EXPRESSIVE-VC: HIGHLY EXPRESSIVE VOICE CONVERSION WITH ATTENTION FUSION OF BOTTLENECK AND PERTURBATION FEATURES

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ABSTRACT

Voice conversion for highly expressive speech is challenging. Current approaches struggle with the balance between speaker similarity, intelligibility, and expressiveness. To address this problem, we propose Expressive-VC, a novel end-to-end voice conversion framework that leverages advantages from both the neural bottleneck feature (BNF) approach and the information perturbation approach. Specifically, we use a BNF encoder and a Perturbed-Wav encoder to form a content extractor to learn linguistic and para-linguistic features respectively, where BNFs come from a robust pre-trained ASR model and the perturbed wave becomes speaker-irrelevant after signal perturbation. We further fuse the linguistic and para-linguistic features through an attention mechanism, where speaker-dependent prosody features are used as the attention query, which results from a prosody encoder with target speaker embedding and normalized pitch and energy of source speech as input. Finally, the decoder consumes the integrated features and the speaker-dependent prosody feature to generate the converted speech. Experiments show that Expressive-VC is superior to several popular systems, achieving both high expressiveness captured from the source speech and high speaker similarity with the target speaker; meanwhile intelligibility is well maintained.

Index Terms— voice conversion, expressive, information perturbation, feature fusion

1. INTRODUCTION

The information conveyed in human speech can be roughly categorized into linguistic, para-linguistic, and non-linguistic aspects, representing language, rhythmic-emotional, and speaker identity respectively [1]. Moreover, non-verbal sounds, such as breathing, laughing, and crying, are also essential in speech communication. Voice conversion (VC) is a technique that alters speaker-related information in a given speech to make it sound like another speaker while preserving the rest of aspects of speech [2], ideally including linguistic, para-linguistic and even non-verbal aspects. It has been widely used in scenarios such as personalized speech synthesis [3] and privacy protection [4]. With the advances of deep learning, voice conversion has drawn much attention in more challenging scenarios such as movie dubbing with highly expressive speech contents.

In voice conversion, the essential task is to decouple the speaker-relevant and -irrelevant information from the source audio and transfer the aforementioned speaker-irrelevant information to the target speaker. This is not a trivial task as those components are highly entangled in speech.

Some disentanglement approaches rely on the fine-grained design of the voice conversion model itself, including adopting specific modules, losses, or learning algorithms in the voice conversion model to constrain the learned feature to represent either linguistic content or speaker identity. For example, vector quantization (VQ) [5–7], adaptive instance normalization [8] and gradient reversal layer (GRL) [9] are adopted to obtain relatively pure linguistic-related feature and remove speaker-related information in the learned feature [5–9]. Furthermore, mutual information (MI) loss can be adopted to minimize the correlation between the speaker and linguistic information in the learned feature [6, 10]. These approaches often face a dilemma in real applications — to maintain reasonable target speaker similarity, there has to be an empirical compensation on the transferred expressiveness; otherwise, the source speaker’s timbre may leak to the target speaker, making converted speech sound somehow like uttered by the source speaker or a mixture of both.

Some prior disentanglement actions can be conducted outside or before the voice conversion model. Taking the decoupled features as input, the VC model can make further disentanglement more easily. In this direction, Phonetic PosteriorGrams (PPGs) and neural network bottleneck features (BNFs) are usually adopted to help the disentanglement. Specifically, BNFs are a set of activation of nodes over time from a neural network bottleneck layer, while PPGs are obtained by stacking a sequence of phonetic posterior probabilistic vectors from the neural network. Both BNFs and PPGs, usually obtained from a well-trained acoustic model in automatic speech recognition (ASR) system, are proven to be linguistic-rich, speaker-independent, and noise-robust. Thus using the PPGs/BNFs as an intermediate representation, the voice conversion process is factorized as a speech-to-BNFs/PPGs module and a BNFs/PPGs-to-speech module, or the so-called recognition-synthesis framework [9,11–13]. In this way, the linguistic information embedded in the source speech can be transferred stably to the target speech. As containing mostly the linguistic information in BNFs/PPGs, the converted speech apparently loses the expressiveness of the source speech to a large extent. The use of extra prosody features, such as pitch, can be a remedy to this problem [14–16].

