Conditioning Trick for Training Stable GANs

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Abstract

In this paper we propose a conditioning trick, called difference departure from normality, applied on the generator network in response to instability issues during GAN training. We force the generator to get closer to the departure from normality function of real samples computed in the spectral domain of Schur decomposition. This binding makes the generator amenable to truncation and does not limit exploring all the possible modes. We slightly modify the BigGAN architecture incorporating residual network for synthesizing 2D representations of audio signals which enables reconstructing high quality sounds with some preserved phase information. Additionally, the proposed conditional training scenario makes a trade-off between fidelity and variety for the generated spectrograms. The experimental results on UrbanSound8k and ESC-50 environmental sound datasets and the Mozilla common voice dataset have shown that the proposed GAN configuration with the conditioning trick remarkably outperforms baseline architectures, according to three objective metrics: inception score, Fréchet inception distance, and signal-to-noise ratio.

1 Introduction

Generative models have been widely used in several audio and speech processing tasks such as speaker verification (Reynolds et al., 2000), enhancement (Chehrehsa & Moir, 2016), synthesis (Raitio et al., 2010), etc. In the last few years, many generative adversarial network (GAN) architectures have been introduced (Bollepalli et al., 2019; Sriram et al., 2018) and they have contributed for tackling such challenging tasks. Furthermore, GANs have been employed in high-level data augmentation for supervised, semi-supervised, and unsupervised audio and speech classification (Hu et al., 2018; Donahue et al., 2018). In augmentation with paired transformations, cycle-consistent GANs have been developed for environmental sound classification (Esmaeilpour et al., 2020b) as well as for more sophisticated tasks such as voice conversion (Fang et al., 2018). A typical GAN runs a minimax game between generator and discriminator networks, where the latter should distinguish the real sample from the generated example. Following such a baseline GAN, many other variants in terms of similarity metric, loss function, and architectures have been introduced such as the Wasserstein GAN (Arjovsky et al., 2017), GANs with least squares loss (Mao et al., 2017), attention-based architectures for adversarially training (Zhang et al., 2019), etc. However, training and tuning such advanced
GAN models have always been a mounting concern and a difficult challenge due to their instability in training (Salimans et al., 2016; Arjovsky & Bottou, 2017; Yang et al., 2017). Our main contribution in this paper is in response to this issue. We propose to condition the generator for minimizing dissimilarity among generated and real samples using a normality metric computed in the spectral domain of Schur decomposition (Van Loan & Golub, 1983). This binding improves stability of the generator and does not limitate exploring all the possible modes during training. Without lack of generalizability, our case study in this work is spectrogram synthesis in the domain of audio and speech processing. Spectrograms are 2D representations of 1D signals without phase information (Lang & Forinash, 1998). Spectrogram either from short-time Fourier transformation (STFT) and its variants such as Mel-frequency cepstral coefficients (Hossan et al., 2010) or discrete wavelet transform (DWT) is a standard and common signal representation in signal processing due to its lower dimensionality which densely encodes local frequency information (Mallat, 1999; Rioul & Vetterli, 1991). The highest recognition accuracies have been achieved for classifiers trained on frequency-magnitude representations (Hanun et al., 2014) and this indicates the importance of yielding high quality and informative spectrograms for improving classification performance.

For objectively measuring the impact of this conditioning on the baseline models and our slightly modified BigGAN architecture (Brock et al., 2019), we compute both the inception score (IS) (Salimans et al., 2016) and Fréchet inception distance (FID) (Heusel et al., 2017). Since the quality of the generated spectrograms might not be easily interpretable by human eye, we reconstruct audio signals with some preserved phase information from original samples and measure the signal-to-noise ratio (SNR). Our experimental results on two complete environmental sound and partial Mozilla common voice datasets have shown considerable improvement in generating diverse signals with high fidelity. The rest of the paper is organized as follows. In Section 2 we review some related works and in Section 3 we explain theories for constraining the generator. We provide our experimental results and associated discussions in Section 4.

2 Background

The generator network $G(z; \theta_g)$ commonly learns to map from $p_z \sim N(0, I)$ or $U[-1, 1]$ to $p_g$ for $z \in \mathbb{R}^d$, and the discriminator network $D(x; \theta_d)$ should maximize $\mathbb{E}_{z \sim p_z}(z) \log (1 - D(G(z)))$ against the generator as defined in (1) (Goodfellow et al., 2014).

$$\min_G \max_D \mathbb{E}_{x \sim p_r(x)} \left[ \log D(x) \right] + \mathbb{E}_{z \sim p_z(z)} \left[ \log (1 - D(G(z))) \right]$$ (1)

The generator $G(z; \theta_g)$ and discriminator $D(x; \theta_d)$ networks are often modeled by convolutional neural networks with different architectures (Radford et al., 2015). The optimization problem of (1) not only requires carefully-tuned hyperparameters, but also is very unstable and often collapses during training (Salimans et al., 2016; Thanh-Tung et al., 2019). Generally, there are two approaches to address this issue. First, changing the optimization functions mainly for the generator (Fedus et al., 2017; Zhang et al., 2019; Karras et al., 2018; Dumoulin et al., 2016; Nowozin et al., 2016; Salimans et al., 2016; Chen et al., 2016; Sønderby et al., 2016; Odena et al., 2017). Likewise, changing the similarity metric from Jensen-Shannon divergence (JSD) to Wasserstein loss (Arjovsky...
et al., 2017) and Pearson χ² divergence in least-square GAN (Mao et al., 2017) have also been proposed. Second, constraining the discriminator network to provide meaningful gradients everywhere to \( G(z; \theta_g) \) (Mescheder et al., 2018; Miyato et al., 2018; Gulrajani et al., 2017) [Kodali et al., 2017].

