Disentanglement of Emotional Style and Speaker Identity for Expressive Voice Conversion

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Abstract

Expressive voice conversion performs identity conversion for emotional speakers by jointly converting speaker identity and emotional style. Due to the hierarchical structure of speech emotion, it is challenging to disentangle the emotional style for different speakers. Inspired by the recent success of speaker disentanglement with variational autoencoder (VAE), we propose an any-to-any expressive voice conversion framework, that is called StyleVC. StyleVC is designed to disentangle linguistic content, speaker identity, pitch, and emotional style information. We study the use of style encoder to model emotional style explicitly. At run-time, StyleVC converts both speaker identity and emotional style for arbitrary speakers. Experiments validate the effectiveness of our proposed framework in both objective and subjective evaluations.

Index Terms: Expressive voice conversion, speaker identity, emotional style, disentanglement, VQMIVC

1. Introduction

Human voice can be emotive and expressive. Emotion is expressed in speech to convey speaker motivation, mood and personality [1–3]. Expressive voice conversion is a task of jointly performing speaker identity and style transfer for emotional speakers while preserving the linguistic information, as illustrated in Figure 1(c).

Voice conversion (VC) typically seeks to convert the speaker identity while preserving the linguistic content [4], as illustrated in Figure 1(a). Earlier studies include Gaussian mixture model (GMM) [5], exemplar methods [6] and sparse representation [7]. Deep learning methods, such as deep neural network (DNN) [8] and recurrent neural network (RNN) [9] have significantly improved the performance. However, these frameworks require parallel training data, which limits their scope of applications. On the other hand, domain translation models, such as CycleGAN [10] or StarGAN [11] are studied for non-parallel training data. These models mostly rely on the cycle-consistency mechanism and they carry forward the source speech style into the converted voices, thus not suitable for expressive voice conversion.

Another way of non-parallel VC is to learn the disentangled speech representations with VAE [12]. VAE allows us to separately manipulate different disentangled features to achieve speaker identity conversion [13–15] or emotion conversion [16–18]. Other techniques to obtain a better disentangled representation include information bottleneck [19, 20], instance normalization [21, 22], and vector quantization (VQ).

(a) Traditional VC  (b) Emotional VC  (c) Expressive VC

Figure 1: A comparison of traditional VC, emotional VC and expressive VC at run-time.

[23, 24]. Recent studies, such as vector quantization and mutual information-based voice conversion (VQMIVC) [25], show the effectiveness of mutual information (MI) loss in reducing the dependencies between different representations, which inspires this study.

A related technique is emotional voice conversion, which converts the emotional state of the speaker while keeping the speaker identity unchanged [26, 27], as illustrated in Figure 1(b). Unlike emotional voice conversion, expressive voice conversion seeks to jointly convert speaker identity and speech style for emotional speakers [3], as shown in Figure 1(c).

As emotional style is an interplay among various speech elements [16, 28], such as speech content, speaker identity, speaking style and pitch, it is advantageous to disentangle the elements for effective expressive voice conversion. For example, such disentanglement allows us to carry over the speech content from the source to the target, but project the target speaker identity and speaking style of one certain emotional state into the target speech. Since speech emotion is highly complex with multiple signal attributes concerning spectrum and prosody [16], it is challenging to model emotional style of arbitrary speakers. Most related studies, such as [3, 29], have only dealt with a multi-speaker expressive voice conversion model.

Our main contributions include: 1) we study the disentanglement of speaker identity and emotional style for expressive voice conversion; 2) we introduce a style encoder to explicitly model emotional style across different speakers, and further employ Style MI loss to reduce the inter-dependency of emotional style and other representations (content, pitch, speaker); 3) the proposed method achieves expressive voice conversion in an unsupervised way without any text transcriptions, speaker or emotion labels; 4) our proposed framework can effectively convert both speaker identity and emotional style from arbitrary emotional speakers at run-time. To our best knowledge, this is the first study for any-to-any expressive voice conversion.

The rest of this paper is organized as follows: Section 2 presents the details of our proposed framework. In Section 3, we report the experimental results. Section 4 concludes the study.
2. Method

We propose an any-to-any expressive voice conversion framework, StyleVC, which can jointly perform both emotional style and speaker identity conversion. VQMIVC [25] is a voice conversion framework based on VAE [12] performing an unsupervised speaker disentanglement. We extend the idea of VQMIVC from speaker identity disentanglement to emotional style disentanglement.

StyleVC consists of a style encoder, a speaker encoder, a content encoder and a decoder as shown in Figure 2. During training, StyleVC learns to disentangle emotional style by employing an emotional style encoder to explicitly extract style representation and adopting mutual information as the correlation metric to reduce the dependencies between emotional style representation and other representations. At run-time, StyleVC allows us to convert both speaker identity and emotional style for any speaker by manipulating different disentangled speech representations.

