One-shot Text-aligned Virtual Instrument Generation Utilizing Diffusion Transformer

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Abstract

Despite the success of emerging text-to-music models based on deep generative approaches in generating music clips for general audiences, they face significant limitations when applied to professional music production.

This paper introduces a one-shot Text-aligned Virtual Instrument Generation model using a Diffusion Transformer (TaVIG). The model integrates textual descriptions with the timbre information of audio clips to generate musical performances, utilizing additional musical structure features such as pitch, onset, duration, offset, and velocity. TaVIG comprises a CLAP-based text-aligned timbre extractor-encoder, a musical structure encoder for extracting MIDI information, and a disentangled representation learning module to ensure effective timbre and structure extraction. The audio synthesis process is based on a Diffusion Transformer conditioned with AdaLN. Additionally, we propose a mathematical framework to analyze timbre and structure disentanglement in MIDI-to-audio tasks.

1 Introduction

Deep learning-based music generation has garnered growing interest in the machine learning community, particularly with the advent of advanced music generation systems [1][2]. However, professional musicians often find such models impractical due to their lack of control over the intermediate generation process. Musicians frequently use virtual instruments, but these tools often come with financial constraints, long tuning periods, and limited natural performance details.

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Recent research focuses on MIDI-to-audio models for neural audio synthesis, which can be categorized into synthesizer-based sound matching models, DDSP-based models [11], and spectrogram generation models. Section 2 will elaborate on related work.

Synthesizer sound matching models depend on pre-existing synthesizers, limiting the variety of timbres and struggling to emulate acoustic sounds. DDSP is promising but confines outputs to specific models like the Sinusoidal plus Noise model.

However, existing models face several challenges:

- **Structure Misalignment:** Polyphonic models may generate extra tracks or misalign instruments with the original MIDI (e.g., [30], [27]).
- **Poor Sound Quality:** Some models produce blurry or artifact-ridden sounds, such as violin audio in [27].
- **Inconsistent Timbre:** Instruments like guitars sometimes sound like other instruments, as seen in [20].
- **Limited Instrument Variety:** Models are often restricted to instruments they've been trained on.
- **Single Note Synthesis:** Some models fail to capture the complexity of full performances and only synthesize single notes [35, 34].

Our work introduces TaVIG (Text-aligned Virtual Instrument Generative model), which synthesizes musical performances from timbre and structure inputs using a Diffusion Transformer (DiT). By utilizing disentangled representation learning, TaVIG separates timbre and structure to ensure accurate note generation. Our approach allows for one-shot multi-note synthesis, with timbre controlled via audio or text prompts, ensuring flexibility and user intent fidelity.

2 Related Work

Synthesizer sound matching estimates parameters to replicate a target sound. Typically, a similar sound is provided, and the system adjusts parameters to match it. Sound2Synth [6] enhances this process by converting sounds into four representations, each processed by dedicated backbones. DDX7 [3] and DiffMoog [38] are based on Yamaha DX7 and Moog synthesizers, while Masuda and Saito [32] integrate sound matching with DDSP for subtractive synthesis.

RNNs have been applied to map MIDI to pitch and loudness via DDSP parameter estimation [15, 4, 18]. DDSP-Piano [37] utilizes Multi-Resolution Spectral Loss and DDSP for piano synthesis, and MIDI-DDSP [40] translates expressive MIDI attributes, such as articulation, into synthesis controls.

For spectrogram generation, GAN-based models like GANsynth [10], GANstrument [33], and HyperGANstrument [42] use adversarial training to match data distributions, with GANstrument and HyperGANstrument enabling timbre interpolation.

Auto-regressive models include LSTM-based mel-to-mel conversion conditioned on instrument embeddings [21] and Deep Performer [9], a Transformer leveraging performer and tempo embeddings. Nercessian et al. [35, 34] employed CLAP [39] to align text and timbre embeddings, integrating them into a timbre-generation framework.

Recent advancements in diffusion models have significantly enhanced MIDI-to-audio generation. Hawthorne et al. [13] integrated a Transformer with a diffusion model, which was further developed by Maman et al. [30] and Kim et al. [20], focusing on performance conditioning and guitar generation, respectively. Liu et al. [27] introduced a diffusion-based MIDI-to-audio system, while Demerle et al. [8] employed adversarial training to capture timbre and structure, leveraging diffusion as the generative backbone.

