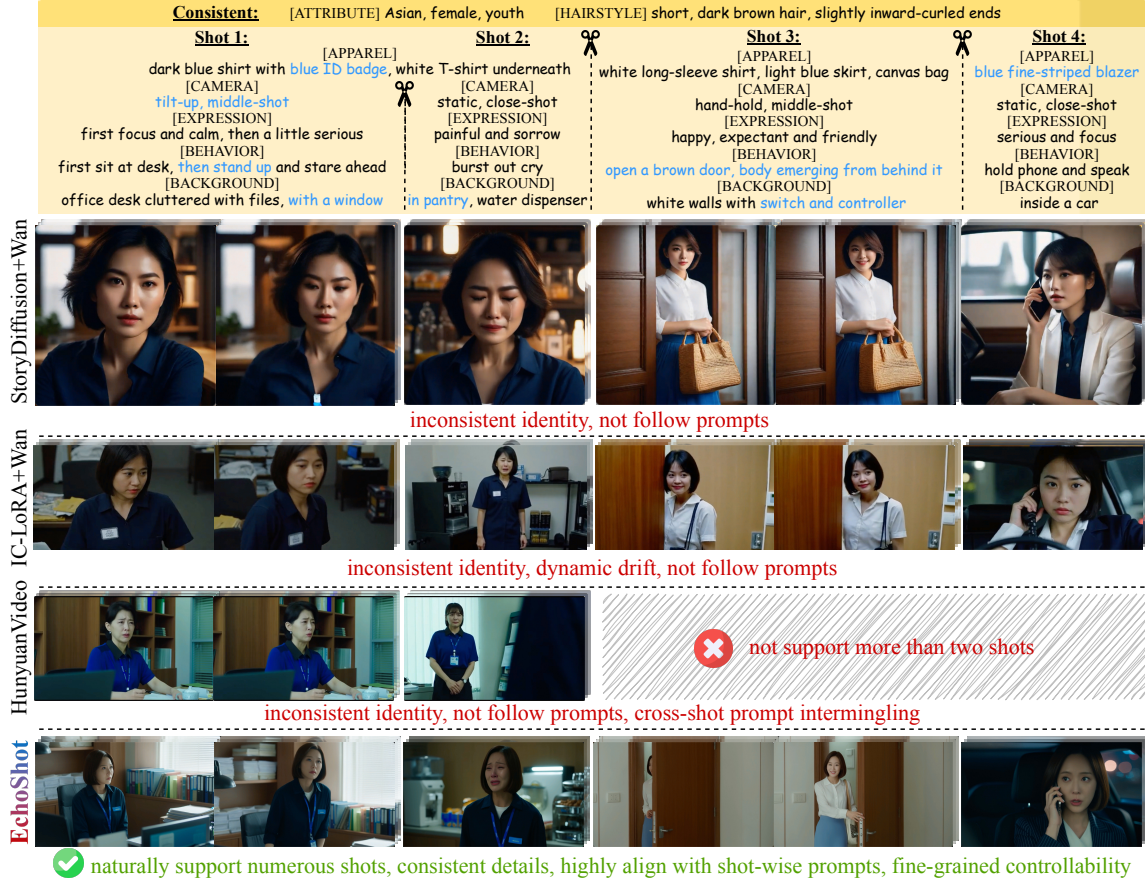


Figure 5: Illustration of EchoShot and baselines in the MT2V task. Key prompts are marked blue. Our method demonstrates superior appearance consistency and fine-grained controllability.

facial embedding extraction and clustering pipeline; 6) remove duplicate videos showing similar content; 7) attach attribute labels, text descriptions, and other necessary structured information based on Gemini 2.0 Flash [1].

Data format and statistics. We deconstruct the content of portrait videos into 8 aspects and establish a unified caption format. To specify, as shown in Fig. 4(a), every clip is annotated with the format "This is a [CAMERA] of a [ATTRIBUTE] . [HAIRSTYLE] . [APPAREL] . [EXPRESSION] . [BEHAVIOR] . [BACKGROUND] . [LIGHTING] . ". The word cloud in Fig. 4(b) reflects the comprehensiveness of our detailed captions, which endows our model with fine-grained controllability of the generated videos. As a result of the curation pipeline, we ultimately build up PortraitGala, which consists of 600k clips showing 400k identities, totaling a video duration of 1k hours. As depicted in Fig. 4(c), our dataset includes 247k single-shot IDs, 107k two-shot IDs, 25k three-shot IDs, and so on, which lays a solid foundation for our multi-shot training paradigm.

4 Experiments

Implementation details. EchoShot is implemented based on Wan-1.3B [43]. Throughout the three tasks, we set the resolution to 832×480 and use a fixed 125 frames, which is equivalent to 7.8 seconds in the real world. We set the phase shift scale j to 4 and the mismatch suppression scale k to 6. The training dataset consists of one-third one-to-one data and two-thirds many-to-one data, and the shot number S varies from 1 to 4. The length of each shot is randomly sampled. All the training is driven by the standard RF loss. The MT2V pretraining takes about 3,500 NVIDIA A100 GPU hours. The PMT2V model and InfT2V model are fine-tuned based on the MT2V weights.



Figure 6: Illustration of EchoShot and baselines in PMT2V task. Baselines exhibit severe bias, poor consistency, and limited controllability, while our method demonstrates superior overall quality.



Figure 7: Illustration of EchoShot in InfT2V task. Our method succeeds in generating infinite shots (10 here) showing the same identity.

Baselines. To evaluate the performance of EchoShot, we compare it with a variety of baselines. For MT2V, we include (1) keyframe-based pipelines, StoryDiffusion [56]+Wan-I2V [43] (SD+W) and IC-LoRA [20]+Wan-I2V [43] (IC+W), (2) HunyuanVideo [24], which supports two shots generation. For PMT2V, we include (1) open-source ConsisID [53], (2) closed-source Kling [4]. All model settings are kept at their default values.

Benchmark. To provide an objective assessment, we instruct LLM to generate 100 sets of multi-shot prompts in the portrait caption format. The prompts are transformed into different versions to match the different text input lengths of baselines. We encompass metrics from three different aspects: (1) Identity consistency. Following [53], we use FaceSim-Arc [14] and FaceSim-Cur [21] to measure the facial consistency across different generated shots. (2) Prompt controllability. We instruct VLM to score the alignment between the video and the corresponding prompt in three dimensions: human appearance (App.), camera and human motions (Mot.), background and lighting (Bg.). (3) Visual quality. Since traditional metrics may not faithfully reflect human preferences, we follow [22] to instruct VLM to score in two dimensions. Static quality (Sta.) covers clarity, color saturation, content layout, etc. Dynamic quality (Dyn.) covers smoothness, temporal consistency, reasonableness, etc.

Method	Identity consistency		Prompt controllability			Visual quality	
	FaceSim-Arc	FaceSim-Cur	App.	Mot.	Bg.	Sta.	Dyn.
StoryDiffusion+Wan-14B	68.65	65.29	83.33	72.50	69.53	63.20	84.68
IC-LoRA+Wan-14B	68.45	65.04	87.59	83.71	75.37	79.49	87.98
HunyuanVideo-13B (2 shots)	64.80	61.25	83.39	68.15	72.37	86.37	87.22
EchoShot-1B (ours)	73.74	69.43	95.84	88.86	94.72	88.91	<u>87.85</u>

Table 1: Metric results in MT2V task. Requiring only 1B parameters, EchoShot tops the scoreboard compared to baselines. The best and second-best scores are denoted **bold** and underlined.

4.1 Qualitative Evaluation

MT2V. As shown in Fig. 5, limitations of baselines are observed: (1) The performance of the keyframe-based pipelines is constrained by keyframe priors. To specify, SD+W fails to follow the detailed prompts (e.g., blue blazer, ID badge), and the visual style appears unnatural. Both SD+W and IC+W exhibit suboptimal consistency across shots. (2) The keyframe-based pipelines exhibit progressive degradation of facial consistency during temporal expansion. For example, the crying person in shot #2 generated by IC+W shows obvious inconsistency with other shots. (3) Simply concatenating the multi-shot prompts, adopted by HunyuanVideo, causes the intermingling of prompts of different shots and inferior controllability. For instance, in the videos generated by HunyuanVideo, the window intended for shot #1 unexpectedly appears in shots #2. By contrast, benefiting from the multi-shot modeling, our EchoShot generates numerous shots with consistent details as well as fine-grained controllability, demonstrating superiority over the baselines. Notably, EchoShot is able to generate a coherent sequence of human actions, such as the "body emerging from behind the door" in shot #2, whereas keyframe-based approaches struggle to achieve.

PMT2V&InfT2V. Fig. 6 illustrates the comparison between our method and baselines in PMT2V task. Primarily trained on a one-to-one portrait dataset, both ConsisID and Kling exhibit severe bias to the reference image and fail to follow the prompts (e.g., the hairstyle and expressions of Emma Watson). Besides, the repeated generation process lacks the ability to maintain consistency across different shots (e.g., the clothes of Morgan Freeman). By contrast, with many-to-one modeling and shot-aware mechanisms, our method achieves consistent appearance, vivid expressions, and precise controllability across shots. Additionally, we visualize the performance of our method in InfT2V task in Fig. 7. Thanks to the RefAttn mechanism, our method is able to generate infinite shots of freely customized prompts while maintaining the same identity of the character.

4.2 Quantitative Evaluation

Metric results. Tab. 1 shows the quantitative metrics of EchoShot and baselines in MT2V. For identity consistency, our method scores the highest 73.74% on FaceSim-Arc and 69.43% on FaceSim-Cur, achieving strong cross-shot identity consistency. In terms of prompt control, our method remarkably scores 95.84% App., 88.86% Mot., and 94.72% Bg., surpassing the baselines by a large margin. Besides, our method scores 88.91% Sta. and 87.85% Dyn., both top-tier. The results prove the overall advantages and the effectiveness of our method.

User study. To present a human-aligned assessment of MT2V, we further conduct a user study involving 20 participants. They are asked to perform binary voting in 45 one-on-one matchups between our method and baselines in terms of the above-mentioned three aspects. As shown in Fig. 8, our method wins at least 70% matchups for identity consistency and prompt controllability, as well as at least 50% matchups for visual quality. The user study reconfirms the superiority of our method, which echoes the metric results.

