Efficient Non-Autoregressive GAN Voice Conversion using VQWav2vec Features and Dynamic Convolution

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Abstract

It was shown recently that a combination of ASR and TTS models yield highly competitive performance on standard voice conversion tasks such as the Voice Conversion Challenge 2020 (VCC2020). To obtain good performance both models require pretraining on large amounts of data, thereby obtaining large models that are potentially inefficient in use. In this work we present a model that is significantly smaller and thereby faster in processing while obtaining equivalent performance. To achieve this the proposed model, Dynamic-GAN-VC (DYGAN-VC), uses a non-autoregressive structure and makes use of vector quantised embeddings obtained from a VQWav2vec model. Furthermore dynamic convolution is introduced to improve speech content modeling while requiring a small number of parameters. Objective and subjective evaluation was performed using the VCC2020 task, yielding MOS scores of up to 3.86, and character error rates as low as 4.3%. This was achieved with approximately half the number of model parameters, and up to 8 times faster decoding speed.

Index Terms: Voice Conversion, General Adversarial Networks, Dynamic Convolution, Efficiency.

1. Introduction

Recently, the state-of-the-art (SOTA) voice conversion (VC) models \cite{1,2,3,4,5,6} have achieved good performance, the generated samples have reached near to human level of voice quality. In the recent Voice Conversion Challenge 2020 (VCC2020) Cascade ASR-TTS \cite{1} obtains competitive performance. It is composed of an automatic speech recognition (ASR) model and a text-to-speech (TTS) model. Both ASR and TTS models are large pretrained autoregressive (AR) Transformer \cite{8} models. Recently, there have been several works showing that Transformer models have parameter and decoding efficiency issues in both ASR \cite{9,10} and TTS \cite{11,12} areas. Hence it would be inefficient to deploy a cascade ASR-TTS model in practical situations where memory and computation resources are limited.

Table \ref{tab:1} presents an overview of cascade ASR-TTS \cite{1} and the proposed model. \cite{1} has more than 100 M (million) parameters in total. It is also notable that cascade ASR-TTS only supports many-to-one conversion direction, which means multiple source and only one target speaker are supported in each model. Hence, in scenarios with multiple target speakers, the parameter efficiency of cascade ASR-TTS is lower than models that support many-to-many conversion direction.

This paper focuses on improving efficiency of cascade ASR-TTS \cite{1}. Instead of using AR models, DYGAN-VC has a non-AR model structure, which is supposed to have better decoding efficiency.

Instead of using the Transformer ASR model, this paper proposes to use VQWav2vec. VQWav2vec \cite{13} is one of speech self-supervised learning models \cite{14,15,16} that encodes speech to features. VQWav2vec aims to learn unsupervised speech representations that benefit multiple downstreaming tasks. Based on Wav2vec \cite{14}, a vector-quantization \cite{17} module is introduced, which is a differentiable clustering method. With the discreteness introduced to the model, VQWav2vec features are supposed to contain speech content information and also be speaker-invariant. As shown in Table \ref{tab:1} comparing to the ASR model used in cascade AST-TTS \cite{1}, as a non-AR model, VQWav2vec is smaller. Additionally, a recent VC work \cite{18} used VQWav2vec features to improve data efficiency.

To improve efficiency of the Transformer TTS model, instead of using computational costly self-attention layers, this paper proposes to use dynamic convolution \cite{19} as a replacement. Lightweight convolution and dynamic convolution \cite{19} are proposed on the purpose of improving efficiency of large Transformer models. They can be seen as lightweight replacements for the computational expensive attention mechanisms of Transformer. Moreover, in a recent speech synthesis work \cite{20}, lightweight convolution has been introduced for better parameter and decoding efficiency.

This paper proposes DYGAN-VC, a novel VC model based on generative adversarial networks (GAN) \cite{21}. Instead of using large AR models as in \cite{1}, DYGAN-VC uses VQWav2vec, which is lightweight. As a replacement of the self-attention layer, dynamic convolution \cite{19} is introduced for better parame-
Table 1: A comparison of VC models. The columns means: (1) use text transcriptions, (2) conversion directions between source and target speakers, many-to-many means multiple source speakers and multiple target speakers (3) number of parameters (4) autoregressive Emb denotes speaker embedding model.

