IDENTITY CONVERSION FOR EMOTIONAL SPEAKERS: A STUDY FOR DISENTANGLEMENT OF EMOTION STYLE AND SPEAKER IDENTITY

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ABSTRACT

Expressive voice conversion performs identity conversion for emotional speakers by jointly converting speaker identity and speaker-dependent emotion style. Due to the hierarchical structure of speech emotion, it is challenging to disentangle the speaker-dependent emotional style for expressive voice conversion. Motivated by the recent success on speaker disentanglement with variational autoencoder (VAE), we propose an expressive voice conversion framework which can effectively disentangle linguistic content, speaker identity, pitch, and emotional style information. We study the use of emotion encoder to model emotional style explicitly, and introduce mutual information (MI) losses to reduce the irrelevant information from the disentangled emotion representations. At run-time, our proposed framework can convert both speaker identity and speaker-dependent emotional style without the need for parallel data. Experimental results validate the effectiveness of our proposed framework in both objective and subjective evaluations.

\textbf{Index Terms}— Expressive voice conversion, speaker identity, speaker-dependent emotional style, disentanglement, VQMIVC

1. INTRODUCTION

Traditional voice conversion (VC) aims to convert the speaker identity while preserving the linguistic content \cite{1}. Earlier studies include Gaussian mixture model (GMM) \cite{2}, exemplar methods \cite{3} and sparse representation \cite{4}. Deep learning methods, such as deep neural network (DNN) \cite{5} and recurrent neural network (RNN) \cite{6} have significantly improved the performance. However, these frameworks require parallel training data, which limits their scope of applications. To enable non-parallel training, domain translation models such as CycleGAN \cite{7} or StarGAN \cite{8} are proposed. We note that these models mostly rely on the cycle-consistency mechanism and introduce a strict pixel-level constraint \cite{9}. As a result, they carry forward the source speech style into the converted voices, which is not suitable for expressive voice conversion.

Another way of non-parallel VC is to learn the disentangled speech representations with VAE \cite{10}. VAE allows us to separately manipulate different disentangled features to achieve speaker identity conversion \cite{11,13} or emotion conversion \cite{14,16}. Other techniques to obtain a better disentangled representation include information bottleneck \cite{17,18}, instance normalization \cite{19,20}, and vector quantization (VQ) \cite{21,22}. Recent studies, such as vector quantization and mutual information-based voice conversion (VQMIVC) \cite{23}, 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 aims to convert the emotional state of the speaker while keeping the speaker identity unchanged \cite{24}. We note that one expresses emotions in an unique way. In other words, the emotional style of an utterance is speaker-dependent \cite{25,26}. Unlike emotional voice conversion, expressive voice conversion seeks to jointly convert speaker identity and speaker-dependent emotional style for emotional speakers \cite{27}. As speaker-dependent emotional style is an interplay among various speech elements \cite{14,28}, 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 speaker-dependent speaking style into the target speech.

Our main contributions include: 1) we study the disentanglement of speaker identity and speaker-dependent emotional style for expressive voice conversion; 2) we introduce a style encoder to explicitly model emotional speech style across different speakers, and further employ MI loss between speaker and emotional style embeddings to reduce the inter-dependency of speaker-dependent features; 3) considering the pitch variants over different speakers, we study to use pitch information as a frame-level condition to achieve a better disentanglement of different speech representations; 4) our proposed framework can effectively convert both speaker identity and speaker-dependent emotional style with multi-speaker emotional speech data at run-time.

The rest of this paper is organized as follows: In Section
2. RELATED WORK

The prosodic style and speaker identity are two important components of human speech. In traditional VC, the focus is on either the conversion of prosodic style or the speaker identity [1]. In expressive voice conversion, we are converting both speaker identity and speaker-dependent emotional style [27]. In this paper, we study a novel expressive voice conversion framework that performs the conversion by effectively disentangling between speaker identity and speaker-dependent emotional style.

