CMMD: Contrastive Multi-Modal Diffusion for Video-Audio Conditional Modeling

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Paper under double-blind review

Abstract

We introduce a multi-modal diffusion model tailored for the bi-directional conditional generation of video and audio. Recognizing the importance of accurate alignment between video and audio events in multi-modal generation tasks, we propose a joint contrastive training loss to enhance the synchronization between visual and auditory occurrences. Our research methodology involves conducting comprehensive experiments on multiple datasets to thoroughly evaluate the efficacy of our proposed model. The assessment of generation quality and alignment performance is carried out from various angles, encompassing both objective and subjective metrics. Our findings demonstrate that the proposed model outperforms the baseline, substantiating its effectiveness and efficiency. Notably, the incorporation of the contrastive loss results in improvements in audio-visual alignment, particularly in the high-correlation video-to-audio generation task. These results indicate the potential of our proposed model as a robust solution for improving the quality and alignment of multi-modal generation, thereby contributing to the advancement of video and audio conditional generation systems.

1 Introduction

Multi-media generation with diffusion models has attracted extensive attention recently. Following breakthroughs in image Ramesh et al. (2022) and audio generation Liu et al. (2023), multi-media generation like video remains challenging due to increased data and content size and the added complexity of dealing with both audio and visual components. Challenges for generating multi-modal content include 1) time variant feature maps leading to computationally expensive architecture and 2) audio and video having to be coherent and synchronized in terms of semantics and temporal alignment.

Existing research has predominantly concentrated on unidirectional cross-modal generation, such as producing audio from video cues Luo et al. (2023); Zhu et al. (2023) and vice versa Jeong et al. (2023); Lee et al. (2023). These approaches typically employ a conditional diffusion model to learn a conditional data distribution $p(x|y)$. Although these models have shown considerable promise, their unidirectional nature is a limitation; a model trained for $p(x|y)$ is not suited for tasks requiring $p(y|x)$. However, Bayes' theorem elucidates that a joint distribution can be decomposed into $p(x, y) = p(x|y)p(y) = p(y|x)p(x)$, suggesting that the construction of a joint distribution inherently encompasses bi-directional conditional distributions. With the advent of the iterative sampling procedure in diffusion models, classifier guidance Dhariwal & Nichol (2021); Song et al. (2021b); Ho et al. (2022) has emerged as a viable approach for training an unconditional model capable of conditional generation. This approach has been extensively adopted in addressing the inverse problems associated with diffusion models, such as image restoration Kawar et al. (2022) and text-driven generation Ramesh et al. (2021).

MM-diffusion Ruan et al. (2023) represents a groundbreaking foray into the simultaneous modeling of video and audio content. The architecture employs a dual U-Net structure, interconnected through cross-attention mechanisms Vaswani et al. (2017), to handle both video and audio signals. Although MM-diffusion demonstrates impressive results in terms of *unconditional* generation quality, it is not without limitations. Firstly, the model's computational complexity, despite the implementation of a random-shift cross-attention mech-

anism, poses challenges for scaling to higher-resolution videos without the assistance of a separate super-resolution model. Secondly, there is room for improvement in both the performance and the analysis of conditional generation, which could be achieved through careful dataset selection and the application of appropriate evaluation metrics.

In this study, we introduce an improved multi-modal diffusion architecture with focus on bi-directional *conditional* generation of video and audio. This model incorporates an optimized design that more effectively integrates video and audio data for conditional generation tasks. Furthermore, we leverage a novel joint contrastive diffusion loss to improve alignment between video and audio pairs. Our comprehensive experiments, conducted using two different datasets, employ both subjective and objective evaluation criteria. We achieve superior quality than the baseline and stronger synchronization without quality loss.

The key contributions can be summarized as follows:

- We present an optimized version of the multi-modal *latent-spectrogram* diffusion model, featuring a pretrained video autoencoder, a vocoder and an easy fusion mechanism. This design aims to more effectively integrate cross-modality information between video and audio, while also enhancing *conditional* sampling quality.
- Drawing inspiration from uni-modal contrastive learning, we propose a novel contrastive loss function tailored for the joint model. This function is instrumental in enhancing the alignment accuracy for the conditional generation of video-audio pairs.
- Our extensive experimental evaluations, performed on two distinct datasets, AIST++ Li et al. (2021) and EPIC-Sound Huh et al. (2023), cover a variety of video-audio scenarios. We propose to use metrics with improved correlation human perception and practical relevance compared to prior work in the field, as we find several widely used metrics to have strong deficiencies. The assessments, based on a range of subjective and objective metrics demonstrate that our method outperforms the existing MM-diffusion Ruan et al. (2023) as well as non-contrastive variants derived from our ablation studies.

2 Related Work

Diffusion Models: Demonstrating remarkable efficacy in image generation tasks, probabilistic diffusion models have emerged as a robust alternative to highly-optimized Generative Adversarial Networks (GANs) Goodfellow et al. (2014). The superior performance of diffusion models is attributed to their stability during the training process Song & Ermon (2019); Ho et al. (2020); Song et al. (2021b); Song & Ermon (2019); Kingma et al. (2021); Dhariwal & Nichol (2021). These models typically employ a parameter-free diffusion process that degrades the original signal, followed by a denoising process using a trained U-Net like architecture to restore the signal. The optimization objective of the diffusion model can be derived from either the variational inference or stochastic differential equation perspectives Ho et al. (2020); Song et al. (2021b). Beyond image generation, there has been increasing interest in leveraging diffusion models for conditional generation tasks, including image compression, translation, and enhancement Saharia et al. (2022b); Preechakul et al. (2022); Yang & Mandt (2022); Saharia et al. (2022a). Recent advancements in diffusion models Ramesh et al. (2022); Rombach et al. (2022) incorporate the diffusion-denoising process in the latent space, aiming to enhance the scalability of diffusion models for high-resolution images. In light of their impressive results in image-related tasks, it is a logical progression to extend the application of these models to video and audio signals Ho et al. (2022); Yang et al. (2022); Blattmann et al. (2023); Voleti et al. (2022); Kong et al. (2020b); Zhang et al. (2023). To learn the joint distribution of a sequence, these models are further refined to account for the temporal coherence of the signals.