2.1. Training Phase

Given an expressive utterance, we first extract Mel-spectrograms \(X = \{x_1, x_2, ... x_T\}\) and fundamental frequency \(F_0\) where \(T\) is the total number of frames. The style encoder \(E_s\) learns to encode the Mel-spectrograms into a fixed-length representation \(Z^s = E_s(X)\). The \(Z^s\) represents the emotional style in the utterance level. The content encoder \(E_c\) extracts content \(Z^c = \{z^c_1, z^c_2, ..., z^c_T/2\}\) from \(X\). The speaker encoder \(E_p\) learns to embed the Mel-spectrograms into a fixed-length speaker embedding: \(Z^p = E_p(X)\). To represent the intonation, \(F_0\) is extracted from the speech waveform and log normalized into zero mean and unit variance. Since the \(F_0\) varies with the speakers, we take the log normalized \(F_0\) as the pitch embedding \(\hat{Z}^f\), and study it separately.

We note that the speaker embedding \(Z^p\) and the emotional style embedding \(Z^s\) represent the speaker identity and the emotional style information at an utterance level. To align with the pitch embedding \(\hat{Z}^f\), we up-sample speaker embedding \(Z^p\), the emotional style embedding \(Z^s\), and the content embedding \(Z^c\) to \(T\) frames. The decoder \(D\) aims to reconstruct acoustic features \(\tilde{X}\) from pitch embedding \(\hat{Z}^f\) and the upsampled speech embedding. A reconstruction loss is calculated between the reconstructed Mel-spectrogram and the ground-truth.

During training, the correlation among different speech representations can be reduced by minimizing the MI loss as follows:

1) **Speaker MI Loss**: A speaker MI loss is applied to speaker style embedding \(Z^p\), content embedding \(Z^c\) and pitch embedding \(\hat{Z}^f\) as follows:

\[
L_{spk-MI} = I(Z^p, Z^c) + I(Z^p, \hat{Z}^f) + I(Z^c, \hat{Z}^f)
\]  

where \(\hat{I}\) represents the unbiased estimation for vCLUB as described in [25]. Speaker MI loss is effective for alleviating the leakage of content and pitch information into the speaker representation from [25].

Motivated by this, we incorporate style mutual information minimization to disentangle emotional style representation and other representations.

2) **Style MI Loss**: A style MI loss is applied to emotional style embedding \(Z^s\), speaker embedding \(Z^p\), content embedding \(Z^c\) and pitch embedding \(\hat{Z}^f\) as follows:

\[
L_{sty-MI} = \hat{I}(Z^s, Z^p) + \hat{I}(Z^s, \hat{Z}^f) + \hat{I}(Z^c, \hat{Z}^f)
\]  

The total MI loss is given as follows:

\[
L_{MI} = \lambda_{sty} L_{sty-MI} + \lambda_{spk} L_{spk-MI}
\]  

where \(\lambda_{sty}\), and \(\lambda_{spk}\) are the weights to control how MI loss enhances the disentanglement. We believe emotional style representation carries more correlation information than other representations. We set \(\lambda_{sty} = 2\lambda_{spk}\) to reduce the correlation information between emotional style representation and other representations.

2.2. Run-time Conversion

At run-time, StyleVC takes a source utterance from one speaker as input, and a reference utterance from another speaker, who is either seen or unseen during training. The content encoder generates the source content embedding from the source utterance. Given the reference emotional utterance from the target speaker, we use the speaker encoder and style encoder to generate speaker and emotional style embedding respectively. We then convert the \(F_0\) with the mean and standard variance calculated from a random seen male/female speaker. We expect that the emotional style embedding can capture emotional style that is related to the target speaker. The decoder learns to generates the converted Mel-spectrograms with the source content embedding, the speaker and emotional style embedding from one target speaker’s utterance, and the converted \(F_0\). The speech waveform is reconstructed with Parallel WaveGAN vocoder [30].

2.3. Emotional Style and Speaker Disentanglement

We analyze the effectiveness of StyleVC on both emotional style disentanglement and speaker identity disentanglement by visualizing the generated speaker embedding from speaker encoder with t-SNE [31] in Figure 3. We perform the experiments on ESD database [18], and use 20 utterances for each seen speaker and each emotion. We observe that each speaker forms an identifiable cluster for each emotion that suggests that we obtain effective speaker embedding.
3. Experiments

We further visualize the emotional style features of 4 seen speakers from 5 different emotions. For each speaker and each emotion, we use 20 utterances. Figure 4 shows that utterances in different emotions are well-separated and utterances spoken by different speakers in the same emotion are mixed-up in every cluster, that suggests we obtain effective speaker-independent emotional style embeddings.