Disentanglement is one of the common techniques in representation learning. VQMIVC [23] is an unsupervised speaker disentanglement voice conversion framework based on VAE [10]. VQMIVC aims to achieve a better disentanglement of speech content, speaker and pitch information. VQMIVC consists of a content encoder, a speaker encoder, a pitch extractor and a decoder. During the training, the speaker encoder learns to encode the input features into a fixed-length speaker representation. The content encoder learns the linguistic information from the speech, and produces a frame-level content representation. The pitch extractor extracts fundamental frequency (F0) to represent the intonation variations. The decoder reconstructs the input features through a combination of source F0 contour, content and speaker representations. MI losses [29–31] are further applied to reduce the inter-dependencies of these internal representations. At run-time, VQMIVC is able to disentangle the input speech into speech content, speaker and pitch information.

Motivated by the success of VQMIVC in speaker disentanglement, we extend the idea and propose a framework that can effectively disentangle the speaker identity and the speaker-dependent emotional style, which will be further introduced in Section 3.

3. PROPOSED FRAMEWORK

The proposed expressive voice conversion framework consists of a speaker encoder, a style encoder, a content encoder and a decoder. During the training, our framework effectively learns the disentanglement of speaker identity, emotional style, content and pitch information. At run-time, it allows us to convert both speaker identity and emotional style by manipulating the disentangled speech representations.

3.1. Training Phase

Given an utterance, we first extract Mel-spectrograms $X = \{x_1, x_2, ... x_T\}$ and fundamental frequency $F_0$ for $T$ frames. The style encoder $E^s$ learns to encode the Mel-spectrograms into a fixed representation $Z^s = E^s(X)$. The $Z^s$ represents the emotional style in the utterance level. The content encoder $E^c$ extract 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 over different speakers, we take the log normalized $F_0$ as the pitch embedding $Z^f$, 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 $Z^f$, 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 $X$ from pitch embedding $Z^f$ and the upsampled speech embedding. A reconstruction loss is calculated between the reconstructed Mel-spectrogram and the ground-truth.

To achieve a better disentanglement, we incorporate mutual information minimization to the training process. The correlation among different speech representations can be de-
creased by minimizing the MI loss as follows:

\[ L_{MI} = \lambda_{sp} \hat{I}(Z^s, Z^p) + \lambda_{sc} \hat{I}(Z^s, Z^c) \]
\[ + \lambda_{sf} \hat{I}(Z^s, Z^f) + \lambda_{pc} \hat{I}(Z^p, Z^c) \]
\[ + \lambda_{pf} \hat{I}(Z^p, Z^f) + \lambda_{cf} \hat{I}(Z^c, Z^f) \]  

where \( \hat{I} \) represents the unbiased estimation for CLUB as described in [23], and \( \lambda_{sp}, \lambda_{sc}, \lambda_{sf}, \lambda_{pc}, \lambda_{pf}, \lambda_{cf} \) represent the trade-off factors between different speech representations.

During the training, the proposed framework effectively learns the disentanglement between content, pitch, speaker identity and emotional style, as shown in Fig. 1. Through the MI losses, the framework learns to reduce the mutual information shared between different speech representations.

3.2. Run-time Conversion

At run-time, the content encoder generates the source content embedding from the source utterance. Given a reference emotional utterance from the target speaker, we use the speaker encoder and style encoder to generate speaker and emotional style embedding respectively. We expect that the emotional style embedding can capture the speaker-dependent emotional style that is related to the target speaker. We then convert the F0 with the mean and standard variance calculated from the validation set of target speaker. The decoder learns to generate the converted Mel-spectrograms with the source content embedding, the speaker and emotional style embedding from the reference, and the converted F0. The speech waveform is reconstructed with Parallel WaveGAN vocoder [32].

3.3. Discussion

To validate the effectiveness of our proposed framework on representation learning, we visualize the generated speaker embedding with T-SNE [33] in Fig. 2. We observe that each speaker forms a well-differentiated cluster for each emotion. These results suggest that the proposed framework can generate effective speaker embedding, which is crucial for expressive voice conversion.

4. EXPERIMENTS

We conduct both objective and subjective evaluations to assess the performance of our proposed framework in terms of the speaker identity and emotional style conversion. We use ESD [24], a multi-speaker emotional speech database with five different emotions, that are neutral, happy, sad, angry and surprise. We choose 8 different speakers (4 male and 4 female) and all 5 emotions to conduct all the experiments. For each speaker and each emotion, we follow the data partition described in ESD, and use 300 utterances for training, 30 utterances for validation, and 20 utterances for evaluation. As a comparative study, we adopt VQMVC [23] as our baseline.

4.1. 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 [2]. 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 layer 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 500 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 [24].