Recently, information perturbation has been introduced to remove speaker timbre in prior for voice conversion [17]. The basic idea of information perturbation is to process all the unwanted information in the speech by signal processing beforehand which can make the neural network learn the essential information effectively. Specifically, information perturbation is adopted to remove speaker-related information in the source speech and thus the linguistic information is subsequently modeled by a content encoder [18]. Beyond the linguistic information, para-linguistic, e.g., emotional
information, can also be preserved after speaker perturbation in the speech [19]. In this way, the voice model no longer suffers from the aforementioned trade-off between speaker similarity and expressiveness. Thus it is promising for an information perturbation based method to transfer all the expressions in the source speech to the target speaker while maintaining good similarity with the target speaker. However, as the perturbation parameters are empirically selected, this kind of method may lack robustness in intelligibility and quality in the converted speech.

To achieve voice conversion for highly expressive source speech, in this paper, we propose Expressive-VC, a novel end-to-end voice conversion framework that leverages advantages from both the neural bottleneck feature approach and the information perturbation approach. Specifically, we use a BNF encoder and a Perturbed-Wav encoder to form a content extractor to learn linguistic and para-linguistic features respectively, where BNFs come from a robust pre-trained ASR model and the perturbed wave is considered to be speaker-irrelevant and after signal perturbation. We further fuse the linguistic and para-linguistic features through a scaled dot-product attention mechanism, where speaker-dependent prosody features are adopted as the attention query, which results from a prosody encoder with target speaker embedding and normalized pitch and energy of source speech as input. Finally, the decoder consumes the fused feature and speaker-dependent prosody feature to generate the converted speech. Extensive experiments demonstrate that Expressive-VC is superior to several competitive systems, achieving both high expressiveness captured from the source speech and high speaker similarity with the target speaker; meanwhile intelligibility is well maintained.

2. PROPOSED APPROACH

To perform expressive voice conversion, we design our Expressive-VC system by fusing robust linguistic information embedded in the bottleneck feature (BNF) and rich para-linguistic information contained in the speaker-attribute-perturbed wave (Perturbed-Wav). As shown in Fig. 1(a), Expressive-VC is based on an encoder-decoder architecture, mainly consisting of four components – content extractor, prosody encoder, decoder, and discriminator.

2.1. Content Extractor

The content extractor is composed of a BNF encoder, a Perturbed-Wav encoder, and a fusion module. The two encoders are designed to learn linguistic and para-linguistic features from source speech, respectively. Subsequently, the fusion module fuses the two types of features for better expressivity and reasonable intelligibility in the converted speech.

BNF & Perturbed-Wav Encoders The BNF encoder takes BNFs as input and output linguistic embedding $H_b$ for the source speech, and the Perturbed-Wav encoder takes the perturbed wave as input to generate para-linguistic-related embedding $H_w$ of the source speech. $H_b$ and $H_w$ $\in \mathbb{R}^{T \times F}$, where $T$ represents the sequence length and $F$ is the dimension of the embeddings. The BNFs are extracted from the source waveform $Y$ by a pre-trained ASR model. The perturbed wave is the waveform perturbed by three signal processing functions: pitch randomization (pr), formant shifting (fs), and random frequency shaping using a parametric equalizer (peq). The pitch randomization function shifts the pitch and scales its range, and the formant shifting function also shifts the formants, which encourages to change of the speaker timbre in the source waveform. By modifying the energy of different frequency bands, the parametric equalizer function further removes the speaker-relevant information. In summary, the speaker perturbation process on the source waveform $Y$ can be simply described as

$$\text{Perturbed}-\text{wav} = \text{pr}(f_s(\text{peq}(Y))),$$  

(1)

where the perturbed wave is regarded as speaker irrelevant while the general linguistic and para-linguistic pattern are maintained.

