

Speech Representation Disentanglement with Adversarial Mutual Information Learning for One-shot Voice Conversion

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Abstract

One-shot voice conversion (VC) with only a single target-speaker’s speech for reference has become a hot research topic. Existing works generally disentangle timbre, while information about pitch, rhythm and content is still mixed together. To perform one-shot VC effectively with further disentangling these speech components, we employ random resampling for pitch and content encoder and use the variational contrastive log-ratio upper bound of mutual information and gradient reversal layer based adversarial mutual information learning to ensure the different parts of the latent space containing only the desired disentangled representation during training. Experiments on the VCTK dataset show the model achieves state-of-the-art performance for one-shot VC in terms of naturalness and intelligibility. In addition, we can transfer characteristics of one-shot VC on timbre, pitch and rhythm separately by speech representation disentanglement. Our code, pre-trained models and demo are available at <https://im1eon.github.io/IS2022-SRDVC/>.

Index Terms: disentangled speech representation learning, mutual information, adversarial learning, gradient reversal layer

1. Introduction

Voice conversion (VC) is a speech task that studies how to convert one’s voice to sound like that of another while preserving the linguistic content of the source speaker [1, 2]. One-shot VC uses only one utterance from target speaker during the inference phase [3, 4, 5, 6]. Since one-shot VC requires small amount of data from the target speaker, it is more suitable with the needs of VC applications. Compare to traditional VC, to realize one-shot VC is more challenging.

Many works for one-shot VC are based on speech representation disentanglement (SRD), which aim to separate speaker information from spoken content as much as possible. The AutoVC [7] comes up with the idea to combine the advantages of generative adversarial network (GAN) [8] and conditional variational auto-encoder (CVAE) [9] since GAN can obtain a good result while CVAE is easy to train. The IVC system and the SEVC system [3] represent the speaker identity as i-vectors and speaker embedding to perform one-shot VC. The unsupervised end-to-end automatic speech recognition and text-to-speech (ASR-TTS) autoencoder framework [10] use multilabel-binary vectors to represent the content of speech to disentangle content from speaker. An F0-conditioned voice conversion system [11] disentangles prosodic features by tuning the

information-constraining bottleneck of an autoencoder. Due to the ability of SRD to disentangle latent space, there are many other methods [5, 7, 8, 12, 13, 14] based on SRD for VC.

Speech information can be decomposed into four components: content, timbre, pitch and rhythm [15]. Rhythm characterizes the speed of the speaker uttering each syllable [16, 17]. Pitch is an important component of prosody [15]. Apparently, rhythm and pitch representations are related to content, which are important speech representations to improve the naturalness of converted speech [18]. The above related works on VC only consider the decoupling of content and timbre representations without considering the rhythm and pitch representations related to the prosody of speech, which may lead to the leakage of information related to pitch and rhythm into the timbre [19].

Recent studies begin to research pitch and rhythm in VC such as SpeechSplit [15], SpeechSplit2.0 [20] and MAP Network [21]. They have provided a great start for the controllable synthesis of each representation. Whereas, their performances can still be improved for one-shot VC. A recent effort VQMIVC [22] provides the pitch information to retain source intonation variations, resulting in high-quality one-shot VC. However, it does not consider the decoupling of rhythm, resulting in that pitch and rhythm still entangle together.

In this paper, we propose adversarial mutual information learning based SRD for one-shot VC. Specifically, we first decompose a speech into four factors: rhythm, pitch, content and timbre. Then we propose a system consisting of four components: (1) Random resampling [23] operation along the time dimension is performed on pitch and content to remove rhythm information; (2) A common classifier is used for timbre to extract features related to speaker identity, and a gradient reversal layer (GRL) based adversarial classifier is used for speaker-irrelevant information (content, pitch and rhythm) to eliminate speaker information in latent space; (3) The variational contrastive log-ratio upper bound (vCLUB) of mutual information (MI) [24] between different representations is used to separate speaker-irrelevant information from each other; (4) A pitch decoder is used to reconstruct normalized pitch contour and a speech decoder is adopted to reconstruct mel-spectrogram. Main contributions of our work are: (1) Implementing one-shot VC with decoupling content, timbre, rhythm and pitch from the speech, which ensures pitch, rhythm and content more speaker-irrelevant and makes timbre more relevant to speaker. (2) Applying SRD with vCLUB and GRL based adversarial mutual information learning without relying on text transcriptions. Experiments show the information leakage issues can be effectively alleviated by applying with adversarial mutual information learning.