There are two approaches that are relevant to our work for improving stability in GAN training. The first one is focused on bijective mapping between \( p_g \) and \( p_r \) using another network such as an autoencoder (Donahue et al., 2016). This ensures a correlation between generated and real samples through a regularization function similar to \( \min \| z - \text{Rec}(G(z)) \|_2 + H(z, \text{Rec}(x)) \) where \( \text{Rec} \) denotes the reconstructor network (autoencoder) and \( H \) is the entropy loss (Srivastava et al., 2017). Besides, some variational autoencoder schemes have been also proposed for avoiding instability (Kingma & Welling, 2014; Rezende et al., 2014). The effectiveness of explicit regularization of loss functions with autoencoder loss has been studied by Che et al. (2016). They have introduced several costly metrics for estimating modes and enhancing quality of the generated samples. A similar metric for encoding random samples from \( p_r \) to \( p_g \) has been developed by Larsen et al. (2015). Both of these approaches incorporate \( \mathcal{L}[x, G(\text{Rec}(x))] \) which is a pixel-wise loss followed by another regularization term. The second approach is spectral normalization (Miyato et al., 2018) which conditions the discriminator to support Lipschitz continuity using singular value decomposition. This approach regularizes \( \theta_d \) (the weight matrix of the discriminator) towards the direction of the top rank (first) singular value. Inspired by Zhang et al. (2019), it has been shown that this regularization can be implemented more effectively for \( G(z; \theta_g) \) as (Brock et al., 2019):

\[
\theta_g = \theta_g - \max(0, \sigma_0 - \sigma_{\text{clamp}}) v_0^\top u_0
\]

where \( \theta_g \) denotes the weight matrix of the generator and \( v_0^\top u_0 \) forms the first basis matrix of \( \theta_g \) after decomposition. The threshold \( \sigma_{\text{clamp}} \) can be set to a predefined value (which implies an additional hyperparameter) or \( \sigma_{\text{clamp}} = \text{sg}(\sigma_1) \); where \( \text{sg} \) stands for the stop-gradient operation. This normalization can be generalized to other subsequent singular values, efficiently computed by Arnoldi method (Golub & Van der Vorst, 2000).

While instability is a common problem when training GANs with any dataset, it is critical for 2D representations of audio and speech, mainly due to the properties of Fourier or wavelet transforms (Esmaeilpour et al., 2020b). In the next section, we explain how to control the generator for producing high fidelity spectrograms through correctly conditioning it.

### 3 Conditioning the Generator

In light of correlating \( p_g \) to \( p_r \) and spectral normalization in response to the instability issue in adversarial training, we condition \( G(z; \theta_g) \) in another spectral domain to enhance the stability and also in order to provide better gradients everywhere to the discriminator. Our conditioning is fundamentally different from employing an autoencoder or regularizing either \( \theta_g \) or \( \theta_d \) through normalizing their singular value(s). Instead of normalizing the top rank eigenvalues of \( \theta_g \) in spectral normalization (Zhang et al., 2019), we asymptotically correlate \( p_g \) to \( p_r \) in such a way that it forces the generator to follow Schur spectral distribution \( p_r \). In fact, we force the generator to get closer to the departure from normality function computed for the original spectrograms in \( p_r \) defined in
the spectral domain of the generalized Schur decomposition \cite{VanLoan&Golub1983}. This binding makes the generator amenable to the truncation trick \cite{Brocketal2019} and the discriminator might converge in fewer iterations. Additionally, it neither limits spanning the entire possible modes nor loses sample variety.

**Lemma.** For an input sample (spectrogram) \( x_i \) from a given distribution, there exists a unitary representation \( Q \in \mathbb{C}^{n\times n} \) in such a way that \cite{Golub&VanLoan2012}:

\[
Q^H x_i Q = V + S
\]

where \( Q^H \) denotes the conjugate transpose of \( Q \) in vector space of Schur decomposition, \( S = \{ s_i \mid i = 0 : n - 1 \} \subset \mathbb{C}^{n\times n} \) is an upper triangular matrix, and \( V = \text{diag}(\lambda_0, \lambda_1, \ldots, \lambda_{n-1}) \) contains eigenvalues of \( x_i \) (\( \lambda_i \) denotes an independent eigenvalue for \( x_i \)). In this unitary vector space, which might also yield a quasi-upper triangular representation for \( S \), \( Q = [q_0 \mid q_1 \mid q_2 \mid \cdots \mid q_{n-1}] \) provides the pencil of \( q_i^T - \lambda_i q_{i+1}^T \) for \( i \leq n - 2 \) which is also known as basis vector for \( x_i \). According to the perpendicularity of the achieved pencils and the support matrix \( S \), we write:

\[
x_i q_k \approx \lambda_k q_k + \sum_{i=0}^{n-1} s_{ik} q_i, \quad k = 0 : n - 1.
\]