2. Background

This section introduces background information for DYGAN-VC. It firstly introduces a comparison of lightweight convolution and dynamic convolution. Then it introduces the differences of AdaIN [22] and WadaIN [23], which is used in DYGAN-VC.

2.1. Lightweight convolution and dynamic convolution

Lightweight convolution is a variant of 1d convolution, it has fewer parameters than vanilla 1d convolution. Given a feature matrix $X \in \mathbb{R}^{b \times t \times c}$, where $b$, $t$, $c$ denote the batch size, the segment length and the number of channels. Lightweight convolution has kernels $K \in \mathbb{R}^{k \times h}$, where $k$ is the kernel size and $h$ is the number of heads. The output $O \in \mathbb{R}^{b \times t \times c}$ is obtained by

$$o_{i,j,p} = \sum_{q=1}^{k} K_{i,j,q} \cdot X_{i,(j+q-\frac{k+1}{2}) \cdot p},$$

where $o_{i,j,p}$ is an element of $O \in \mathbb{R}^{b \times t \times c}$.

Lightweight convolution splits the feature dimension of $X$ to $h$ groups, where features in one group share one kernel. By doing this, the number of parameters of one lightweight convolution layer is $k \times h$, which is less than a traditional 1d convolution layer.

Based on lightweight convolution, dynamic convolution introduces an additional kernel generation mechanism that generates kernels from input features $X$, so that the shape of the kernels $K'$ for dynamic convolution becomes $[h, b, t, k, h]$.

The following shows the formation of the kernel generation mechanism. After a linear layer and a GLU layer, the feature matrix $X'$ can be obtained by

$$X' = GLU(XW_1 + b_1).$$

The dynamic convolution kernel $K' \in \mathbb{R}^{b \times t \times k \times h}$ can be generated through a linear layer.

$$K' = X'W_2 + b_2.$$  

The output of dynamic convolution can be obtained by using the generated kernel $K'$ and the feature $X$

$$o'_{i,j,p} = \sum_{q=1}^{k} K'_{i,j,q} ([\frac{p-q}{2}]) \cdot X'_{i,(j+q-\frac{k+1}{2}) \cdot p},$$

where $W_1 \in \mathbb{R}^{c \times (2k+c)}$, $b_1 \in \mathbb{R}^{2c}$, $W_2 \in \mathbb{R}^{c \times (k+h)}$, $b_2 \in \mathbb{R}^{k \times h}$ are trained parameters. $o'_{i,j,p}$ is an element of the output $O' \in \mathbb{R}^{b \times t \times c}$.

The dynamic kernel generation mechanism produces a kernel for each time step ($K' \in \mathbb{R}^{b \times t \times k \times h}$), instead of using one kernel ($K \in \mathbb{R}^{k \times h}$) across all time steps. Hence, dynamic convolution gains a better ability for modeling local dynamic information, such as speech content.

2.2. AdaIN and WadaIN

Figure 2 shows a comparison between AdaIN and WadaIN, where $x$ and $o$ denotes inputs and outputs, $\gamma$ and $\beta$ are affine parameters, $W$ denotes convolution kernels, $s$ is speaker embeddings.

Figure 3: Overview of DYGAN-VC. The model is composed of a generator and a discriminator, $s$ denotes target speaker embeddings.

Figure 4 shows a comparison between AdaIN [22] and WadaIN [23]. Given features $x$ and target speaker embeddings $s$, AdaIN adapts features $x$ to target speakers. It normalizes $x$ across the time dimension. The normalized features $x'$ are transformed with affine parameters $\beta$ and $\gamma$. The affine parameters are produced from target speaker embeddings $s$ through a linear layer.

