Coarse-to-Fine Text-to-Music Latent Diffusion

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***Abstract*—We introduce `DiscoDiff`, a text-to-music generative model that utilizes two latent diffusion models to produce high-fidelity 44.1kHz music hierarchically. Our approach significantly enhances audio quality through a coarse-to-fine generation strategy, leveraging residual vector quantization from the Descript Audio Codec. We consolidate this coarse-to-fine design through an important observation that the audio latent representation can be split into a primary and secondary part, controlling music content and details accordingly. We validate the effectiveness of our approach and text-audio alignment through various objective metrics. Furthermore, we provide access to high-quality synthetic captions for the MTG-Jamendo and FMA datasets, as well as open-sourcing `DiscoDiff`'s codebase and model checkpoints.**

***Index Terms*—Text-to-music generation, latent diffusion model, residual vector quantization**

I. Introduction

Generating coherent long-form music at the waveform level presents significant challenges due to the intricate, multi-scale structure of music. Music spans extensive temporal patterns, from rhythm patterns lasting fractions of seconds to minute-long melodies and song structures. This complexity necessitates methods that can handle both the fine details and longer temporal patterns simultaneously. Recent advancements in audio generation address this challenge by utilizing neural audio codecs [1]–[4], compressing the audio, and reducing the sampling rate by multiple orders of magnitude. This compressed latent audio representation can then be used by generative models, such as large-language models or diffusion models to synthesize high-fidelity audio.

Building on this foundation, we leverage two key properties of the Descript Audio Codec [3]. First, the encoder produces a hierarchical set of nine tokens, derived from training with Residual Vector Quantization (RVQ), which encapsulates the multi-scale structure of the audio. Second, each of these nine tokens is encoded in a continuous 8-dimensional space, where each token's contribution is additive in constructing the final latent embedding.

In this work, we introduce `DiscoDiff`, a novel method for text-to-music generation that operates in a coarse-to-fine manner on the continuous latent representation of the Descript Audio Codec [3]. `DiscoDiff` contains two 1D diffusion models capable of generating high-fidelity music at 44.1 kHz. Our method differs from previous latent audio diffusion approaches [5], [6], by directly leveraging the hierarchical RVQ patterns.

We exploit these properties by using a coarse-to-fine generative approach as proposed in the text-to-speech domain [7]. The first diffusion model is responsible for generating the continuous latent embedding of the first token, which encapsulates the coarsest level of audio information. The secondary diffusion model is conditioned on the first token and generates the continuous latent representation of the remaining eight tokens, progressively refining the audio. To train `DiscoDiff` we generate high-quality captions for the MTG-Jamendo [8] and FMA [9] datasets, as well as filtering sub-par samples from FMA by means of a likelihood estimation.

Our contributions can be summarized as follows:

- We propose the application of a coarse-to-fine latent audio diffusion process, leading to enhanced sample quality in music generation.
- We curate and provide a quality ranking of the FMA dataset, filtered according to the likelihood that the samples belong to a distribution of high-quality music. Additionally, we open-source high-quality synthetic captions generated for MTG-Jamendo and FMA datasets.
- We release model checkpoints and accompanying code as open-source resources, supporting reproducibility and further advancements in the field of generative music.[1]

II. Related Work

Text-to-music models require two necessary parts: a generative model and a text-conditioning module.

Auto-regressive models like WaveNet [10] initiate music generation by synthesizing waveforms sample-by-sample. Recent advancements [11]–[13], use transformers to generate waveform latents, achieving high-quality samples. Denoising Diffusion Probabilistic Models (DDPM) [14] and Latent Diffusion Models (LDM) [15] offer faster sampling than auto-regressive models. DiffWave [16], Noise2Music [5], and Riffusion [17] demonstrate the effectiveness of diffusion models for waveform and spectrogram generation.

Recent latent diffusion models outperformed direct waveform or spectrogram generation [18]–[21]. Stable Audio [6] achieved excellent results, thanks to the advances in compressed audio latent representation with audio encoder-decoders (codecs) such as SoundStream [1], EnCodec [2], and Descript Audio Codec (DAC) [3]. Residual vector quantization (RVQ) is normally used for further compression.