Therefore with the general assumption of quasi-upper triangular subspaces with the normal span of \( \{ q_0, q_1, \ldots, q_k \} \) for \( k = 0 : n - 1 \), we can conclude that the choice of \( S \) should be independent of \( Q \) \cite{Golub&VanLoan2012}. Accordingly, we can compute its Frobenius norm using \( \lambda_i \) as:

\[
\| S \|^2_F = \| x_i \|^2_F - \sum_{i=0}^{n-1} | \lambda_i |^2 \equiv \Delta^2(x_i)
\]

where \( \Delta^2 \) is known as departure from normality (DFN) \cite{Golub&VanLoan2012}. For ensuring the correlation between \( x_r \) and \( x_g \) randomly drawn from \( p_r \) and \( p_g \) in their designated vector spaces (span of \( q_s \)), the DFN metric should support \( | \Delta^2(x_j) - \Delta^2(x_i) | < \epsilon \) for a small enough \( \epsilon \). Such a DFN condition also ensures the consistency of corresponding pencils and contributes to the generalized form of Schur decomposition with \( Q_k^H x_r Z_k = R_k^H (V_k + S_k) \) and \( Q_k^H x_g Z_k = R_k^H (V_k + S_k) \), where \( R_k = Q_k^H (x_r x_g^{-1} Q_k) \) and \( Z_k \) is also unitary and supports for \( \lim_{i \to \infty} (Q_k, Z_k) = (Q, Z) \) \cite{Golub&VanLoan2012}. The intuition behind exploiting these basis vectors is providing pencils of \( x_n^r - \lambda_i x_n^g \) for learning the original distribution \( p_r \) by the generator. The derivable pencils are not necessarily normal in the span of their associated subspaces, however, their linear combination imparts \( p_r \) to \( p_g \) (in the closed form). Furthermore, diagonal values in \( V \) constitute coefficient of basis vectors (sub-pencils in their manifolds) and represent local properties of the given input sample.

**Proposition.** The DFN metric in the form \( | \Delta^2(x_g) - \Delta^2(x_r) | < \epsilon \) ensures the correlation of \( x_g \sim p_g \) and \( x_r \sim p_r \) in the spectral domain with a measurable error term \( \epsilon \).

**Proof.** Since \( \Delta^2(.) \) is differentiable in its designated subspaces, we can find an upper bound for \( \epsilon \). For all \( x_i := \max(\text{diag}(S_i)) \) we assume \( g_r(x_i) = \Delta^2(x_i) \in \mathbb{C}^{n+1} \) with degree
$n + 1$ and $g_{n}(x) = \Delta^{2}(G(z))$ $\in \mathbb{C}^{n}$ with degree $n$ are differentiable over the interval $[\bar{\omega}_{\text{inf}}, \bar{\omega}_{\text{sup}}]$, therefore we can approximate the error function as (Phillips, 2003):

\[
e(x) = g_{r}(x) - g_{n}(x) = \frac{g_{n}(x)}{(n + 1)!} \prod_{i=0}^{n} (x - x_{i})
\]

where $\xi \in (\bar{\omega}_{\text{inf}}, \bar{\omega}_{\text{sup}})$ with the marginal condition using the second derivative $|\partial_{r}(x)| < g$ for $0 \leq g < 1$ and $n = 1$ we write:

\[
g_{r}(x) - g_{n,1}(x) = (x - x_{i}) (x - x_{i+1}) \frac{\partial_{r}(\xi)}{2!} \Rightarrow \partial_{r}(x) = 2x - (x_{i} + x_{i+1}) = 0 \Rightarrow x = \frac{x_{i} + x_{i+1}}{2} \quad \Box \quad (7)
\]

Herein, $|e(x)|$ measures how the dynamic $\Delta^{2}_{2}(\cdot)$ is close to the static $\Delta^{2}_{2}(\cdot)$ and equivalently measures the correlation between $p_{r}$ and $p_{n}$. We experimentally demonstrate that minimizing the generator $G(z)$, subject to:

\[
\|E_{z \sim p_{r}(z)} \Delta^{2}(G(z)) - E_{z \sim p_{r}(z)} \Delta^{2}(z)\| < \epsilon
\]

yields high quality spectrograms and improves stability.

### 3.1 Fast DFN Approximation

Computing $\sum_{i=0}^{n-1} |\lambda|^{2}$ as defined in (5) can be computationally prohibitive since it involves recursive multiplication of pencils. In response to this issue, $f_{V}(\lambda_{i})$ can be defined as a polynomial function originating from the absolute product of eigenvalues (Edelman, 1993; Van Loan & Golub, 1983):

\[
\sum_{i=0}^{n-1} |\lambda|^{2} \approx \sum_{i=0}^{n-1} \left( \prod_{i=0}^{n-1} f_{V}(\lambda_{i}) \prod_{i \neq j} |\lambda_{i} - \lambda_{j}| \left( \frac{e^{-\sum_{j=0}^{n-1} \lambda_{j}^{2}/2}}{\text{Normal distribution}} \right) \right)
\]