4.2. Objective Evaluation

We calculate Mel-cepstral distortion (MCD) to measure the spectral distortion in Table 1. We observe that our proposed framework...
### Table 1. The objective evaluation results with intra-gender and inter-gender settings.

|                | MCD [dB] | Speaker Verification | Prosody Evaluation |
|----------------|----------|----------------------|--------------------|
|                | VQMIVC [23] | Proposed | VQMIVC [23] | Proposed | Target | VQMIVC [23] | Proposed | VQMIVC [23] | Proposed |
| **Intra-gender** |          |          |          |          |        |          |          |          |        |
| Neutral        | 5.29     | 5.29     | 0.88     | 0.91     | 0.95   | 36.04    | 36.00    | 121.19   | 120.77  |
| Happy          | 6.24     | 6.25     | 0.85     | 0.87     | 0.96   | 42.43    | 39.38    | 111.95   | 106.68  |
| Surprise       | 6.64     | 6.63     | 0.81     | 0.85     | 0.96   | 60.84    | 59.91    | 109.77   | 106.00  |
| Angry          | 6.78     | 6.74     | 0.84     | 0.87     | 0.94   | 46.48    | 44.22    | 100.35   | 97.57   |
| **Inter-gender** |         |          |          |          |        |          |          |          |        |
| Neutral        | 5.82     | 5.79     | 0.92     | 0.91     | 0.96   | 36.31    | 34.69    | 103.42   | 102.53  |
| Happy          | 6.28     | 6.08     | 0.86     | 0.85     | 0.94   | 51.01    | 50.28    | 133.58   | 130.16  |
| Sad            | 5.62     | 5.58     | 0.85     | 0.89     | 0.94   | 43.39    | 40.81    | 118.09   | 116.23  |
| Surprise       | 6.48     | 6.33     | 0.81     | 0.86     | 0.94   | 47.83    | 43.51    | 161.26   | 160.72  |
| Angry          | 6.98     | 6.77     | 0.91     | 0.92     | 0.94   | 54.36    | 49.66    | 115.05   | 110.71  |

Table 2. MOS scores for speech quality by 14 listeners.

| Framework       | MOS       |
|-----------------|-----------|
| VQMIVC [23]     | 3.45±0.26 |
| Proposed Framework | 3.54±0.27 |

framework consistently outperforms the baseline for inter-gender setting, and still achieves remarkable performance for intra-gender setting.

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

We further conduct speaker verification experiments with a pre-trained speaker verification model [2]. We report the speaker verification results for the target, VQMIVC, and our proposed framework in Table 1. We observe that our proposed framework consistently achieves the best verification results for intra-gender setting, which is encouraging. For inter-gender setting, we note that our proposed framework still can achieve comparable results with the baseline. These results indicate the superior performance of our proposed framework in terms of the speaker identity conversion.

### 4.3. Subjective Evaluation

We conduct 3 listening experiments to assess the speech quality, speaker similarity and emotional style similarity. 14 subjects participate in all the experiments, and each of them listens to 90 converted utterances in total.

We first report the mean opinion scores (MOS) in Table 2 where a higher MOS score indicates a better speech quality. As shown in Table 2, our proposed framework outperforms the baseline in terms of speech quality.

We then conduct an ABX preference test to evaluate the speaker similarity, where all the listeners are asked to listen to the reference and the converted utterances respectively, and choose the one that sounds closer to the reference in terms of the speaker identity. As shown in Fig. 3, our proposed frame-

Fig. 3. ABX preference results for speaker similarity with 95% confidence interval.

work achieves a better result than the baseline. This observation validates the effectiveness of our proposed framework on speaker identity conversion.

We further conduct another ABX preference test to evaluate the emotional style similarity. From Fig. 4, we observe that our proposed framework significantly outperforms the baseline framework in terms of emotional style similarity. This suggests that our proposed framework achieves a better performance on converting the speaker-dependent emotional style, which further validates our idea on emotional style disentanglement.

Fig. 4. ABX preference results for emotional style similarity with 95% confidence interval.

### 5. CONCLUSION

In this paper, we study the disentanglement of speaker identity and emotional speech style for expressive voice conversion. We propose a framework based on VQMIVC to jointly convert the speaker identity and speaker-dependent emotional style. We introduce a style encoder to explicitly model the 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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