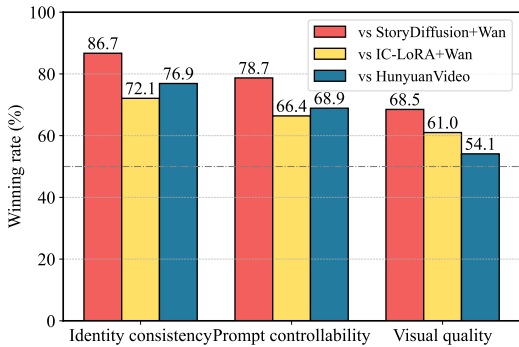


Figure 8: User study. The overall high winning rate proves that EchoShot better aligns with human preferences.

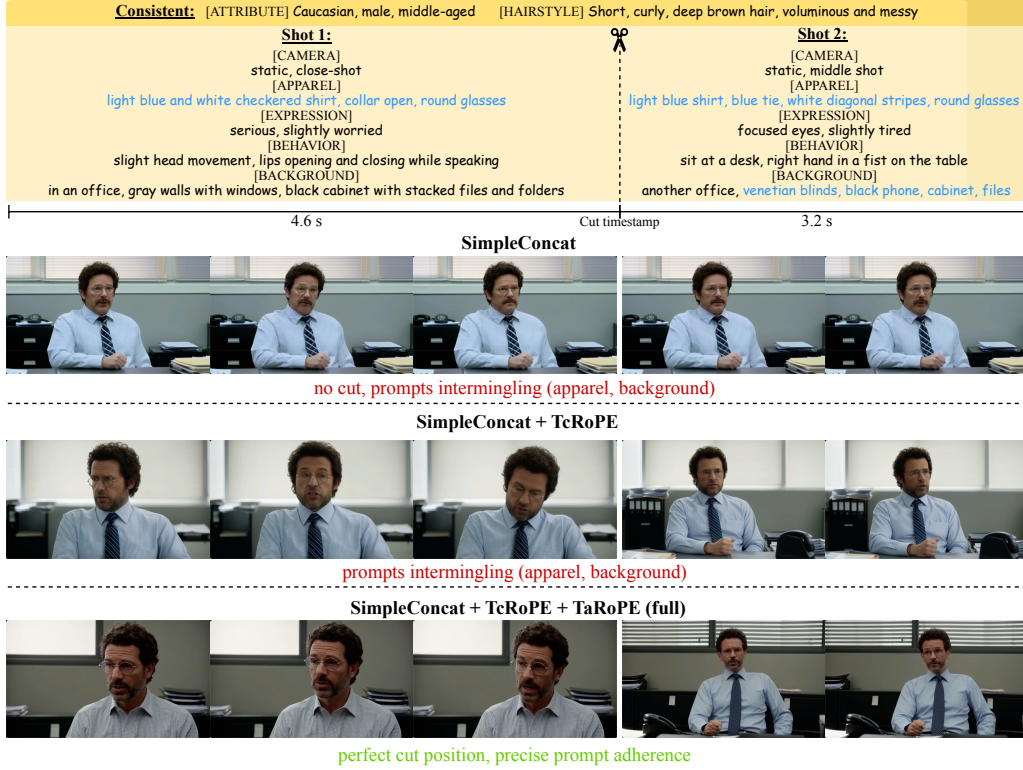


Figure 9: Illustration of generated videos of three ablation models, which confirms that TcRoPE and TaRoPE mechanisms perform as expected.

4.3 Ablation Study

To verify the effectiveness of each proposed mechanism, we carry out an ablation study. For rapid assessment, we build a reduced-scale dataset for ablation training. We construct three ablation models: (1) SimplyConcat (SC), which concatenates the videos and the captions from different shots indiscriminately, and applies vanilla RoPE. (2) SC+TcRoPE, which only applies the TcRoPE mechanism. (3) SC+TcRoPE+TaRoPE is our full method. As shown in Fig. 9, SC struggles to recognize the difference between shots, causing failure of shot transition. Though it occasionally generates multi-shot videos, the shot transition positions are elusive and uncontrolled. With the modeling of shot-wise boundaries, SC+TcRoPE enables shot transitions at given timestamps. Yet, both SC and SC+TcRoPE exhibit an intermingling effect between prompts from different shots (e.g., the clothes are the same across shots, though given different descriptions), likely caused by simple caption concatenation. In contrast, our full method demonstrates precise shot-wise prompt adherence without intermingling.

5 Conclusion

We introduce EchoShot, a novel framework for multi-shot portrait generation that addresses the limitations of existing single-shot pipelines. EchoShot achieves high-quality, identity-consistent multi-shot video synthesis with flexible user-defined control over content and appearance through two shot-aware RoPE mechanisms: TcRoPE and TaRoPE. Furthermore, we develop PortraitGala, a large-scale, high-fidelity human-centric video dataset designed to support cross-shot identity consistency and fine-grained controllability. Extensive experiments confirm that EchoShot surpasses existing methods in both quantitative metrics and qualitative assessments. Notably, EchoShot provides a promising solution to enhance artistic workflows in real-world applications.

Limitation. Our framework currently lacks the capability to directly extend shots from previous content, thereby limiting the generation of longer, continuous video segments within a single shot. Additionally, generating consistent multi-subject scripts is a promising direction for future work.

Acknowledgements

This work was supported in part by NSFC under Grant 62192781, 62172326, 62137002, 62302384, Research Project Funded by the State Key Laboratory of Communication Content Cognition under Grant No. A202403, and the Project of China Knowledge Centre for Engineering Science and Technology.

References

- [1] Gemini 2.0 flash. <https://deepmind.google/technologies/gemini/flash/>.
- [2] Gen 4. <https://runwayml.com/research/introducing-runway-gen-4>.
- [3] Hailuo. <https://hailuoai.com/create>.
- [4] Kling. <https://klingai.com/>.
- [5] Pyscenedetect. <https://www.scenedetect.com/>.
- [6] Veo 2. <https://deepmind.google/technologies/veo/veo-2/>.
- [7] Vidu. <https://www.vidu.cn/create/character2video>.
- [8] Hritik Bansal, Yonatan Bitton, Michal Yarom, Idan Szpektor, Aditya Grover, and Kai-Wei Chang. Talc: Time-aligned captions for multi-scene text-to-video generation. *arXiv preprint arXiv:2405.04682*, 2024.
- [9] Andreas Blattmann, Tim Dockhorn, Sumith Kulal, Daniel Mendelevitch, Maciej Kilian, Dominik Lorenz, Yam Levi, Zion English, Vikram Voleti, Adam Letts, et al. Stable video diffusion: Scaling latent video diffusion models to large datasets. *arXiv preprint arXiv:2311.15127*, 2023.
- [10] Tim Brooks, Bill Peebles, Connor Holmes, Will DePue, Yufei Guo, Li Jing, David Schnurr, Joe Taylor, Troy Luhman, Eric Luhman, et al. Video generation models as world simulators. *OpenAI Blog*, 2024.
- [11] Fabian Caba Heilbron, Victor Escorcia, Bernard Ghanem, and Juan Carlos Niebles. Activitynet: A large-scale video benchmark for human activity understanding. In *CVPR*, 2015.
- [12] Joao Carreira, Eric Noland, Chloe Hillier, and Andrew Zisserman. A short note on the kinetics-700 human action dataset. *arXiv preprint arXiv:1907.06987*, 2019.
- [13] Tsai-Shien Chen, Aliaksandr Siarohin, Willi Menapace, Ekaterina Deyneka, Hsiang-wei Chao, Byung Eun Jeon, Yuwei Fang, Hsin-Ying Lee, Jian Ren, Ming-Hsuan Yang, et al. Panda-70m: Captioning 70m videos with multiple cross-modality teachers. In *CVPR*, 2024.
- [14] Jiankang Deng, Jia Guo, Niannan Xue, and Stefanos Zafeiriou. Arcface: Additive angular margin loss for deep face recognition. In *CVPR*, 2019.
- [15] Patrick Esser, Sumith Kulal, Andreas Blattmann, Rahim Entezari, Jonas Müller, Harry Saini, Yam Levi, Dominik Lorenz, Axel Sauer, Frederic Boesel, et al. Scaling rectified flow transformers for high-resolution image synthesis. In *ICML*, 2024.
- [16] Yuwei Guo, Ceyuan Yang, Anyi Rao, Zhengyang Liang, Yaohui Wang, Yu Qiao, Maneesh Agrawala, Dahua Lin, and Bo Dai. Animatediff: Animate your personalized text-to-image diffusion models without specific tuning. *arXiv preprint arXiv:2307.04725*, 2023.
- [17] Yuwei Guo, Ceyuan Yang, Ziyang Yang, Zhibei Ma, Zhijie Lin, Zhenheng Yang, Dahua Lin, and Lu Jiang. Long context tuning for video generation. *arXiv preprint arXiv:2503.10589*, 2025.
- [18] Zinan Guo, Yanze Wu, Chen Zhuowei, Peng Zhang, Qian He, et al. Pulid: Pure and lightning id customization via contrastive alignment. *NeurIPS*, 2024.
- [19] Xirui Hu, Jiahao Wang, Hao Chen, Weizhan Zhang, Benqi Wang, Yikun Li, and Haishun Nan. Dynamicid: Zero-shot multi-id image personalization with flexible facial editability. In *ICCV*, 2025.

