THE METHODOLOGY FOR STEREO IMAGE LEARNING REPRESENTATION

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ABSTRACT

[1]

***Index Terms*—** Generative model, Multi-channel audio, Learning representation

1. INTRODUCTION

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Overall, we propose an ·. We show promising results on stereo audio generation problem with our new dataset. In summary, the main contributions of this work are:

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2. RELATED WORK

2.1. Audio Generative Model

The earliest audio-generated models for audio tends to focus on speech synthesis. These datasets require handling variable length, and WaveNet [1] used autoregressive method for variable length inputs and outputs. A flow-based WaveGlow [2] has emerged that compensates for slow speed of autoregressive models. In comparison to speech, audio generation for music is relatively in the development stage. [3] proposed to use WaveNet for generate single musical note, but it was still slow and global latent conditioning was impossible. GANSynth [4] with Generative Adversarial Network solves these shortcomings and provides high-fidelity and locally-coherent audio by modeling log magnitudes and instantaneous frequencies with sufficient frequency resolution in the spectral domain. With the current technology, it is possible to learn a single note of a variety of instruments to convincingly describe the sound of a real instrument, and to create a variety of synthesizers for interpolation between two instruments. In spite of such breakthrough development, the reason that the generated musical notes cannot be used for commercial music is that the generated result is a single channel. Despite this breakthrough, the generated musical notes cannot replace commonly used virtual instruments due to the limitation of a single channel.

[1]Dataset and code are available on `https://github.com/changwoonchoi/ml2020`

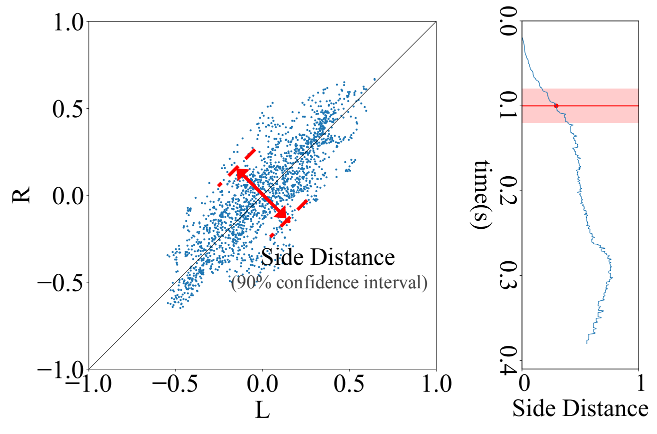
2.2. Multi-Channel Audio

In deep learning, multi-channel settings are mainly used for speech separation [5], speech enhancement [6], and speech recognition [7] due to their ability to utilize information about speech source location. On the other hand, [8] proposed a upmixing conversion of the mono signal to pseudo stereo in order to enhance the audio effect. However, as far as we know, there are still no attempts to generate high-fidelity multi-channel audio. It is thought that it is necessary to learn the difference while maintaining the coherency of both channels to form a spatial sense of sound. A technique referred to as "mid-side coding" exploits the common part of a stereophonic input signal by encoding the sum and difference signals of the two input signals rather than the input signals themselves.([9]) Therefore, for a high-performance multi-channel audio generative model in the future, we would like to train the GANSynth baseline through the mid-side coding to verify whether this attempt is able to effectively learn stereo image.

3. PROPOSED METHOD

4. EXPERIMENTS

In this section, we first propose our novel representation of stereo audio, *'Side distance' (D_{side}) and 'Short-time Side Distance (STSD)'*. Next, we introduce existing metrics for evaluating sample generation, then propose our new metrics for evaluating stereo image generation by combining existing metrics with side distance and STSD. We then compare the proposed method using M-S channels with previous method using L-R channels.



(a) Side Distance (b) STSD

Fig. 1: Stereo audio representation. (a) shows the vectorscope and side distance, (b) shows the STSD.

4.1. Representation for stereo audio

The goal of generative model is to learn to produce samples that look similar to the ones on which it has been trained. Therefore, in order to evaluate the generative model, a proper distance metric between the generated samples and the samples from the dataset is essential. Until now, however, a metric of measuring the similarity between stereo images has never been suggested. In this chapter, we propose a novel representation of stereo audio that allows us to define the distance metric between them.