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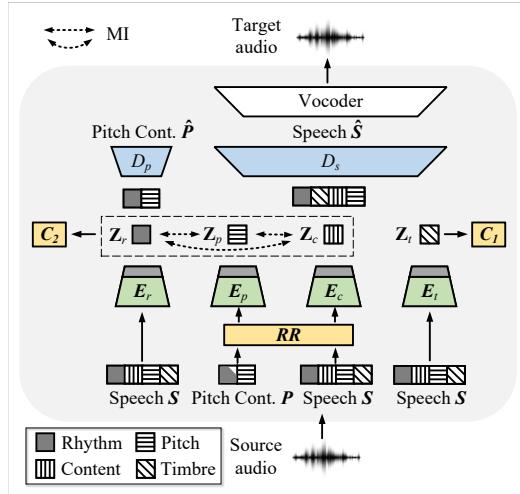


Figure 1: Framework of proposed model. ‘Pitch Cont.’ is short for the normalized pitch contour. Rhythm block with holes represents not all the rhythm information. Signals are represented as blocks to denote their information components.

2. Proposed Approach

We aim to perform one-shot VC effectively by SRD. In this section, we first describe our system architecture. Then we introduce the adversarial mutual information learning and show how one-shot VC on different speech representation is achieved.

2.1. Architecture of the proposed system

As shown in Fig.1, the architecture of the proposed model is composed of six modules: rhythm encoder, pitch encoder, content encoder, timbre encoder, pitch decoder and speech decoder.

Speech representation encoders: Inspired by SpeechSplit [25], the rhythm encoder E_r , pitch encoder E_p , content encoder E_c have the same structure, which consists of a stack of 5×1 convolutional layers and a stack of bidirectional long short-term memory (BiLSTM) layers. Besides mel-spectrogram, the pitch contour also carries information of rhythm [15]. Before the input mel-spectrogram S and normalized pitch contour P are fed to the content encoder and pitch encoder, random resampling [23] operation along the time dimension is performed to remove rhythm information. The model only relies on the rhythm encoder to recover the rhythm information. The speaker encoder [5] E_t is used to provide global speech characteristics to control the speaker identity. Denote the random resampling operation as $RR(\cdot)$, then we have:

$$\begin{aligned} Z_r &= E_r(S), \quad Z_c = E_c(RR(S)), \\ Z_t &= E_t(S), \quad Z_p = E_p(RR(P)) \end{aligned} \quad (1)$$

Decoders: The speech decoder D_s takes the output of all encoders as its input, and outputs speech spectrogram \hat{S} . The input to the pitch decoder D_p is Z_p and Z_r . The output of D_p is generated normalized pitch contour \hat{P} . As for implementation details, Fig.2 shows the network architecture used in our experiments.

$$\hat{S} = D_s(Z_r, Z_p, Z_c, Z_t), \quad \hat{P} = D_p(Z_r, Z_p) \quad (2)$$

During training, the output of D_s tries to reconstruct the input spectrogram S , the output of D_p tries to reconstruct the

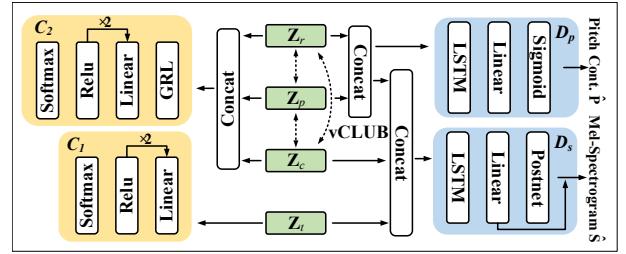


Figure 2: The architecture of proposed model.