- [20] Lianghua Huang, Wei Wang, Zhi-Fan Wu, Yupeng Shi, Huanzhang Dou, Chen Liang, Yutong Feng, Yu Liu, and Jingren Zhou. In-context lora for diffusion transformers. *arXiv preprint arXiv:2410.23775*, 2024.
- [21] Yuge Huang, Yuhan Wang, Ying Tai, Xiaoming Liu, Pengcheng Shen, Shaoxin Li, Jilin Li, and Feiyue Huang. Curricularface: Adaptive curriculum learning loss for deep face recognition. In *CVPR*, 2020.
- [22] Ziqi Huang, Yinan He, Jiashuo Yu, Fan Zhang, Chenyang Si, Yuming Jiang, Yuanhan Zhang, Tianxing Wu, Qingyang Jin, Nattapol Chanpaisit, Yaohui Wang, Xinyuan Chen, Limin Wang, Dahua Lin, Yu Qiao, and Ziwei Liu. Vbench: Comprehensive benchmark suite for video generative models. In *CVPR*, 2024.
- [23] Rahima Khanam and Muhammad Hussain. Yolov11: An overview of the key architectural enhancements. *arXiv preprint arXiv:2410.17725*, 2024.
- [24] Weijie Kong, Qi Tian, Zijian Zhang, Rox Min, Zuozhuo Dai, Jin Zhou, Jiangfeng Xiong, Xin Li, Bo Wu, Jianwei Zhang, et al. Hunyuanvideo: A systematic framework for large video generative models. *arXiv preprint arXiv:2412.03603*, 2024.
- [25] Hui Li, Mingwang Xu, Yun Zhan, Shan Mu, Jiaye Li, Kaihui Cheng, Yuxuan Chen, Tan Chen, Mao Ye, Jingdong Wang, et al. Openhumanvid: A large-scale high-quality dataset for enhancing human-centric video generation. *arXiv preprint arXiv:2412.00115*, 2024.
- [26] Zhen Li, Mingdeng Cao, Xintao Wang, Zhongang Qi, Ming-Ming Cheng, and Ying Shan. Photomaker: Customizing realistic human photos via stacked id embedding. In *CVPR*, 2024.
- [27] Bin Lin, Yunyang Ge, Xinhua Cheng, Zongjian Li, Bin Zhu, Shaodong Wang, Xianyi He, Yang Ye, Shenghai Yuan, Liuhan Chen, et al. Open-sora plan: Open-source large video generation model. *arXiv preprint arXiv:2412.00131*, 2024.
- [28] Haonan Lin, Yan Chen, Jiahao Wang, Wenbin An, Mengmeng Wang, Feng Tian, Yong Liu, Guang Dai, Jingdong Wang, and Qianying Wang. Schedule your edit: A simple yet effective diffusion noise schedule for image editing. In *NeurIPS*, 2024.
- [29] Yaron Lipman, Ricky T. Q. Chen, Heli Ben-Hamu, Maximilian Nickel, and Matthew Le. Flow matching for generative modeling. In *ICLR*, 2023.
- [30] Fuchen Long, Zhaofan Qiu, Ting Yao, and Tao Mei. Videostudio: Generating consistent-content and multi-scene videos. In *ECCV*, 2024.
- [31] Guoqing Ma, Haoyang Huang, Kun Yan, Liangyu Chen, Nan Duan, Shengming Yin, Changyi Wan, Ranchen Ming, Xiaoni Song, Xing Chen, et al. Step-video-t2v technical report: The practice, challenges, and future of video foundation model. *arXiv preprint arXiv:2502.10248*, 2025.
- [32] Leland McInnes, John Healy, and Steve Astels. hdbscan: Hierarchical density based clustering. *Journal of Open Source Software*, 2017.
- [33] Kepan Nan, Rui Xie, Penghao Zhou, Tiehan Fan, Zhenheng Yang, Zhijie Chen, Xiang Li, Jian Yang, and Ying Tai. Openvid-1m: A large-scale high-quality dataset for text-to-video generation. In *ICLR*, 2025.
- [34] William Peebles and Saining Xie. Scalable diffusion models with transformers. In *ICCV*, 2023.
- [35] A Polyak, A Zohar, A Brown, A Tjandra, A Sinha, A Lee, A Vyas, B Shi, CY Ma, CY Chuang, et al. Movie gen: A cast of media foundation models. *arXiv preprint arXiv:2410.13720*, 2024.
- [36] Robin Rombach, Andreas Blattmann, Dominik Lorenz, Patrick Esser, and Björn Ommer. High-resolution image synthesis with latent diffusion models. In *CVPR*, 2022.
- [37] Christoph Schuhmann. Aesthetic predictor. <https://github.com/christophschuhmann/improved-aesthetic-predictor>.

- [38] Uriel Singer, Adam Polyak, Thomas Hayes, Xi Yin, Jie An, Songyang Zhang, Qiyuan Hu, Harry Yang, Oron Ashual, Oran Gafni, et al. Make-a-video: Text-to-video generation without text-video data. In *ICLR*, 2023.
- [39] Khurram Soomro, Amir Roshan Zamir, and Mubarak Shah. Ucf101: A dataset of 101 human actions classes from videos in the wild. *arXiv preprint arXiv:1212.0402*, 2012.
- [40] Jianlin Su, Murtadha H. M. Ahmed, Yu Lu, Shengfeng Pan, Wen Bo, and Yunfeng Liu. Roformer: Enhanced transformer with rotary position embedding. *Neurocomputing*, 2024.
- [41] Quan Sun, Yuxin Fang, Ledell Wu, Xinlong Wang, and Yue Cao. Eva-clip: Improved training techniques for clip at scale. *arXiv preprint arXiv:2303.15389*, 2023.
- [42] Yoad Tewel, Omri Kaduri, Rinon Gal, Yoni Kasten, Lior Wolf, Gal Chechik, and Yuval Atzmon. Training-free consistent text-to-image generation. *TOG*, 2024.
- [43] Team Wan, Ang Wang, Baole Ai, Bin Wen, Chaojie Mao, Chen-Wei Xie, Di Chen, Feiwei Yu, Haiming Zhao, Jianxiao Yang, et al. Wan: Open and advanced large-scale video generative models. *arXiv preprint arXiv:2503.20314*, 2025.
- [44] Jiahao Wang, Caixia Yan, Haonan Lin, Weizhan Zhang, Mengmeng Wang, Tieliang Gong, Guang Dai, and Hao Sun. Oneactor: Consistent subject generation via cluster-conditioned guidance. *NeurIPS*, 2024.
- [45] Jiahao Wang, Caixia Yan, Weizhan Zhang, Haonan Lin, Mengmeng Wang, Guang Dai, Tieliang Gong, Hao Sun, and Jingdong Wang. Spotactor: Training-free layout-controlled consistent image generation. In *AAAI*, 2025.
- [46] Qiuheng Wang, Yukai Shi, Jiarong Ou, Rui Chen, Ke Lin, Jiahao Wang, Boyuan Jiang, Haotian Yang, Mingwu Zheng, Xin Tao, et al. Koala-36m: A large-scale video dataset improving consistency between fine-grained conditions and video content. *arXiv preprint arXiv:2410.08260*, 2024.
- [47] Qixun Wang, Xu Bai, Haofan Wang, Zekui Qin, Anthony Chen, Huaxia Li, Xu Tang, and Yao Hu. Instantid: Zero-shot identity-preserving generation in seconds. *arXiv preprint arXiv:2401.07519*, 2024.
- [48] Ziyi Wu, Aliaksandr Siarohin, Willi Menapace, Ivan Skorokhodov, Yuwei Fang, Varnith Chordia, Igor Gilitschenski, and Sergey Tulyakov. Mind the time: Temporally-controlled multi-event video generation. *arXiv preprint arXiv:2412.05263*, 2024.
- [49] Liangbin Xie, Xintao Wang, Honglun Zhang, Chao Dong, and Ying Shan. Vfhq: A high-quality dataset and benchmark for video face super-resolution. In *CVPR*, 2022.
- [50] Yuxiao Yang, Hualian Sheng, Sijia Cai, Jing Lin, Jiahao Wang, Bing Deng, Junzhe Lu, Haoqian Wang, and Jieping Ye. Echomotion: Unified human video and motion generation via dual-modality diffusion transformer. *arXiv preprint arXiv:2512.18814*, 2025.
- [51] Zhuoyi Yang, Jiayan Teng, Wendi Zheng, Ming Ding, Shiyu Huang, Jiazheng Xu, Yuanming Yang, Wenyi Hong, Xiaohan Zhang, Guanyu Feng, et al. Cogvideox: Text-to-video diffusion models with an expert transformer. In *ICLR*, 2025.
- [52] Jianhui Yu, Hao Zhu, Liming Jiang, Chen Change Loy, Weidong Cai, and Wayne Wu. Celebv-text: A large-scale facial text-video dataset. In *CVPR*, 2023.
- [53] Shenghai Yuan, Jinfa Huang, Xianyi He, Yunyuan Ge, Yujun Shi, Liuhan Chen, Jiebo Luo, and Li Yuan. Identity-preserving text-to-video generation by frequency decomposition. In *CVPR*, 2025.
- [54] Canyu Zhao, Mingyu Liu, Wen Wang, Weihua Chen, Fan Wang, Hao Chen, Bo Zhang, and Chunhua Shen. Moviedreamer: Hierarchical generation for coherent long visual sequence. *arXiv preprint arXiv:2407.16655*, 2024.

- [55] Mingzhe Zheng, Yongqi Xu, Haojian Huang, Xuran Ma, Yexin Liu, Wenjie Shu, Yatian Pang, Feilong Tang, Qifeng Chen, Harry Yang, et al. Videogen-of-thought: Step-by-step generating multi-shot video with minimal manual intervention. *arXiv preprint arXiv:2503.15138*, 2025.
- [56] Yupeng Zhou, Daquan Zhou, Ming-Ming Cheng, Jiashi Feng, and Qibin Hou. Storydiffusion: Consistent self-attention for long-range image and video generation. *NeurIPS*, 2024.
- [57] Hao Zhu, Wayne Wu, Wentao Zhu, Liming Jiang, Siwei Tang, Li Zhang, Ziwei Liu, and Chen Change Loy. Celebv-hq: A large-scale video facial attributes dataset. In *ECCV*, 2022.

NeurIPS Paper Checklist

1. Claims

Question: Do the main claims made in the abstract and introduction accurately reflect the paper's contributions and scope?

Answer: [\[Yes\]](#)

Justification: We accurately reflect our contributions and scope in the abstract and introduction.

Guidelines:

- The answer NA means that the abstract and introduction do not include the claims made in the paper.
- The abstract and/or introduction should clearly state the claims made, including the contributions made in the paper and important assumptions and limitations. A No or NA answer to this question will not be perceived well by the reviewers.
- The claims made should match theoretical and experimental results, and reflect how much the results can be expected to generalize to other settings.
- It is fine to include aspirational goals as motivation as long as it is clear that these goals are not attained by the paper.

2. Limitations

Question: Does the paper discuss the limitations of the work performed by the authors?

Answer: [\[Yes\]](#)

Justification: We discuss the limitations in Conclusion.