3 Method

In Figure , we present the envisioned four-phase framework for the MIDI-to-Audio model, comprising the following components:

1. a text-aligned timbre extractor-encoder
2. a musical structure encoder
3. a disentangled representation learning module
4. an audio synthesis model

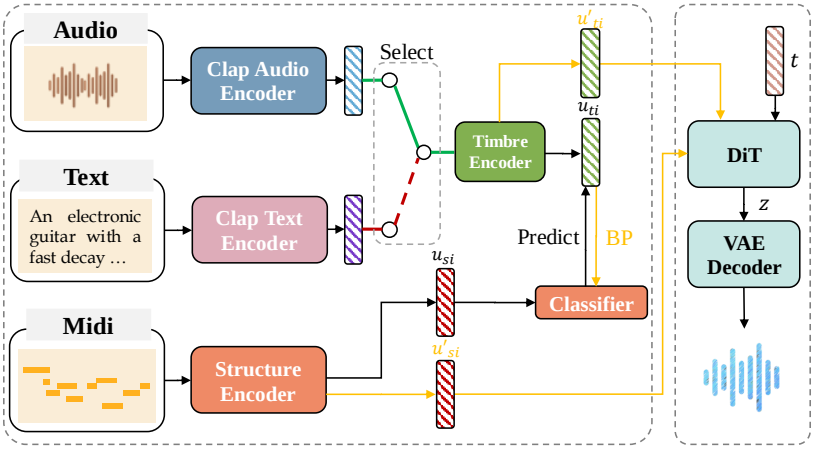

Figure 1: The overall architecture of our model. During training, either text or audio is randomly selected as the timbre prompt corresponding to the MIDI input. The timbre information $\mathbf{u}_{ti}$ is obtained through the pretrained CLAP encoder and Timbre encoder, which serves as the global condition for the DiT model. The MIDI's pianoroll is passed through the Structure encoder to obtain the structural information $\mathbf{u}_{si}$, which is used as the prepend condition for the DiT model. The DiT predicts the VAE latent $\mathbf{z}$ from noise, which is then decoded to generate audio that simultaneously contains both the timbre $\mathbf{u}_{ti}$ and the structure $\mathbf{u}_{si}$. A classifier is used to predict $\mathbf{u}_{ti}$ from the structure $\mathbf{u}_{si}$, ensuring the disentanglement between the two. The black lines show the predictor optimization process while the orange lines show the diffusion training process. BP stands for BackPropogation.

3.1 Notations

Let (Ω_t, F_t, P_t) and (Ω_s, F_s, P_s) are the probability spaces of timbre and structure random variables. Denote $\mathbf{U}_t$ and $\mathbf{U}_s$ random matrices defined in these two probability spaces that containing the timbre and structure information of the same audio clip respectively, and $\mathbf{u}_{ti}$, $\mathbf{u}_{si}$ represent related realization samples. We denote the random matrices defined in the probability space (Ω_w, F_w, P_w) representing audio clips in the form of waveform as $\mathbf{W}_i$ and its realization as $\mathbf{w}_i$. $\mathbf{z} \in \mathbb{R}^{C \times \frac{T}{c} \times \frac{F}{c}}$ is the latent that encoded by the VAE[23], where C, c, T and F represent the number of channels of the compressed latents, compression rate, length of time and frequency. $TE(\cdot)$ and $SE(\cdot)$ represent timbre encoder and structure encoder respectively. B stands for B.

3.2 Text-aligned Timbre Extractor-Encoder

We leverage the CLAP model [39] to generate a standardized 512-dimensional representation for paired audio and text inputs. Pretrained on musical signals with a contrastive loss function, this model aligns audio and text embeddings, enabling either modality to serve interchangeably as input to our system. The audio encoder, E_a, uses the HTS-AT architecture [5], while the text encoder, E_t, is based on RoBERTa [28]. We further finetune this model on a custom dataset of timbre-related texts paired with descriptive audio clips.

This approach allows us to work exclusively with audio data during language model training, avoiding the need for extensive text annotations in the audio dataset. Given the high computational demand of training CLAP from scratch, we instead employ a pretrained CLAP model as a cross-modality encoder, which we finetune on our timbre text dataset. The resulting 512-dimensional vector is subsequently fed, after a linear projection, into a timbre structure following the method in [8].