input normalized pitch contour P . Decoders are jointly trained with encoders by minimizing the reconstruction losses:

$$\mathcal{L}_{s\text{-recon}} = \mathbb{E} [\|\hat{S} - S\|_1^2 + \|\hat{S} - S\|_2^2] \quad (3)$$

$$\mathcal{L}_{p\text{-recon}} = \mathbb{E} [\|\hat{P} - P\|_2^2] \quad (4)$$

2.2. Adversarial mutual information learning

As shown in Fig.1, we use common classifier C_1 and adversarial speaker classifier C_2 to recognize the identity of speaker. The vCLUB [24] is used to compute the upper bound of MI for irrelevant information of the speaker. A measure of the dependence between two different variables can be formulated as:

$$\mathcal{I}(X, Y) = \int_X \int_Y P(X, Y) \log \frac{P(X, Y)}{P(X)P(Y)} \quad (5)$$

where $P(X)$ and $P(Y)$ are the marginal distributions of X and Y respectively, and $P(X, Y)$ denotes the joint distribution of X and Y .

Gradient Reverse: Assumed the speaker information u is related to timbre Z_t only, while independent of rhyme Z_r , pitch Z_p and content Z_c . First, we aim to disentangle speaker-irrelevant information $\{Z_r, Z_p, Z_c\}$ from speaker relevant timbre Z_t . Instead of directly minimizing $\mathcal{I}(\{Z_r, Z_p, Z_c\}, Z_t)$, we can maximize $\mathcal{I}(Z_t, u)$ and minimize $\mathcal{I}(\{Z_r, Z_p, Z_c\}, u)$ respectively, which can be implemented as common classifier C_1 and adversarial speaker classifier C_2 . As shown in Fig.2, the input of C_1 is Z_t and the input of C_2 is $\{Z_r, Z_p, Z_c\}$. GRL [26] is inserted in C_2 as the adversarial classifier. The two classifiers can be formulated as:

$$\begin{aligned} \mathcal{L}_{\text{com-cls}} (\theta_{e_{c_1}}, \theta_{c_1}) &= - \sum_{k=1}^K \mathbb{I}(u == k) \log p'_k \\ \mathcal{L}_{\text{adv-cls}} (\theta_{e_{c_2}}, \theta_{c_2}) &= - \sum_{k=1}^K \mathbb{I}(u == k) \log p_k \end{aligned} \quad (6)$$

where $\mathbb{I}(\cdot)$ is the indicator function, K is the number of speakers and u denotes speaker who produced speech x , p_k is the probability of speaker k , $\theta_{e_{c_1}}$ denotes the parameters of E_t , and $\theta_{e_{c_2}}$ denotes the parameters of $\{E_r, E_p, E_c\}$. θ_{c_1} and θ_{c_2} denote the parameters of C_1 and C_2 respectively.

Mutual information: A vCLUB of mutual information is defined by:

$$\begin{aligned} \mathcal{I}(\mathbf{X}, \mathbf{Y}) &= \mathbb{E}_{p(\mathbf{X}, \mathbf{Y})} [\log q_\theta(\mathbf{Y} | \mathbf{X})] \\ &\quad - \mathbb{E}_{p(\mathbf{X})} \mathbb{E}_{p(\mathbf{Y})} [\log q_\theta(\mathbf{Y} | \mathbf{X})] \end{aligned} \quad (7)$$

where $\mathbf{X}, \mathbf{Y} \in \{Z_r, Z_p, Z_c\}$, $q_\theta(Y|X)$ is a variational distribution with parameter θ to approximate $p(Y|X)$. The unbiased

estimator for vCLUB with samples $\{\mathbf{x}_i, \mathbf{y}_i\}$ is:

$$\hat{\mathcal{I}}(\mathbf{X}, \mathbf{Y}) = \frac{1}{N^2} \sum_{i=1}^N \sum_{j=1}^N [\log q_\theta(\mathbf{y}_i | \mathbf{x}_i) - \log q_\theta(\mathbf{y}_j | \mathbf{x}_i)]. \quad (8)$$

where $\mathbf{x}_i, \mathbf{y}_i \in \{\mathbf{Z}_{r_i}, \mathbf{Z}_{p_i}, \mathbf{Z}_{c_i}\}$.