Feature Fusion Module Obtaining robust and rich content representation including both linguistic and para-linguistic information from source speech is essential in VC tasks. As discussed earlier, BNFs are considered to be linguistic-rich but lose most of the expressivity in speech. By contrast, the embedding extracted from the speaker-perturbed wave may contain rich expressive aspects of speech. An intuitive idea to combine both features by simple addition or concatenation. However, we believe that the fusion should be done dynamically because the contributions from linguistic and para-linguistic aspects vary through time. For example, non-verbal sounds such as breathing may have a low contribution from the BNF embedding but a high contribution from the Perturbed-wav embedding. Note that those non-verbal sounds are not explicitly modeled in an acoustic model of ASR.

To realize dynamic fusion, we propose an attention-based fusion module to effectively combine the linguistic feature $H_b$ and para-linguistic feature $H_w$. As shown in Fig. 1 (b), the concatenation result of $H_b$ and $H_w$ is used as key $K \in \mathbb{R}^{T \times 2 \times F}$ and value $V \in \mathbb{R}^{T \times 2 \times F}$. The output of prosody encoder (described in Section 2.2) $H_p$ is used as query $Q \in \mathbb{R}^{T \times F \times 1}$ to integrate the linguistic and para-linguistic information in $H_b$ and $H_w$. In other words, we use the general prosody pattern of the source speech (source speaker timbre removed) to weigh the fusion of the two branches. Following the attention mechanism in [20], we use the scaled dot-product operation as the similarity measure. The whole process of the proposed fusion module can be described as:

$$K = V = \text{concat}(H_b, H_w)$$  

(2)

$$Q = H_p$$  

(3)

$$\text{attention}(Q, K) = \text{softmax}(\frac{QK}{\sqrt{F}}),$$  

(4)

$$H_f = \text{attention}(Q, K)V$$  

(5)
Table 1: Comparison between Expressive-VC (with ablation), BNF-VC, Perturb-VC, and AGAIN-VC, in terms of speaker similarity MOS (SMOS) and naturalness MOS (NMOS) with confidence intervals of 95% under 3 voice conversion scenarios. Character Error Rate (CER) is also calculated for intelligibility measure. CER for source speech is 6.1% (non-expressive) and 10.3% (expressive).

|                  | Non-expressive | Expressive | Non-verbal | Overall |
|------------------|----------------|------------|------------|---------|
|                  | NMOS † | SMOS † | CER | NMOS † | SMOS † | CER | NMOS † | SMOS † | CER |
| BNF-VC           | 3.97±0.03 | 3.91±0.05 | 7.3 | 3.81±0.04 | 3.59±0.05 | 11.5 | 3.75±0.02 | 3.59±0.05 | 3.84±0.04 | 3.70±0.03 |
| Perturb-VC       | 3.67±0.04 | 3.32±0.04 | 9.7 | 3.55±0.05 | 3.66±0.05 | 16.9 | 3.76±0.05 | 3.22±0.06 | 3.66±0.05 | 3.41±0.03 |
| AGAIN-VC         | 2.81±0.04 | 3.16±0.05 | 14.1 | 2.80±0.03 | 2.96±0.03 | 22.2 | 2.66±0.04 | 2.77±0.03 | 2.76±0.04 | 2.96±0.05 |
| Expressive-VC    | 4.00±0.05 | 3.81±0.04 | 8.7 | 4.05±0.04 | 3.78±0.03 | 11.8 | 4.06±0.04 | 3.83±0.04 | 4.04±0.03 | 3.81±0.04 |
| - Fusion Module  | 3.57±0.05 | 3.62±0.03 | 9.2 | 3.68±0.05 | 3.59±0.03 | 14.9 | 3.90±0.03 | 3.61±0.03 | 3.71±0.04 | 3.61±0.04 |
| - L_{G_{0}}, L_{D_{0}} | 3.88±0.03 | 3.72±0.04 | 8.8 | 3.79±0.03 | 3.75±0.04 | 13.5 | 3.37±0.05 | 3.41±0.02 | 3.68±0.03 | 3.63±0.05 |
| - Speed Avg      | 3.71±0.04 | 3.71±0.03 | 10.4 | 3.96±0.05 | 3.75±0.03 | 18.1 | 3.46±0.03 | 3.27±0.03 | 3.71±0.03 | 3.58±0.03 |