Advancements in Video-Audio Cross-Modality Models: The domain of deep generative models has recently experienced a significant uptick in interest, particularly in the area of cross-modal generation—an application that is currently undergoing rapid evolution. Historically, the majority of research in this field has been primarily focused on text-to-visual tasks, as evidenced by various studies Li et al. (2019); Singer

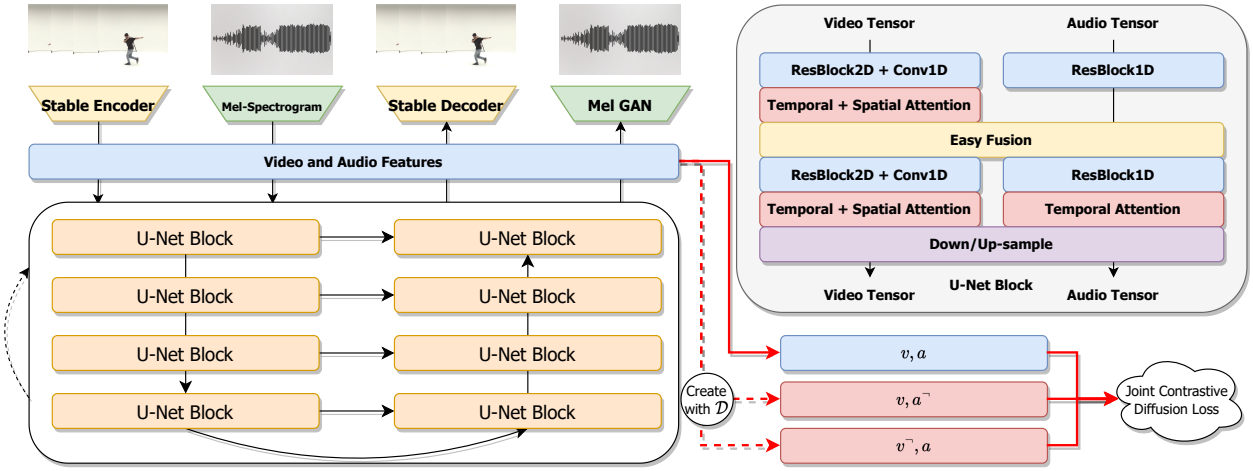

Figure 1: Overview of our proposed architecture and method. The detailed implementation of each U-Net block is depicted in the upper right corner. Training of the diffusion model is performed on latent-spectrogram space.

et al. (2022); Gafni et al. (2022); Zhang et al. (2023). However, a discernible trend towards the more intricate audio-video modality has emerged Lee et al. (2022); Ge et al. (2022); Di et al. (2021), driven by the potential to create more innovative and engaging content within this sphere. Concurrently, diffusion models have begun to assume a pivotal role in related research. These models, with their unique ability to model complex distributions, have found a natural application in the cross-modal generation task. For example, TPoS Jeong et al. (2023) and Soundini Lee et al. (2023) are two recent models that demonstrate proficiency in audio-to-video generation. Their success underscores the potential of diffusion models in this domain. Other models such as CDCD Zhu et al. (2023) and Diff-Foley Luo et al. (2023) specifically target the video-to-audio problem. These models represent a growing interest in reverse modality tasks, expanding the boundaries of what is possible in the realm of cross-modal generation. Notably, MM-diffusion Ruan et al. (2023), which emphasizes the simultaneous generation of both video and audio, is, to our knowledge, the first model capable of managing both video-to-audio and audio-to-video generation. Despite its impressive performance in low-resolution unconditional generation, its computational efficiency and conditional generation performance warrant further investigation.

3 Method

In this section, we provide an overview of the diffusion model employed, followed by a description of the intricacies of the architecture design of the proposed model. Finally, we introduce the joint contrastive loss that enhances the alignment of video and audio components. An overview of our model is shown in Fig. 1.

3.1 Video-Audio Joint Diffusion Model

Diffusion models represent a category of hierarchical latent variable models used for data generation through a series of iterative stochastic denoising steps Sohl-Dickstein et al. (2015); Ho et al. (2020); Song et al. (2021a); Song & Ermon (2019). These models establish a joint distribution encompassing both the original data, denoted as $\mathbf{x}_0$, and its perturbed variants $\mathbf{x}_{1:N}$. In this framework, there are two key processes at play: the diffusion process, denoted as q, which progressively erases structural information, and its counterpart, p_θ, which regenerates the structure. These processes involve Markovian dynamics across a sequence of transitional steps Ho et al. (2020), symbolized as n and can be described using the following equations:

$$\begin{aligned} q(\mathbf{x}_n|\mathbf{x}_{n-1}) &= \mathcal{N}(\mathbf{x}_n|\sqrt{1-\beta_n}\mathbf{x}_{n-1}, \beta_n\mathbf{I}); \\ p_\theta(\mathbf{x}_{n-1}|\mathbf{x}_n) &= \mathcal{N}(\mathbf{x}_{n-1}|\mu_\theta(\mathbf{x}_n, n), \beta_n\mathbf{I}). \end{aligned} \tag{1}$$

The variance, denoted as $\beta_n \in (0, 1)$, typically adheres to a predetermined schedule, such as linear or cosine scheduling Nichol & Dhariwal (2021). Notably, the diffusion process is parameter-free, while the denoising process relies on a neural network parameterized by θ to predict the posterior mean.

Denoising diffusion models introduced a practical objective function for training the reverse process Ho et al. (2020); Salimans & Ho (2022); Hang et al. (2023):

$$L(\theta, \mathbf{x}_0) = \mathbb{E}_{n,\epsilon}[w(n)||\mathbf{x}_0 - \mathbf{x}_\theta(\mathbf{x}_n(\mathbf{x}_0), n)||^2 \tag{2}$$

where n follows a uniform distribution Unif$\{1, ..., N\}$, ϵ is sampled from a standard normal distribution, $\mathbf{x}_n(\mathbf{x}_0) = \sqrt{\alpha_n}\mathbf{x}_0 + \sqrt{1-\alpha_n}\epsilon$, $\mathbf{x}_\theta(\cdot)$ reconstruct $\mathbf{x}_0$ and $\alpha_n = \prod_{i=1}^{n}(1-\beta_i)$. This formula characterizes a universal diffusion model loss with an adjustable weighting term, $w(n)$, which connects various parameterizations of the prediction model θ:

$$\begin{aligned} &\textit{equation } 2 \equiv \mathbb{E}_{n,\epsilon}[||\epsilon - \epsilon_\theta(\mathbf{x}_n(\mathbf{x}_0), n)||^2], \text{when } w(n) = \frac{\alpha_n}{1-\alpha_n} \\ &\text{or } \mathbb{E}_{n,\epsilon}[||\mathbf{v} - \mathbf{v}_\theta(\mathbf{x}_n(\mathbf{x}_0), n)||^2], \text{when } w(n) = \frac{1}{1-\alpha_n} \end{aligned} \tag{3}$$

where ϵ_θ represents the most commonly used parameterization in previous works Karras et al. (2022); Ho et al. (2020); Ruan et al. (2023); Dhariwal & Nichol (2021); Rombach et al. (2022); Song et al. (2021a), and $\mathbf{v}_\theta$ (velocity) has also shown promising results with a more stable training process Salimans & Ho (2022). We adopt the latter method to train our model.

