Pureformer-VC: Non-parallel One-shot Voice Conversion with Pure Transformer Blocks and Triplet Discriminative Training

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Abstract—One-shot voice conversion(VC) aims to change the timbre of any source speech to match that of the target speaker with only one speech sample. Existing style transfer-based VC methods relied on speech representation disentanglement and suffered from accurately and independently encoding each speech component and recomposing back to converted speech effectively. To tackle this, we proposed Pureformer-VC, which utilizes Conformer blocks to build a disentangled encoder, and Zipformer blocks to build a style transfer decoder as the generator. In the decoder, we used effective styleformer blocks to integrate speaker characteristics effectively into the generated speech. The models used the generative VAE loss for encoding components and triplet loss for unsupervised discriminative training. We applied the styleformer method to Zipformer's shared weights for style transfer. The experimental results show that the proposed model achieves comparable subjective scores and exhibits improvements in objective metrics compared to existing methods in a one-shot voice conversion scenario.

 ${\it Index\ Terms} \hbox{---} voice\ conversion,\ VAE,\ Style former,\ Conformer,\ Zipformer.$

I. Introduction

Voice conversion(VC) aims to convert the speaker's timbre in speech to the target speaker's while keeping the content unchanged. It is usually text-independent because the model only learns the sound characteristics within target utterances.

Researchers have recently focused on many-to-many and any-to-one voice conversion, where models learn from non-parallel data. Motivated by the concept of image style transfer from the field of computer vision, various approaches leveraging generative adversarial networks (GANs) have been implemented for GANs-based voice conversion [1]–[6]. Among these approaches, speaker encoder assist the generator in learning the transformation relationships between different domains with the critical style transfer module, such as AdaIN and WadaIN [7], [8]. These methods apply normalization

parameterized affine to the hidden variances or the weights of convolution layers. Although the generated results are acceptable, GAN training is challenging due to convergence difficulties and sensitivity to the imbalance of the dataset.

From the perspective and assumption that speech can be decomposed into multiple components(*e.g.* timbre, pitch, content, and rhythm) [9], the disentanglement-based VC is worth considering. This allows neural networks to learn representations of each speech component separately by multiple encoders and a decoder [9], [10]. During training, different encoders are fed with the homologous spectrogram respectively and obtain independent speech component representations. The decoder is responsible for reassembling the various components into speech for reconstruction training. However, the present methods involve force decomposition in Speech-Split [9], [10], instance normalization with INVC [11], and information bottleneck in AutoVC [12], which can not ensure perfect disentanglement and reconstruction.

Based on the previous narrative, we propose a practical VC framework called Pureformer-VC. We declare that a successful disentangled voice conversion based on an encoder-decoder framework should depend on three factors: (1) A reasonable encoder and decoder design. (2) An optimization objective with representational discriminability, and (3) A well-functioning style transfer module within the decoder to fuse speech components and recover the speech. In this paper, we propose the Pureformer-VC framework to satisfy the three factors. The framework contains the content encoder, speaker encoder, decoder, and vocoder. Based on the excellent success of sequence modeling with effective transformer blocks, we propose constructing the content encoder with Conformer blocks containing IN operation and decoder with Zipformer blocks [13], considering their excellent performance

in speech linguistic modeling [14]. In the Zipformer blocks, we apply the style transfer mechanism in Styleformer [15] that is demonstrated to fuse the speaker information into the generated speech successfully. We also constructed the speaker encoder with Conformer blocks, but it does not include IN for avoiding to filter out speaker information. When considering the training optimization objective, we introduced a triplet loss [16] besides the reconstruction loss to let the model learn the distances between the utterances of different timbres. In this paper, our contributions are mainly the following points.

- We proposed the one-shot voice conversion framework named Pureformer-VC. The main blocks are constructed by Conformer and Zipformer blocks.
- For better style transfer, the shared weights in Zipformer are applied with the styleformer mechanism.
- We conducted one-shot voice conversion experiments on the VCTK datasets. The evaluation results show that our proposed method achieves comparable or even better results in various VC scenarios than existing methods.