where $H_f \in \mathbb{R}^{T \times F}$ is the output of the fusion module.

2.2. Prosody Encoder

To better preserve the prosody in the source speech and obtain high speaker similarity with the target speech, inspired by [18], a prosody encoder is used to learn the speaker-related prosody representation. First, pitch ($f_0$) and energy ($e$) are extracted from the source speech $Y$ and then z-score normalization is performed on the pitch to remove the source speaker’s timbre, yielding a speaker-independent prosody. Then the conditional layer normalization (CLN) [21] is used to generate the target speaker-related prosody feature $H_p$ by using the target speaker embedding as the conditional information:

$$H_p = \text{concat}(\gamma f_0 - \mu(f_0) + \beta, e) \quad (6)$$

where $\gamma$ and $\beta$ are scale and bias vectors about speaker embedding, while $\mu(f_0)$ and $\sigma(f_0)$ stand for utterance level mean and variance of $f_0$ respectively. $H_p$ has two usages—one is used as the attention query in the aforementioned fusion module while another is fed to the decoder together with the content extractor output.

2.3. Decoder and Discriminator

With the input of source speech and target speaker identity, our proposed model directly reconstructs waveform without an explicit vocoder. Our decoder follows HiFi-GAN [22] using multiple discriminators for adversarial training, including multi-period discriminator (MPD), multi-scale discriminator (MSD), and multi-resolution spectrum discriminator. We denote the three discriminators as $D$ and the rest part of the proposed Expressive-VC model as generator $G$. The loss functions of $G$ and $D$ can be described as:

$$L_G(Y, \hat{Y}) = L_{adv_g}(Y, \hat{Y}) + L_{fm}(Y, \hat{Y}) + L_{stft}(Y, \hat{Y}),$$

$$L_D(Y, \hat{Y}) = L_{adv_d}(Y, \hat{Y}),$$

where $Y$ and $\hat{Y}$ are ground-truth and predicted waveform. $L_{adv_g}$ and $L_{adv_d}$ are the adversarial loss of the generator and discriminator respectively. Besides, the feature matching loss $L_{fm}$ [23] and the multi-resolution STFT loss $L_{stft}$ [24] are also adopted. As mentioned in Section 2.4, except predicting waveform $\hat{Y}$ from fusion content $H_f$, $H_w$ is also used to directly reconstruct waveform $\hat{Y}_w$. The overall objective function is described as

$$L_{total_g}(Y, \hat{Y}_t, \hat{Y}_w) = L_G(Y, \hat{Y}_t) + L_G(Y, \hat{Y}_w),$$

$$L_{total_d}(Y, \hat{Y}_t, \hat{Y}_w) = L_{adv_g}(Y, \hat{Y}_t) + L_{adv_g}(Y, \hat{Y}_w).$$

2.4. Training Strategy for Forcing Feature Fusion

Ideally, the fusion module should learn to obtain linguistic information from $H_b$ while extracting para-linguistic information from $H_{av}$ that $H_b$ cannot represent well. However, in practice, since BNFs are more related to linguistic information than the perturbed waveform, learning linguistic information from the BNF encoder is much easier than that from the Perturbed-wave encoder. Consequently, the fusion module tends to only focus on the linguistic information $H_b$ extracted from BNFs, causing the failure of the fusion module and the Perturbed-wave encoder. To encourage better feature fusion, the convergence speed and content extraction ability of the Perturbed-wave encoder need to be particularly strengthened during training. As shown in the red arrow in Fig. 1(a), bypassing the fusion module, $H_w$ and $H_p$ are directly added and then fed into the decoder for waveform reconstruction. Through this auxiliary training, the Perturbed-wave encoder can be directly guided by waveform reconstruction and optimized faster. Finally, with this training trick and the prosody encoder provided query, the fusion module can perform more reasonable fusion between $H_b$ and $H_w$.