where it imparts a normal distribution and closely relates to the joint density function of the eigenvalues for a random symmetric matrix $\bar{\Omega}_{k \times k} := (\varrho + \varrho^{T})/2$. We derive $\varrho$ by downsampling a given input spectrogram (i.e., $x_{n \times n}$) by a factor of two. Every single element of the derived Toeplitz matrix (5) should be also distributed according to a normal distribution (Van Loan & Golub, 1983). The probability distribution of $\bar{\Omega}$ which is also known as Gaussian orthogonal ensemble (Alt et al., 1995; Wu et al., 1990) for the eigenvalues of $\lambda$ has the form of (Edelman, 1993):

\[
\frac{2^{-k/2}}{\prod_{i=1}^{k} \nu(i/2)} \prod_{i \neq j}^{k-1} |\lambda_{i} - \lambda_{j}| e^{-0.5 \sum_{i=0}^{n-1} \lambda_{i}^{2}}
\]

where $\nu(\cdot)$ denotes Minkowski function (Panti, 2008, Thompson & Thompson, 1996). Accordingly, the summation of (9) for fast approximation (5) is the expectation over the
determinants of $\mathcal{O}$ as (Edelman, 1993):

$$\frac{1}{k!} \sum_{i=0}^{n-1} \left( \prod_{i=0}^{n-1} f_V(\lambda_i) \prod_{i \neq j}^{n-1} |\lambda_i - \lambda_j| e^{-\sum \lambda_i^2/2} \right) \approx \left\{ 2^{k/2} \prod_{i=0}^{k-1} \nu(i/2) \right\} E_{\mathcal{O}} \det \left( \mathcal{U} \right)$$ (11)

Although there are some analytical approaches for closely approximating $f_V(\lambda_i)$, we simply use $\mathcal{U}$ since it is normally distributed over $x$ and $\lambda_i \to 0$ for $i > 0.5 \cdot k$. Therefore $\det(\mathcal{U})$ gives an acceptable approximation.

4 Experimental Results

In this section, we provide details of our experiments on two benchmarking environmental sound datasets: UrbanSound8K (Salamon et al., 2014) and ESC-50 (Piczak, 2015). We have also conducted a brief ablation study for Mozilla common voice (MCV). The first two datasets include 8,732 and 2,000 short environmental audio signals ($\leq$ 5 sec) organized in 10 and 50 different classes, respectively. MCV consists of 4,257 recorded hours of multi-language speeches ($\leq$ 7 sec) and the corresponding text transcriptions.

For generating DWT spectrograms, we use complex Morlet mother function with static sampling frequency of 16 kHz and frame length of 50 ms with 50% overlapping. We represented each spectrogram using three different visualizations of linear, logarithmic, and logarithmic-real magnitude scales (see Appendix B) (Esmaeilpour et al., 2020a). For STFT spectrograms, we set the number of filters to 2,048 with the hop length of 1,024 and reflect padding in overlapping audio chunks of 50 ms (with ratio 0.5) (Esmaeilpour et al., 2020a). Meanwhile, we apply pitch shifting (Salamon & Bello, 2017) with scales 0.75, 0.9, 1.15, and 1.5 for audio signals with length $\leq$ 2 seconds for data augmentation (Esmaeilpour et al., 2020).

Our baseline model is the SA-GAN architecture (Zhang et al., 2019) using the hinge loss objective for smooth training (Lim & Yeo, 2017). Since we employ class-conditional (CC) learning similar to Mirza & Osindero (2014), the generator receives CC batch-norm as suggested by De Vries et al. (2017). For the discriminator, we run the identical procedure with projection (Miyato & Koyama, 2018) following the same optimization procedure in the baseline SA-GAN, however with some modifications in the number of channels and applying spectral regularization for the generator network. We have evaluated different options for initializing both networks, such as Glorot (Glorot & Bengio, 2010) and variants of $\mathcal{N}(0, I)$ (e.g., $\mathcal{N}(0, 0.02I)$) (Radford et al., 2016). Since this choice noticeably affects the training performance (Brock et al., 2019) and requires to be evaluated individually according to properties of the dataset, we eventually used orthogonal regularization (Saxe et al., 2014).

Figure 1 depicts the performance of four GAN architectures trained on logarithmic DWT spectrograms. All these models undergo collapse at different iterations which forces to early stop the training. All the subsequent quality measurements on the performance of these models will be conducted on the checkpoints prior to collapse. We compute the $|\Delta^2(x_g) - \Delta^2(x_r)|$ for each model to demonstrate collapse without imposing the difference DFN condition on their generators (see inequality (8)). These plots corroborate

[https://voice.mozilla.org/en/datasets]
the positive impact of spectral normalization on delaying collapse at further iterations. The best performance of this normalization is when it is applied only on $D(x; \theta_d)$ (see Figures 1(b) and 1(c)), though incorporating it into both $G(z; \theta_g)$ and $D(x; \theta_d)$ still outperforms the baseline SA-GAN.

Figure 1: The typical plot of the difference DFN measures for a random non-convolution layer in $G(z; \theta_g)$ trained on STFT and logarithmic DWT representations of UrbanSound8K dataset. (a) The baseline SA-GAN, (b) the BigGAN architecture with spectral normalization in both $G(z; \theta_g)$ and $D(x; \theta_d)$, (c) the BigGAN configuration with spectral normalization only in $D(x; \theta_d)$, and (d) the scaled up (by a factor of 2) configuration for (c). Arrows in these sub-figures refer to collapse onsets.