By minimizing (8), we can decrease the correlation among different speaker-irrelevant speech representations. The MI loss is:

$$\mathcal{L}_{MI} = \hat{\mathcal{I}}(\mathbf{Z}_r, \mathbf{Z}_p) + \hat{\mathcal{I}}(\mathbf{Z}_r, \mathbf{Z}_c) + \hat{\mathcal{I}}(\mathbf{Z}_p, \mathbf{Z}_c) \quad (9)$$

At each iteration of training, the variational approximation networks which are trained to maximize the log-likelihood $\log q_\theta(\mathbf{Y} | \mathbf{X})$ is first optimized, and then the VC network is optimized. The loss of VC network can be computed as:

$$\mathcal{L}_{VC} = \mathcal{L}_{s\text{-recon}} + \mathcal{L}_{p\text{-recon}} + \alpha \mathcal{L}_{\text{com-cls}} + \beta \mathcal{L}_{\text{adv-cls}} + \gamma \mathcal{L}_{MI} \quad (10)$$

2.3. One-shot VC on different speech representations

Take general voice conversion (timbre conversion) as example. Rhythm $\mathbf{Z}_{r_{src}}$, pitch $\mathbf{Z}_{p_{src}}$ and content $\mathbf{Z}_{c_{src}}$ representations are extracted from the source speaker’s speech S_{src} . While timbre $\mathbf{Z}_{t_{tgt}}$ is extracted from the target speaker’s speech S_{tgt} . The decoder then generates the converted mel-spectrograms as $D_s(\mathbf{Z}_{r_{src}}, \mathbf{Z}_{p_{src}}, \mathbf{Z}_{c_{src}}, \mathbf{Z}_{t_{tgt}})$. To convert rhythm, we feed the target speech to the rhythm encoder E_r to get the $\mathbf{Z}_{r_{tgt}}$. If we want to convert pitch, we feed the normalized pitch contour of the target speaker to the pitch encoder E_p . Besides, three double-aspect conversions (rhythm+pitch, rhythm+timbre, and pitch+timbre) and all-aspect conversion are similar.

3. Experiments

3.1. Experiment setup

All experiments are conducted on the VCTK corpus [27], which are randomly split into 100, 3 and 6 speakers as training, validation and testing sets respectively. For acoustic features extraction, all audio recordings are downsampled to 16kHz, and the mel-spectrograms are computed through a short-time Fourier transform with Hann windowing, 1024 for FFT size, 1024 for window size and 256 for hop size. The STFT magnitude is transformed to mel scale using 80 channel mel filter bank spanning 90 Hz to 7.6 kHz. For pitch contour, z-normalization is performed for each utterance independently.

The proposed VC network is trained using the ADAM optimizer [28] (learning rate is e-4, $\beta_1 = 0.9$, $\beta_2 = 0.98$) with a batch size of 16 for 800k steps. We set $\alpha = 0.1$, $\beta = 0.1$, $\gamma = 0.01$ for equation (10) and use a pretrained WaveNet [29] vocoder to convert the output mel-spectrogram back to the waveform. Due to the lack of explicit labels of the speech components, the degree of SRD are hard to evaluate [25]. Therefore, we focus on the timbre conversion by comparing with other one-shot VC models (Please note that we are able to transfer four representations of the one-shot VC as the demo shows, not just the timbre of target speaker). We compare our proposed method with AutoVC [7], ClsVC[30], AdaIN-VC [5], VQVC+ [14] and VQMIVC [22], which are among the state-of-the-art one-shot VC methods.