Video-Audio Modeling Our approach to video-audio joint modeling follows a design analogous to the uni-modal diffusion model. Here, the data point $\mathbf{x}$ comprises two modalities: the video signal $v_{0..N}$ and audio signal $a_{0..N}$. Consequently, the optimization objective resembles the form in equation 3:

$$\mathcal{L}_{\text{jdiff}} = \mathbb{E}_{n,\epsilon}[||\mathbf{v} - \mathbf{v}_\theta(v_n, a_n, n)||^2] \tag{4}$$

where $\mathbf{v}$ represents the velocity parameterization for both video and audio, specifically $\mathbf{v} = [\sqrt{\alpha_n}\epsilon_v - \sqrt{1-\alpha_n}v_0, \sqrt{\alpha_n}\epsilon_a - \sqrt{1-\alpha_n}a_0]$. This implies that the model $\mathbf{v}_\theta$ simultaneously predicts two outputs, embodying a joint diffusion model that effectively manages both modalities.

Guided Conditional Generation An intriguing aspect of diffusion models is their capacity to enable conditional generation through guidance from a classifier, even in the context of models trained without conditioning Dhariwal & Nichol (2021). Typically, this guidance method involves an additional classifier, $p_\phi(y|x)$, and utilizes the gradient term $\nabla_x p_\phi(y|x)$ to adjust the sampling direction during the denoising process.

However, in our model, which considers both video and audio modalities, we can employ a more straightforward *reconstruction guidance* approach Ho et al. (2022). Under a video-to-audio generation scenario, we can formalize conditional generation as follows (audio-to-video shares a similar formulation):

$$\begin{aligned} &1.\ v_n \sim q(v_n|v_0) \text{ with } \epsilon_v \\ &2.\ \mathbf{v}_v, \mathbf{v}_a = \mathbf{v}_\theta(v_n, a_n, n) \\ &3.\ \hat{v}_0 = \frac{\sqrt{\alpha_n}\epsilon_v - \mathbf{v}_v}{\sqrt{1-\alpha_n}}, \bar{a}_0 = \frac{\sqrt{\alpha_n}\epsilon_a - \mathbf{v}_a}{\sqrt{1-\alpha_n}} \\ &4.\ \hat{a}_0 = \bar{a}_0 - \lambda\sqrt{\alpha_n}\nabla_{a_0}||v_0 - \hat{v}_0||^2 \\ &5.\ a_{n-1} = \sqrt{\alpha_{n-1}}\hat{a}_0 + \sqrt{1-\alpha_{n-1}}\epsilon_a \end{aligned} \tag{5}$$

where the gradient guidance is weighted by λ, and in the case of $\lambda = 0$, the generation scheme is equivalent to the *replacement* method Song et al. (2021b). Both ϵ_a and ϵ_v are drawn from an isotropic Gaussian prior at the start of the iteration. Therefore, these equations depict an intermediate stage of the conditional generation process using the DDIM sampling method Song et al. (2021a). Although the speed of sampling is not the primary focus of our model, alternative ODE or SDE solvers can be employed to expedite the denoising sampling process Lu et al. (2022); Karras et al. (2022).

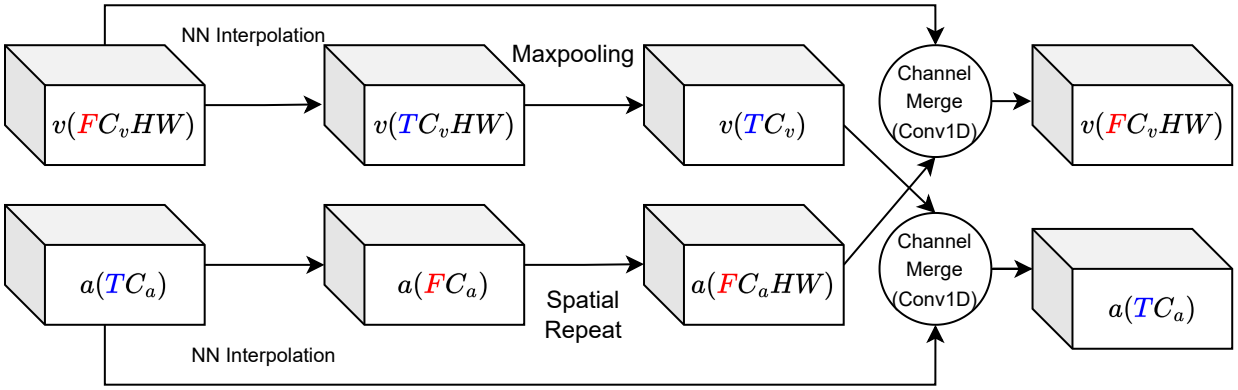

Figure 2: Easy Fusion: For brevity, we use the symbol v to denote video tensors, where F (Frames) $\times$ C_v (Channels) $\times$ H (Height) $\times$ W (Width) represents the shape of the tensor. Similarly, we use the symbol a to represent audio tensors, with T (Timesteps) $\times$ C_a (Channels) denoting the shape of the audio tensor. v and a tensors are concurrently processed and merged in the final step. NN interpolation represents nearest neighbor interpolation.

3.2 Architecture

Much like previous works on diffusion models, our architectural framework adheres to the U-Net-based design paradigm Ho et al. (2020; 2022); Ruan et al. (2023); Rombach et al. (2022); Ronneberger et al. (2015). However, to effectively process signals originating from dual modalities with distinct dimensionalities, we employ a combination of 2D+1D Residual blocks with Temporal-Spatial attentions for video inputs. For audio inputs, we only use 1D Residual blocks with Temporal Attention. While the foundational structure draws some inspiration from MM-diffusion Ruan et al. (2023), we have implemented a more efficient feature fusion mechanism tailored to conditional generation requirements.