Furthermore, we have evaluated the impact of increasing the batch size on the performance of GANs during training while monitoring the difference DFN measure along iterations. We scaled up the batch size to 256 and 512 aiming at covering more modes and providing better gradients to both $G(z; \theta_g)$ and $D(x; \theta_d)$ (Brock et al., 2019). Figure 1(d) depicts this effect for the BigGAN with batch size of 512 and regularized $\theta_d$ using spectral normalization. According to this graph although this GAN keeps its stability until about 100k iterations, it undergoes complete collapse afterward. Moreover, the difference DFN measure is considerably improved compared to other three GANs which indicates convergence in fewer iterations. We additionally scaled up the number of channels (width) in each layer of the networks by a factor of 2 at the cost of doubling the number of required parameters. However this did not rectify nor delay the collapse at higher iterations.

We slightly modify the BigGAN architecture for class conditional (CC) training (see Appendix A). Three major settings in CC training are required to adapt our benchmarking datasets. Firstly setting the conditional vector ($c$-embedding) and secondly, the skip connection (direct skip-$z$) from the given noise vector according to the designated probability distribution. While using separate layers for $c$-embeddings has been proposed by Miyato et al. (2018), we also found shared embeddings (Perez et al. 2018; Brock et al. 2019) outperforms the latter. For the skip-$z$ connection probe, we firstly evaluated splitting $z \sim \mathcal{N}(0, I)$ and $z \sim \mathcal{N}(0, 0.02I)$ vectors into smaller chunks (we set to 20) and concatenating them into $c$-embeddings in each level of resolution as suggested by Brock et al. (2019), then explored a couple of other variants (Denton et al., 2015; Goodfellow et al., 2014). We ended up to concatenate the vector $z$ in its entire dimension to $c$-embeddings (Brock et al. 2019). Finally, the third setting is the number of units in each hidden layer of the networks (the channel multiplier). Increasing this hyperparameter relatively affects the IS and FID scores for the model.

Our objective evaluations are summarized in Table 1 and the number of iterations
Recently an improved version of this regularization has been introduced and results to early collapse at about 25k iterations while trained on logarithmic DWT spectrograms (resolution $128 \times 128$) by running spectral normalization and difference DFN measure $\|\theta_d^\top \theta_d - I\|_F^2$. This regularization prohibitively affects the generator and results to early collapse at about 25k iterations while trained on logarithmic DWT spectrograms. Recently an improved version of this regularization has been introduced [Brock et al., 2019]:

$$R_\beta = \beta \|	heta_d^{\top} \theta_d - I\|_F^2$$

where $\beta$ is a small hyperparameter. This regularization prohibitively affects the generator and results to early collapse at about 25k iterations while trained on logarithmic DWT spectrograms. Recently an improved version of this regularization has been introduced [Brock et al., 2019]:

$$R_\beta = \beta \|	heta_d^{\top} \theta_d \odot (1 - I)\|_F^2$$

### 4.1 Orthogonal Regularization vs. Difference DFN

The orthogonal regularization [Brock et al., 2019] has been proposed for smooth training, which to some extent, makes a better trade-off between sample variety and fidelity by constraining over $\theta_d$ as:

$$R_\beta = \beta \|	heta_d^{\top} \theta_d - I\|_F^2$$

### Table 1: Comparison of the inception score (higher is better) and Fréchet inception distance (lower is better) for our proposed modification to BigGAN trained on logarithmic DWT spectrograms (resolution $128 \times 128$) by running spectral normalization and difference DFN minimization on $D(x; \theta_d)$ and $G(z; \theta_g)$, respectively. Scores are averaged over 5k generated spectrograms over 10 different runs for each dataset. Values inside parenthesis in the last two columns correspond to linear-DWT, logarithmic-real-DWT, and STFT representations. Accordingly, up-/down-ward arrows denote increase/decrease in scores relative to the logarithmic DWT. The best results are shown in boldface.

| Dataset | Orthogonal Regularization | Iteration $\times 1000$ | IS       | FID       |
|---------|---------------------------|-------------------------|----------|-----------|
| US8K    | False $(batch = 256)$ $(ch. = 64)$ | $132 \ (\downarrow 3.50, \uparrow 1.148, -)$ | $43.12 \pm 1.46$ | $44.57 \pm 2.93$ |
|         | True $(batch = 256)$ $(ch. = 96)$ | $138 \ (\downarrow 2.64, \uparrow 1.54, -)$ | $46.89 \pm 0.12$ | $29.06 \pm 1.18$ |
|         | False $(batch = 512)$ $(ch. = 64)$ | $134 \ (\downarrow 2.41, \uparrow 1.78, -)$ | $49.61 \pm 0.12$ | $21.75 \pm 0.31$ |
|         | True $(batch = 512)$ $(ch. = 96)$ | $133 \ (\uparrow 1.94, \uparrow 2.72, \downarrow 27.19)$ | $52.36 \pm 1.19$ | $21.93 \pm 1.11$ |
| ESC-50  | False $(batch = 256)$ $(ch. = 64)$ | $148 \ (\uparrow 0.64, \uparrow 5.63, -)$ | $68.76 \pm 3.14$ | $34.61 \pm 2.23$ |
|         | True $(batch = 256)$ $(ch. = 96)$ | $(\downarrow 7.91, \downarrow 19.68)$ | $71.94 \pm 1.42$ | $29.81 \pm 3.15$ |
|         | False $(batch = 512)$ $(ch. = 64)$ | $139 \ (\downarrow 1.47, \downarrow 2.38, -)$ | $71.46 \pm 0.26$ | $29.03 \pm 1.05$ |
|         | True $(batch = 512)$ $(ch. = 96)$ | $145 \ (\uparrow 3.55, \uparrow 1.95, -)$ | $73.69 \pm 1.47$ | $23.03 \pm 2.47$ |