Guidelines:

- The answer NA means that the paper has no limitation while the answer No means that the paper has limitations, but those are not discussed in the paper.
- The authors are encouraged to create a separate "Limitations" section in their paper.
- The paper should point out any strong assumptions and how robust the results are to violations of these assumptions (e.g., independence assumptions, noiseless settings, model well-specification, asymptotic approximations only holding locally). The authors should reflect on how these assumptions might be violated in practice and what the implications would be.
- The authors should reflect on the scope of the claims made, e.g., if the approach was only tested on a few datasets or with a few runs. In general, empirical results often depend on implicit assumptions, which should be articulated.
- The authors should reflect on the factors that influence the performance of the approach. For example, a facial recognition algorithm may perform poorly when image resolution is low or images are taken in low lighting. Or a speech-to-text system might not be used reliably to provide closed captions for online lectures because it fails to handle technical jargon.
- The authors should discuss the computational efficiency of the proposed algorithms and how they scale with dataset size.
- If applicable, the authors should discuss possible limitations of their approach to address problems of privacy and fairness.
- While the authors might fear that complete honesty about limitations might be used by reviewers as grounds for rejection, a worse outcome might be that reviewers discover limitations that aren't acknowledged in the paper. The authors should use their best judgment and recognize that individual actions in favor of transparency play an important role in developing norms that preserve the integrity of the community. Reviewers will be specifically instructed to not penalize honesty concerning limitations.

3. Theory assumptions and proofs

Question: For each theoretical result, does the paper provide the full set of assumptions and a complete (and correct) proof?

Answer: [\[Yes\]](#)

Justification: We provide the theoretical analysis in Method and Appendix.

Guidelines:

- The answer NA means that the paper does not include theoretical results.
- All the theorems, formulas, and proofs in the paper should be numbered and cross-referenced.
- All assumptions should be clearly stated or referenced in the statement of any theorems.
- The proofs can either appear in the main paper or the supplemental material, but if they appear in the supplemental material, the authors are encouraged to provide a short proof sketch to provide intuition.
- Inversely, any informal proof provided in the core of the paper should be complemented by formal proofs provided in appendix or supplemental material.
- Theorems and Lemmas that the proof relies upon should be properly referenced.

4. Experimental result reproducibility

Question: Does the paper fully disclose all the information needed to reproduce the main experimental results of the paper to the extent that it affects the main claims and/or conclusions of the paper (regardless of whether the code and data are provided or not)?

Answer: [\[Yes\]](#)

Justification: We submitted codes in the supplementary materials. We try to describe all the necessary details in Experiment and Appendix.

Guidelines:

- The answer NA means that the paper does not include experiments.
- If the paper includes experiments, a No answer to this question will not be perceived well by the reviewers: Making the paper reproducible is important, regardless of whether the code and data are provided or not.
- If the contribution is a dataset and/or model, the authors should describe the steps taken to make their results reproducible or verifiable.
- Depending on the contribution, reproducibility can be accomplished in various ways. For example, if the contribution is a novel architecture, describing the architecture fully might suffice, or if the contribution is a specific model and empirical evaluation, it may be necessary to either make it possible for others to replicate the model with the same dataset, or provide access to the model. In general, releasing code and data is often one good way to accomplish this, but reproducibility can also be provided via detailed instructions for how to replicate the results, access to a hosted model (e.g., in the case of a large language model), releasing of a model checkpoint, or other means that are appropriate to the research performed.
- While NeurIPS does not require releasing code, the conference does require all submissions to provide some reasonable avenue for reproducibility, which may depend on the nature of the contribution. For example
 - (a) If the contribution is primarily a new algorithm, the paper should make it clear how to reproduce that algorithm.
 - (b) If the contribution is primarily a new model architecture, the paper should describe the architecture clearly and fully.
 - (c) If the contribution is a new model (e.g., a large language model), then there should either be a way to access this model for reproducing the results or a way to reproduce the model (e.g., with an open-source dataset or instructions for how to construct the dataset).
 - (d) We recognize that reproducibility may be tricky in some cases, in which case authors are welcome to describe the particular way they provide for reproducibility. In the case of closed-source models, it may be that access to the model is limited in some way (e.g., to registered users), but it should be possible for other researchers to have some path to reproducing or verifying the results.

5. Open access to data and code

Question: Does the paper provide open access to the data and code, with sufficient instructions to faithfully reproduce the main experimental results, as described in supplemental material?

Answer: [Yes]

Justification: We submitted codes in the supplementary materials. We will release the model and the dataset officially online with detailed instructions after preparations.

Guidelines:

- The answer NA means that paper does not include experiments requiring code.
- Please see the NeurIPS code and data submission guidelines (<https://nips.cc/public/guides/CodeSubmissionPolicy>) for more details.
- While we encourage the release of code and data, we understand that this might not be possible, so “No” is an acceptable answer. Papers cannot be rejected simply for not including code, unless this is central to the contribution (e.g., for a new open-source benchmark).
- The instructions should contain the exact command and environment needed to run to reproduce the results. See the NeurIPS code and data submission guidelines (<https://nips.cc/public/guides/CodeSubmissionPolicy>) for more details.
- The authors should provide instructions on data access and preparation, including how to access the raw data, preprocessed data, intermediate data, and generated data, etc.
- The authors should provide scripts to reproduce all experimental results for the new proposed method and baselines. If only a subset of experiments are reproducible, they should state which ones are omitted from the script and why.
- At submission time, to preserve anonymity, the authors should release anonymized versions (if applicable).
- Providing as much information as possible in supplemental material (appended to the paper) is recommended, but including URLs to data and code is permitted.

6. Experimental setting/details

Question: Does the paper specify all the training and test details (e.g., data splits, hyper-parameters, how they were chosen, type of optimizer, etc.) necessary to understand the results?

Answer: [Yes]

Justification: We describe the details in Appendix. We also submitted codes in the supplementary materials.

Guidelines:

- The answer NA means that the paper does not include experiments.
- The experimental setting should be presented in the core of the paper to a level of detail that is necessary to appreciate the results and make sense of them.
- The full details can be provided either with the code, in appendix, or as supplemental material.

7. Experiment statistical significance

Question: Does the paper report error bars suitably and correctly defined or other appropriate information about the statistical significance of the experiments?

Answer: [Yes]

Justification: We report the standard deviation as the error bars in Appendix.

Guidelines:

- The answer NA means that the paper does not include experiments.
- The authors should answer "Yes" if the results are accompanied by error bars, confidence intervals, or statistical significance tests, at least for the experiments that support the main claims of the paper.
- The factors of variability that the error bars are capturing should be clearly stated (for example, train/test split, initialization, random drawing of some parameter, or overall run with given experimental conditions).
- The method for calculating the error bars should be explained (closed form formula, call to a library function, bootstrap, etc.)
- The assumptions made should be given (e.g., Normally distributed errors).

- It should be clear whether the error bar is the standard deviation or the standard error of the mean.
- It is OK to report 1-sigma error bars, but one should state it. The authors should preferably report a 2-sigma error bar than state that they have a 96% CI, if the hypothesis of Normality of errors is not verified.
- For asymmetric distributions, the authors should be careful not to show in tables or figures symmetric error bars that would yield results that are out of range (e.g. negative error rates).
- If error bars are reported in tables or plots, The authors should explain in the text how they were calculated and reference the corresponding figures or tables in the text.

8. Experiments compute resources

Question: For each experiment, does the paper provide sufficient information on the computer resources (type of compute workers, memory, time of execution) needed to reproduce the experiments?

Answer: [Yes]

Justification: We provide information of the compute resources in Experiment and Appendix.

Guidelines:

- The answer NA means that the paper does not include experiments.
- The paper should indicate the type of compute workers CPU or GPU, internal cluster, or cloud provider, including relevant memory and storage.
- The paper should provide the amount of compute required for each of the individual experimental runs as well as estimate the total compute.
- The paper should disclose whether the full research project required more compute than the experiments reported in the paper (e.g., preliminary or failed experiments that didn't make it into the paper).

9. Code of ethics

Question: Does the research conducted in the paper conform, in every respect, with the NeurIPS Code of Ethics <https://neurips.cc/public/EthicsGuidelines>?

Answer: [Yes]

Justification: We try our best to conform with the NeurIPS Code of Ethics.

Guidelines:

- The answer NA means that the authors have not reviewed the NeurIPS Code of Ethics.
- If the authors answer No, they should explain the special circumstances that require a deviation from the Code of Ethics.
- The authors should make sure to preserve anonymity (e.g., if there is a special consideration due to laws or regulations in their jurisdiction).

10. Broader impacts

Question: Does the paper discuss both potential positive societal impacts and negative societal impacts of the work performed?

Answer: [Yes]

Justification: We discuss the societal impacts in Appendix.

Guidelines:

- The answer NA means that there is no societal impact of the work performed.
- If the authors answer NA or No, they should explain why their work has no societal impact or why the paper does not address societal impact.
- Examples of negative societal impacts include potential malicious or unintended uses (e.g., disinformation, generating fake profiles, surveillance), fairness considerations (e.g., deployment of technologies that could make decisions that unfairly impact specific groups), privacy considerations, and security considerations.

- The conference expects that many papers will be foundational research and not tied to particular applications, let alone deployments. However, if there is a direct path to any negative applications, the authors should point it out. For example, it is legitimate to point out that an improvement in the quality of generative models could be used to generate deepfakes for disinformation. On the other hand, it is not needed to point out that a generic algorithm for optimizing neural networks could enable people to train models that generate Deepfakes faster.
- The authors should consider possible harms that could arise when the technology is being used as intended and functioning correctly, harms that could arise when the technology is being used as intended but gives incorrect results, and harms following from (intentional or unintentional) misuse of the technology.
- If there are negative societal impacts, the authors could also discuss possible mitigation strategies (e.g., gated release of models, providing defenses in addition to attacks, mechanisms for monitoring misuse, mechanisms to monitor how a system learns from feedback over time, improving the efficiency and accessibility of ML).

11. Safeguards

Question: Does the paper describe safeguards that have been put in place for responsible release of data or models that have a high risk for misuse (e.g., pretrained language models, image generators, or scraped datasets)?

Answer: [\[Yes\]](#)

Justification: The models will be protected by the safeguards of the Wan-2.1 model.

Guidelines:

- The answer NA means that the paper poses no such risks.
- Released models that have a high risk for misuse or dual-use should be released with necessary safeguards to allow for controlled use of the model, for example by requiring that users adhere to usage guidelines or restrictions to access the model or implementing safety filters.
- Datasets that have been scraped from the Internet could pose safety risks. The authors should describe how they avoided releasing unsafe images.
- We recognize that providing effective safeguards is challenging, and many papers do not require this, but we encourage authors to take this into account and make a best faith effort.

12. Licenses for existing assets

Question: Are the creators or original owners of assets (e.g., code, data, models), used in the paper, properly credited and are the license and terms of use explicitly mentioned and properly respected?

Answer: [\[Yes\]](#)

Justification: We try our best to credit all the assets in Reference.