For text conditioning, T5 [22] is widely used in text-to-audio models like Make-an-Audio [23] and Noise2Music [5]. Mustango [24] employs FLAN-T5 [25], an instruction-tuned version of T5. Another approach, audio-text embedding, differs from pure-text embedding. The w2v-BERT model [26]

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[1]https://github.com/ETH-DISCO/discodiff

produces joint audio-text embeddings for text conditioning, leading to models like AudioLM [12]. MuLan [27] introduces unsupervised learning for MusicLM [28], while CLAP [29] recently emerged as an open-source model for generating 128-dimensional joint embeddings for audio and text. Stable audio uses CLAP for text conditioning.

III. Method

We start by introducing the core components of our method. Instead of generating raw waveforms, we model sequences of continuous embeddings from a neural codec. These embeddings offer a structured and efficient representation of audio, enabling scalable generation. While autoregressive models, which predict one token at a time based on previous outputs, are the most intuitive choice for handling such sequences, they are not the only option.

A. DDPM

In this work, we use Denoising Diffusion Probabilistic Models (DDPM) [14], [30]. DDPMs learn to reverse a Markov chain of T steps. Starting from the original data sample $\mathbf{x}^{(0)}$, Gaussian noise is gradually added in the forward process until the data becomes nearly indistinguishable from pure noise $\mathbf{x}^{(T)} \sim \mathcal{N}(0, \mathbf{I})$. The model is trained to reverse this process, denoising $\mathbf{x}^{(T)}$ step by step to reconstruct $\mathbf{x}^{(0)}$. During generation, the model begins with pure noise $\mathbf{x}^{(T)}$ and iteratively refines it to produce a coherent sample. DDPMs offer advantages over autoregressive models, such as parallel sample generation, which accelerates generation times for long sequences and enhances sample diversity.

B. Neural Codec: DAC

For the audio representation, we use the Descript Audio Codec (DAC) to compress the audio waveform. DAC initially converts the single dimension waveform $\mathbf{w} \in \mathbb{R}^{512L}$, sampled at $44.1kHz$, into an audio embedding sequence $\mathbf{Z} \in \mathbb{R}^{D\times L}$ of frame rate $44.1kHz/512 \approx 86.1fps$. Subsequently, these embeddings go through Residual Vector Quantization (RVQ) with $K = 9$ codebooks to be further compressed.

A distinctive feature of DAC that significantly contributes to our method is the dimensionality reduction of the embedding from $D = 1024$ to $d = 8$ using learned linear projections. Specifically in latent query process as shown in Fig. 1, we have computation for $i = 0, \ldots K-1$:

$$\begin{aligned} \hat{\mathbf{X}}_i = \mathbf{P}_i \mathbf{Z}_i, \quad (\mathbf{P}_i \in \mathbb{R}^{d\times D},\ \mathbf{Z}_0 = \mathbf{Z}) \\ \mathbf{X}_i = \arg\min_{\mathbf{X}\in\mathcal{X}_i} \|\mathbf{X} - \hat{\mathbf{X}}_i\|_2 \\ \mathbf{Z}_{i+1} = \mathbf{Z}_i - \mathbf{Q}_i \mathbf{X}_i, \quad (\mathbf{Q}_i \in \mathbb{R}^{D\times d}) \end{aligned} \tag{1}$$

where $\mathbf{P}_i, \mathbf{Q}_i$ is the learned in/out-projection weight in DAC, $\mathbf{Z}_i$ is the i^{th} residual and $\mathcal{X}_i$ notates the i^{th} codebook. This mechanism was introduced to address the unbalanced codebook visitation problem inherent in the RVQ process. The smaller embeddings $\mathbf{X}_i$ are concatenated together forming the DAC latent

$$\mathbf{X} = \text{concat}(\mathbf{X}_0, \ldots, \mathbf{X}_{K-1}) \in \mathbb{R}^{Kd\times L} \tag{2}$$

