CVC: CONTRASTIVE LEARNING FOR NON-PARALLEL VOICE CONVERSION

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ABSTRACT
Cycle consistent generative adversarial network (CycleGAN) and variational autoencoder (VAE) based models have gained popularity in non-parallel voice conversion recently. However, they usually suffer from difficulty in model training and unsatisfactory results. In this paper, we propose CVC, a contrastive learning-based adversarial model for voice conversion. Compared to previous methods, CVC only requires one-way GAN training when it comes to non-parallel one-to-one voice conversion, while improving speech quality and reducing training time. CVC further demonstrates performance improvements in many-to-one voice conversion, enabling the conversion from unseen speakers.

Index Terms— Non-parallel Voice Conversion, Contrastive Learning, Noise Contrastive Estimation

1. INTRODUCTION

In voice conversion (VC), given a speech signal from a source speaker, we aim to convert it to the voice of a target speaker while preserving the speech content. Undoubtedly, developing VC method requires speech data from both speakers. Early frameworks, such as [1, 2, 3], were typically developed using parallel speech data, i.e., the source and target speech pairs share the same linguistic content and are temporally aligned. However, the availability of parallel speech pairs is very limited due to the humongous cost in data collection, therefore more recent studies are focused on non-parallel VC.

Non-parallel VC can be formulated as a regression problem of approximating a mapping function from source domain to target domain, i.e. a domain-to-domain transformation. Cycle consistent adversarial network (CycleGAN) [4] was first introduced to tackle unpaired image translation problem which is comparable to non-parallel VC since both tasks require domain-to-domain transformation. It follows that several state-of-the-art works in non-parallel VC, such as CycleGAN-VC [5, 6] and StarGAN-VC [7, 8], are based on the cycle-consistency mechanism, where a consistency loss has been applied to construct an invertible mapping such that the generated speech can sufficiently preserve the speech content from the source speaker.

Although cycle consistency is an effective mechanism for controlling the quality of the generation process, it is often too restrictive in real-life scenarios. This setting is especially difficult for speech signals from one domain containing additional information compared to the other domain. Moreover, it is known that GANs are notoriously difficult to train. The situation could be worse when training CycleGAN models which consist of two GANs in order to accomplish the inverse mapping. Thus, developing such models may involve great training cost and extra tuning.

Besides the adversarial approaches mentioned above, there are also works based on auto-encoder (AE) and variational auto-encoder (VAE). AutoVC [9] used AE to construct a suitable bottleneck that allows the network to separately encode content information into latent representations. The solution presented in [10] applies a regular VAE, along with latent sampling and the Gaussian reparameterization trick [11], which is one of the early attempts on non-parallel VC. In more recently emerged works, VAE has been combined with contrastive predictive coding (CPC) [12] to tackle voice conversion. In [13], CPC is used as an additional regularization objective for enhancing the content encoder. VQVAE-CPC [14] used vector-quantized VAE (VQ-VAE) [15] where the quantized latent representations could discard undesired attributes from the source speech more effectively.

Inspired by the recent work [16] for unpaired image translation, we propose a concise contrastive learning-based model for voice conversion, i.e. CVC, which contains two explicit training objectives, namely the adversarial and contrastive losses. Compared to CycleGAN, CVC only uses a regular one-way GAN structure. In contrast to the previous CPC-VAE based approaches, we aim to establish correspondence between source and target content, by applying contrastive losses at different levels (scales) of the spectral features. In the end, we will show that CVC outperforms two competitive baselines in different metrics.
2. CONTRASTIVE VOICE CONVERSION

Under the unsupervised voice conversion learning setting, the general goal is to learn a spectral mapping from source domain $\mathcal{X}$ to target domain $\mathcal{Y}$ without using parallel speech pairs. Here, each domain can be defined as either a single speaker or multiple speakers treated as an entity. Our proposed CVC is capable of conducting both one-to-one and many-to-one voice conversion. This can be achieved through two distinct training objectives, which will be explained in this section.