3. EXPERIMENTS

3.1. Experimental Setup

In the experiments, all testing VC models are trained on an internal Mandarin corpus, containing about 100K neutral utterances and 60K expressive utterances uttered by 230 speakers. One male speaker and one female speaker are reserved as the target speakers for voice conversion tests. A set of 30 speech recordings, including typical reading (non-expressive), and expressive and non-verbal clips, are used as source data, 10 utterances for each category. The selected recordings are converted to the two target speakers using the proposed model and all the comparison models to further perform evaluations. All the speech utterances are resampled to 24 kHz. For perturbation methods, we conducted formant shifting, pitch randomization, and random frequency shaping to the waveform with the same perturbation coefficient as NANSY [17]. Besides, speed augmentation is adopted to enrich prosody diversity [12], using a random multiplier of 1.1-1.5. During training, augmented and original waveforms are fed to the VC model alternatively. Mel spectrum, pitch, and energy are computed with a 50ms frame length and 10ms hop size. The ASR system for BNF extraction is a conformer-based model trained on a Mandarin ASR corpus WenetSpeech [25], implemented by WeNet toolkit [26]. In our implementation, the BNF encoder consists of two convolution layers, each followed by layer normalization. The Perturbed-wave encoder consists of convolution layers with four strides, downsampled by a factor of 6, 5, 5, and 2, each of which is also followed by a layer normalization. The architecture and hyper-parameters of the prosody encoder, decoder, and discriminator follow the origin configuration in [18].

To validate the performance of the proposed model in highly expressive voice conversion, BNF-VC [15], Perturb-VC [18], and AGAIN-VC [8] are used as our comparison systems, all implemented using the same training data described above. BNF-VC, based on the BNF framework and helped with explicit prosody modeling, is a good representative of balancing intelligibility, expressiveness, and speaker similarity. Perturb-VC is a newly perturbation-based end-to-end model while AGAIN-VC is another popular approach that has open-source code.\footnote{https://github.com/KimythAnly/AGAIN-VC}
3.2. Subjective Evaluation

We conduct Mean Opinion Score (MOS) tests to evaluate the naturalness and speaker similarity of different models. Since this paper aims to perform highly expressive voice conversion, the naturalness metric considers the consistency between source speech and converted speech in terms of expressiveness and pronunciation. Higher naturalness MOS score means converted speech can better maintain the expressiveness of the source speech. In both MOS tests, there are 20 listeners participated. Particularly for the speaker similarity test, we use the target speaker’s real recording as a reference. We recommend the readers listen to our samples2.

**Speech Naturalness Evaluation** The results shown in Table 1 indicate that our proposed Expressive-VC can achieve the best performance in speech naturalness. Specifically, in the non-expressive scenario, BNF-VC gets a similar score to Expressive-VC, which shows that BNF can well represent content information of speech in this scenario. For expressive validation, all comparison systems show performance degradation. Expressive-VC gets a higher MOS score which shows that Expressive-VC can capture more rich content with para-linguistic information. Particularly for non-verbal cases, Expressive-VC has obvious superiority in naturalness and the MOS score remains at the same level with expressive and non-expressive cases.

**Speaker Similarity Evaluation** The results of MOS tests in terms of speaker similarity for different models are also shown in Table 1, in which higher MOS means better performance. In the non-expressive scenario, BNF-VC achieves higher speaker similarity than other systems. We also notice that speaker similarity still remains at a high level for non-verbal cases of Expressive-VC. In expressive and non-verbal scenarios, compared with BNF-VC, Perturb-VC, and AGAIN-VC, the proposed method achieves better performance in speaker similarity. Considering the overall performance of speaker similarity and the superiority of the proposed method in the naturalness, Expressive-VC shows better performance in the highly expressive voice conversion.