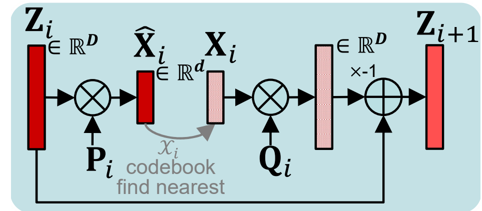

Fig. 1. The i^{th} latent query step, as given in Eq. 1. Starting with the audio embedding $\mathbf{Z}_0$ and iterating this process, we obtain residuals $\mathbf{Z}_i, i = 1, \ldots, K-1$ and dim-reduced latents $\mathbf{X}_i, i = 0, \ldots, K-1$. In-projection $\mathbf{P}_i$ maps the D-dim residual into a smaller latent $\hat{\mathbf{X}}_i$ of dimension d. $\mathbf{X}_i$ is found through the VQ process and then projected out through $\mathbf{Q}_i$ back into the D dimensional space, forming the next residual.

which is our generation target. Importantly, this reduction allows us to generate 9 smaller latents of size 8 instead of a single embedding of size 1024, simplifying the generation task. We call this procedure "DAC latent query process".

C. Generation Patterns

Due to the nature of the RVQ process, it is reasonable to expect a hierarchical structure among the $K = 9$ embeddings. Analogous to Principal Component Analysis (PCA), the first embedding $\mathbf{X}_0$ is likely to capture the most significant and coarse features of $\mathbf{Z}$, while subsequent embeddings $\mathbf{X}_1$, $\mathbf{X}_2$, ..., $\mathbf{X}_8$ capture increasingly refined details. This inherent structure raises an important question: in what order should the 9 smaller embeddings be generated?

Several patterns have been explored in previous work [13]. We refer the reader to Figure 1 of [13] for a schematic representation of these possible generation patterns. Through experimentation, we found that the "Coarse First Pattern" proposed in VALL-E [7] performs the best for diffusion models given a fixed training compute budget. This pattern involves splitting the $K = 9$ embeddings into two groups: the primary latent

$$\mathbf{X}_{\text{pri}} = \mathbf{X}_0 \in \mathbb{R}^{d\times L} \tag{3}$$

and the secondary latents

$$\mathbf{X}_{\text{sec}} = \text{concat}(\mathbf{X}_1, \ldots, \mathbf{X}_{K-1}) \in \mathbb{R}^{(K-1)d\times L} \tag{4}$$

D. `DiscoDiff`

Fig. 2 illustrates our general pipeline, in which two diffusion U-nets with 1.2B parameter each are trained from scratch, while the parameters of the DAC module as well as the conditioning models remain frozen.

Conditioning: Our approach leverages text embedding $\mathbf{c}$ obtained from Flan-T5 Large [25] model, which is introduced into the diffusion models via cross-attention layers. The weights of the Flan-T5 model are kept frozen during the training process.

Training: The primary and secondary models $f_{\text{pri}}, f_{\text{sec}}$ are trained independently, but both using an ℓ_1 loss function. The training input for the secondary model is the concatenation of the ground-truth primary latent $\mathbf{X}_0^{(0)}$ with the noisy secondary latents $\mathbf{X}_{\text{sec}}^{(t)}$. The secondary model is specifically trained to denoise the secondary latents.