2.1. Adversarial training

In contrast to the previous CycleGAN-based approaches, CVC only requires a single GAN, which largely simplifies the training process. The generator network $G$ can be divided into two components, an encoder $G_{enc}$ followed by a decoder $G_{dec}$. For a given dataset of non-parallel speech instances $X = \{x \in \mathcal{X}\}$, $Y = \{y \in \mathcal{Y}\}$, $G_{enc}$ and $G_{dec}$ are applied sequentially to generate the output spectrogram $\hat{y} = G_{dec}(G_{enc}(x))$. An adversarial loss $[17]$ is then applied to encourage $\hat{y}$ to approach the spectral features of the target domain $\mathcal{Y}$:

$$L_{GAN}(G_{X \rightarrow Y}, D_Y) = \mathbb{E}_{y \sim Y} \log D(y) + \mathbb{E}_{x \sim X} \log (1 - D(G(x)))$$  \hspace{1cm} (1)

where $D$ is the discriminator network.

2.2. Establishing mutual correspondence via contrastive learning

In VC, a successfully converted speech should be equipped with the target speaker style while fully preserving the content of the source speech. However, both information, i.e. content and speaker information, are inherently entangled within the spectral feature, and adversarial training can only guarantee style transfer in the results. One trivial solution is that we get a spectral feature, and adversarial training can only guarantee one possible solution. Instead, we introduce a contrastive learning objective to establish mutual correspondence between source and target domains.

For a given dataset of non-parallel speech instances $X = \{x \in \mathcal{X}\}$, $Y = \{y \in \mathcal{Y}\}$, the fundamental objective in contrastive learning is to add to the speech the style of the corresponding "positive" sample $v^+$ while fully preserving the corresponding "negative" samples $v^-$. The query, positive and $N$ negatives are transformed to $M$-dimensional vectors, i.e. $q, v^+ \in \mathbb{R}^M$ and $v^- \in \mathbb{R}^{N \times M}$. This problem setting can be expressed as a multi-classification task with $N + 1$ classes:

$$\ell(q, v^+, v^-) = -\log \left( \frac{\exp(\frac{q \cdot v^+}{\tau})}{\exp(\frac{q \cdot v^+}{\tau}) + \sum_{n=1}^{N} \exp(\frac{q \cdot v_n^-}{\tau})} \right)$$ \hspace{1cm} (2)

where $v_n^-$ denotes the n-th negative sample and $\tau$ is a temperature parameter, as suggested in SimCLR [19], which scales the similarity distance between $q$ and other samples. The cross-entropy term in (2) represents the probability of matching $q$ with the corresponding positive sample $v^+$. Thus, iteratively minimizing the negative log-crossentropy is equivalent to establishing mutual correspondence between the query and sample space.

In our VC task, we draw the $N + 1$ positive/negative samples internally from the source spectrogram $x \in \mathcal{X}$, and the query $q$ is selected from the generated spectrogram $\hat{y}$. From Figure 1 it can be seen that the selected samples are treated as "patches" that capture local information among the spectrograms. This setup is motivated by the logical assumption that the global correspondence between $x$ and $\hat{y}$ is determined by the local, i.e. patch-wise, correspondences. In other words, patch-wise optimization on multi-scale features would eventually lead to the convergence from local to global correspondence.

Since the encoder $G_{enc}$ is a multi-layer network that maps $x$ into feature stacks after each layer, we choose $L$ layers and pass their feature stacks through a small MLP network $P$. The output of $P$ is $P(G_{enc}(x)) = \{v^1, ..., v^N, v^{N+1}\}$, where $l \in \{1, 2, ..., L\}$ denotes the index of the chosen encoder layers and $G_{enc}^l(x)$ is the output feature stack of the $l$-th layer.

Fig. 1. Patch-wise contrastive learning for one-way voice conversion. The phoneme type of "hello world" is taken as an example since we aim to preserve the content information among other features. A generated spectral patch (red) representing "HH" should match its corresponding input patch (blue) "HH", in comparison to other random patches "AH", "W" or "D". We use a multi-scale patch-wise contrastive loss [16], which establishes mutual correspondence between source and generated spectrograms. This enables one-way voice conversion using non-parallel corpora. Note that the MLP component has been ignored during inference.
Similarly, we can obtain the query set by encoding the generated spectrogram \( \hat{y} \) into \( \{ q^1, \ldots, q^N, q^{N+1} \} = P(G_{\text{enc}}(\hat{y})) \). Now let \( v^n_\ell \in \mathbb{R}^M \) and \( v^{(N+1)}_\ell \in \mathbb{R}^{N \times M} \) denote the corresponding positive sample and the \( N \) negative samples, respectively, where \( n \) is the sample index and \( M \) is the channel size of \( P \). By referring to Eq. (2), our second training objective can be expressed as:

\[
L_{\text{NCE}}(G_{\text{enc}}, P, X) = \mathbb{E}_{x \sim X} \sum_{\ell=1}^{L} \sum_{n=1}^{N+1} \ell(q^n_\ell, v^n_\ell, v^{(N+1)}_\ell) \tag{3}
\]

which is the average NCE loss from all \( L \) encoder layers.