4.1.1. Side distance

When y is a stereo audio of length T, we define *'side distance'* D_{side} as following:

$$D_{side}(y) = \frac{\sqrt{2}}{2}(\max_{t\in[0,T)}[y_L(t)-y_R(t)]-\min_{t\in[0,T)}[y_L(t)-y_R(t)]) \tag{1}$$

where y_L and y_R are left and right channel of stereo audio y. For robustness, we use the 0.95, 0.05 quantiles of $y_L(t) - y_R(t)$ instead of maximum and minimum. The side distance can be viewed as an index indicating how far the given stereo audio is spread as visualized in Fig. 1a

4.1.2. Short-time Side Distance (STSD)

Although side distance is an indicator of how wide the given stereo audio is spread in the auditory space, it cannot express the change of the stereo image over time. Therefore, we introduce the concept of *'Short-time Side Distance (STSD)'* to capture the characteristics of the stereo image over time. The STSD is a sequence of side distance of a windowed signal. The procedure to obtain STSD is to divide a longer time signal into shorter segments of equal length and then compute side distance on each shorter segment. Formally,

$$STFT(y(t)) = D_{side}(y(\tau)w(t)) \tag{2}$$

where $w(t)$ is a window function which is nonzero for short period of time. As depicted in Fig.1b, STSD contains the change in the side distance of the windowed short fragment of signal over time.

4.2. Evaluation metrics

Following prior work, we use earth mover's distance (EMD), proposed by [10] to measure the similarity between two distributions. Formally, EMD is defined as follows:

$$\text{EMD}(s_1, s_2) = \min_{\phi:s_1\rightarrow s_2} \sum_{x\in s_1} \|x-\phi(x)\|_2$$

where s_1 and s_2 are two distributions and ϕ is a bijection between them. Note that s_1 and s_2 can be any distribution. One can use STSD of stereo audio as s_1 and s_2.

Let S_g be the set of generated stereo audios and S_r be the set of reference audios with $|S_g| = |S_r|$. To evaluate generative models, we consider the three metrics, MMD, COV which are introduced by [11] and 1-NNA proposed by [12].

- **Coverage (COV)** measures the fraction of stereo audios in the reference set that are matched to at least one stereo audio in the generated set. For each stereo audio in the generated set, its nearest neighbor in the reference set is marked as a match:

$$\text{COV}(S_g, S_r) = \frac{|\{\arg\min_{Y\in S_r} D_{side}(X,Y)|X \in S_g\}|}{|S_r|},$$

  While coverage is able to detect mode collapse, it does not evaluate the quality of generated stereo audios.

- **Minimum matching distance (MMD)** is proposed to complement coverage as a metric that measures quality. For each stereo audio in the reference set, the distance to its nearest neighbor in the generated set is computed and averaged:

$$\text{MMD}(S_g, S_r) = \frac{1}{|S_r|}\sum_{Y\in S_r}\min_{X\in S_g} D_{side}(X,Y),$$

- **1-nearest neighbor accuracy (1-NNA)** is proposed by Lopez-Paz and Oquab [12] for two-sample tests, assessing whether two distributions are identical. Let $S_{-X} = S_r \cup S_g - \{X\}$ and N_X be the nearest neighbor of X in S_{-X}. 1-NNA is the leave-one-out accuracy of the 1-NN classifier:

$$\text{1-NNA}(S_g, S_r) = \frac{\sum_{X\in S_g} \mathbb{1}[N_X \in S_g] + \sum_{Y\in S_r} \mathbb{1}[N_Y \in S_r]}{|S_g| + |S_r|},$$

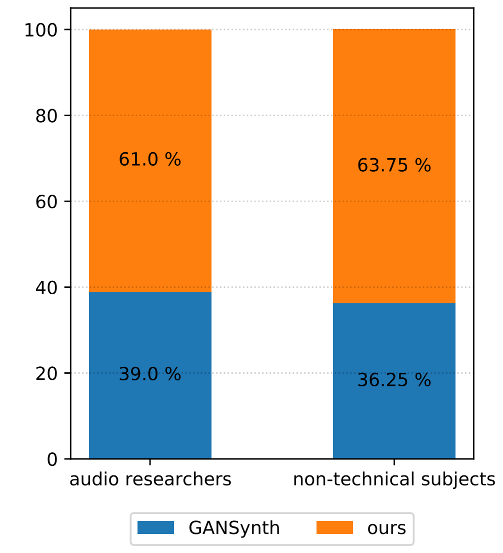


Fig. 2: caption

where $\mathbb{1}[\cdot]$ is the indicator function. For each sample, the 1-NN classifier classifies it as coming from S_r or S_g according to the label of its nearest sample. If S_g and S_r are sampled from the same distribution, the accuracy of such a classifier should converge to 50% given a sufficient number of samples. The closer the accuracy is to 50%, the more similar S_g and S_r are, and therefore the better the model is at learning the target distribution.

4.3. Experimental results

4.3.1. Dataset and implementation details

In this work, we propose a new dataset contains stereo audios with rich stereo images. The dataset consists of EDM stabs with 400ms time duration. Further details can be found in Appendix B. As mentioned in Section 3,

4.3.2. Quantitative results

We trained both our model and GANSynth [4] with same epochs in our training set.