Latent-Spectrogram Diffusion The training and evaluation of a multi-modal diffusion model can pose significant computational challenges. To address this issue, we adopt a methodology akin to latent diffusion Rombach et al. (2022) for the purpose of reducing the feature dimensionality. In particular, we employ a pre-trained autoencoder to compress video frames into a concise representation while minimizing the loss of semantic information. This approach not only enables our model to accommodate higher video resolutions within GPU memory limitations but also enhances its ability to capture temporal dependencies in videos Blattmann et al. (2023). For audio signals, we use a time-frequency representation, specifically the Mel-spectrogram. This transformation yields a more compact representation with frequency channels that closely align with human auditory perception.

Improved MelGAN Vocoder The conversion of the generated Mel spectrogram back to an audio waveform was accomplished by training a vocoder on the MelGAN Kumar et al. (2019) architecture. We incorporated several improvements from the Hifi-GAN Kong et al. (2020a) model, such as transitioning to a least-squares GAN loss and adjusting the loss weightings, with a particular emphasis on the Mel-spectrogram loss.

Easy Fusion and Implicit Cross-Attention Our model's capacity to handle inputs and outputs from two distinct modalities presents a considerable challenge in terms of aligning feature maps and merging semantic information for cross-modal conditioning. While conventional cross-attention mechanisms Vaswani et al. (2017) offer an approach to bridging these signals, they can become computationally inefficient as the length of time sequences increases. In contrast, MM-Diffusion Ruan et al. (2023) resorts to randomly truncating time windows to alleviate the computational load, yet this method inevitably results in a loss of receptive field.

In response to this challenge, we introduce our easy fusion method, illustrated in Fig. 2. This method incorporates a computationally efficient design, including nearest neighbor, pooling, and repetition, to guarantee that both video and audio tensors maintain consistent temporal/spatial shapes, enabling their concatenation along the channel dimension. Another crucial consideration is that the current most of the U-Net designs for diffusion models incorporates a self-attention module Ruan et al. (2023); Rombach et al. (2022); Ho et al. (2022), offering the potential to alleviate computational overhead from cross-attention. Within the context of easy fusion, we assume that the attention module can be described by:

$$\text{CrossAttention}(v, a) \cong \text{SelfAttention}(\text{EasyFusion}(v, a)). \tag{6}$$

We posit that the self-attention operating in this manner implicitly signifies the existence of an inherent cross-attention mechanism, thereby fully leveraging the U-Net architecture without additional attention block.

3.3 Joint Contrastive Training

To improve the synchronization of video and audio in our model, we draw inspiration from the principles of contrastive learning Oord et al. (2018). This approach has proven effective in maximizing the mutual information $I(a; v)$ for video-to-audio conditional generation Zhu et al. (2023); Luo et al. (2023). The CDCD Zhu et al. (2023) method seamlessly integrates contrastive loss into the video-to-audio conditional diffusion models, as given by

$$\begin{aligned} \mathcal{L}_{\text{cont}} &:= \mathbb{E}_A \log \left[1 + \frac{p_\theta(a_{0:N})}{q(a_{0:N}|v_0)} M \mathbb{E}_{A'} \left[\frac{p_\theta(a^{\neg}_{0:N}|v_0)}{q(a^{\neg}_{0:N})} \right] \right] \\ &\equiv \mathcal{L}_{\text{cdiff}}(a_{0:N}, v_0) - \eta \sum_{a^{\neg}_0 \in A'} \mathcal{L}_{\text{cdiff}}(a^{\neg}_{0:N}, v_0) \end{aligned} \tag{7}$$

Here, L_{cdiff} represents the unimodal conditional diffusion loss, where v denotes the conditioning videos, and M and η denote the number of negative samples. Set A encompasses the true corresponding audio samples, and A' denotes the set of mismatched negative samples within one batch.

The above formulation pertains to training a classifier-free conditional diffusion model. To adapt this approach to our joint diffusion loss, as described in equation 4, we observe that we are training an implicit conditional diffusion model $p_\theta(a_{n-1}|a_n, v_n)$. equation 5 demonstrates that v_n can be directly calculated during conditional generation:

$$v_n \sim q(v_n|v_0) = \sqrt{\alpha_n} v_0 + \sqrt{1 - \alpha_n} \epsilon_v \tag{8}$$

which implies that $v_{1:N}$ is fixed with a given ϵ_v and v_0. Given this deterministic relationship between v_n and v_0, we can assume $p_\theta(a_{n-1}|a_n, v_0) \approx p_\theta(a_{n-1}|a_n, v_n)$ in equation 7. Thus, we can bridge equation 7 to our jointly trained multi-modal diffusion model. For video-to-audio generation, we can follow the same method above by swapping v and a. Finally, the resulting joint contrastive loss can be represented by the following three terms:

$$\begin{aligned} \mathcal{L}_{\text{cont}} = \mathcal{L}_{\text{jdiff}}(a_{0:N}, v_{0:N}) &- \eta \mathbb{E}_{a^{\neg}_0 \sim A'} \mathcal{L}_{\text{jdiff}}(a^{\neg}_{0:N}, v_{0:N}) \\ &- \eta \mathbb{E}_{v^{\neg}_0 \sim V'} \mathcal{L}_{\text{jdiff}}(a_{0:N}, v^{\neg}_{0:N}) \end{aligned} \tag{9}$$

where V' denotes the set of negative samples for a_0 and η adjusts the weight of the contrastive term. It's important to note that, instead of iterating over all the V' and A' samples, we choose to randomly draw a subset from them per gradient descent step to reduce GPU memory consumption.

Creating Negative Samples In absence of a pre-existing high-quality dataset for contrastive learning, we can generate negative samples through data augmentation. Specifically, we employ the following methods to create V' and A' in the context of paired positive data a, v. For brevity, we will only outline the generation of negative audio samples $a^{\neg}$. The creation of negative videos $v^{\neg}$ follows a similar formulation:

- Random Temporal Shifts: We apply random temporal shifts to a, moving it backward or forward by a random duration within some hundreds of milliseconds.