II. RELATED WORK

A. Style Transfer Learning in VC

Style transfer learning teaches the voice conversion models to fuse different speech representations. Accordingly, the style transfer function accepts the source speaker-independent representations and one target speaker-dependent representation. Chou et al. [11] first found that instance normalization can filter out the speaker information and preserve the source content in INVC. Then, the IN function was widely used in the GANsbased VC. [4], [5]. In addition, the WadaIN method applies affine operations to the convolutional kernel and convolves the source data, thereby modifying the style of the source data in the WadaIN-VC [6]. However, these models are CNNbased. To utilize the self-attention mechanism in Transformer, the Attention-AdaIN-VC [17] inserted the styleformer block into the CNN blocks and gained a better voice conversion effect. In general, we continue using the styleformer transfer mechanism(STM) function in this paper.

III. METHODOLOGY

A. Overall Architecture of Pureformer-VC

The overall architecture of Pureformer-VC is illustrated in Figure 1(a). Pureformer-VC includes the content encoder, decoder, speaker encoder, and vocoder. We used the pretrained Hifi-GAN generator as vocoder. [18].

B. Styleformer Transfer Mechanism(STM) in Decoder

We constructed the decoder with 4 Zipformer blocks with STM as shown in Figure 1(b). The decoder reintegrates the content and timbre representations of the speech. Therefore, we apply the STM to the weights in self-attention of Zipformer blocks. During the model initialization phase, the STM firstly initializes some attention weights. With affine operations later, the weights are imbued with the style characteristics of the split speaker embedding vector S1, S2. Then, we adopt weight normalization(WN) [19] on the parameters to get

better convergence performance. The WN accepts the weight and normalizes it at the outcoming dimension. By the WN operation, we scale the output of each weight back to unit standard deviation. The WN helps the model to accelerate convergence in training after the attention calculation with stylized weights.

C. Content Encoder with VAE Training

The content encoder parameterizes and approximates the variational distribution of $q_{\phi}(z|x)$. We constructed each Conformer block with instance normalization and an AveragePooling1D layer to squeeze the time dimension to half times. There are 4 continuous blocks, and finally, output the reparameterization of content representation $z_c = \mu + \sigma * e$. It turns out to optimize the ELBO of logp(x):

$$L_{elbo} = E[log P_{\theta}(x|z)] - KL(q_{\phi}(z|x)||p(z)) \tag{1}$$

where ϕ denotes the encoder network and θ represents the decoder. The first term above is the reconstruction loss, while the second is the KullbackLeibler divergence between the approximate posterior and the prior. Thus, the VAE training loss can be summarized as [20]:

$$L_{vae} = E[|x - x_{dec}|] + \frac{1}{2} * E[\mu^2 + \sigma^2 - log(\sigma^2) - 1]$$
 (2)

D. Speaker Encoder with AAM-Softmax Loss

The speaker encoder can extract the timbre representations from Mel-spectrograms. We use the backbone of multiple Conformer blocks **without instance normalization** from MFA-Conformer [21] to extract the hidden feature. Then, the AAM-softmax layer, a parameterized loss function for finding cluster centres, is used to enhance the embeddings.

E. Triplet loss and Data Sample Strategy

In the previous disentanglement-based VC, the source Melspectrogram and the target one(accepted by the speaker encoder) were the same in the training stage but differed in the inference stage. This weakened the model's generalization capability. To tackle this problem, we employ the triplet loss [16] as Figure 2 shows, which is an unsupervised learning technique with discriminative training and enables the speaker encoder to learn the differences in timbre among various voices.

In the training stage, we sample three utterance segments of equal length from the dataset as anchor sample x_{anc} , positive sample x_{pos} , and negative sample x_{neg} . As shown in Figure 2, the anchor sample and positive sample have the same timbre, while the negative sample comes from another speaker differing from the anchor. Thus, let the nm denote the L2 normalization. We can use the speaker encoder outputs of the three samples to calculate a triplet loss:

$$e_{anc}, e_{pos}, e_{neq} = E_s(x_{anc}), E_s(x_{pos}), E_s(x_{neq})$$
 (3)