This table also compares the effect of batch size and number of channels on the performance of our slightly modified BigGAN using spectral normalization and difference DFN measure. According to this table, doubling the batch size considerably improves both the IS and FID. Among different configurations for the GAN, models trained on three visualizations of DWT spectrograms dominantly outperform the STFT. We conjecture that this is due to the complexity of Morlet mother function [Young, 2012] compared to sinusoidal transform in STFT.
where $\mathbf{1}$ refers to a matrix with constant values of 1. This regularization term binds to minimize local similarity among filters. In our experiment we found out $\beta \in (10^{-4}, 10^{-5}]$ is the best range for STFT and DWT spectrograms except for the logarithmic-real. Upon running several exploratory experiments, we set $\beta = 10^{-4}$ for it. Unlike orthogonal regularization, the difference DFN does not involve weight matrix manipulations at each layer. This considerably reduces the computational cost for training and makes the discriminator converge in fewer iterations and remarkably delays the collapse at higher iterations. Table 1 shows the positive effect of orthogonal regularization while used with minimized DFN measure.

4.2 Spectrogram Fidelity and variety

Similar to Brock et al. (2019), our modification to the BigGAN makes the model amenable to truncation for $p_r \sim \mathcal{N}(0, \alpha I)$ where the threshold $\alpha \in [0, 1)$. Smaller values for $\alpha$ negatively affects the total number of spectrogram variety however, considerably boosts the quality of the generated samples. This trade-off (see a relevant study in Marchesi (2017)) also affects the actual value of $\epsilon$ in computing difference DFN measure (inequality (8)). Averaged over different experiments on logarithmic DWT representations, for $\alpha \leq 0.5$ we achieve $\epsilon \leq 37.16$. This indicates higher quality of the generated spectrogram at the cost of losing sample variety. Likewise, increasing $\epsilon$ expands the sample variety but with degraded sample quality (see Figure 2). Our GAN architecture for $\alpha \leq 0.2$ generates oversmoothed spectrograms as a result of a poorly conditioned model and increases (explodes) $\epsilon$ toward higher values.

![Figure 2: Generated logarithmic DWT spectrograms using our modified BigGAN with spectral normalization and minimized DFN measure.](image)

The truncation trick directly increases the IS and specifically for $\alpha = 0.25$ we noticed 12.3% improvement in generating high quality logarithmic DWT spectrograms compared to $\alpha = 2$ or $\mathcal{U}[-1, 1]$. Moreover, a slight reduction in $\alpha$ positively impacts the FID by reducing the score 10% on average, however, when $\alpha \to 0$ the FID sharply increases. Whereas FID, the IS does not penalize sample variety, however, it rewards precision and this turns out to be a biased objective evaluation on the quality of generated spectrograms (Brock et al. 2019). Moreover, interpretation and quality analysis of the generated spectrograms could be very difficult to human eyes. To address this issue, we reconstruct
the audio signals from them and measure the SNR. This requires access to the phase information for each spectrogram and unfortunately we could not successfully train our model with phase vectors. Although, there are some approaches for phase approximation or reconstructing signal almost without phase information using GAN, we noticed they often introduce noise (ambient, background, hissing, etc.) to the reconstructed signal. We eventually opted to utilize subjective phase vectors from original known samples. Figure 3 shows that spectrograms with lower values of α and ϵ better reconstruct audio signals in terms of quality (see Appendix B for additional information).

4.3 Summary and Ablation Study

In this section we compare the best performance of our proposed model with other GANs considering 256 × 256 and 128 × 128 input resolutions, as shown in Table 2. We use the ablated model for MCV dataset on 100k randomly selected recordings shorter than five seconds. Moreover, we objectively compare the quality of the reconstructed signals using the SNR\(^2\) (Kereliuk et al., 2015). A high SNR means the reconstructed signal has low noise. Table 2 summarizes the results on four spectrogram representations averaged over 5k generated spectrogram at 10 different runs for each dataset. Doubling the resolution to 256×256 improves both the IS and the FID, however roughly doubles the number of training parameters. Adding this note to the truncation trade-off, we can conclude that for synthesizing high quality sounds, we need to tune three major hyperparameters: α, large batch sizes, and high resolutions. Table 2 also shows the results of an ablation study on UrbanSound8K and the conclusions are similar to those on MCV.