Algorithm 1 Training the joint diffusion model with a contrastive loss. $\mathcal{D}$ denotes the training dataset.

repeat
  $v_0, a_0 \sim \mathcal{D}$
  Create V' and A' with $\mathcal{D}$ and v_0, a_0
  $v_0^{\neg}, a_0^{\neg} \sim V', A'$ # draw multiple negative samples
  $n \sim \mathcal{U}(1, 2, .., N)$
  $(\epsilon_a, \epsilon_a^{\neg}, \epsilon_v, \epsilon_v^{\neg}) \sim \mathcal{N}(\mathbf{0}, \mathbf{I})$
  $(a_n, v_n) = \sqrt{\alpha_n}(a_0, v_0) + \sqrt{1-\alpha_n}(\epsilon_a, \epsilon_v)$
  $(a_n^{\neg}, v_n^{\neg}) = \sqrt{\alpha_n}(a_0^{\neg}, v_0^{\neg}) + \sqrt{1-\alpha_n}(\epsilon_a^{\neg}, \epsilon_v^{\neg})$
  $L = ||\mathbf{v} - \mathbf{v}_\theta(v_n, a_n, n)||^2$
  $L^{\neg} = ||\mathbf{v} - \mathbf{v}_\theta(v_n^{\neg}, a_n, n)||^2 + ||\mathbf{v} - \mathbf{v}_\theta(v_n, a_n^{\neg}, n)||^2$
  $L_{\text{cont}} = L - \eta L^{\neg}$
  $\theta = \theta - \varepsilon \nabla_\theta L_{\text{cont}}$ (learning rate: ε)
until converge

- Random Segmentation and Swapping: We randomly draw a separate audio segment, denoted as a_d, with the same length as a. Subsequently, we sample a random split point on both a_d and a, allowing us to construct $a^{\neg}$ as either concatenate($a_d^{\text{left}}, a^{\text{right}}$) or concatenate($a^{\text{left}}, a_d^{\text{right}}$).

- Random Swapping: In this method, we randomly select a different audio segment, a_d, of the same length as a, and substitute a with a_d.

The detailed training procedure is outlined in Algorithm 1.

4 Experiments

This section details the comprehensive evaluation of our Contrastive Muldi-Modal Diffusion (CMMD) model, which we conducted using both subjective and objective measures on two distinct datasets. Furthermore, we demonstrate the speedup of our model resulting from its more efficient design. Additional details and results will be available in supplemental material.

Datasets Our evaluation leverages two datasets, each offering unique challenges and scenarios within the audio-video domain: **AIST++** Li et al. (2021) is derived from the AIST Dance Database Tsuchida et al. (2019). This dataset features street dance videos with accompanying music. It serves a dual purpose in our evaluation, being used for both video-to-audio and audio-to-video tasks. The **EPIC-Sound** Huh et al. (2023) dataset consists of first-person view video recordings that capture a variety of kitchen activities, such as cooking, that are characterized by a strong audio-visual correlation. Due to the significant motion and camera movement in the videos, which complicates visual learning, we use EPIC-Sound exclusively for video-to-audio evaluation.

Baselines The MM-Diffusion model Ruan et al. (2023) stands as the only known baseline capable of handling both video-to-audio and audio-to-video synthesis tasks. For our comparison, we employed the official MM-Diffusion implementation, utilizing weights trained on the 1.6 s 10fps AIST++ dataset at a resolution of 64×64. Additionally, we present results from nCMMD, a variant of our CMMD model that does not incorporate contrastive loss.

Feature Extraction & Data Preprocessing We sampled 18 frames from 10 fps video sequences and the corresponding 1.8s audio at 16kHz. Video frames underwent center cropping and resizing to a 128×128 resolution, or optionally downsampling to 64×64 for a comparison with the MM-Diffusion baseline. The audio samples represented in a Mel Spectrogram have 80 channels and 112 time steps. During test time, we use twice the training sequence length, i.e., 36 video frames, if not specified otherwise.

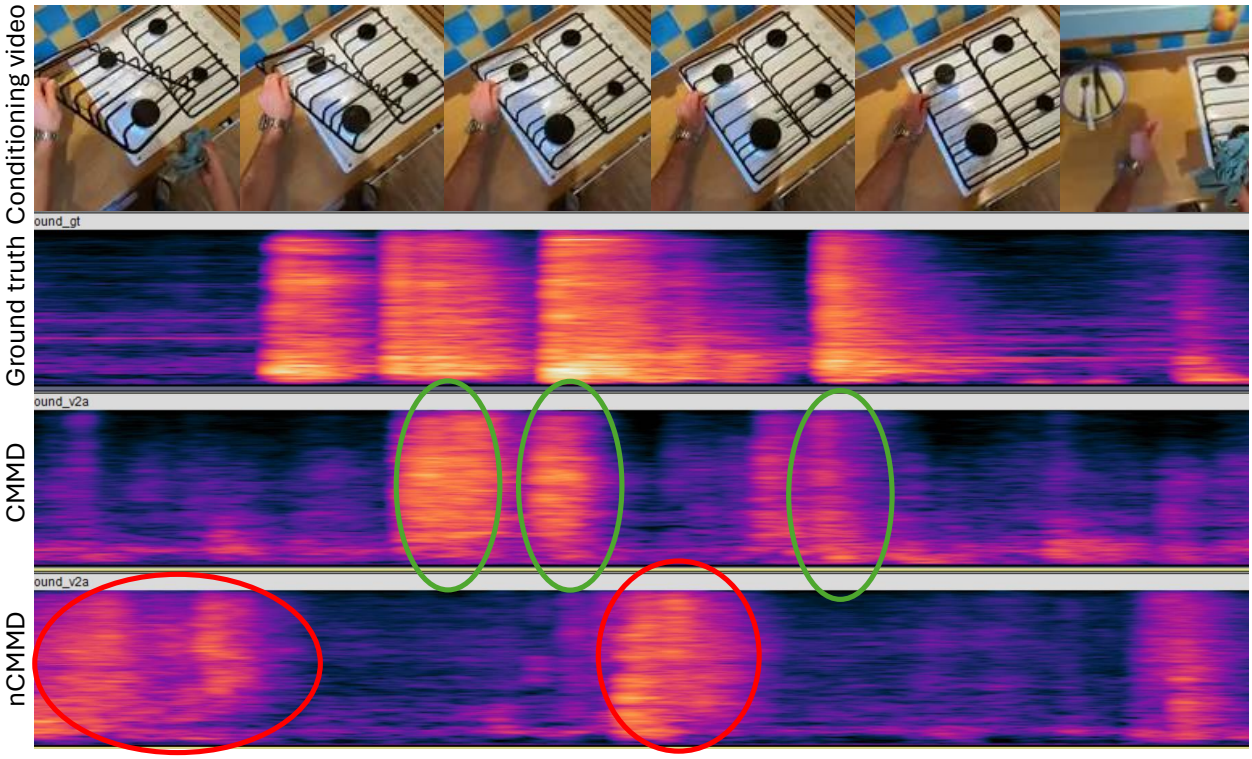

Figure 3: Conditioning video (top) with ground truth spectrogram below. The two bottom spectrograms show the generated audio with CMMD and nCMMD conditioned on the video. Sound events are highlighted with a green circle for matches and a red circle for mismatches.