### 2.3. Overall objective

In addition to the two objectives discussed above, we have also employed an identity loss \( L_{\text{identity}} = L_{\text{NCE}}(G_{\text{enc}}, P, Y) \) which utilizes the NCE expression in Eq. (3). By taking the NCE loss on the identity generation process, i.e. generating \( \hat{y} \) from \( y \), we are likely to prevent the generator from making unexpected changes. Now we can define our final training objective as:

\[
L_{\text{CVC}} = L_{\text{GAN}}(G_{X \rightarrow Y}, D_Y) + \lambda L_{\text{NCE}}(G_{\text{enc}}, P, X) + \mu L_{\text{NCE}}(G_{\text{enc}}, P, Y) \tag{4}
\]

where \( \lambda \) and \( \mu \) are two parameters for adjusting the strengths of the NCE and the identity loss.

### 3. EXPERIMENTS

In this section, we will introduce the training schemes of our proposed model which was evaluated on one-to-one and many-to-one voice conversion experiments. Besides, some listening demos are available online[^1].

#### 3.1. Training Schemes

**VCTK corpus**[^20], which contains 44 hours of utterances from 109 speakers, was used to evaluate our proposed model. It is a suitable dataset for addressing non-parallel VC because each speaker reads different sentences, except the rainbow passage and the elicitation paragraph. For the one-to-one VC experiment, utterances from two different speakers, i.e. the source and target speaker, were used for training. And 50 utterances from the source speaker, which were disjoint to the training utterances, were selected for model evaluation. Moreover, the many-to-one VC experiment involved multiple source speakers which were treated as a single source domain. Similar to the one-to-one VC experiment, 50 novel utterances from each source speaker were selected for evaluation. Please note that the utterances from 9 chosen speakers were excluded in this experiment, in order to use them to also evaluate the model performance on unseen source speakers after training. We used a fix duration of 2s for training efficiency, and those less than 2s were taken away because zero padding would introduce tremendous redundancy and cause NCE loss difficult to converge. Before training, all of the utterances were first converted to 24 kHz and 32-bit precision in floating-point PCM format. Then, we extracted 80-dimensional log-Mel-spectrogram features from them, with 25 ms frame length and 10 ms frame-shift, and used a frame-level energy-based voice activity detector (VAD) to filter out non-speech frames. Finally, our proposed CVC was trained with a batch size of 1 and an initial learning rate of 2e-4 for 1000 epochs, using the Adam optimizer. The weights in Eq. (4) were set to \( \lambda = 1, \mu = 1 \). Besides, the Parallel WaveGAN (PWG) vocoder[^21] was used for reconstructing the waveform signals from the converted log-Mel-spectrograms. Further training schemes and hyperparameter settings are available with the code[^3].

#### 3.2. Evaluation Metrics

We performed two subjective tests on Amazon Mechanical Turk (MTurk)[^3]. The first test used the mean opinion score (MOS)[^22] metric to evaluate the converted utterances from the one-to-one VC experiment. For each utterance, the listeners were asked to rate a score of 1-5 (higher score indicates better quality) on the voice naturalness and a score of 1-4 on the voice similarity, given the target voice. In contrast to the first test, the second test used the comparison mean opinion score (CMOS) metric. This test aimed to evaluate the converted utterances, from the 9 unseen source speakers, in the many-to-one VC experiment. The listeners were asked to distinguish between the utterances generated by CVC and the baseline model, in terms of better naturalness and voice similarity.

Furthermore, the voice encoder system[^23], which is an objective test, was applied to evaluate the voice similarity between each converted utterance and its corresponding target utterance. Specifically, we used Resemblyzer[^4], an open-source text-independent speaker verification system, which is applicable to compute the voice similarity in non-parallel VC. This system yields scores that ranges from 0 to 1, where 0 corresponds to different speakers with high confidence, and 1 corresponds to the same speaker with high confidence.