3.3 Musical Structure Encoder

We use music files in MIDI format, which is a symbolic representation of music, similar to a musical score. A MIDI file consists of multiple tracks, each of which is assigned to a specific instrument. We regard the MIDI sequence S of a single track as structural information. We utilize the `pretty_midi` library to read MIDI files and extract the discrete piano roll sequence $s \in [0,1]^{128\times T}$, where 128 represents the standard MIDI pitch range from 0 to 127 (corresponding to MIDI note numbers), and T is the length of the discretized MIDI sequence.

We selected the same encoder network as in previous work, which is composed of multiple convolutional blocks. Each convolutional block processes the input through BatchNorm1d, SiLU activation, Conv1d layers, Dropout, and skip connections, progressively extracting temporal features. The number of channels begins at 128, corresponding to the MIDI pitch, and gradually increases through the convolutional layers until the output is a feature with u_t channels.

3.4 Audio Synthesis with Latent Diffusion Transformer

In traditional Latent Diffusion Model used in audio synthesis task, the original waveform $\mathbf{x} \in \mathbb{R}^{\mathbb{T}}$ is converted into a mel-spectrogram $\mathbf{X} \in \mathbb{R}^{T\times F}$ using short time Fourier transformation (STFT) and mel filter bank. Then the mel-spectrogram is sent into a variational autoencoder (VAE) to obtain a latent representation $\mathbf{z} \in \mathbb{R}^{C\times \frac{T}{c}\times \frac{F}{c}}$, which can also be recognized as $\mathbf{z}_0$ in the language of diffusion models.

In the forward process of diffusion models [17], which is the training phase, the model gradually add noise to the ground truth $\mathbf{z}_0$ by sampling from the following distributions:

$$q\left(\boldsymbol{z}_n \mid \boldsymbol{z}_{n-1}\right) = \mathcal{N}\left(\boldsymbol{z}_n; \sqrt{1-\beta_n}\boldsymbol{z}_{n-1}, \beta_n \boldsymbol{I}\right)$$
$$q\left(\boldsymbol{z}_n \mid \boldsymbol{z}_0\right) = \mathcal{N}\left(\boldsymbol{z}_n; \sqrt{\bar{\alpha}_n}\boldsymbol{z}_0, (1-\bar{\alpha}_n)\boldsymbol{\varepsilon}\right)$$

where α_i and β_i, $i \in \{1,\ldots,n\}$ are parameter related to the assumption of the diffusion models, $\mathcal{N}(\mathbf{v};\mu,\mathbf{\Sigma})$ represent the probability density function of the random variable $\mathbf{v}$ which follows the distribution of $\mathcal{N}(\mu,\mathbf{\Sigma})$. $\boldsymbol{\varepsilon} \sim \mathcal{N}(\mathbf{0},\mathbf{I})$ and the final step of the representation $\mathbf{z}_n \sim \mathcal{N}(\mathbf{0},\mathbf{I})$. In the training phase, a denoising neural network $\boldsymbol{\varepsilon}_\theta$ is trained to predict $\mathbf{z}_0$ from the noised latent $\mathbf{z}_n$ on the following diffusion loss:

$$L_{DiT} = \mathbb{E}_{\boldsymbol{z}_0,\boldsymbol{\varepsilon},n} \left\|\boldsymbol{\varepsilon} - \boldsymbol{\varepsilon}_\theta\left(\boldsymbol{z}_n, n, \mathbf{g}, \mathbf{p}\right)\right\|_2^2 \tag{1}$$

where $\mathbf{g}$ and $\mathbf{p}$ stand for global condition and prepend condition in DiT respectively.

Compared to other diffusion models, DiTs shows its edge on effectively capturing data dependencies and producing high-quality results. Recent studies highlight DiTs' impressive image generation capabilities, especially through techniques like Stable Diffusion 3, and their success in video generation, demonstrated by the Sora framework [29]. As [26] had shown, Diffusion Transformer (DiT) shows great capacity of preserving the quality of the generated audio.

The technical details about encoder, decoder and the DiT block is coverd in A.2.