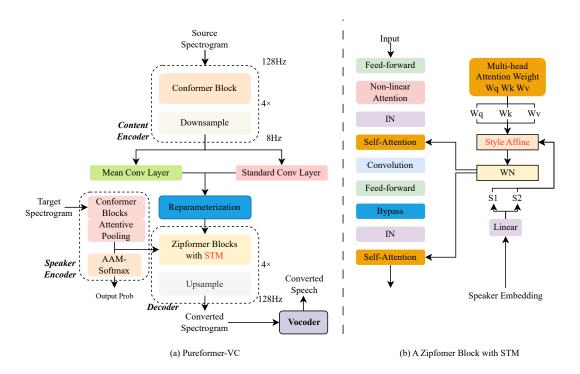


Fig. 1. The architecture of Pureformer-VC.

$$L_{tri} = E[nm(e_{anc}) * nm(e_{pos})^t] -$$

$$E[nm(e_{anc}) * nm(e_{neq})^t] + \delta$$

$$(4)$$

The δ is a hyper-parameter to control the speaker similarity.

F. Training Objective

The training objective of the Pureformer-VC model includes VAE loss, AAM-softmax loss, and triplet loss. The total VAE loss contains two outputs y_1, y_2 as Figure 2 shows, and can be denote as:

$$L_{t-vae} = \lambda_1 (L_{rec}(x_{anc}, x_{pos}) + L_{rec}(x_{anc}, x_{neg})) + \lambda_2 (L_{KL}(x_{anc}, x_{pos}) + L_{KL}(x_{anc}, x_{pos}))$$
 (5)

The AAM-softmax loss can be calculated by the three true labels of samples C and the speaker encoder's predictions:

$$L_{t-aam} = \sum_{c_i \in C} L_{aam}(c_i, x_i)$$
 (6)

Finally, the triplet loss helps the speaker encoder to distinguish the embeddings. The total training objective is as follows:

$$L_{total} = L_{t-vae} + \lambda_3 L_{t-aam} + \lambda_4 L_{tri} \tag{7}$$

G. Vocoder

The vocoder has the same structure as the HiFi-GAN generator. In our study, the vocoder was pre-trained in the same dataset as the voice conversion training.

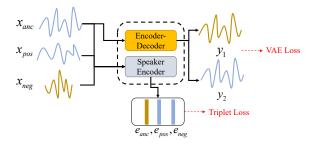


Fig. 2. The illustration of training objective.

IV. EXPERIMENTS AND RESULTS

A. Experimental Setup

Datasets. To evaluate the effectiveness of Pureformer-VC, we conducted a comparative experiment and an ablation study on VCTK corpus [22]. The VCTK corpus includes 109 speakers, each reading about 400 utterances. During training, ten speakers are randomly selected as unseen speakers for one-shot VC. The Mel-spectrogram extraction is as the same as HiFi-GAN work. In the sampling stage, it will randomly sample an utterance from a speaker and sample two utterances from another speaker to form a training subset x_{anc} , x_{pos} , x_{neg} .

Training Setup. In the training stage, the batch size is 16. The learning rate is constant at 2×10^{-4} . The Pureformer-VC is trained by Adam optimizer [25] with $\beta_1 = 0.9, \beta_2 = 0.99, \epsilon = 1 \times 10^{-6}$. The λ_1 is set to 10 and λ_2 ranges from $1 \times 10 - 4$ to 1. The λ_3, λ_4 are set to 1. The δ is 0.3.

Baseline Setup. We compared Pureformer-VC with recent VC frameworks, such as AdaIN-VC [11], AutoVC [12],

TABLE I Comparison of baseline and proposed methods for many-to-many and one-shot VC (with 95% confidence interval).

VC method	Many-to-many			One-shot		
	MCD	MOS	VSS	MCD	MOS	VSS
AdaIN-VC [11]	7.64 ± 0.24	3.11 ± 0.13	2.82 ± 0.19	7.38 ± 0.14	3.04 ± 0.21	2.45 ± 0.16
AutoVC [12]	6.68 ± 0.21	2.76 ± 0.16	2.45 ± 0.23	8.08 ± 0.15	2.68 ± 0.17	2.39 ± 0.14
VQMIVC [23]	6.24 ± 0.13	3.20 ± 0.14	3.32 ± 0.12	5.59 ± 0.10	3.16 ± 0.18	3.02 ± 0.18
MAIN-VC [24]	5.28 ± 0.11	3.44 ± 0.12	3.25 ± 0.16	5.42 ± 0.13	3.24 ± 0.18	3.29 ± 0.11
Pureformer-VC(w/o AAM-softmax)	5.05 ± 0.11	3.42 ± 0.12	3.05 ± 0.16	5.25 ± 0.12	3.20 ± 0.11	3.10 ± 0.11
Pureformer-VC(w/o triplet)	5.50 ± 0.09	3.55 ± 0.12	3.55 ± 0.14	5.25 ± 0.11	3.32 ± 0.15	3.21 ± 0.10
Pureformer-VC	5.10 ± 0.12	3.64 ± 0.13	3.56 ± 0.13	5.40 ± 0.10	3.36 ± 0.15	3.35 ± 0.12

