CYCLETRANSGAN-EVC: A CYCLEGAN-BASED EMOTIONAL VOICE CONVERSION MODEL WITH TRANSFORMER

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ABSTRACT
In this study, we explore the transformer’s ability to capture intra-relations among frames by augmenting the receptive field of models. Concretely, we propose a CycleGAN-based model with the transformer and investigate its ability in the emotional voice conversion task. In the training procedure, we adopt curriculum learning to gradually increase the frame length so that the model can see from the short segment till the entire speech. The proposed method was evaluated on the Japanese emotional speech dataset and compared to several baselines (ACV AE, CycleGAN) with objective and subjective evaluations. The results show that our proposed model is able to convert emotion with higher strength and quality.

Index Terms— emotional speech conversion, cycle-consistent adversarial networks

1. INTRODUCTION
Emotional voice conversion is a special type of voice conversion (VC), which aims to transform an utterance’s emotional features into a target one while retaining the semantic information and speaker identity. Some earlier research in this field focused on mapping the prosody and spectrogram with partial least square regression [1], Gaussian Mixed Model (GMM) [2, 3], and the sparse representation method [4, 5]. Recently, some researchers leverage deep learning methods to improve the performance of EVC, such as deep neural network (DNN) [6, 7], sequence-to-sequence model (seq2seq) with long-short-term memory network (LSTM) [8], convolutional neural network (CNN) [9], as well as their combinations with the attention mechanism [10]. However, these models require to be trained on parallel data, that is, both the source and target should be from the same speaker and have identical linguistic information but in different emotions.

To reduce the models’ reliance on parallel training data, some novel frameworks are introduced into this field. Gao et al. [11] proposed a nonparallel data-driven emotional speech conversion method with an auto-encoder. Lately, Ding et al. [12] adopted vector quantized variational autoencoders (VQ-VAE) with the group latent embedding (GLE) for nonparallel data training. Moreover, to better learn the mapping function between non-parallel data distributions, cycle-consistent adversarial network (CycleGAN) [13, 14] and variational autoencoder-generative adversarial network (VAE-GAN) [15] were introduced to EVC task. Furthermore, Moritani et al. [16] employed starGAN to realize non-parallel spectral envelope transformation. These EVC models with CNN-based layers trained on non-parallel data all achieved a not bad performance.

Despite the progress made in non-parallel data training, there remains some room to improve the quality of converted emotional voice. Because speech is a time series with rich acoustic features, there are some interactive temporal relationships among frames need to be considered. Although CNNs are well-known for their ability to handle temporal data. To process speech data, which is a sort of lengthy temporal sequence, CNN-based models must be stacked very deep in order to widen the receptive field. However, the temporal intra-relations would be diluted layer by layer with this manner and make the model suffer from some instability problems such as mispronunciations and skipped phonemes.

Considering to augment the receptive field of models and the ability to capture intra-relations among frames, the transformer has been widely discussed in the field of computer vision [17] and natural language processing [18], and its attention distance is also explored. However, few studies have investigated the capabilities of transformers for the task of speech generation or conversion. Therefore, to solve the aforementioned problem, in this study:

- We proposed a CycleGAN-based model with the transformer and investigated its ability in the EVC task, we named our model CycleTransGAN.
- Moreover, to enhance the model’s ability for converting emotional voice, we adopted curriculum learning to...
gradually increase the frame length during the training.

- The proposed method was evaluated on the Japanese emotional speech dataset and compared to several baselines (i.e. ACVAE [19], CycleGAN [13]) and the different configurations of our proposed model.

2. PROPOSED METHOD

2.1. Preprocessing

In this study, we extracted F0 and spectrogram from the speech as our model’s inputs inspired by Zhou et al. [13], Ming et al. [20], and Kaneko et al. [21]. The following contents demonstrate how the extraction was conducted.