3.5 Disentangled Representation Learning Module

We assume that $\mathbf{U}_t$ and $\mathbf{U}_s$ are not correlated, i.e. $\mathrm{cov}(\mathbf{U}_t, \mathbf{U}_s) = 0$. This assumption is reasonable since correct timbre shift in music performing would not change the the pitch of each note, and vice versa. Therefore, the audio clip $\mathbf{W}_i$ can be formulated into a function of two uncorrelated random matrices:

$$\mathbf{W}_i = f(\mathbf{U}_t, \mathbf{U}_s) \tag{2}$$

where $f : (\Omega_t, F_t, P_t) \times (\Omega_s, F_s, P_s) \mapsto (\Omega_w, F_w, P_w)$.

Ideally , we wish our text-aligned timbre extractor-encoder and structure encoder can serve as the following two functions:

$$g_t(\mathbf{W}_i) = g_t(f(\mathbf{U}_t, \mathbf{U}_s)) = \mathbf{U}_t, \tag{3}$$
$$g_s(\mathbf{W}_i) = g_s(f(\mathbf{U}_t, \mathbf{U}_s)) = \mathbf{U}_s \tag{4}$$

If $TE = g_t$ and $SE = g_s$, then the information of timbre and musical structure is completely disentangled. Our timbre encoder TE and structure encoder SE should serve an under-optimized g_t and g_s:

$$TE(\mathbf{w}_i) = TE(f(\mathbf{u}_{ti}, \mathbf{u}_{si})) = \mathbf{u}_{ti}, \tag{5}$$

$$SE(\mathbf{w}_i) = SE(f(\mathbf{u}_{ti}, \mathbf{u}_{si})) = \mathbf{u}_{si} \tag{6}$$

Therefore, our goal in this disentangled representation learning module is to minimize the correlation of embedding provided by TE and SE. Inspired by [8], we optimize a predictor function $h(\cdot)$ trying to recover samples of $\mathbf{u}_{ti}$ only using the information in $\mathbf{u}_{si}$, $i \in \{1, \ldots, \mathrm{B}\}$ and use it as an negative guidance, i.e. preventing $h(\cdot)$ to correctly predict $\mathbf{u}_{ti}$ from $\mathbf{u}_{si}$:

$$L_{pred} = -\mathbb{E}_{\mathbf{U}_t, \mathbf{U}_s} \left[\|\mathbf{U}_t - h(\mathbf{U}_s)\|\right] \tag{7}$$

$$= -\Sigma_{i=1}^{B} \left[\|\mathbf{u}_{ti} - h(\mathbf{u}_{si})\|\right] / \mathrm{B} \tag{8}$$

Overall Architecture In odd number training steps, we fix the TE and SE to optimize the predictor as well as training the DiT. On the contrary, we fix the predictor instead and train TE, SE and the DiT in even number training steps.

$$L = L_{DiT} + \lambda L_{pred} \tag{9}$$

where λ is a hyper parameter controlling learning emphasis on the disentangled representation learning.

4 Experiments

4.1 Datasets

We adopt two synthetic dataset: Slakh2100 and Nysnth and three real dataset: Maestro, Guitarset and the URMP dataset. For details about the datasets, please see A.1.

4.2 Results

Specific training settings are given in A.3. For the VAE, we adopted the architecture and training parameters from Stable Audio Open[12], using a sampling rate of 44,100 Hz but converting from stereo to mono. We trained the model for 50k steps to ensure that the VAE can faithfully reconstruct the instrument sounds.

Condition	**Dataset**	**FAD$_{\text{Vggish}}$** $\downarrow$	**FAD$_{\text{Encodec}}$** $\downarrow$	**Transcription F1** $\uparrow$	**Clap Score** $\uparrow$
Clap$_{\text{audio}}$	Slakh	0.51	2.23	0.47	0.090
Clap$_{\text{text}}$	Slakh	0.25	2.28	0.53	0.135
Clap$_{\text{audio}}$	Nsynth	0.52	2.34	0.48	0.150
Clap$_{\text{text}}$	Nsynth	0.29	1.78	0.54	0.152
Ground Truth	-	0.00	1.00	1.00	-

Table 1: Experimental results on audio quality and pitch accuracy. Metrics are computed separately for each evaluation dataset.