### 3.1. Experimental Setup

All the speech data is sampled at 16 kHz and saved in 16 bits. We extract 80-dimensional Mel-spectrograms and one-dimensional F0 as the acoustic features. At run-time, F0 is converted through the logarithm Gaussian (LG) normalized transformation [5]. The style encoder consists of a 6-layer stack of 2D convolutions with batch normalization (BN) and ReLu activation, a GRU layer, and two fully connected (FC) layers followed by ReLU. The content encoder contains a CNN with the stride of 2, 512-dimensional LC layer, a codebook with 512 64-dimensional learnable vectors and a 256-dimensional RNN layer. The speaker encoder consists of 8 ConvBank layers, 12 CNN layers and 4 linear layers. The decoder has an LSTM layer with 1024 nodes, 3 CNN layers, 2 1024-dimensional LSTM layers and an 80-dimensional linear layer. The whole framework is optimized with Adam with 15-epoch warm-up. We set the learning rate to 1e-3, and half it every 100 epochs. The total number of epochs is 800 with a batch size of 128. We use a publicly available version\(^1\) of Parallel WaveGAN as the vocoder, and train it with ESD dataset. We set \(\lambda_{\text{spk}} = 0.01\) and \(\lambda_{\text{sty}} = 0.02\).

We evaluate our model in three scenarios: the conversion between seen speakers, denoted as S2S; the conversion between seen speakers and unseen speakers, denoted as S2U; and the conversion between unseen speakers, denoted as U2U.

### 3.2. Objective Evaluation

We calculate Mel-cepstral distortion (MCD) to measure the spectral distortion in Table 1. We observe that our proposed framework consistently outperforms the baseline in terms of lower MCD values for S2S, S2U and U2U. This indicates the effectiveness of our proposed framework.

We then calculate F0-RMSE to evaluate pitch disentanglement performance. From Table 1, we observe that our proposed framework always achieves a better performance than the baseline for all the emotions by obtaining a lower F0-RMSE values. This observation validates the effectiveness of our proposed framework in terms of the prosody conversion.

An open-source pre-trained speaker verification model\(^2\) is utilized to measure the speaker similarity between a converted utterance and a target utterance, as conducted in previous studies [29, 32]. We observe that StyleVC outperforms the baseline in terms of speaker identity disentanglement by achieving higher SV accuracy. These results indicate the superior performance of our proposed framework in terms of the speaker identity conversion.

### 3.3. Subjective Evaluation

We conduct listening experiments to assess the speech quality, speaker similarity and emotional style similarity. 14 subjects participate in all the experiments. Each of them listens to 162 converted utterances in total.

We first report the mean opinion scores (MOS) for S2S, S2U and U2U in Table 2, where a higher score indicates a better speech quality. As shown in Table 2, the StyleVC framework outperforms the baseline in terms of speech quality, which validates the proposed speaker identity conversion and emotional style conversion.

We then conduct three ABX preference tests to evaluate the speaker similarity in S2S, S2U and U2U settings, where all the listeners are asked to listen to the reference and the converted ut-

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\(^1\)https://github.com/kan-bayashi/ParallelWaveGAN

\(^2\)https://github.com/resemble-ai/Resemblyzer
We conduct ablation studies to validate the effectiveness of each term in Style MI loss, as shown in eq (2). We calculate MCD on converted speech of seen speakers from angry emotion. We report the results in Table 3. From the results, we observe Style MI loss, the combination of three MI terms ($I_{Z^u, Z^c}$, $I_{Z^u, Z^f}$, $I_{Z^f, Z^c}$) outperforms the baseline with only Speaker MI loss in both inter-gender and intra-gender settings. And it achieves best performance among other combinations of MI terms with lower MCD values in the average setting.

### 3.4. Ablation studies

We conduct ablation studies to validate the effectiveness of each term in Style MI loss, as shown in eq (2). We calculate MCD on converted speech of seen speakers from angry emotion. We report the results in Table 3. From the results, we observe Style MI loss, the combination of three MI terms ($I_{Z^u, Z^c}$, $I_{Z^u, Z^f}$, $I_{Z^f, Z^c}$) outperforms the baseline with only Speaker MI loss in both inter-gender and intra-gender settings. And it achieves best performance among other combinations of MI terms with lower MCD values in the average setting.

### 4. Conclusion

In this paper, we study the disentanglement of speaker identity and emotional speech style for any-to-any expressive voice conversion. We propose a framework named StyleVC to jointly convert the speaker identity and emotional style. We introduce a style encoder to explicitly model emotional style, and use MI losses to eliminate the shared information between different speech representations. Experimental results show that our proposed framework outperforms the baseline. Future directions include the study of duration modeling for expressive voice conversion.

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