[24] analysed the effects of AdaIN for a image generation task, where AdaIN was proved to cause artifacts in the generated images. In a recent VC system [25], WadaIN also showed advantages on voice quality. As a replacement of AdaIN, WadaIN does not normalize or adapt features. It rather scales the channel dimension of convolution kernels. As shown in Figure 8, convolution kernels $W$ are adapted to target speakers by a linear transform. The adapted kernels $W'$ can be obtained as follows:

$$W' = \gamma + W,$$

where $W_1 \in \mathbb{R}^{c \times (2k+c)}$, $b_1 \in \mathbb{R}^{2c}$, $W_2 \in \mathbb{R}^{c \times (k+h)}$, $b_2 \in \mathbb{R}^{k \times h}$ are trained parameters. $o'_{i,j,p}$ is an element of the output $O' \in \mathbb{R}^{b \times t \times c}$.

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where $W_1 \in \mathbb{R}^{c \times (2k+c)}$, $b_1 \in \mathbb{R}^{2c}$, $W_2 \in \mathbb{R}^{c \times (k+h)}$, $b_2 \in \mathbb{R}^{k \times h}$ are trained parameters. $o'_{i,j,p}$ is an element of the output $O' \in \mathbb{R}^{b \times t \times c}$.

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$$W' = \gamma + W,$$
where $\gamma$ is an affine parameter generated from target speaker embeddings $s$ through a linear layer. The adapted convolution kernels $W'$ are used in a convolution layer where the input features are $x$.

### 3. DYGAN-VC: a lightweight GAN model for voice conversion

This section introduces the model architecture and the training objectives of DYGAN-VC. As shown in Figure 3, DYGAN-VC is composed of a generator and a discriminator. The generator takes VQWav2vec features $z$ as input and generates speech samples according to target speaker embeddings. The discriminator takes in the generated speech samples and returns a probability of the generated speech samples being real speech. The generator and the discriminator are trained adversarially. At inference time, only the generator is used.

#### 3.1. A new generator architecture: a combination of dynamic convolution and WadaIN

Figure 1 (c) shows the architecture of the generator. It uses 1d convolution as the input layer and also as the output layer. The generator contains 6 identical intermediate blocks. Each block includes a dynamic convolution layer, a 1d convolution layer and a WadaIN layer. In each intermediate block, layer normalization [26] and residual connections are applied as in [5].

The novel intermediate block in the generator is inspired by AdaSpeech [27], which was proposed for a speaker adaptation task for TTS based on a Transformer TTS model [25]. In AdaSpeech, each self-attention layer is followed by a variant of the AdaIN layer [22]. Different from the original Transformer model [8] which applies linear layers after the self-attention layers, the design of AdaSpeech enables the Transformer model to adapt features to target speakers. More importantly, this design also maintains the voice quality of generated speech samples. Hence, DYGAN-VC follows this idea and proposes to combine dynamic convolution layers with WadaIN layers [24]. Considering parameter efficiency, DYGAN-VC uses dynamic convolution instead of heavy self-attention layers. Moreover, as an extension of AdaIN, WadaIN enhances voice quality. By using this new combination, DYGAN-VC achieves both parameter efficiency and voice quality.

#### 3.2. Discriminator architecture

The discriminator uses the same architecture as in StarGANv2-VC [4], except the maximum hidden size is reduced from 512 to 128. The discriminator has a 1d convolution layer as input and also as the output layer. The generator contains 2d convolution layers and an average pooling layer for downsampling. After 4 residual convolution blocks, there is a 2d convolution layer, a global average pooling layer, and a WadaIN layer in each intermediate block. More details, please refer to [2].

#### 3.3. Training objectives

Given VQWav2vec features $z \in Z$ and speaker embeddings $s \in S$, the generator $G(z, s)$ generates converted speech samples $\hat{x} \in \mathcal{X}$. The discriminator $D(x)$ takes in real speech samples $x \in \mathcal{X}$ and the converted samples $\hat{x}$ and returns probabilities $y \in [0, 1]$ of the input being real speech.