For extracting the F0 feature, the F0 contour was extracted first, then, the continuous wavelet transform (CWT) was adopted to decompose it into multiple temporal scales (see Eq.1).

\[ W(F0)(\tau, t) = \tau^{-1/2} \int F0(x)\phi\left(\frac{x - t}{\tau}\right)dx \] (1)

In this study, we set the CWT analysis at 10 scales with one octave apart, which can be represented as:

\[ W_i(F0)(t) = W_i(F0)(2^{i+1} T_0, t)(i + 2.5)^{-5/2} \] (2)

where \( i \in [1, 10] \) and \( T_0 = 5ms \). Finally, the signal is approximately reconstructed as:

\[ F0(t) = \sum_{i=1}^{10} W_i(F0)(t)(i + 2.5)^{-5/2} \] (3)

For the spectrogram extraction, a three-step method so-called CheapTrick [22] was adopted. First, we calculated the power spectrogram based on the windowed waveform as Eq.4, the \( y(t) \) stands for the waveform, while \( w(t) \) indicates the window function:

\[ \int_{-\pi/2}^{\pi/2} (y(t)w(t))^2dt = 1.125 \int_{0}^{T_0} y^2(t)dt \] (4)

Second, CheapTrick technique smooths the spectrogram with a window of width \( 2w_0/3 \), where \( w_0 = 2\pi/T_0 \):

\[ P(w) = \frac{3}{2w_0} \int_{-w_0/3}^{w_0/3} P(w + \sigma)d\sigma \] (5)

After that, the liftering is carried out in the quefrency domain to eliminate the fluctuation:

\[ P(w) = exp(\mathcal{F}[l_s(\tau)l_q(\tau)p_s(\tau)]) \]

\[ l_s(\tau) = \frac{\sin(\pi F0\tau)}{\pi F0\tau} \]

\[ l_q(\tau) = q_0 + 2q_1 \cos(2\pi \tau/T_0) \]

\[ p_s(\tau) = \mathcal{F}^{-1}[\log(P(w))] \] (6)
where \( F \) and \( F^{-1} \) stands for the Fourier transform and its inversion respectively. \( l_{\tau}(\tau) \) indicates the liftering function for smoothing the signal, \( l_{\tau}(\tau) \) stands for the liftering function for spectral recovery. \( p_s(\tau) \) represents the Cepstrum of \( P(w) \). \( q_0 \) and \( q_1 \) were set to 1.18 and -0.09 respectively.

2.2. Model and Training Strategy

Given the extracted F0 and spectrogram, we constructed a CycleGAN-based model with the transformer to learn the converting function on non-parallel data (see Fig.1).

For converting spectrogram, we first employed the 1-dimensional CNN to encode the features. Meanwhile, another CNN branch with sigmoid activation function was designed, and multiply it with the encoded features for selecting the salient ones. Then, we inserted a normalization layer after the CNN layer and repeated this CNN-based block two times. After that, a residual convolutional followed with a transformer layer was designed to capture the temporal relationships among timesteps. The position embedding was added before feeding features to the transformer. This block was also repeated two times. Subsequently, the CNN-based block with a normalization layer was used to do the feature selection again. Finally, we did a post processing with a 1-dimensional CNN.

For converting F0, the structure of the neural network was similar to the one for the spectrogram. By considering the quantity of information carried by F0 is much less than that of the spectrogram, we removed the transformer layer and only utilized each block once to reduce the number of trainable parameters.

The CNN-based block was also used in the discriminator. Firstly, we encoded features and selected the salient ones. Then, inserted a normalization layer after the CNN layer and reused this block three times. Finally, a dense layer with a sigmoid activation was employed to output the real/fake label. Note that the types of CNN utilized in the discriminator were different for spectrogram and F0; for spectrogram, the 2-dimensional CNN was used, while the 1-dimensional CNN was employed for F0. Furthermore, the proposed discriminator not only produced a label at the utterance level, but also gave multiple outputs (fine-grained level) that presented the real or false samples according to the frames to determine how close each frame was to the real samples.

The CycleGAN framework is incorporated with three types of loss: (1) consistency loss, (2) identity loss, and (3) adversarial loss. Thus, the loss functions for training the proposed model were defined as follows: (1) Eq.7 demonstrates the cycle-consistency loss, where \( x_a \) and \( x_b \) are samples from A emotion and B emotion, respectively, \( G_{A\rightarrow B} \) presents a generator to convert a sample from A to B, and \( G_{B\rightarrow A} \) for B to A. We calculated the L1 loss to compare the distance between the reconstructed sample and the original one, noted as \( ||\cdot||_1 \). This loss is supposed to make the emotional information of the input consistent with the target one.

\[
L_{cyc}(G_{A\rightarrow B},G_{B\rightarrow A}) = E_{x_a}||G_{B\rightarrow A}(G_{A\rightarrow B}(x_a)) - x_a||_1 + E_{x_b}||G_{A\rightarrow B}(G_{B\rightarrow A}(x_b)) - x_b||_1
\]

(7)

(2) Eq.8 introduces the identity loss, which encourages the generator to convert the input while retaining the original linguistic information.