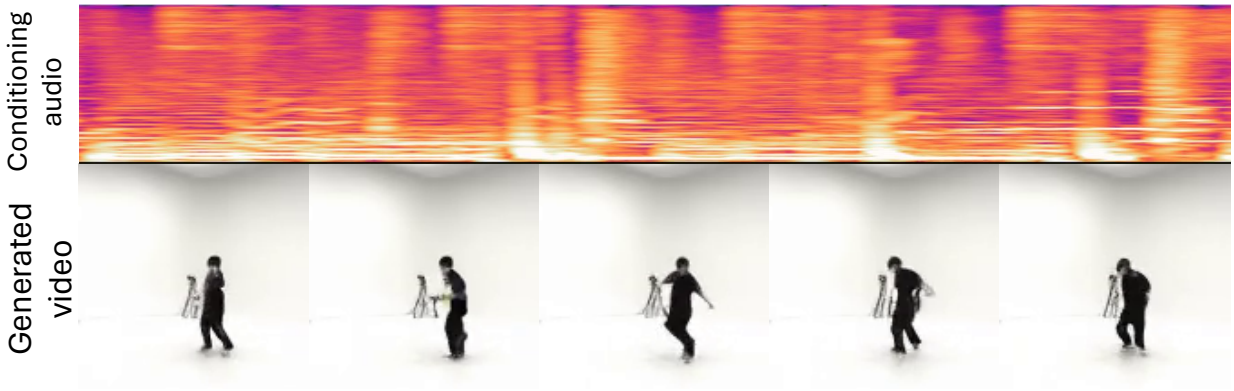

Figure 4: Generated video with CMMD conditioned on the audio shown as spectrogram above.

As outlined in Section 3.2, we encoded videos using the Gaussian VAE from the Stable Diffusion project Rombach et al. (2022), which effectively reduces image resolution by a factor of eight in both width and height. We utilized the pre-trained model weights[1] without further fine-tuning.

For audio features, we transformed waveforms sampled at 16 kHz into 80-bin mel spectrograms using a Short-Time Fourier Transform (STFT) with a 32 ms window and 50% overlap, yielding a time resolution of 16 ms. The MelGAN vocoder was improved by the loss weightings from Hifi-GAN Kong et al. (2020a) and notably improved by training on sequences of 4 s, as opposed to the originally suggested 0.5 s. This

[1]https://huggingface.co/stabilityai/sd-vae-ft-mse

Model	time	#params	video dim	latent dim	ms/FE
(n)CMMD	1.8s	106M	128×128	16×16	136
(n)CMMD	1.8s	106M	512×512	64×64	299
MM-Diff Ruan et al. (2023)	1.6s	133M	64×64	-	721

Table 1: Comparison of model size and computational complexity, where ms/FE represents milliseconds per function evaluation; (n)CMMD operates on a downsampled latent representation.

adjustment aligns with the MelGAN architecture's receptive field of approximately 1.6 s. The vocoder was trained on the entire AudioSet Gemmeke et al. (2017) to ensure a broad sound reconstruction capability.

Model Hyperparameters Our nCMMD model was trained over 700,000 gradient steps with a batch size of 8 for versions excluding contrastive loss. For the full-fledged CMMD model, we began fine-tuning from a checkpoint at 400,000 steps of the nCMMD with $\eta = 5 \times 10^{-5}$ suggested by CDCD Zhu et al. (2023), continuing until 700,000 steps with a reduced batch size of 2. The Adam optimizer was employed with an initial learning rate of 1×10^{-4}, which was exponentially annealed every $80,000$ steps until 2×10^{-5}. To create contrastive samples, we applied random shifts of $2 - 4$ frames (equivalent to $200 - 400$ ms) to either video or audio. We employ a cosine variance schedule for α_n, and utilize 200 DDIM sampling steps for conditional generation.

4.1 Model Efficiency and Size

Before generative performance evaluation, we present a comparative evaluation of the inference efficiency between different backbone U-Net models on RTX Titan, as summarized in Table 1. To ensure a fair comparison, both models were executed on a 64×64 resolution space with a batch size of one. Notably, for (n)CMMD, this 64^2-dimensional latent space is equivalent to operating on a 512×512 pixel space. For MM-Diffusion, we activated gradient caching for the best performance. Our evaluation involved a series of 100 denoising steps applied to video-to-audio generation tasks, from which we derived the average runtime. Additionally, the (n)CMMD model processed sequences of 1.8 s in length, compared to the 1.6 s sequences used by MM-Diffusion. Despite handling longer sequences, our model demonstrated a significant performance advantage, operating more than twice as fast and requiring 20% fewer parameters than the baseline model.

4.2 Metrics

Fréchet Distance Objective metrics to capture the perceived quality of video and audio are often difficult to develop and have many imperfections. Especially in generative tasks, where new content is created and no ground truth is available, such metrics are to be used with care. Popular approaches are statistical metrics, which compare generated and reference distributions in some embedding space, such as the *Fréchet Audio Distance (FAD)* Kilgour et al. (2019) and *Fréchet Video Distance (FVD)* Unterthiner et al. (2018). We assess FVD in a pairwise manne Yang et al. (2022); Voleti et al. (2022): calculating the score between the conditional generation results and the corresponding ground truth test sets. To measure audio quality, we calculate FAD using CLAP embeddings Elizalde et al. (2023), which have been shown recently in Gui et al. (2023) to represent acoustic quality much better than the widely used VGGish features. FAD scores are calculated using the FAD toolkit Gui et al. (2023) both individually for each generated sample and for the entire set of samples generated by one model, using the test set as a reference.