VQMIVC [23], and MAIN-VC [24]. These models are all of disentanglement-VC.

B. Metrics and Evaluation

We assess the generated speech's naturalness and intelligibility using subjective metrics like the mean opinion score (MOS). For evaluating timbre similarity with the target speech, we use objective metrics, including voice similarity score (VSS) and Mel-cepstral distortion (MCD). Higher scores indicate better voice conversion effectiveness.

Mean opinion score (MOS). The MOS score ranges from 1 to 5, where higher scores indicate higher speech quality. Voice similarity score (VSS). The VSS assesses the degree of resemblance between the generated and the authentic speech. Mel-cepstral distortion (MCD). The MCD is an objective quantitative measure that evaluates the divergence between the source and generated Mel-cepstral.

C. Experimental Results

Table I presents a comparative analysis of the Pureformer-VC against baseline methods across both many-to-many and one-shot voice conversion settings. In the context of many-to-many voice conversion, Pureformer-VC attains performance on par with the established baseline methods. In the realm of one-shot voice conversion, Pureformer-VC surpasses other methodologies, particularly excelling on the objective metric. As demonstrated in Table I, we explored removing either the AAMSoftmax loss or the triplet loss from the training objectives to evaluate the model's ability to represent timbre in the embedded vectors during training. It is observable that without employing these two losses, the model's Voice VSS remains relatively consistent with the baseline model's. Hence, the incorporation of these losses aids in enhancing the model's voice conversion expressiveness.

D. Ablation Study

We conduct ablation experiments to validate the effects of triplet loss and AAM-softmax loss on disentanglement. We set up the following models:(a) Pureformer-VC model. (b) The Pureformer-VC model without triplet loss. (c) The Pureformer-VC model without AAM-softmax loss. We used a resemblyzer detect synthetic speech and evaluate conversion quality. It assigns scores to fake (i.e., the VC model's experimental outputs) and authentic utterances from the target speaker after learning the target's characteristics from 10 additional genuine

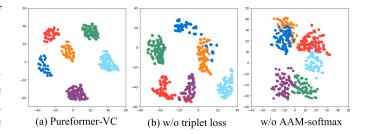


Fig. 3. The visualization of speaker representations extracted from 6 unseen speakers' utterances.

utterances. A higher score signifies a closer resemblance in timbre and superior speech quality. The results are detailed in the Table II. For a visual evaluation of each model's disentanglement capability, the t-SNE scatter plots of the speaker representations are depicted in Figure 3. The AAM-softmax loss significantly impacts the clustering of speaker embedding vectors, while the triplet loss assists in creating more distinct boundaries between categories.

TABLE II
FAKE DETECTION SCORE COMPARISON FOR ABLATION STUDY ABLATION

Method	Detection Score
Pureformer-VC	0.75 ± 0.03
w/o triplet loss	0.65 ± 0.07
w/o AAM-Softmax	0.52 ± 0.12

V. CONCLUSION

In this paper, we introduced a novel approach to voice conversion leveraging a pure transformer network constructed as a VAE encoder-decoder framework called Pureformer-VC. Within the decoder, we integrated a styleformer module, which has enhanced the model's capacity for style transfer. Furthermore, we enhanced the effectiveness of the speaker encoder by incorporating the triplet loss and AAMSoftmax loss. These additions have significantly improved the model's ability to capture and represent the nuances of different speaking voices, leading to more accurate and robust voice conversion. In conclusion, the Pureformer-VC model, bolstered by the strategic use of specialized loss functions and style adaptation mechanisms, presents a substantial advancement in the field of voice conversion.

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