#### 3.3. One-to-one VC Experiment

Here, two state-of-the-art baselines, i.e. CycleGAN-VC[^6] and VAE-VC[^10], were compared to our proposed CVC in one-to-one VC task. Please note that in the original work of CycleGAN-VC, World vocoder[^24] was applied to reconstruct the waveform signals. However, in order to make fair comparison, we changed this setting to log-Mel-spectrogram.

[^1]: https://github.com/Tinglok/CVC
[^2]: https://www.mturk.com/
[^3]: https://github.com/resemble-ai/Resemblyzer
[^4]: https://tinglok.netlify.com/files/cvc/
Table 1. A comparison objective voice similarity (ranging from 0 to 1) of our proposed CVC with other baseline models on the VCTK dataset, where the best results are shown in bold.

| Gender     | One to One | Many to One | Many (unseen) to One |
|------------|------------|-------------|----------------------|
|            | CVC        | CycleGAN [6]| VAE [10]             | CVC        | CycleGAN [6]| VAE [10]             | CVC        | CycleGAN [6]|            |
| Male-Male  | 0.963      | 0.961       | 0.816                | 0.947      | 0.941       | 0.778                | 0.992      | 0.984       |            |
| Male-Female| 0.979      | 0.964       | 0.805                | 0.942      | 0.926       | 0.803                | 0.952      | 0.935       |            |
| Female-Female | 0.965   | 0.937       | 0.828                | 0.966      | 0.945       | 0.831                | 0.963      | 0.958       |            |
| Female-Male | 0.982      | 0.979       | 0.874                | 0.981      | 0.979       | 0.845                | 0.988      | 0.984       |            |

Fig. 2. MOS results on voice naturalness (left) and similarity (right) for one-to-one VC, where the error bars denote 95% confidence interval.

+ PWG vocoder [21] as used in CVC. For VAE-VC, we used the official implementation\[^1\]. It can be seen from Table 1 that CVC has higher objective voice similarity scores on both inter-gender and intra-gender conversions, which implies CVC generates better speaker timbre. Furthermore, when the target speaker is a female, the score differences between CVC and the baseline models are relatively large, showing that CVC is more suitable for high frequency modeling. Besides, as shown in Figure 2, the MOS scores of CVC are also better than the other baseline models, thus indicating that has better content and timbre encoding abilities than the others. Results in both experiments demonstrate that our proposed model yields better one-to-one voice conversion performance.

Besides performance, we also compared the training time between CVC and CycleGAN-VC under the same environmental condition, where a cluster that contains 64 AMD Ryzen Threadripper 2990WX 32-Core Processor CPU and 1 GeForce RTX 2080 Ti GPU was used for training. As the result, the time elapsed of CVC (518 min) was less than that of CycleGAN-VC (574 min), suggesting that CVC only needs 90.2% of CycleGAN-VC’s training time. This follows our expectation since CVC only uses a regular GAN structure.

3.4. Many-to-one VC Experiment

This experiment consists of two explicit parts. The first part evaluates the performance of CVC on the seen source speakers while the second part evaluates on the 9 unseen source speakers. Please note that only CycleGAN-VC was used as the baseline model in the second part because VAE-VC is not capable of generating utterances from unseen source speakers. The objective similarity scores of the first and second part are shown in the last two columns of Table 1. Interestingly, when the target speaker is male, the voice similarity score is better than when it is female, suggesting that it may be easier to convert to a low frequency voice than a high frequency voice. Besides, CVC surpasses CycleGAN-VC and VAE-VC in both inter-gender and intra-gender conversions, which manifests that CVC has better timbre conversion capability than the baseline models.

Furthermore, according to Figure 3, the naturalness and similarity CMOS of CVC also outperform CycleGAN-VC in both inter-gender and intra-gender conversions. Hence, it can be stated that CVC is more effective than the state-of-the-art baseline models in both the objective and subjective metrics.

4. CONCLUSION

In this paper, we proposed a concise method, i.e. CVC, for preserving content information in non-parallel voice conversion problems, where contrastive learning is highlighted as an effective mechanism for establishing correspondence between source input and generated output. Experimental results show that CVC yields better subjective and objective scores than the baseline models in both one-to-one and many-to-one voice conversion tasks. For future work, CVC can be simply generalized towards many-to-many voice conversion by adding speaker embeddings to the network, which could be a promising direction. Moreover, we can explore the potential of CVC on one-shot VC task, since the contrastive-based models have shed some light on this area.

[^1]: https://github.com/JeremyCCChau/vae-npvc
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