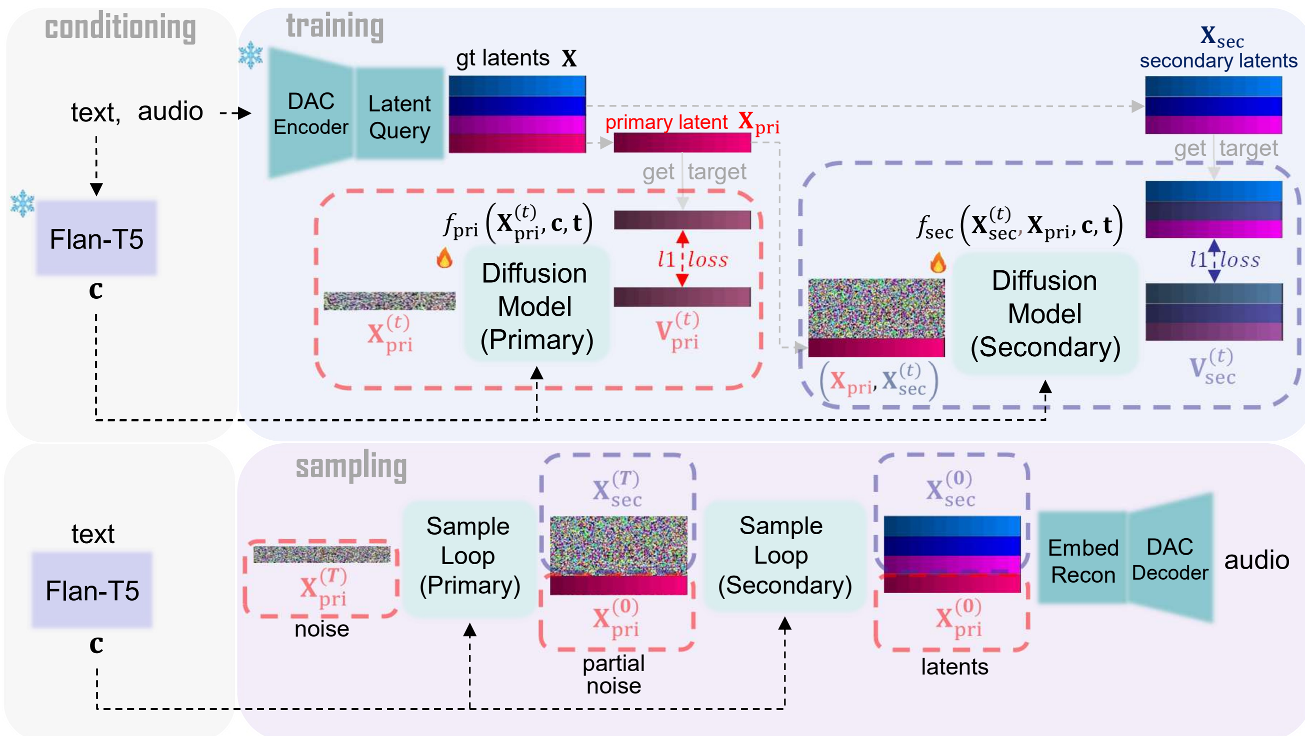

Fig. 2. `DiscoDiff` training and sampling pipeline. Our diffusion model is trained to generate the continuous DAC latents, which are obtained through first encoding the audio and then applying the latent query. "Latent query" is the process described in Eq. 1 and Eq. 2, while "embed recon" refers to the computation described in Eq. 5. The term $\mathbf{V}^{(t)}$, the direct output of diffusion denoising U-net, refers to the "v" objective in v-diffusion.

Sampling Given a text input, we first compute the text condition $\mathbf{c}$ using the Flan-T5 model. Then, the sampling process involves two diffusion sampling loops—primary and secondary—that work together to produce the DAC latents. First, we sample the primary latent $\tilde{\mathbf{X}}_{\text{pri}} \in \mathbb{R}^{d\times L}$, or equivalently $\tilde{\mathbf{X}}_0$, through running a T-step diffusion sampling loop with primary model, starting from Gaussian noise $\mathbf{X}_{\text{pri}}^{(T)} \sim \mathcal{N}(0, \mathbf{I}_{d\times L})$. Next, we sample the secondary latents $\tilde{\mathbf{X}}_{\text{sec}}$ with the secondary model through a T-step diffusion sampling loop, starting from Gaussian noise $\mathbf{X}_{\text{sec}}^{(T)} \sim \mathcal{N}(0, \mathbf{I}_{(K-1)d\times L})$, which yields the next latents $\tilde{\mathbf{X}}_1, \ldots, \tilde{\mathbf{X}}_{K-1}$. Finally, all latents are combined to reconstruct the embedding $\tilde{\mathbf{Z}} \in \mathbb{R}^{D\times L}$ using:

$$\begin{aligned} \tilde{\mathbf{Z}} &= \sum_{i=0}^{K-1} \tilde{\mathbf{Z}}_i, \quad \tilde{\mathbf{Z}}_i = \mathbf{Q}_i \check{\mathbf{X}}_i, \quad (\mathbf{Q}_i \in \mathbb{R}^{D\times d}) \\ \check{\mathbf{X}}_i &= \arg\min_{\mathbf{X}\in\mathcal{X}_i} \|\mathbf{X} - \tilde{\mathbf{X}}_i\|_2, \;\; i = 0, \ldots K-1, \end{aligned} \tag{5}$$

where $\mathcal{X}_i$ is the i^{th} codebook. Finally, $\tilde{\mathbf{Z}}$ is fed into the DAC decoder to generate the final waveform.

IV. Experiments

A. Datasets

To develop a fully open-source model, we train `DiscoDiff` using two publicly available music datasets: MTG-Jamendo [8] and Free Music Archive (FMA) [9]. Jamendo includes over 55,000 Creative Commons-licensed tracks (3,778 hrs), annotated with genre, instrument, and mood/theme tags. FMA offers 106,574 tracks (8,232 hrs) with genre and artist tags. During training, audio tracks in both datasets are chunked into 29 second segments.

Music Captioning: Since the training datasets lack captions, we generate them via the following pipeline:

1) Use SALMONN [31] to generate raw descriptions.
2) Summarize tags into concise strings (e.g., "Genre: classical; instruments: strings, harp").
3) Use ChatGPT-3.5-turbo to generate captions through rephrasing raw SALMONN descriptions guided by tags, with preference given to tags over raw descriptions.

Data Cleaning: To avoid degrading model quality, we excluded FMA tracks with low musicality (in common aesthetics) such as experimental music. Hence, we created a high-quality FMA subset resembling the Jamendo dataset in musical characteristics. This involved selecting FMA tracks with a high likelihood of matching Jamendo's profile:

1) Extract CLAP embeddings for each Jamendo track, creating a set $\mathcal{D}_{\text{clap}} = \{\mathbf{c}_{\text{aud}}^{(i)}\}$.
2) Fit a d_c-dimensional Gaussian distribution $\mathcal{N}(\bar{\mathbf{c}}_{\text{aud}}, \Sigma_{\text{aud}})$ to approximate Jamendo's distribution.
3) Compute the log-likelihood $\log p$ of each FMA track's CLAP embedding under this distribution.
4) Rank FMA tracks by their log-likelihood values and select the top 20%.

TABLE I

COMPARISON OF FAD AND CLAP SCORES BETWEEN EXISTING MODELS AND OUR MODEL ON MUSICCAPS. **`DiscoDiff`** W/ PL IS ONLY THE SECONDARY MODEL SAMPLED WITH GROUND-TRUTH PRIMARY LATENT. INFERENCE REFERS TO THE TIME NEEDED TO GENERATE A SAMPLE, DURATION REFERS TO THE LENGTH OF THE SAMPLE. WE LIST IF THE CHECKPOINT IS AVAILABLE AND IF THE MODEL WAS TRAINED ON OPEN-SOURCE DATA.