Guidelines:

- The answer NA means that the paper does not use existing assets.
- The authors should cite the original paper that produced the code package or dataset.
- The authors should state which version of the asset is used and, if possible, include a URL.
- The name of the license (e.g., CC-BY 4.0) should be included for each asset.
- For scraped data from a particular source (e.g., website), the copyright and terms of service of that source should be provided.
- If assets are released, the license, copyright information, and terms of use in the package should be provided. For popular datasets, paperswithcode.com/datasets has curated licenses for some datasets. Their licensing guide can help determine the license of a dataset.
- For existing datasets that are re-packaged, both the original license and the license of the derived asset (if it has changed) should be provided.

- If this information is not available online, the authors are encouraged to reach out to the asset’s creators.

13. **New assets**

Question: Are new assets introduced in the paper well documented and is the documentation provided alongside the assets?

Answer: [\[Yes\]](#)

Justification: We will provide documentation when we officially release the codes.

Guidelines:

- The answer NA means that the paper does not release new assets.
- Researchers should communicate the details of the dataset/code/model as part of their submissions via structured templates. This includes details about training, license, limitations, etc.
- The paper should discuss whether and how consent was obtained from people whose asset is used.
- At submission time, remember to anonymize your assets (if applicable). You can either create an anonymized URL or include an anonymized zip file.

14. **Crowdsourcing and research with human subjects**

Question: For crowdsourcing experiments and research with human subjects, does the paper include the full text of instructions given to participants and screenshots, if applicable, as well as details about compensation (if any)?

Answer: [\[Yes\]](#)

Justification: We include the instructions of user study in Appendix.

Guidelines:

- The answer NA means that the paper does not involve crowdsourcing nor research with human subjects.
- Including this information in the supplemental material is fine, but if the main contribution of the paper involves human subjects, then as much detail as possible should be included in the main paper.
- According to the NeurIPS Code of Ethics, workers involved in data collection, curation, or other labor should be paid at least the minimum wage in the country of the data collector.

15. **Institutional review board (IRB) approvals or equivalent for research with human subjects**

Question: Does the paper describe potential risks incurred by study participants, whether such risks were disclosed to the subjects, and whether Institutional Review Board (IRB) approvals (or an equivalent approval/review based on the requirements of your country or institution) were obtained?

Answer: [\[Yes\]](#)

Justification: We discuss the related issues in Appendix.

Guidelines:

- The answer NA means that the paper does not involve crowdsourcing nor research with human subjects.
- Depending on the country in which research is conducted, IRB approval (or equivalent) may be required for any human subjects research. If you obtained IRB approval, you should clearly state this in the paper.
- We recognize that the procedures for this may vary significantly between institutions and locations, and we expect authors to adhere to the NeurIPS Code of Ethics and the guidelines for their institution.
- For initial submissions, do not include any information that would break anonymity (if applicable), such as the institution conducting the review.

16. **Declaration of LLM usage**

Question: Does the paper describe the usage of LLMs if it is an important, original, or non-standard component of the core methods in this research? Note that if the LLM is used only for writing, editing, or formatting purposes and does not impact the core methodology, scientific rigorousness, or originality of the research, declaration is not required.

Answer: [Yes]

Justification: We describe the usage in Experiment.

Guidelines:

- The answer NA means that the core method development in this research does not involve LLMs as any important, original, or non-standard components.
- Please refer to our LLM policy (<https://neurips.cc/Conferences/2025/LLM>) for what should or should not be described.

EchoShot: Multi-Shot Portrait Video Generation

Appendix

Table of Contents

A	Mathematical Formulation	23
A.1	Derivation of Rotary Position Embedding	23
A.2	Proof of Claim about Attention Score with TaRoPE	24
B	Details of PortraitGala	25
B.1	Data Processing	25
B.2	Data Distribution	26
B.3	Dataset Examples	26
C	More Experimental Details	28
D	Extra Experiments	29
D.1	Motivation Verification	29
D.2	More Quantitative Results	29
D.3	Quantitative Ablation Study	30
D.4	Parameter Analysis	30
E	EchoShot Gallery	31
F	Clarification about User Study	32
G	Societal Impacts and Safeguards	33

A Mathematical Formulation

A.1 Derivation of Rotary Position Embedding

In Sec. 3.1, we introduce Rotary Position Embedding (RoPE) in vanilla models. Based on it, we propose two shot-aware mechanisms, TcRoPE and TaRoPE. Here, we provide the complete denotation of RoPE, following [40].

1D-RoPE. The proposed TaRoPE is based on 1D-RoPE, which is intended for sequential modality along a single dimension. Given a position-indexed query $\mathbf{q}_m \in \mathbb{R}^d$ or key vector $\mathbf{k}_m \in \mathbb{R}^d$, 1D-RoPE can be expressed as:

$$\tilde{\mathbf{q}}_m = \text{1D-RoPE}(\mathbf{q}_m, m) = \mathbf{R}_{\Theta_{1D}, m}^d \mathbf{q}_m, \quad (6)$$

$$\tilde{\mathbf{k}}_m = \text{1D-RoPE}(\mathbf{k}_m, m) = \mathbf{R}_{\Theta_{1D}, m}^d \mathbf{k}_m, \quad (7)$$

where $\mathbf{R}_{\Theta_{1D}, m}^d$ is the rotary matrix, denoted as:

$$\begin{pmatrix} \cos m\theta_1 & -\sin m\theta_1 & 0 & 0 & \cdots & 0 & 0 \\ \sin m\theta_1 & \cos m\theta_1 & 0 & 0 & \cdots & 0 & 0 \\ 0 & 0 & \cos m\theta_2 & -\sin m\theta_2 & \cdots & 0 & 0 \\ 0 & 0 & \sin m\theta_2 & \cos m\theta_2 & \cdots & 0 & 0 \\ \vdots & \vdots & \vdots & \vdots & \ddots & \vdots & \vdots \\ 0 & 0 & 0 & 0 & \cdots & \cos m\theta_{\frac{d}{2}} & -\sin m\theta_{\frac{d}{2}} \\ 0 & 0 & 0 & 0 & \cdots & \sin m\theta_{\frac{d}{2}} & \cos m\theta_{\frac{d}{2}} \end{pmatrix}, \quad (8)$$

with pre-defined parameters $\Theta_{1D} = \{\theta_i = 10000^{-\frac{2(i-1)}{d}}, i \in [1, 2, \dots, \frac{d}{2}]\}$. Thus, the proposed TaRoPE in Eq. (3) can be further written as:

$$\tilde{\mathbf{q}}_{i,s}^{ca} = \text{TaRoPE}(\mathbf{q}_{i,s}^{ca}, s) = \text{1D-RoPE}(\mathbf{q}_{i,s}^{ca}, s \cdot k) = \mathbf{R}_{\Theta_{1D}, s \cdot k}^d \mathbf{q}_{i,s}^{ca}, \quad (9)$$

$$\tilde{\mathbf{k}}_{i,s}^{ca} = \text{TaRoPE}(\mathbf{k}_{i,s}^{ca}, s) = \text{1D-RoPE}(\mathbf{k}_{i,s}^{ca}, s \cdot k) = \mathbf{R}_{\Theta_{1D}, s \cdot k}^d \mathbf{k}_{i,s}^{ca}. \quad (10)$$

3D-RoPE. The proposed TcRoPE is based on 3D-RoPE, which is an extension of 1D-RoPE tailored for video modality. Given a 3D-position-indexed $\mathbf{q}_{t,h,w} \in \mathbb{R}^d$ or key vector $\mathbf{k}_{t,h,w} \in \mathbb{R}^d$, 3D-RoPE can be denoted as:

$$\tilde{\mathbf{q}}_{t,h,w} = \text{3D-RoPE}(\mathbf{q}_{t,h,w}, t, h, w) = \mathbf{R}_{\Theta_{3D}, t, h, w}^d \mathbf{q}_{t,h,w}, \quad (11)$$

$$\tilde{\mathbf{k}}_{t,h,w} = \text{3D-RoPE}(\mathbf{k}_{t,h,w}, t, h, w) = \mathbf{R}_{\Theta_{3D}, t, h, w}^d \mathbf{k}_{t,h,w}, \quad (12)$$

where $\mathbf{R}_{\Theta_{3D}, t, h, w}^d$ can be denoted as:

$$\begin{pmatrix} \cos t\theta_1 & -\sin t\theta_1 & \cdots & 0 & 0 & 0 & 0 & \cdots & 0 & 0 & 0 & 0 & 0 & \cdots & 0 & 0 \\ \sin t\theta_1 & \cos t\theta_1 & \cdots & 0 & 0 & 0 & 0 & \cdots & 0 & 0 & 0 & 0 & 0 & \cdots & 0 & 0 \\ \vdots & \vdots & \ddots & \vdots & \vdots & \vdots & \vdots & \ddots & \vdots & \vdots & \vdots & \vdots & \vdots & \ddots & \vdots & \vdots \\ 0 & 0 & \cdots & \cos t\theta_{\frac{d}{6}} & -\sin t\theta_{\frac{d}{6}} & 0 & 0 & \cdots & 0 & 0 & 0 & 0 & \cdots & 0 & 0 \\ 0 & 0 & \cdots & \sin t\theta_{\frac{d}{6}} & \cos t\theta_{\frac{d}{6}} & 0 & 0 & \cdots & 0 & 0 & 0 & 0 & \cdots & 0 & 0 \\ 0 & 0 & \cdots & 0 & 0 & \cos h\theta_1 & -\sin h\theta_1 & \cdots & 0 & 0 & 0 & 0 & \cdots & 0 & 0 \\ 0 & 0 & \cdots & 0 & 0 & \sin h\theta_1 & \cos h\theta_1 & \cdots & 0 & 0 & 0 & 0 & \cdots & 0 & 0 \\ \vdots & \vdots & \ddots & \vdots & \vdots & \vdots & \vdots & \ddots & \vdots & \vdots & \vdots & \vdots & \ddots & \vdots & \vdots \\ 0 & 0 & \cdots & 0 & 0 & 0 & 0 & \cdots & \cos h\theta_{\frac{d}{6}} & -\sin h\theta_{\frac{d}{6}} & 0 & 0 & \cdots & 0 & 0 \\ 0 & 0 & \cdots & 0 & 0 & 0 & 0 & \cdots & \sin h\theta_{\frac{d}{6}} & \cos h\theta_{\frac{d}{6}} & 0 & 0 & \cdots & 0 & 0 \\ 0 & 0 & \cdots & 0 & 0 & 0 & 0 & \cdots & 0 & 0 & \cos w\theta_1 & -\sin w\theta_1 & \cdots & 0 & 0 \\ 0 & 0 & \cdots & 0 & 0 & 0 & 0 & \cdots & 0 & 0 & \sin w\theta_1 & \cos w\theta_1 & \cdots & 0 & 0 \\ \vdots & \vdots & \ddots & \vdots & \vdots & \vdots & \vdots & \ddots & \vdots & \vdots & \vdots & \vdots & \ddots & \vdots & \vdots \\ 0 & 0 & \cdots & 0 & 0 & 0 & 0 & \cdots & 0 & 0 & 0 & 0 & \cdots & \cos w\theta_{\frac{d}{6}} & -\sin w\theta_{\frac{d}{6}} \\ 0 & 0 & \cdots & 0 & 0 & 0 & 0 & \cdots & 0 & 0 & 0 & 0 & \cdots & \sin w\theta_{\frac{d}{6}} & \cos w\theta_{\frac{d}{6}} \end{pmatrix} \quad (13)$$