The reconstruction loss can be defined as follows:

$$L_{\text{recon}} = E_{x,z,s}||x - G(z,s)||. \quad (6)$$

The least-square adversarial losses are used as in [23]. The losses for the generator and the discriminator can be defined as follows:

$$L_{adv}^G = E_{z,s}(1 - D(G(z,s)))^2, \quad (7)$$

$$L_{adv}^D = E_x[(1 - D(x))^2] + E_{z,s}[D(G(z,s))^2]. \quad (8)$$

The overall losses for the generator and the discriminator are as follows:

$$L^D = L_{adv}^D, \quad (9)$$

$$L^G = \lambda L_{recon} + L_{adv}^G. \quad (10)$$

where $\lambda$ is a hyper-parameter set as 5.

### 4. Experimental setup

#### 4.1. Dataset

This work uses the first track dataset of VCC2020 [7]. The dataset contains 8 English speakers, including 4 female speakers and 4 male speakers. In average, each speaker has 5 minutes of data, so the whole dataset contains 40 minutes of audio data. The speakers are composed of 4 sources speakers (2 female, 2 male) and 4 target speakers (2 female, 2 male), so there are $4 \times 4 = 16$ conversion pairs in total. There are 70 training samples and 25 testing samples for each speaker. This work uses 60 samples for training, 10 samples for validation and 25 samples for testing.

#### 4.2. Baseline models

The Cascade ASR-TTS model [1] is the official baseline model of VCC2020 [7]. This work uses the official recipe [1] as implementation.

#### 4.3. Evaluation

Objective evaluations and subjective evaluations are conducted. Four objective metrics are used: mel-cepstrum distortion (MCD), character error rate (CER), word error rate (WER) and MOSNet [29]. The MCD, CER and WER results were calculated using the official baseline implementation. The MOSNet score was calculated using crank [30].

Mean opinion score (MOS) human evaluations were conducted as subjective evaluations. The generated speech samples were evaluated for naturalness and similarity. Listening tests were conducted on the MTurk [31] platform. For naturalness, listeners were asked to mark a speech sample at five (1-5) grades. For speaker similarity, the listeners were asked to mark a speech sample at five (1-5) grades given a reference speech sample. In order to recognize listeners with bad behaviours, ground truth speech samples and random noise samples were included in test sets. After removing 2 outlier listeners, 192 listeners participated the listening tests. The test set contains 400 samples for each model, resulting in 1200 samples in total. Each sample is evaluated by at least 2 listeners for both naturalness and speaker similarity.

References:

[1] https://github.com/espnet/espnet/tree/master/egs/vcc20/vc1_task1

[2] https://www.mturk.com
Table 2: Objective evaluation results. F-F, F-M, M-F, M-M denote conversion directions, F means female, M means male. MCD, MOS, CER, WER denote mel-cepstral distortion, MOSNet, character error rate (%) and word error rate (%), respectively. Please note that models presented in this table have large differences, please refer to Table 1 for details.

| Model             | F-F | F-M | M-F | M-M |
|-------------------|-----|-----|-----|-----|
|                  | MCD/MOS/CER/WER | MCD/MOS/CER/WER | MCD/MOS/CER/WER | MCD/MOS/CER/WER |
| Cascade ASR-TTS   | 6.65/3.87/5.4/10.1 | 6.19/3.42/9.1/15.0 | 6.62/3.86/5.8/10.7 | 6.14/3.42/8.1/13.6 |
| DYGAN-VC          | 7.56/4.25/5.5/11.2 | 7.04/3.47/6.2/13.4 | 7.52/4.20/3.4/10.2 | 7.03/3.79/8.5/10.7 |

Table 3: Subjective evaluation results with 95% confidential intervals, Nat and Sim denote naturalness and speaker similarity. Please note that models presented in this table have large differences, please refer to Table 1 for details.