3.2. Experimental results and analysis

3.2.1. Conversion Visualization

Fig.3 shows the pitch contours of the source (female speaker), target (male speaker) and converted speeches with the content

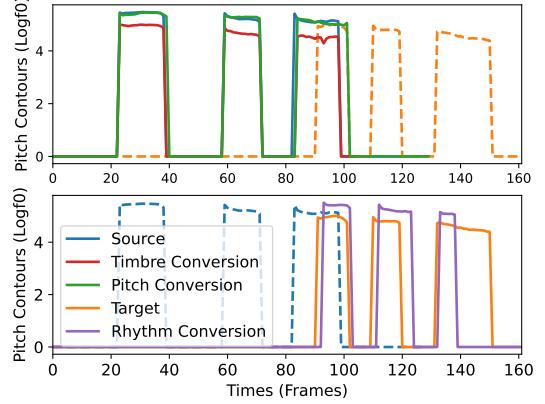


Figure 3: Pitch contours without normalization of single-aspect conversion results with the content ‘Please call Stella’.

“Please call Stella”. Please note we use parallel speech data to visualize the results. For timbre conversion, the pitch contour of the converted speech matches average pitch of the target speech but retains detailed characteristics of the source pitch contour. For pitch conversion, on the other hand, the converted pitch contour tries to mimic detailed characteristics of the target speech with average pitch value close to the source one. For rhythm conversion, the converted pitch contour is located at the target position as expected. Furthermore, the timber conversion result in Fig.3 also confirms to the common sense that the average pitch of the converted speech decreases from female to male.

3.2.2. Subjective Evaluation

Subjective tests are conducted by 32 listeners with good English proficiency to evaluate the speech naturalness and speaker similarity of converted speeches generated from different models. The speech audios are presented to subjects in random order. The subjects are asked to rate the speeches on a scale from 1 to 5 with 1 point interval. The mean opinion scores (MOS) on naturalness and speaker similarity are reported in the first two rows in Table 1. The proposed model outperforms all the baseline models in terms of speech naturalness, and has a comparable performance with VQMIVC in terms of speaker similarity.

3.2.3. Objective Evaluation

For objective evaluation, we use mel-cepstrum distortion (MCD) [31], character error rate (CER), word error rate (WER) and pearson correlation coefficient (PCC) [32] of $\log F_0$. MCD measures the spectral distance between two audio segments. The lower the MCD is, the smaller the distortion, meaning that the two audio segments are more similar to each other. To get the alignment between the prediction and the reference, we use dynamic time warping (DTW). CER and WER of the converted speech evaluate whether the converted voice maintains linguistic content of the source voice. CER and WER are calculated by the transformer-based automatic speech recognition (ASR) model trained on the librispeech [33], which is provided by ESPnet2 [34]. To evaluate intonation variations of the converted voice, PCC between F_0 of source and converted voice is calculated. To evaluate the proposed method objectively, 50 conversion pairs are randomly selected. The results for different

Table 1: Evaluation results of different models. Speech naturalness and speaker similarity are results of MOS with 95% confidence intervals. '*' denotes the proposed model. ‘w/o’ is short for ‘without’ in ablation study. ‘ \mathcal{L}_{CLS} ’ denotes the $\mathcal{L}_{com\text{-}cls}$ and $\mathcal{L}_{adv\text{-}cls}$.

Methods	AutoVC	ClsVC	AdaIN-VC	VQVC+	VQMIVC	Our Model*	w/o $\mathcal{L}_{p\text{-}recon}^*$	w/o \mathcal{L}_{MI}^*	w/o \mathcal{L}_{CLS}^*
Naturalness	2.42±0.13	2.82±0.14	2.38±0.15	2.68±0.13	3.70±0.13	3.82±0.13	3.59±0.13	3.47±0.13	1.81±0.18
Similarity	2.80±0.19	3.19±0.18	2.95±0.21	3.08±0.22	3.61±0.19	3.59±0.20	3.24±0.17	3.21±0.14	2.55±0.19
MCD(dB)	6.87	6.76	7.95	8.25	5.46	5.23	6.45	5.56	9.54
CER(%)	32.69	42.90	29.09	38.17	10.08	9.60	19.63	6.91	65.00
WER(%)	47.09	63.35	39.56	52.43	16.99	14.81	28.15	13.35	92.96
$\log F_0$ PCC	0.656	0.700	0.715	0.612	0.829	0.768	0.759	0.764	0.672