Temporal Alignment For the dancing videos from AIST++, to evaluate the temporal alignment of generated music, we use a beat tracking approach similarly as in Ruan et al. (2023) to measure the rhythmic synchronicity. The music beats are estimated using librosa McFee et al. (2023) beat tracker and the hit rate between beats of generated and ground truth audio is computed. We propose to use a tolerance of ± 100 ms, which corresponds approximately to the average perceivable audio-visual synchronicity thresholds found in literature Younkin & Corriveau (2008). For reference, we also use a larger tolerance of ± 500 ms, to show how significantly this can improve accuracy. Since the beat tracking method is applicable only to musical content, we reserve the alignment assessment for EPIC-Sound to subjective evaluation.

	CMMD	nCMMD	MM-Diff Ruan et al. (2023)
16 frames (64)	623	633	945
18 frames (64)	873	905	1351
32 frames (64)	858	947	1540
18 frames (128)	989	1088	N/A
36 frames (128)	958	1093	N/A

Table 2: FVD results (AIST++). Numbers in parentheses indicate the resolution of the evaluated frames.

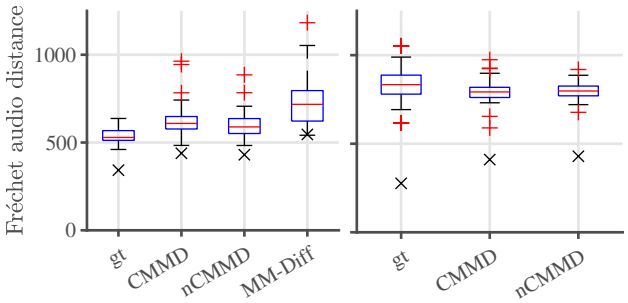

Figure 5: Per-sample (boxes) and per-set (×) Frechet audio distance (FAD) results for AIST++ (left) and EPIC-Sound (right). FAD is calculated using CLAP embeddings with the respective test set as reference. Note that the per-set FAD scores for ground truth (gt) are larger than zero as only the small subset of the test set used in the evaluation is compared to the whole test set used as reference. Comparing FAD scores for identical set sizes avoids sample size bias Gui et al. (2023).

Subjective Evaluation We conducted a user study with 14 participants to evaluate the audio-visual quality and synchronicity. For each example, we asked two or three questions about the quality of the generated content and the temporal alignment of video and audio events on MOS scales from 1 (worst) to 5 (best). Specifically, for *generated video*, we asked to rate the *video quality* and the *temporal alignment*. For *audio generation* from AIST++ dance videos, we asked to rate separately the *acoustic* and *musical quality*, and the *temporal synchronization* of the dancer to the music. For the EPIC-Sound cases, we asked to rate the *acoustic* and *semantic quality*, and the *temporal synchronization* of events. Semantic quality refers to whether the type of sounds heard make sense given the scene seen in the video without paying attention to temporal synchronization.

4.3 Objective Evaluation Results

The FVD results for the proposed model and baseline comparisons are presented in Table 2. The results demonstrate that (n)CMMD outperforms MM-Diffusion across various resolutions and sequence lengths, with CMMD showing a slight advantage over nCMMD. Notably, we observed a more noticeable decline in performance for MM-Diffusion when the generation sequence length deviated from the length used during training.

Fig. 5 illustrates the comparison of audio quality in a video-to-audio generation scenario. Our CMMD model surpasses the baseline in AIST++ music audio quality, as demonstrated by both per-sample FAD Gui et al. (2023) and batch FAD metrics. However, when compared to nCMMD, the improvement is modest, and this observation holds true for both the AIST++ and EPIC-Sound datasets.

Table 3 presents the beat alignment results for the AIST++ audios. The table compares three different methods: CMMD, nCMMD, and MM-Diffusion. In terms of beat tracking accuracy within a 100 ms tolerance, CMMD performs the best, showing a improvement of 1-4%. For a more lenient tolerance of 500 ms, nCMMD demonstrates slightly higher accuracy with a hit rate of 91%. However, the difference in hit rates between nCMMD and CMMD is not substantial. It's important to note that a larger tolerance window

	CMMD	nCMMD	MM-Diff Ruan et al. (2023)
Hitrate (500 ms)	89%	91%	89%
Hitrate (100 ms)	**45%**	44%	41%

Table 3: Comparison of Beat Tracking Accuracy (AIST++). The values in parentheses indicate the allowable margin of error for beat timing, with a smaller window representing a stricter standard. Higher hit rates within lower tolerance thresholds signify superior temporal alignment.

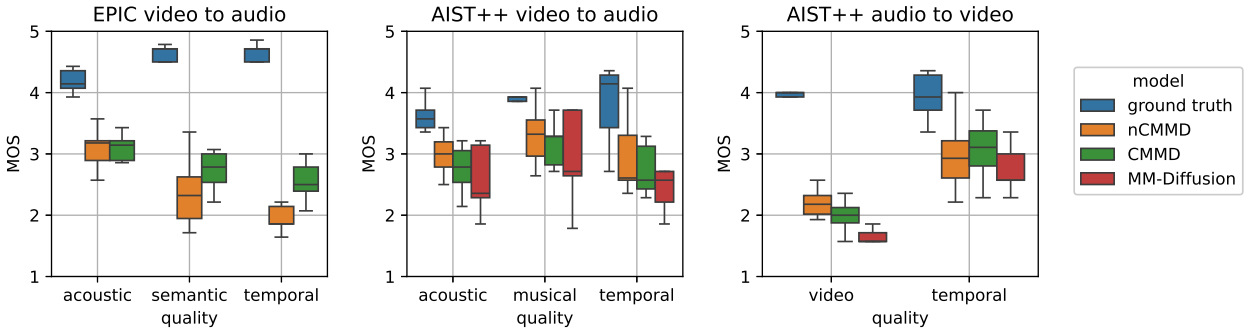

Figure 6: Subjective results from user study for EPIC-Sound video conditioned audio generation (left), AIST++ dance video conditioned audio generation (center), and audio conditioned video generation (right).

allows for more flexibility in matching the beat timing, which may result in a higher hit rate but potentially less precise alignment with the reference beats.

In the generation processes of audios for EPIC-Sound and videos for AIST++, our primary reliance is on subjective evaluation, given the absence of robust metrics. To supplement this assessment, we present EPIC-Sound audio generation visualization provided in Fig. 3, where we can observe that CMMD has better alignment with the ground truth than nCMMD in terms of temporal sound event alignment. Additionally, Fig. 4 presents a qualitative sample showcasing audio-to-video generation in the context of AIST++.