**Ablation Study** To investigate the importance of our proposed methods in Expressive-VC, three ablation systems were obtained by dropping the fusion module, auxiliary training loss ($\mathcal{L}_{c, \text{L}}$, $\mathcal{L}_{D, \text{L}}$), and speed augmentation, referred to as -Fusion Module, -$\mathcal{L}_{c, \text{L}}$, $\mathcal{L}_{D, \text{L}}$, and -Speed Aug. Note that when dropping the fusion module, the fusion of features is performed by direct concatenation. As shown in Table 1, dropping these methods brings obvious performance degradation in terms of speech naturalness and speaker similarity. Specifically, without the fusion module, the concatenation of two features cannot be dynamically adjusted, leading to performance degradation. Besides, when $\mathcal{L}_{c, \text{L}}$ and $\mathcal{L}_{D, \text{L}}$ are discarded, the process of feature fusion fails, and the performance drops in both naturalness and speaker similarity. As can be seen, speed speech augmentation also contributes to the proposed system’s performance.

3.3. Objective Analysis

**Character Error Rate** We use the same pre-trained ASR model for BNF extraction to recognize the source speech, converted non-expressive and expressive speech clips. The character error rate is also reported in Table 1. We can see that AGAIN-VC obtains the highest CER, indicating bad intelligibility. By contrast, our Expressive-VC has a similar CER to BNF-VC, while both systems induce a small CER increase as compared with the source speech. We also notice that the CER is much higher for expressive clips as compared with non-expressive counterparts. We believe expressive speech is more difficult to recognize by a regular ASR system. In summary, the proposed system still can maintain reasonable intelligibility.

**Visualization on Fusion Process** To further study the process of feature fusion, as shown in Fig. 2, three speech recordings containing normal speech, shouting, and gasping are used as source speech to obtain the mel spectrums and attention weights. Note that the weight curves vary from 0 to 1, indicating the proportion of $H_b$ in the fusion feature. As can be seen, compared with the weight curve of normal speech in Fig. 2(a), the weight curves of Fig. 2(b) and Fig. 2(c) are much lower when shouting and gasping happen, indicating that the $H_w$ extracted from the perturbed waveform is more involved in the fusion process. Moreover, the shouting in Fig. 2(b) gradually weakens over time, corresponding to a gradual increase in the weight of $H_b$, demonstrating that the model can flexibly adjust the proportion of $H_b$ and $H_w$ in the fusion feature according to the expression and pronunciation in different times. These suggest that the two features are fused as we expected: $H_b$ from BNFs mainly contains linguistic formation and the $H_w$ from perturbed waveform provides additional para-linguistic information.

**Pitch Correlation** To further verify the expressiveness of each system, we calculate the Pearson correlation coefficients of energy and pitch between the source and converted speech of all systems. The higher the Pearson correlation coefficient of the model, the higher the accuracy of the predicted prosodic attributes. Table 2 shows that the proposed system has the highest LF0 and energy correlations. It illustrates that the proposed system can better maintain the expressive aspects of the source speech compared to the comparison systems.

4. CONCLUSIONS

In this paper, we propose Expressive-VC for highly expressive voice conversion. This task is challenging due to the difficulty of maintaining both the linguistic and para-linguistic information in the source speech while achieving high-quality voice conversion with the target speaker’s timbre. To this end, multiple feature fusion is proposed in a specifically designed network structure, leveraging the advances from both the bottleneck feature approach and the signal perturbation approach. Extensive experiments show that Expressive-VC achieves superior performance in highly expressive voice conversion tasks, including non-verbal sound conversion.

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2Demo: https://nzqian.github.io/Expressive-VC.github.io/
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