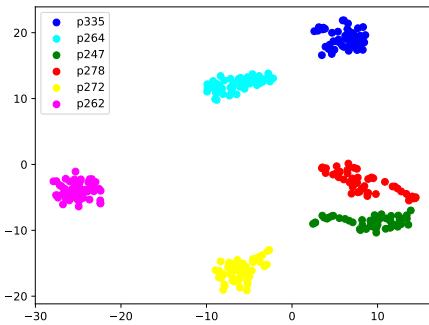


Figure 4: The visualization of speaker embedding. None of these speakers appeared in training.

methods are shown in Table 1. It can be seen that our proposed model outperforms baseline systems on MCD. And our model achieves the lowest CER and WER among all methods, which shows the proposed method has better intelligibility with preserve the source linguistic content. In addition, our model achieves a higher $\log F_0$ PCC, which shows the ability of our model in transforming and preserving the detailed intonation variations from source speech to the converted one. $\log F_0$ PCC of VQMIVC is higher because the pitch information is directly fed to the decoder, without passing through the random resampling operation and pitch encoder.

Besides, Fig.4 illustrates timber embedding Z_t of different speakers visualized by tSNE method. There are 50 utterances sampled for every speaker to calculate the timbre representation. As can be seen, timber embeddings are separable for different speakers. In contrast, the timber embeddings of utterances of the same speaker are close to each other. The result indicates that our timber encoder E_t is able to extract timbre Z_t as speaker information u .

To further evaluate the quality of one-shot VC on different speech representations, we use a well-known open-source toolkit, Resemblyzer¹, to make the fake speech detection test. On a scale of 0 to 1, the higher the score is, the more authentic the speech is. 50 utterances are used for each model. The average scores are shown in Fig.5. Our model performs well on one-shot VC on different speech representations.

3.2.4. Ablation study

Moreover, we conduct ablation study that addresses performance effects from different learning losses in equation (10),

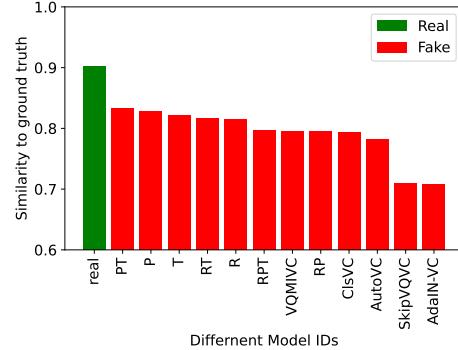


Figure 5: Results of fake speech detection. ‘P’, ‘T’ and ‘R’ denotes pitch, timbre and rhythm conversion respectively.

with results shown in the last three columns of Table 1. From the results, when the model is trained without the loss of pitch decoder D_p ($\mathcal{L}_{p\text{-}recon}$) or vCLUB (\mathcal{L}_{MI}), the model is still able to perform one-shot VC and outperforms most of the baseline models, but the speech naturalness and speaker similarity both decrease. When the losses of common classifier C_1 and adversarial speaker classifier C_2 (\mathcal{L}_{CLS}) are removed, the results are poor and no longer perform the VC task well.

4. Conclusions

In this paper, based on the disentanglement of different speech representations, we propose an approach using adversarial mutual information learning for one-shot VC. To make the timbre information as similar as possible to the speaker, we use a common classifier of the timbre. Also, we use GRL to keep speaker-irrelevant information as separate from the speaker as possible. Then pitch and content information can be removed from rhyme information by random resampling. The pitch decoder ensures that the pitch encoder gets the correct pitch information. The vCLUB makes speaker-irrelevant information as separate as possible. We achieve proper disentanglement of rhythm, content, speaker and pitch representations and are able to transfer different representations style in one-shot VC separately. The naturalness and intelligibility of one-shot VC is improved by speech representation disentanglement (SRD) and the performance and robustness of SRD is improved by adversarial mutual information learning.

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¹<https://github.com/resemble-ai/Resemblyzer>

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