with pre-defined parameters $\Theta_{3D} = \{\theta_i = 10000^{-\frac{2(i-1)}{d}}, i \in [1, 2, \dots, \frac{d}{6}]\}$. Thus, the proposed TcRoPE in Eq. (2) can be further written as:

$$\tilde{\mathbf{q}}_{t,h,w,s}^{sa} = \text{TcRoPE}(\mathbf{q}_{t,h,w,s}^{sa}, t, h, w, s) = \text{3D-RoPE}(\mathbf{q}_{t,h,w}^{sa}, t+s \cdot j, h, w) = \mathbf{R}_{\Theta_{3D}, t+s \cdot j, h, w}^d \mathbf{q}_{t,h,w,s}^{sa}, \quad (14)$$

$$\tilde{\mathbf{k}}_{t,h,w,s}^{sa} = \text{TcRoPE}(\mathbf{k}_{t,h,w,s}^{sa}, t, h, w, s) = \text{3D-RoPE}(\mathbf{k}_{t,h,w}^{sa}, t+s \cdot j, h, w) = \mathbf{R}_{\Theta_{3D}, t+s \cdot j, h, w}^d \mathbf{k}_{t,h,w,s}^{sa}. \quad (15)$$

A.2 Proof of Claim about Attention Score with TaRoPE

In Eq. (4), we give a concise formulation of the attention score after TaRoPE with claims. We provide a detailed proof of the claim here. Given queries of the s_1 -th shot \mathbf{q}_{s_1} and keys of the s_2 -th shot \mathbf{k}_{s_2} , if we divide them into 2-component pairs along the channel dimension, the inner product of their TaRoPE-enhanced representations can be written as a complex number multiplication:

$$\begin{aligned}
\tilde{\mathbf{A}}_{s_1, s_2} &= (\mathbf{R}_{\Theta, k s_1}^d \mathbf{q}_{s_1})^\top (\mathbf{R}_{\Theta, k s_2}^d \mathbf{k}_{s_2}) \\
&= \text{Re} \left[\sum_{i=0}^{\frac{d}{2}-1} \mathbf{q}_{s_1, [2i:2i+1]} \mathbf{k}_{s_2, [2i:2i+1]}^* e^{ik(s_1-s_2)\theta_i} \right] \\
&= \sum_{i=0}^{\frac{d}{2}-1} (q_{s_1, 2i} k_{s_2, 2i} + q_{s_1, 2i+1} k_{s_2, 2i+1}) \cos(k(s_1-s_2)\theta_i) \\
&\quad + (q_{s_1, 2i} k_{s_2, 2i} - q_{s_1, 2i+1} k_{s_2, 2i+1}) \sin(k(s_1-s_2)\theta_i),
\end{aligned} \tag{16}$$

where $\mathbf{k}_{s_1, [2i:2i+1]}$ represents the $2i^{\text{th}}$ to $(2i+1)^{\text{th}}$ components of \mathbf{k}_{s_1} and $k_{s_1, 2i}$ represents the $2i^{\text{th}}$ component of \mathbf{k}_{s_1} . Note that the scalar k without subscripts is the mismatch suppression scale. When \mathbf{q}_{s_1} and \mathbf{k}_{s_2} are from the same shot (i.e., $s_1 = s_2$), Eq. (16) can be simplified as:

$$\tilde{\mathbf{A}}_{s_1, s_2} = \sum_{i=0}^{\frac{d}{2}-1} (q_{s_1, 2i} k_{s_2, 2i} + q_{s_1, 2i+1} k_{s_2, 2i+1}) = \mathbf{q}_{s_1} \mathbf{k}_{s_2} = \mathbf{A}_{s_1, s_2}, \tag{17}$$

which indicates that the attention score with TaRoPE remains exactly the same as that without TaRoPE.

To investigate the behavior of Eq. (16) as $k(s_1 - s_2)$ varies, we follow [40] to denote $\mathbf{h}_i = \mathbf{q}_{[2i:2i+1]} \mathbf{k}_{[2i:2i+1]}^*$, $S_j = \sum_{i=0}^{j-1} e^{i(s_1-s_2)\theta_i}$, and let $h_{\frac{d}{2}} = 0$, $S_0 = 0$, we can rewrite Eq. (16) using Abel transformation:

$$\sum_{i=0}^{\frac{d}{2}-1} \mathbf{q}_{[2i:2i+1]} \mathbf{k}_{[2i:2i+1]}^* e^{i(s_1-s_2)\theta_i} = \sum_{i=0}^{\frac{d}{2}-1} h_i (S_{i+1} - S_i) = - \sum_{i=0}^{\frac{d}{2}-1} S_{i+1} (h_{i+1} - h_i). \tag{18}$$

$$\begin{aligned}
\left| \sum_{i=0}^{\frac{d}{2}-1} \mathbf{q}_{[2i:2i+1]} \mathbf{k}_{[2i:2i+1]}^* e^{i(s_1-s_2)\theta_i} \right| &= \left| \sum_{i=0}^{\frac{d}{2}-1} S_{i+1} (h_{i+1} - h_i) \right| \\
&\leq \sum_{i=0}^{\frac{d}{2}-1} |S_{i+1}| |h_{i+1} - h_i| \\
&\leq \left(\max_i |h_{i+1} - h_i| \right) \sum_{i=0}^{\frac{d}{2}-1} |S_{i+1}| \\
&\leq \sum_{i=0}^{\frac{d}{2}-1} |S_{i+1}|
\end{aligned} \tag{19}$$

We plot the graph of the value of $f(x) = \sum_{i=0}^{\frac{d}{2}-1} |S_{i+1}|$ as $x = k(s_1 - s_2)$ varies in $[0, 50]$ in Fig. 10, which shows a monotonically decreasing function. By synthesizing the above derivations, we arrive at the conclusion of Eq. (4).

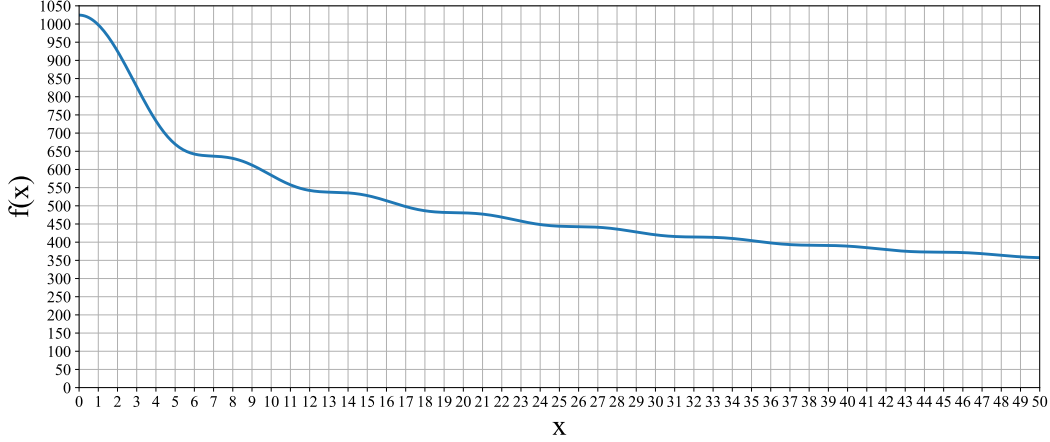


Figure 10: Graph of the attention score $f(x)$ as x varies.

B Details of PortraitGala

B.1 Data Processing

We detail the construction of the PortraitGala dataset here, adhering to the methodology outlined in Sec. 3.4. The PortraitGala dataset comprises a collection of video resources, drawing from three primary sources: 1) publicly available, high-quality portrait datasets such as CelebV-HQ [57] and CelebV-Text [52]; 2) subsets extracted from large-scale, open-source video datasets including OpenVid-1M [33] and OpenHumanVid [25]; and 3) a selection of videos obtained from various websites, encompassing both films and television series. In its entirety, the original dataset encompassed 26,967 hours of video footage.

The curation process began with rigorous filtering of raw video material to ensure quality and relevance. Specifically, we eliminated videos exhibiting vertical aspect ratios or substandard resolution, retaining only those conforming to the criteria: width > height > 480 pixels. Given the extended duration of many source videos and the presence of multiple camera shots within them, we employed PySceneDetect [5] to segment these videos into discrete, single-shot clips. Furthermore, to maintain high aesthetic quality, clips with an aesthetic score, as determined by [37], below a threshold of 4 were discarded.

To ensure that each video clip in PortraitGala featured only one individual, we implemented a person counting procedure leveraging YOLOv11 [23] for person detection and tracking. Subsequently, person identities were assigned using an improved version of HDBSCAN [32], a density-based clustering algorithm, coupled with a proprietary facial embedding extraction technique. A remaining challenge was the identification and removal of near-duplicate video clips depicting the same individual performing similar actions within a consistent setting. To address this, we simply employed Non-Maximum Suppression based on the detected person bounding boxes, specifically for videos with matching person IDs. Through rigorous manual verification, we achieve a clustering accuracy exceeding 99%, demonstrating that all video clips assigned identical identifiers consistently depict the same individual throughout.

Finally, attributes pertaining to camera shot composition and shot type were derived using internal analytical methods. Supplementary attribute labels and descriptive text were generated with the aid of Gemini 2.0 Flash [1] using the prompt below.