4.3.3. Comparing audio quality to concurrent work

To better compare our method with concurrent work, we perform a subjective analysis over the stereo audios generated by both methods. In Fig[], we show the percentages of participants based on how they voted for the plausibility comparisons between ours and GANSynth [4]. The study employed 15 participants with different backgrounds - 5 audio researchers, 10 non-technical subjects. The participants are asked to choose the better audio between ours and other work. We can observe that our method received better results on both audio researcher group and non-technical subject group.

	COV (↑)	MMD (↓)	1-NNA (↓)
GANSynth [4]	34.55	1.42	76.22
Ours	**45.31**	**1.05**	**68.66**

Table 1: Quantitative comparison results of stereo audio generation on our dataset. The best results are marked in bold. Note that MMD is multiplied by 10^3.

5. CONCLUSION

In this paper, we propose a novel, yet simple, training scheme for a stereo audio generative model. Also we introduce a new dataset composed of two channel stereo audios with rich stereo images. By reparameterizing the L-R channel into M-S channel, the experiments on the proposed dataset demonstrate that our proposed training scheme gives promising results on every evaluation metrics (MMD, COV, 1-NNA). Furthermore, the study on human evaluations shows that our method is superior to the conventional method in terms of audio quality.

6. REFERENCES

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A. ADDITIONAL IMPLEMENTATION DETAILS

In this section we provide several additional details that are not provided in the main sections.

A.1. Neural Network Architecture

Generator	Output Size	k_{width}	k_{height}	$k_{filters}$	Nonlinearity
concat(Z, pitch)	(1, 1, 264)	-	-	-	-
conv2d	(2, 16, 256)	2	16	256	PN(LReLU)
conv2d	(2, 16, 256)	3	3	256	PN(LReLU)
upsample 2x2	(4, 32, 256)	-	-	-	-
conv2d	(4, 32, 256)	3	3	256	PN(LReLU)
conv2d	(4, 32, 256)	3	3	256	PN(LReLU)
upsample 2x2	(8, 64, 256)	-	-	-	-
conv2d	(8, 64, 256)	3	3	256	PN(LReLU)
conv2d	(8, 64, 256)	3	3	256	PN(LReLU)
upsample 2x2	(16, 128, 256)	-	-	-	-
conv2d	(16, 128, 256)	3	3	256	PN(LReLU)
conv2d	(16, 128, 256)	3	3	256	PN(LReLU)
upsample 2x2	(32, 256, 256)	-	-	-	-
conv2d	(32, 256, 128)	3	3	128	PN(LReLU)
conv2d	(32, 256, 128)	3	3	128	PN(LReLU)
upsample 2x2	(32, 512, 128)	-	-	-	-
conv2d	(32, 512, 64)	3	3	64	PN(LReLU)
conv2d	(32, 512, 64)	3	3	64	PN(LReLU)
upsample 2x2	(32, 1024, 64)	-	-	-	-
conv2d	(32, 1024, 32)	3	3	32	PN(LReLU)
conv2d	(32, 1024, 32)	3	3	32	PN(LReLU)
generator output	(32, 1024, 4)	1	1	4	Tanh
Discriminator	**Output Size**	k_{width}	k_{height}	$k_{filters}$	**Nonlinearity**
spectrogram image	(32, 1024, 4)	-	-	-	-
conv2d	(32, 1024, 32)	1	1	32	LReLU
conv2d	(32, 1024, 32)	3	3	32	LReLU
conv2d	(32, 1024, 32)	3	3	32	LReLU
downsample 1x2	(32, 512, 32)	-	-	-	-
conv2d	(32, 512, 64)	3	3	64	LReLU
conv2d	(32, 512, 64)	3	3	64	LReLU
downsample 1x2	(32, 256, 64)	-	-	-	-
conv2d	(32, 256, 128)	3	3	128	LReLU
conv2d	(32, 256, 128)	3	3	128	LReLU
downsample 2x2	(16, 128, 128)	-	-	-	-
conv2d	(16, 128, 256)	3	3	256	LReLU
conv2d	(16, 128, 256)	3	3	256	LReLU
downsample 2x2	(8, 64, 256)	-	-	-	-
conv2d	(8, 64, 256)	3	3	256	LReLU
conv2d	(8, 64, 256)	3	3	256	LReLU
downsample 2x2	(4, 32, 256)	-	-	-	-
conv2d	(4, 32, 256)	3	3	256	LReLU
conv2d	(4, 32, 256)	3	3	256	LReLU
downsample 2x2	(2, 16, 256)	-	-	-	-
concat(x, minibatch std.)	(2, 16, 257)	-	-	-	-
conv2d	(2, 16, 256)	3	3	256	LReLU
conv2d	(2, 16, 256)	3	3	256	LReLU
discriminator output	(1, 1, 1)	-	-	1	-

Table 2: Full description of our neural network architecture.

A.2.

B. DATASET DETAILS