4.4 Subjective Evaluation Results

In the subjective evaluation we used 85 videos. We used 5 different conditions (audio or video as conditioning), two different sample generations per CMMD and nCMMD model, one sample each per ground truth and baseline. For AIST++ we evaluated audio to video and video to audio generation. For EPIC-Sound, we evaluated only video to audio and there is no MM-Diffusion baseline available.

The Mean Opinion Scores (MOS) are shown as boxplots in Fig. 6. We can see that the raters reliably detected the ground truth samples giving it the highest score, though often the scale was not used fully. For the generated dance visuals from AIST++ audio (Fig. 6 top right), we can observe a significantly higher rating of our proposed models over MM-Diffusion baseline. The nCMMD model has a slightly higher video quality, but the difference is at the border of significance. The CMMD model shows a trending but non-significant better temporal alignment than nCMMD. We tested statistical significance with Wilcoxon signed-rank test with p-value < 0.05.

For audio generation based on AIST++ dance video conditions (Fig. 6 top left), we can not observe statistically significant differences between the models and the baseline, although also here a slight but insignificant trend of better quality for the non-contrastive loss is observed. The proposed models have a lower quality spread than the baseline.

For audio generation from EPIC-Sound videos (Fig. 6 bottom left), CMMD significantly outperforms nCMMD in terms of semantic quality and temporal alignment due to the use of the contrastive loss.

4.5 Discussion

The results on the EPIC-Sound and AIST++ audio to video show a very clear benefit of the contrastive loss to enforce stronger temporal synchronization and semantic alignment. Most subjective results in Fig. 6indicate that it may be possible that the model trades off a small amount of quality for better synchronization in some cases. On the other hand, FVD suggests slightly better performance for CMMD. Note that those trends are statistically not significant, so we can conclude a comparable audio and video quality of CMMD and nCMMD, while CMMD significantly improves temporal synchronization. The temporal synchronization results are generally less conclusive for the AIST++ dance data, possibly due to the fact that the alignment of human dancers with music may be harder to judge for several reasons: 1) the dancers may vary in tempo or their internal rhythm may be judged in ambiguous ways. 2) being off by one or two full beats may appear as being in sync again.

5 Conclusion

The multi-modal diffusion model we presented marks an advancement in the field of bi-directional conditional generation of video and audio. Introduction of a more effective and efficient design and the joint contrastive loss were shown to be beneficial improvements. Our experiments across various datasets validate our model's superior performance over existing baselines. The model not only excels in the quality of generation but also shows advantage in alignment performance, especially in scenarios demanding tight audio-visual correlation. This research paves the way for future innovations in video and audio conditional generation. Moving forward, the model can serve as a foundational architecture for subsequent developments aimed at further refining the quality and alignment of generated video-audio contents.

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A Additional Details On Model Structure

Configurable Components	Diffusion U-Net
Base channel	128
Channel scale multiply	1,2,3,4
Video downsample scale	H/2, W/2
Audio downsample scale	T/2
Attention dimension	64
Attention heads	Channel // Attention Dim
Diffusion noise schedule	cosine
Diffusion steps	1000 for training
Prediction target	$\mathbf{v}$
Sample method	DDIM
Sample step	200
η	5

Table 4: Supplemental Diffusion U-Net configuration details.

A.1 MelGAN vocoder

We used the official *MelGAN* architecture[2] Kumar et al. (2019) with only modifications in training procedure and loss weightings. We found that the proposed architecture form HiFi-GAN Kong et al. (2020a) did not work better, but the loss weights provide a significant improvement. We noticed that the receptive field of the convolutional net is around 1.6 s, but training sequences are proposed to 8192 samples, which is even less than 0.5 s at the used sampling rate of 22.5 kHz. We noticed a large performance improvement by simply increasing our training sequence lengths to 4 s.

We trained on full Audioset data ($\sim$5000 h) in 16 kHz and augmentation by random biquad filtering to ensure generalization to arbitrary sounds.

Configurable Components	MelGAN
Mel bins	80
Sampling rate	16 kHz
Trainable parameters	4.27 M
Training sequence length	65536 samples
Feature loss weight	2
Mel spectrum loss weight	10

Table 5: MelGAN Configuration

B Subjective Evaluation Details

In this section, we show the set of questions employed in our subjective evaluation. Participants are tasked with assigning a numerical rating on a scale ranging from 1(worst) to 5(best) for each question.

[2]https://github.com/descriptinc/melgan-neurips

AIST++ video-to-audio generation.

1. Please rate the **acoustic quality** of the music, **independent of the visual aspect**.
   - Low quality might be pure noise, heavily distorted sound or non-musical audio.
   - Penalize any acoustic degradations like distortions, thin or muffled sound or other artifacts.
   - High quality is a good sounding dance music without severe artifacts.
2. Please rate the **musical quality**. Consider the following attributes in your judgement:
   - Does the music have a fluid rhythm or does the beat change randomly?
   - Does the music have a melodical theme or does it not sound appealing?
3. Please rate the **temporal synchronization** between dancer and the music.
   - Do the movements of the dancer seem to fit and be in sync with the music?

AIST++ audio-to-video generation.

1. Please rate the **quality** of the **video, independent of the sound**.
   - Very low quality might be very blurry or unrecognizable content.
   - Penalize artifacts like strange appearing body parts, separating bodies, physically impossible movements, etc.
   - High quality is a naturally looking video of a dancer. Required to answer. Single choice.
2. Please rate the **temporal synchronization** between dancer and the music: Do the movements of the dancer seem to fit and be in sync with the music?

EPIC-Sound video-to-audio generation.

1. Please rate the **quality** of the sound, **independent of the visual aspect**.
   - Low quality might be pure noise or heavily distorted sound.
   - Penalize any acoustic degradations like distortions, thin or muffled sound or other artifacts.
   - High quality is a naturally and realistic sounding recording with a POV camera.
2. Please rate the **semantic relevance of audio, independent of the visual temporal alignment**:
   - Could the audio you hear appear in the environment you see (something out of the field of view could make this sound)?
   - Penalize sounds that would not appear in this kitchen scene.
   - Give a high rating, if the sounds you hear could appear in this kitchen scene, regardless of the video.
3. Please rate the **temporal correlation** between the audio and video events.
   - Do the audio events you hear occur at the same time as in the video?

C Additional Qualitative Examples

We offer .mp4 files as supplementary qualitative samples. Kindly utilize any video player to access the attached .mp4 files.