1. You are now going to describe the film for audience. The description should be as detailed, comprehensive, and logical as possible.
2. The output must be in English, around 600 words.
3. Do not use vague words such as "appear to be" or "seem." Your descriptions must be definitive, precise, and highly accurate.

4. There is only one main person, and all descriptions revolve around this person.
5. All sentences must be affirmative statements. No questions or negative sentences are allowed.
6. Do not determine the gender of the main character. Use "the person," "the person is," or "the person's" as pronouns.
7. Please provide a description of the entire video, rather than describing each individual image.
8. Each input requires descriptions of the following eight aspects, with each aspect not exceeding 100 words, and the key points of the descriptions between the aspects should not overlap:
 - (a) **Hairstyle:** Provide a detailed and comprehensive description of the hairstyle of the person. Start with 'The person's hair ...'.
 - (b) **Expression:** Provide a detailed and comprehensive description of the expressions and emotions of the person. (If there are any temporal changes in expression, also need describe in detail.) Start with 'The person's expression ...'.
 - (c) **Apparel:** Provide a detailed and comprehensive description of the clothing worn by the person (including lower body garments if visible). If there are accessories (e.g., glasses, earrings, watches), describe them as well. Start with 'The person wears ...'.
 - (d) **Behavior:** Provide a detailed and comprehensive description of the behavior of the person (e.g., actions, interactions with objects). Start with 'The person ...'.
 - (e) **Background:** From the perspective of film set design, provide a detailed and comprehensive description of the background and environment. Start with 'The background ...'.
 - (f) **Lighting:** From the perspective of film analysis, provide a detailed and comprehensive description of the overall lighting conditions. 'The lighting ...'.

B.2 Data Distribution

We perform a statistical analysis on some key aspects of PortraitGala dataset, depicted in Fig. 11. The shot-scale distribution indicates that most videos are middle-shot (37.8%), followed by close-shot (33.6%), long-shot (15.9%), and full-shot (12.7%). In terms of gender distribution, male individuals are predominant at 56.7%, while female individuals constitute 39.7%, and others make up 3.6%. The age-group distribution shows a vast majority of youth individuals at 74.9%, with middle-aged individuals at 22.6%, and other age groups at 2.5%. Finally, ethnicity distribution reveals that 51.2% of the shown individuals are white people, 19.3% are black people, 11.4% are Asian people, and 18.1% are other ethnicities. This statistic breakdown highlights the diversity present in the PortraitGala dataset.

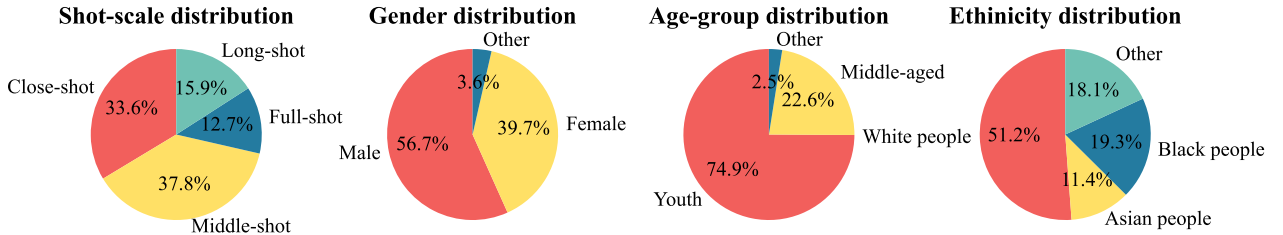


Figure 11: Distribution of key aspects of PortraitGala.

B.3 Dataset Examples

To provide a clear and intuitive representation of the dataset, we present a gallery of multi-shot video instances in Fig. 12. It highlights the diversity of the video distribution and the granularity of the captions.

C More Experimental Details

All the training is carried out on NVIDIA A100 80GB GPUs. The MT2V pretraining takes 3,500 GPU hours while the PMT2V and InfT2V take additional 2000 and 1000 GPU hours, respectively. Throughout the training, all the important settings are listed below:

Parameter	Value
Video height	480
Video width	832
Video frame	125
FPS	16
Batchsize	2
Train timesteps	1000
Train shift	5.0
Optimizer	AdamW
Learning rate	8e-6
Weight decay	0.001
Sample timesteps	50
Sample shift	5.0
Sample guidance scale	5.0

Table 2: Experimental settings of EchoShot.

D Extra Experiments

D.1 Motivation Verification

The pivotal core of our method is the multi-shot text-to-video modeling with the proposed two mechanisms, TcRoPE and TaRoPE. To affirm our motivation as well as verify the effectiveness, we conduct an intuitive experiment between EchoShot and the vanilla model. To specify, we perform a three-shot portrait video generation with EchoShot given three cut timestamps and three prompts. For the vanilla model, we concatenate the three prompts together as a input and perform standard generation. During generation, we collect the self-attention scores and cross-attention scores of the DiT blocks, average them and plot the heatmaps. As shown in Figs. 13(a) and (b), the vanilla model indiscriminately allocates attention to the visual tokens and the textual tokens, which is suitable for single-shot video modeling. Yet in the context of multiple shots, the vanilla model fails to differentiate the shots. By contrast, as shown in Fig. 13(c), TcRoPE establishes a inter-shot boundary during self-attention calculation, with the extra rotation naturally reduce the interactions of features from different shots while enhance that from the same shot. Additionally, TcRoPE allows the model to flexibly allocate attention to potentially crucial pixels, whether from the same shot or from different shots. Fig. 13(d) confirms a similar conclusion to the above one, in the context of TaRoPE and cross-attention.

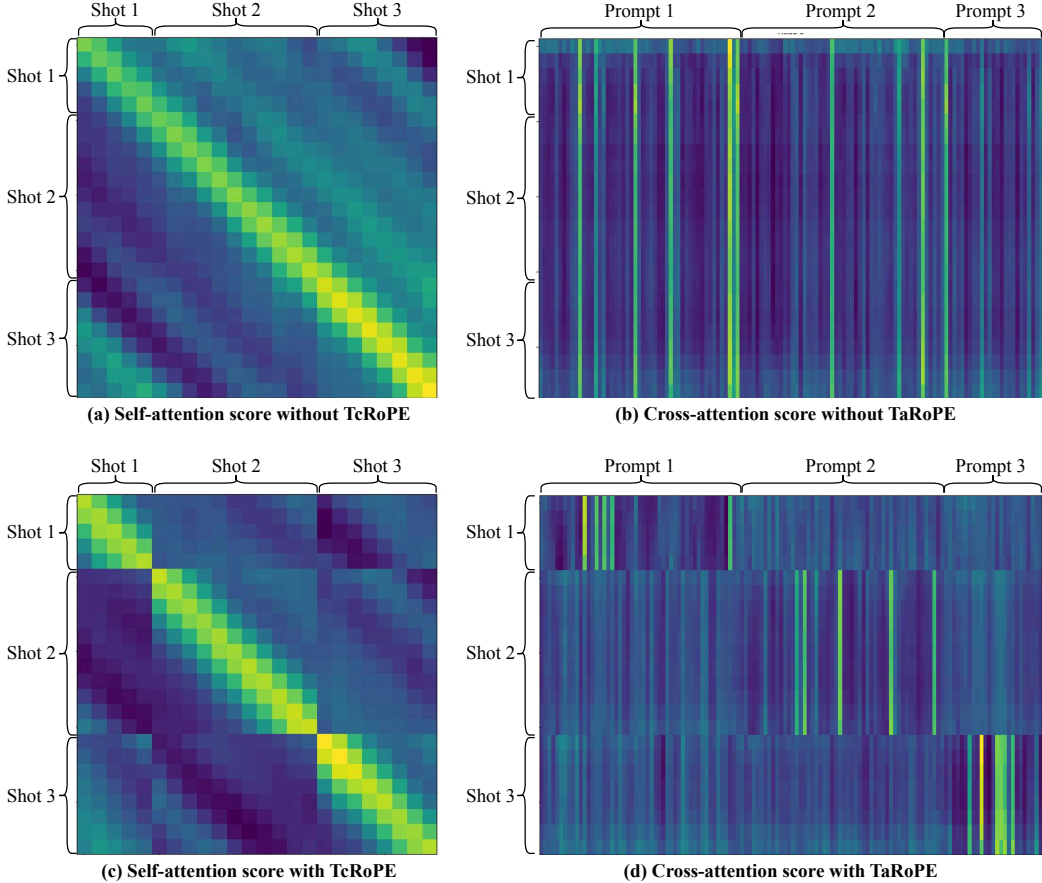


Figure 13: Visualization of self-attention score matrix w/ and w/o TcRoPE and cross-attention score matrix w/ and w/o TaRoPE.

D.2 More Quantitative Results

In Tab. 1, we present the quantitative results. As a supplement, we propose the stand deviation results of these metrics across the test set here.

Method	Identity consistency		Prompt controllability			Visual quality	
	FaceSim-Arc	FaceSim-Cur	App.	Mot.	Bg.	Sta.	Dyn.
StoryDiffusion+Wan-14B	68.65	65.29	83.33	72.50	69.53	63.20	84.68
IC-LoRA+Wan-14B	68.45	65.04	87.59	83.71	75.37	79.49	87.98
HunyuanVideo-13B (2 shots)	64.80	61.25	83.39	68.15	72.37	86.37	87.22
EchoShot-1B (ours)	73.74	69.43	95.84	88.86	94.72	88.91	87.85

Method	Identity consistency		Prompt controllability			Visual quality	
	FaceSim-Arc	FaceSim-Cur	App.	Mot.	Bg.	Sta.	Dyn.
StoryDiffusion+Wan-14B	6.24	6.86	9.50	22.47	21.29	15.20	2.57
IC-LoRA+Wan-14B	7.02	6.75	10.16	18.41	19.77	13.08	2.68
HunyuanVideo-13B (2 shots)	9.16	8.28	10.13	18.35	17.95	5.76	3.51
EchoShot-1B (ours)	7.13	7.91	6.51	11.25	6.68	4.90	2.77

Table 3: Metric results (mean and standard deviation) in MT2V task.

Method	Cut control	Identity consistency		Prompt controllability			Visual quality	
		FaceSim-Arc	FaceSim-Cur	App.	Mot.	Bg.	Sta.	Dyn.
SC	No	75.24	70.61	55.79	59.16	47.56	81.90	75.24
SC+TcRoPE	Yes	74.77	69.85	81.72	72.84	74.22	84.32	81.69
SC+TcRoPE+TaRoPE(full)	Yes	75.83	70.58	94.12	87.41	93.96	84.10	83.46

Table 4: Metric results of three ablation models on reduced-scale dataset.