| Model             | F-F | F-M | M-F | M-M |
|-------------------|-----|-----|-----|-----|
|                  | Nat/Sim | Nat/Sim | Nat/Sim | Nat/Sim |
| Cascade ASR-TTS   | 3.81±0.12/3.70±0.12 | 3.81±0.12/3.84±0.12 | 3.90±0.12/3.83±0.14 | 3.82±0.12/3.83±0.16 |
| DYGAN-VC          | 3.80±0.13/3.79±0.13 | 3.74±0.13/3.84±0.13 | 3.86±0.13/3.94±0.13 | 3.83±0.13/3.92±0.12 |

Table 4: A comparison between options of dynamic convolution, lightweight convolution, AdaIN and WadaIN, results are averaged over all 16 conversion pairs.

| Model          | MCD  | MOSNet | CER% | WER% |
|----------------|------|--------|------|------|
| lconv+AdaIN    | 7.36 | 3.89   | 5.4  | 11.5 |
| dyconv+AdaIN   | 7.35 | 3.96   | 6.3  | 12.8 |
| lconv+WadaIN   | 7.29 | 4.01   | 6.1  | 12.4 |
| dyconv+WadaIN  | 7.29 | 4.00   | 5.2  | 11.2 |

Table 5: A comparison of the decoding speed, RTF denotes real time factor, which is the average time for generating one second of waveform on cpu.

| Model         | RTF |
|---------------|-----|
| Cascade ASR-TTS | 46.1 |
| DYGAN-VC      | 5.4 |

4.4. Implementations

80 dimensional mel-spectrograms are used as features, window size is 40 ms and hop size is 10 ms. The vocoder model is the Parallel WaveGAN model [31]. The learning rate for the generator and the discriminator is 1e-4 and 2e-5, respectively. Batch size is 8, and speaker embeddings are extracted using the speaker encoder model in [32]. At training time, speech utterances are cropped to segments of 128 frames. Adam [33] is used as optimizers. The model is trained for 100 epochs and the training takes about 40 minutes to converge on one gpu. For more details, please refer to implementation [3].

5. Results

5.1. Objective results

Table 2 demonstrates objective evaluation results for four conversion directions. Generally speaking, considering all four directions, the performance of DYGAN-VC is at the same level of the baseline model. Comparing DYGAN-VC with cascade ASR-TTS, the latter model has better MCD results for all directions. This might because cascade ASR-TTS is composed of AR models, hence it has better ability to model target speaker properties. DYGAN-VC has better MOSNet scores for all directions. DYGAN-VC has better CER and WER results for F-M, M-F and M-M directions but worse results for F-F directions.

5.2. Subjective results

Table 3 demonstrates subjective evaluation results for all conversion directions. Comparing DYGAN-VC with cascade ASR-TTS, for naturalness MOS scores, cascade ASR-TTS has better results than DYGAN-VC except M-M direction. However, the distance of naturalness MOS scores between them is within 0.1, for example, for F-F direction, DYGAN-VC achieves 3.80, which is very close to 3.81 of cascade ASR-TTS. As for speaker similarity, DYGAN-VC has better results than Cascade ASR-TTS except F-M direction.

5.3. Ablation study

To further study the effects of the proposed new combination of dynamic convolution and WadaIN, this work compares objective results for all possible combinations, as shown in Table 4. The combination of dynamic convolution and WadaIN reaches the best results for MCD, CER and WER, except MOSNet.

5.4. Decoding speed

Table 5 compares the decoding speed on cpu at inference time. This work reports the real time factor (RTF) as decoding speed. Since cascade ASR-TTS is an AR model, it has a slower decoding speed than non-AR DYGAN-VC.

6. Conclusion

This paper proposes DYGAN-VC, a novel GAN VC model with high efficiency. Instead of using a ASR model, DYGAN-VC uses VQWav2vec, which is lightweight and faster. Furthermore, DYGAN-VC introduces dynamic convolution, which enhances speech content modeling and keeps a lightweight model. Comparing to the SOTA models, DYGAN-VC has high efficiency, and also achieves comparable level of performance of SOTA. For future work, the authors will investigate zero shot VC.
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