5 Conclusion

In this paper, we have proposed a conditioning trick for the generator network based on the difference DFN measure in the spectral domain of Schur decomposition. We have experimentally demonstrated its positive impact in improving model stability at larger resolutions.

\(^2\)SNR\(_{\text{db}}\)(x, y) = 20\log_{10} \frac{P_x(x)}{P_y(x)} where \(P_x(.)\) denotes the power of the signal.
Table 2: Comparison of average IS, FID and SNR for different models trained on logarithmic DWT spectrograms. Outperforming values are in bold. Spectral normalization applied only on $D(\mathbf{x}; \theta_d)$ for all the BigGANs and its modified variant (the proposed architecture). Res. stands for resolution.

| Dataset | Model           | Res. | IS            | FID            | SNR$_{db}$ |
|---------|-----------------|------|---------------|----------------|------------|
|         | SA-GAN (baseline) | 128  | 59.14 ± 2.24  | (↓ 4.54, ↓ 1.46, −) | 41.91      |
|         | BigGAN          | 128  | 54.95 ± 1.04  | (↑ 2.14, ↓ 3.48, −) | 46.93      |
|         | BigGAN (+DFN)   | 128  | 35.57 ± 2.92  | (↑ 1.02, ↑ 3.46, −) | 51.01 ± 2.18 | 53.72      |
|         | Proposed (+DFN) | 128  | 50.79 ± 0.14  | (↓ 3.30, ↓ 2.48, −) | 43.37 ± 1.65 | 56.91      |
|         |                 | 256  | **56.20 ± 1.73** | (↓ 4.03, ↓ 2.95, −) | **36.31 ± 3.63** | **62.89** |
|         | SA-GAN (baseline) | 256  | 34.72 ± 0.23  | (↑ 1.17, ↑ 2.39, −) | −          |
|         | BigGAN          | 256  | 39.16 ± 5.07  | (↓ 4.56, ↓ 3.94, −) | 37.26 ± 3.53 | 48.14      |
|         | BigGAN (+DFN)   | 256  | 48.62 ± 0.23  | (−, ↑ 2.39, −) | 25.63 ± 2.42 | 55.17      |
|         | Proposed (+DFN) | 256  | **57.91 ± 2.19** | (↓ 7.48, ↓ 4.88, ↓ 15.34) | **16.33 ± 1.87** | **63.24** |

Table 2: Comparison of average IS, FID and SNR for different models trained on logarithmic DWT spectrograms. Outperforming values are in bold. Spectral normalization applied only on $D(\mathbf{x}; \theta_d)$ for all the BigGANs and its modified variant (the proposed architecture). Res. stands for resolution.

iterations for both baseline self-attention and on a slightly modified BigGAN architecture for class-conditional learning. We have also shown that our training scenario makes the model amenable to truncation and this helps to make a trade-off between spectrogram quality and variety. According to three objective metrics of IS, FID, and SNR, models conditioned with DFN outperform baselines in generating high quality spectrograms and less noisy reconstructed audio and speech signals.

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### A Appendix

Figure 4 depicts the schematic of our slightly modified version of BigGAN (Brock et al., 2019). This architecture uses the ResNet (He et al., 2016) with different channel multipliers and shared class embeddings in the generator. Unlike the BigGAN architecture, we constantly use 3 × 3 padded convolution with stride of 2. For the skip-connection, we use static chunks of 20-D in accordance with each residual block. Details of the networks are shown in Table 3 and Table 4.

As suggested (Brock et al., 2019) for the CC conditioning in each residual block, the linear projection has been used where the bias and gain projections are centered at 0 and 1, respectively. We use Orthogonal initialization (Saxe et al., 2014) for both generator and discriminator networks. For the choice of the optimier, Adam (Kingma & Ba, 2014) is utilized with β1 = 0.0 and β2 = 0.9. The learning rate is set to 2 · 10⁻⁴ and 3 · 10⁻⁵ for discriminator and generator at both resolutions. The rest of settings for baselines are the same as (Zhang et al., 2019) implemented in TensorFlow (Abadi et al., 2016).

### B Appendix

We highly recommend reviewing these sources (Agbinya, 1996; Bahoura & Rouat, 2001) about DWT representations for audio and speech signals. Then we draw attentions to
Figure 4: The proposed architecture which is the slightly modified version of BigGAN in [Brock et al., 2019]. (Top): The generator architecture, (middle): a residual block in generator, (bottom): a residual block in discriminator.
Table 3: Our slightly modified BigGAN architecture for the resolution 128 × 128 spectrograms. Channel stands for the width multiplier in both networks. The rest of the settings such as standing statistics for batch normalization (at the test time) are the same as [Brock et al., 2019].

| Generator          | Discriminator                     |
|--------------------|-----------------------------------|
| $z \in \mathbb{R}^{120} \sim \mathcal{N}(0, I)$ | RGB Spectrogram $x_g \in \mathbb{R}^{128 \times 128 \times 3}$ |
| Linear (20 + 128)  | Residual Block (channel → 2 channel) |
| (→ 4 × 4 × 16 channel) | Non-local Block (64 × 64) |
| Residual Block (16 channel → 4 channel) | Residual Block (channel 2 → 8 channel) |
| Residual Block (4 channel → 1 channel) | Residual Block (channel 8 → 16 channel) |
| Non-local Block (128 × 128) | ReLU, Global Sum Pooling |
| Batch Normalization, ReLU, Convolution tanh | Linear → 1 |