D.3 Quantitative Ablation Study

We further conduct a quantitative ablation study following Sec. 4.3 in Tab. 4. Benefiting from the curated high-quality multi-shot dataset, the identity consistency and visual quality of three ablation models exhibit minimal variation. In terms of prompt controllability, the full model demonstrates significant advantages over the comparing models, echoing the qualitative results. The ablation study confirms that TcRoPE and TaRoPE mechanisms perform as expected.

D.4 Parameter Analysis

Our method relies primarily on two key hyperparameters, the phase shift scale j in Eq. (2) and the mismatch suppression scale k in Eq. (3). To investigate the appropriate parameter selection, we conduct an intuitive parameter analysis with the reduced-scale dataset. We leverage the mathematical analysis and empirically pick several typical values, $j \in \{2, 4, 6\}$, $k = 6$ and $j = 4$, $k \in \{2, 6, 12\}$. The quantitative results of the models under different settings are shown in Tab. 5. To summarize, a too small j excessively enhances the inter-shot visual interactions, leading to occasional cut failure and prompt intermingling with low prompt controllability scores. While a too large j nearly blocks the interactions, causing identity inconsistency with low identity consistency scores. Similarly, a too small k gives rise to prompt intermingling while a too large k results in a slightly decrease in scores. Consolidating the results, we choose $j = 4$, $k = 6$ as the default setting.

Method	Identity consistency		Prompt controllability			Visual quality	
	FaceSim-Arc	FaceSim-Cur	App.	Mot.	Bg.	Sta.	Dyn.
j=2,k=6	75.45	70.64	88.75	82.10	85.28	80.97	81.67
j=6,k=6	70.19	67.30	94.25	88.29	92.66	83.18	82.03
j=4,k=2	75.12	69.73	84.20	76.69	80.16	80.55	81.02
j=4,k=12	74.98	69.45	92.15	86.82	92.73	83.50	83.91
j=4,k=6(ours)	75.83	70.58	94.12	87.41	93.96	84.10	83.46

Table 5: Metric results of different parameter settings on reduced-scale dataset.

E EchoShot Gallery

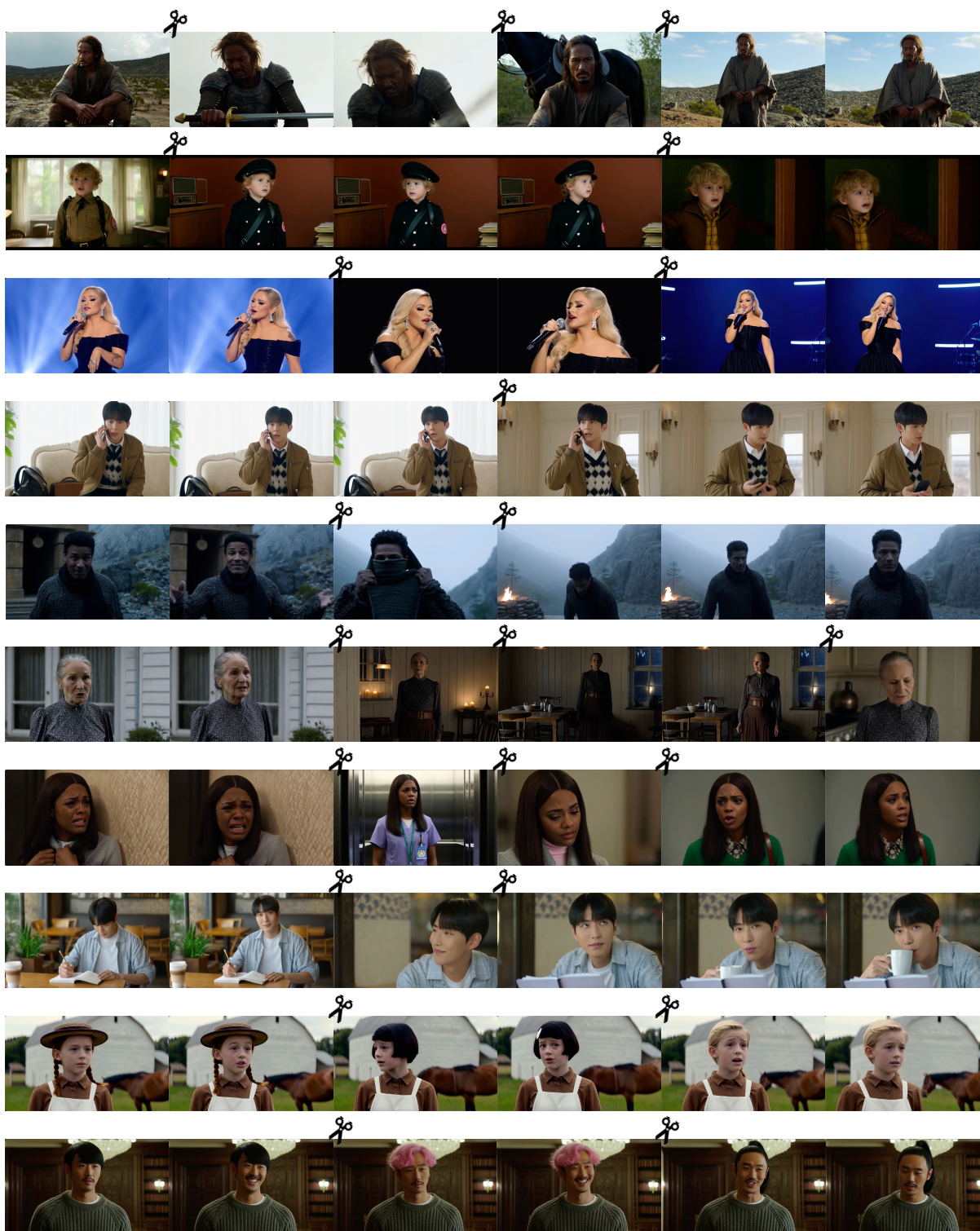


Figure 14: Illustration of generated videos by EchoShot.

F Clarification about User Study

Instructions for Participants

Thank you for participating in our study!

We appreciate your willingness to contribute to our research. Below, you will find detailed instructions on how to complete the tasks involved in this study. Please read this information carefully before beginning.

1. Purpose of the Study

The goal of this study is to evaluate different methods for generating multi-shot portrait videos showing the same identity. Your feedback will help us evaluate which method produce videos with best quality. Your participation is highly valuable to us!

2. Task Overview

You will be asked to compare two methods by evaluating their outputs in a series of one-on-one matchups. Each matchup will present results generated by our proposed method and a random baseline method (both anonymous). Your task is to vote for your preferred option in each matchup based on the following criteria:

- **Identity Consistency:** Which method better preserves the same identity of the human (e.g., facial features, expressions, and overall appearance) across all frames and shots in the video?
- **Prompt Controllability:** Which method more accurately follows the given prompts (e.g., appearance, motions, expressions, and background) in the generated video?
- **Visual Quality:** Which method produces a video with higher visual quality, considering factors like sharpness, smoothness of motion, and absence of artifacts (e.g., blurriness or unnatural textures)?

3. How to Complete the Task

- You will complete **45 matchups** in total.
- For each matchup, you will see two outputs side by side.
- To cast your vote, click on the button corresponding to your preferred option.
- There are no right or wrong answers. Please choose the option that feels best to you.

4. Time Commitment

The study should take approximately **20-30 minutes** to complete. You can work at your own pace, but we recommend completing the task in one sitting to ensure consistency.

5. Voluntary Participation

Your participation in this study is entirely **voluntary**. You are free to withdraw at any time without penalty or explanation. If you decide to withdraw, your responses will not be included in the analysis.

6. Compensation

This study does not provide financial compensation. However, your contribution is greatly appreciated and will directly support advancements in this field of research.

7. Privacy and Data Use

- Your responses will be anonymized and used solely for research purposes.
- No personally identifiable information will be collected or stored.

8. Questions or Concerns

If you have any questions about the study or encounter technical issues, please contact us. We are happy to assist you.

9. Consent

By proceeding with the study, you confirm that:

- You have read and understood the instructions.
- You agree to participate voluntarily.
- You understand that you can withdraw at any time without penalty.

Thank you again for your time and effort. Let's get started!

Compensation. Participants were informed that their participation was entirely voluntary based on their willingness to contribute to scientific research, without financial compensation. No incentives or pressures were applied to encourage involvement. Participants could withdraw at any time.

Minimal risks. Before beginning the study, participants were provided with detailed information about the purpose of the research, and their rights as participants. Consent was obtained from all participants prior to their involvement. The risks associated with this study were minimal. The tasks posed no physical, psychological, or emotional harm to participants. Participants were only required to perform binary voting tasks, which involved evaluating outputs generated by different methods. All interactions were conducted through a secure online platform, ensuring privacy and anonymity. No sensitive data or personally identifiable information was collected during the study.

Approval. This study received approval from the research institution.

G Societal Impacts and Safeguards

The advancements in multi-shot portrait video generation, as exemplified by our work on EchoShot, present profound societal impacts across numerous domains. By enabling high-quality, identity-consistent, and content-controllable portrait video creation, EchoShot democratizes access to advanced video production tools, empowering creators of all skill levels to produce professional-grade visual media. This innovation streamlines workflows in industries such as filmmaking, advertising, virtual avatars, and social media content creation, leading to significant improvements in efficiency, cost savings, and creative flexibility. The ability to generate consistent multi-shot videos with fine-grained control over attributes like facial expressions, outfits, and motions has the potential to revolutionize storytelling, personalized media, and digital human modeling.

However, the rapid adoption of such generative technologies also raises important challenges. Job displacement may occur for traditional video editors and artists who rely on conventional methods, necessitating reskilling and adaptation to remain competitive in an evolving job market. Ethical concerns are equally critical, as the misuse of generated videos (e.g., creating deepfakes, impersonations, or misleading content) can undermine public trust and exacerbate misinformation. Ensuring that models like EchoShot are trained on unbiased datasets is essential to prevent the reinforcement of harmful stereotypes or biases in generated content. To address these issues, we inherit safeguards from foundational models Wan2.1, including mechanisms for detecting inappropriate or harmful outputs, while adhering to strict usage guidelines. Furthermore, by open-sourcing our models and dataset, we aim to foster transparency, encourage responsible use, and facilitate community-driven improvements in ethical generative AI development.