5 Conclusions

In this paper, we introduced TaVIG, a one-shot Text-aligned Virtual Instrument Generation model using a Diffusion Transformer. We evaluated TaVIG on both the Slakh and NSynth datasets, using transcription F1 scores to assess the alignment of generated music with the provided MIDI, and FAD scores to measure audio quality.

This work provides a step forward in bridging the need of music production industry and machine learning technology. Future work will focus on refining the disentanglement of centain timbres and structures, improving the diversity of generated timbres but maintaining the loyalty to the text prompts, and extending the model's ability to handle polyphonic and complex instrumentations in real-world scenarios.

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A Appendix

A.1 Dataset

To ensure the model encounters a wide variety of timbres, our approach to dataset selection focuses on including as many timbres as possible, each with detailed text descriptions.

Synthetic Data To ensure the variety of timbre, synthesized data are needed.

- Slakh2100_flac_redux: The Synthesized Lakh Dataset (SLAKH) [31] is a multi-track audio and MIDI dataset for music source separation and multi-instrument transcription. Created from the Lakh MIDI Dataset v0.1 using high-quality virtual instruments, it features 2100 tracks with aligned MIDI, synthesized from 187 patches across 34 instrument classes. For this study, we focus on 400 hours of non-percussive instrument stems.
- The NSynth dataset is a large, structured collection of 300,000 isolated musical notes from 1,000 diverse instruments, with detailed labels for pitch, velocity, instrument type, and acoustic qualities.

Real Data To capture natural performance nuances, we focus on datasets with real audio recordings:

- **Maestro** [14]: A dataset of approximately 200 hours of paired MIDI-audio piano recordings from classical piano competitions, annotated with composer and piece information.
- **Guitarset** [41]: A 6-hour collection of live guitar performances, featuring both solos and accompaniment across various genres and playing styles.
- **URMP** [25]: A dataset of pieces performed by various classical instruments, including brass, woodwinds, and strings. We use approximately 4 hours of monophonic instrumental recordings.

We construct timbre descriptions using the template: A {INSTRUMENT SOURCE} {INSTRUMENT FAMILY} WITH {SOUND QUALITY} PLAYING IN {STYLE}. For example:

- **Instrument Source**: electric, acoustic, synthesized, etc.
- **Instrument Family**: piano, guitar, bass, etc.
- **Sound Quality**: decay, delay, reverb, etc.
- **Style**: Jazz, Flamenco, Blues, etc.

If specific information is unavailable, the corresponding description is omitted.

A.2 Technical Details

The encoder and decoder in our VAE follow the same architecture as DAC[24]. DAC is a neural codec that offers high compression and high fidelity; however, we modify its bottleneck by replacing RVQ with VAE.. Before the conditional embeddings $\mathbf{g}$ and $\mathbf{p}$ are fed into the DiT block, Patchify is conducted to convert the 2D latent representations encoded by the VQ-VAE into an one-dimensional representation. The denoising network ε_θ is formulated as a DiT block with adaLN-Zero conditoning mechanism. The adaLN-Zero mechanism can be decomposed into two main parts, Adaptive Layer Normalization (AdaLN) and the adaZero-Block. The core idea of AdaLN is to use $\mathbf{g}$ and $\mathbf{p}$ to learn two normalization parameters β and γ (not sure), which is obtained by adding up time slice features t and conditional features β. In addition, DiT also has a regression scaling parameter after each residual connection α. While adaZero-Block initialize some training parameters as zeros to accelerate the training process.

A.3 Training Settings

For the DiT model, we configured a 12-layer transformer with a latent dimension of 768 and trained it for 50k steps using a learning rate of 1e-5. We evaluated the model's performance under different CLAP conditions and across different validation datasets. Since the text descriptions in Nsynth are more detailed and the timbre information is more complete, we also compared the results with those from the synthetic dataset Slakh. For audio quality evaluation, we use the Frechet Audio Distance (FAD) [19] to measure how well the generated audio aligns with the dataset distribution for both reconstruction and transfer tasks. We compute FAD using embeddings from VGGish [16] and Encodec [7].To assess whether the generated audio aligns with the structural information provided by the MIDI, we use CREPE [22] to extract pitch and compute the Onset F1 score using mir_eval[36].