\[
L_{id}(G_{A\rightarrow B},G_{B\rightarrow A}) = E_{x_a}||G_{B\rightarrow A}(x_a) - x_a||_1 + E_{x_b}||G_{A\rightarrow B}(x_b) - x_b||_1
\]

(8)

(3) The adversarial loss is demonstrated as following equations, where \( D_A \) and \( D_B \) annotate discriminators for emotions A and B, respectively. The final adversarial loss is defined as \( L_{adv} = L_{adv}^A + L_{adv}^B \). This loss attempts to tell whether a generator follows the target distribution.

\[
L_{adv}^A(G_{B\rightarrow A},D_A) = E_{x_a}[D_A(x_a)] + E_{x_b}[log(1 - D_A(G_{A\rightarrow B}(x_b)))]
\]

\[
L_{adv}^B(G_{A\rightarrow B},D_B) = E_{x_a}[D_B(x_a)] + E_{x_b}[log(1 - D_B(G_{B\rightarrow A}(x_a)))]
\]

Finally, the overall loss function is defined as:

\[
L = L_{adv} + \alpha L_{cyc} + \beta L_{id}
\]

(10)

where \( \alpha \) and \( \beta \) are constants that will be defined during training. After converting spectrogram and F0, we employed WORLD vocoder [23] to synthesize the waveform.
3. EXPERIMENT

3.1. Dataset

A Japanese emotional speech dataset [24] that contains non-parallel happy, anger, sad, and neutral utterances was used in this study. Each category of this dataset has 1070 utterances in total. We assigned 1000 utterances to the training set and the left 70 utterances for the testing set, the duration of each emotion is presented in Table 1. In this dataset, each sample has a similar corresponding one in other emotions. However, these similar samples are not paralleled. Samples of different emotions are used to express similar meanings with different expressions and modal particles.

3.2. Settings and Baselines

The hyper-parameters were set as Fig. 1 shows. Moreover, we designed a training schedule with curriculum learning. As the Algorithm 1 demonstrates, we gradually increased the length of input with 0.5 second every 500 epochs to allow the model to see from the short speech to the long one. This strategy was supposed to introduce more detailed emotional features to the model. Furthermore, the learning rate was decaying, and the weight constant $\beta$ was changed to 0.5 from 1 after 325 epochs, and reset back to 1 every 500 epochs.

As for baselines, we retrained the ACVAE [19] and CycleGAN [13] on the Japanese emotional speech dataset and compare the performance with the proposed model. Additionally, to verify the effects of the fine-grained level discriminator and curriculum learning, we modified our proposed to different configurations, i.e., CycleTransGAN (without curriculum learning and fine-grained level discriminator), CycleTransGAN-CL (with curriculum learning only), CycleTransGAN-All (with curriculum learning and fine-grained level discriminator).

3.3. Results

We adopted Mean Opinion Score (MOS) to subjectively evaluate emotional level, voice quality and naturalness of the samples. We invited 15 subjects to participate in all the experiments, and each subject evaluated 20 original utterances from the dataset and 75 converted utterances. Fig. 2 presents the evaluation results with 95% confidence interval. The ground truth is the score of original emotional samples. For the scores of emotion evaluation, the CycleTransGAN-All model achieves the highest score for happy emotion, while the CycleTransGAN-CL achieves the highest score for angry and sad emotions. As for the evaluation of voice quality and naturalness, the CycleTransGAN-all outperforms all the other models. These results of CycleTransGAN-CL and CycleTransGAN imply that using curriculum learning improves emotional feature conversion by allowing the model to learn from the shorter segment up to the entire sample. This is because the emotion of speech tends to appear in partly rather than in the whole speech, and the fine-grained level discriminator somewhat distracts the ability of the model to focus on the salient segment. Therefore, it leads to CycleTransGAN-All becomes inferior to CycleTransGAN-CL in terms of emotion similarity.

4. CONCLUSION

In this study, we proposed a CycleGAN-based emotional voice conversion model with a transformer, which is named CycleTransGAN. With the help of the transformer, the model is able to augment the receptive field to a wider range, which allows the generated speech to be more consistent in terms of temporal features, solving the instability problems of mispronunciations and skipped phonemes to some extent. The experiment results show that the proposed models improve emotion similarity, voice quality, and naturalness. However, the clarity and emotional strength of the speech generated by the proposed models still need some further improvements. Future works will mainly focus on these parts.
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