Table 4: The modified BigGAN architecture for 256 × 256 spectrograms. This architecture has one additional residual network compared to smaller resolution 128.

| Generator          | Discriminator                     |
|--------------------|-----------------------------------|
| $z \in \mathbb{R}^{140} \sim \mathcal{N}(0, I)$ | RGB Spectrogram $x_g \in \mathbb{R}^{256 \times 256 \times 3}$ |
| Linear (20 + 128)  | Residual Block (channel → 2 channel) |
| (→ 4 × 4 × 16 channel) | Non-local Block (64 × 64) |
| Residual Block (16 channel → 4 channel) | Residual Block (2 channel → 4 channel) |
| Residual Block (4 channel → 4 channel) | Residual Block (4 channel → 8 channel) |
| Residual Block (4 channel → 1 channel) | Residual Block (8 channel → 16 channel) |
| Non-local Block (128 × 128) | ReLU, Global Sum Pooling |
| Batch Normalization, ReLU, Convolution tanh | Linear → 1 |

The clarification of three visualizations for DWT spectrograms. Briefly, the following code snippet explains linear, logarithmic, and logarithmic real visualizations.

```c
static float linearDWTspectrogram(float *data)
{
    /* Generating linear visualization for DWT spectrogram */
    Real part: data[0], Imaginary part: data[1]
    return sqrt(data[0]*data[0]+data[1]*data[1]);
}

static float logDWTspectrogram(float *data)
{
    /* Generating logarithmic visualization for DWT spectrogram */
    return log(sqrt(data[0]*data[0]+data[1]*data[1]));
}

static float logRealDWTspectrogram(float *data)
{
    /* Generating logarithmic–real visualization for DWT spectrogram */
    if (data[0] == 0.0) {
        return 0.0;
    }
```
We carefully train (early stopped at checkpoints before overtraining or potential col- lapse) our proposed GAN architecture (the modified version of BigGAN with DFN) separately on the generated visualizations of DWT spectrograms. Afterwards, we illustrate some generated spectrograms. Additionally, we reconstruct each spectrogram into audio signals (one channel) with a predefined original phase matrix to measure relative SNR (see Figures 5-10).

We encourage readers listen to some reconstructed speech signals from the synthesized logarithmic DWT spectrograms using our proposed GAN architecture which are included in the supplementary folder. There are six signals in this folder which their details are listed herein:

1. **Original speech:** This is a random original file from MCV dataset.

2. **Synthesized speech 1:** The reconstructed speech using the identical phase information from the aforementioned original speech. The synthesized spectrogram is generated by the model with $\epsilon = 34.53$ and $\alpha = 0.25$.

3. **Synthesized speech 2:** The reconstructed speech using the identical phase information from the aforementioned original speech. The synthesized spectrogram is generated by the model with $\epsilon = 47.05$ and $\alpha = 0.50$.

4. **Synthesized speech 3:** The reconstructed speech using the identical phase information from the aforementioned original speech. The synthesized spectrogram is generated by the model with $\epsilon = 56.37$ and $\alpha = 1$.

5. **Synthesized speech 4:** The reconstructed speech using the identical phase information from the aforementioned original speech. The synthesized spectrogram is generated by the model with $\epsilon = 78.14$ and $\alpha = 2$.

6. **Synthesized speech 5:** The reconstructed speech using the approximated phase information as proposed in (Krawczyk & Gerkmann, 2014). The synthesized spectrogram is generated by the model with $\epsilon = 34.53$ and $\alpha = 0.25$.

There is (relatively) no sensible background or ambient noise in the reconstructed speech signals with synthesized spectrograms and original phase information (synthesized speech 1-4). Although, reconstructing signals with approximated phase vectors (i.e., synthesized speech 5) adds noticeable noises to the signals, still the speech is understandable. This denotes the critical role of high quality spectrogram in reconstruction.

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3 Res. = 256, batch = 512, ch. = 96 with spectral normalization and difference DFN on discriminator and generator, respectively.
Figure 5: Generated logarithmic DWT spectrograms with our modified BigGAN and DFN for a random signal $\text{sig}_1$. Synthesized signals are reconstructed with the original phase.

Figure 6: Generated logarithmic DWT spectrograms with our modified BigGAN and DFN for another random signal $\text{sig}_2$. Synthesized signals are reconstructed with the original phase.
Figure 7: Generated linear DWT spectrograms with our modified BigGAN and DFN for a random signal $\text{sig}_1$. Synthesized signals are reconstructed with the original phase.

Figure 8: Generated linear DWT spectrograms with our modified BigGAN and DFN for another random signal $\text{sig}_2$. Synthesized signals are reconstructed with the original phase.
Figure 9: Generated logarithmic-real DWT spectrograms with our modified BigGAN and DFN for a random signal $\text{sig}_1$. Synthesized signals are reconstructed with the original phase.

Figure 10: Generated logarithmic-real DWT spectrograms with our modified BigGAN and DFN for another random signal $\text{sig}_2$. Synthesized signals are reconstructed with the original phase.