Model	$\text{FAD}_{\text{vgg}} \downarrow$	$\text{CLAP}_{\text{score}} \uparrow$	Inference (s)	Duration (s)	SR (kHz)	Checkpoint	OS Data
DAC Enc-Decoded	1.1	0.46	-	-	44.1	-	-
`DiscoDiff` w/ PL	1.3	0.43	8 s	29 s	44.1	-	-
MusicGen-L [13]	3.8	0.31	242 s	95 s	32	yes	no
Riffusion [17]	14.8	0.19	25 s	5 s	44.1	yes	no
Noise2Music [5]	2.1	-	36 s	30 s	24	no	no
AudioLDM2 [19]	3.1	0.22	107 s	10 s	48	yes	yes
Moûsai [18]	7.5	0.23	49.2 s	43 s	48	no	no
`DiscoDiff`	4.1	0.34	16 s	29 s	44.1	yes	yes

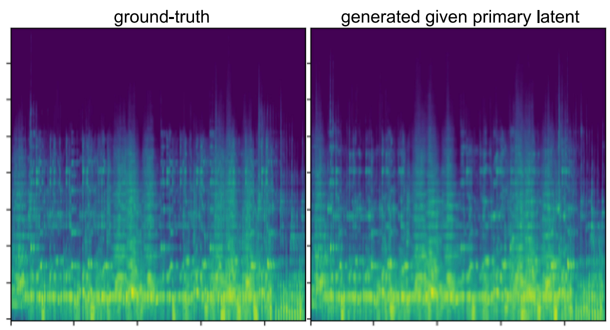

Fig. 3. Mel-spectrogram comparison between ground-truth (left) and audio generated by the secondary model given ground-truth primary latents (right).

Based on listening tests, we selected the top 20% of FMA files according to their log-likelihood scores. We release the likelihood scores of the FMA dataset[2].

Test Dataset: For evaluation, we use the MusicCaps dataset [28], which contains 5,521 music examples, each 10 seconds long and paired with English captions. These examples are a curated subset of the AudioCaps dataset [32], with 2,858 samples from the evaluation set and 2,663 samples from the AudioSet training split.

B. Effectiveness of Secondary Model

During our evaluation of the secondary model, which is trained to predict the secondary latents $\mathbf{X}_{\text{sec}}$, based on the primary latents $\mathbf{X}_{\text{pri}}$, we observed that it reconstructs audio that closely resembles the original input. This phenomenon is illustrated in Fig. 3, where the generated audio (right) is nearly indistinguishable from the ground truth (left), as shown by the mel-spectrograms. This observation suggests that the primary latents are primarily responsible for governing the core content of the audio, while the secondary latents are crucial for refining the audio's details. This insight underpins our coarse-to-fine strategy, where the first model generates a coarse representation (i.e., the primary latents $\mathbf{X}_{\text{pri}}$) and the secondary model subsequently refines this representation by generating the secondary latents $\mathbf{X}_{\text{sec}}$.

[2]https://huggingface.co/datasets/disco-eth/jamendo-fma-captions

C. Evaluation

We test `DiscoDiff` on the evaluation set of MusicCaps. Table I presents the evaluations results of `DiscoDiff` based on two main metrics:

FAD (Fréchet Audio Distance): FAD [33] assesses the quality of generated audio by comparing audio embeddings between generated samples and ground-truth audio, using VGGish [34] for extraction. Lower FAD values indicate better quality.

CLAP Score: The cosine similarity between CLAP audio and text embeddings [29] measures alignment between generated audio and its caption. A higher score means better semantic relevance.

Despite being trained on a limited amount of publicly available data, `DiscoDiff` demonstrates competitive performance when compared to closed-source diffusion models. In terms of audio quality and conditioning effectiveness, `DiscoDiff` surpasses both Riffusion and Mousai. However, due to the smaller and less diverse training data compared to models such as Stable Audio and MusicGen, our model produces audio with less diversity, which accounts for its comparatively lower performance in this area. Thanks to the use of a diffusion-based approach, `DiscoDiff` achieves faster inference times than most existing models, particularly the autoregressive architectures.

V. CONCLUSION

We introduced a coarse-to-fine generation approach within a latent diffusion framework to generate DAC latents, which can be decoded to 44.1 kHz audio. This approach builds on the key insight that the primary latent dictates the core audio content, while the secondary latents refine the finer audio details. Consequently, we first generate the primary latent and then conditionally generate the secondary latents. Furthermore, we release high-quality synthetic captions and a cleaned version of the FMA dataset, improving its musical quality.

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