TOWARDS FINE-GRANDED PROSODY CONTROL FOR VOICE CONVERSION

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ABSTRACT

In a typical voice conversion system, prior works utilize various acoustic features (e.g., the pitch, voiced/unvoiced flag, aperiodicity) of the source speech to control the prosody of generated waveform. However, the prosody is related with many factors, such as the intonation, stress and rhythm. It is a challenging task to perfectly describe the prosody through acoustic features. To deal with this problem, we propose prosody embeddings to model prosody. These embeddings are learned from the source speech in an unsupervised manner. We conduct experiments on our Mandarin corpus re-coded by professional speakers. Experimental results demonstrate that the proposed method enables fine-grained control of the prosody. In challenging situations (such as the source speech is a singing song), our proposed method can also achieve promising results.

Index Terms— voice conversion, Phonetic Posterior-Grans (PPGs), prosody embeddings, LPCNet

1. INTRODUCTION

Voice conversion (VC) is a technique to modify the source speaker’s voice to sound like that of the target speaker while keeping the linguistic content unchanged.

Recently, Phonetic PosteriorGrans (PPGs) have been successfully applied to non-parallel VC and achieved both high naturalness and high speaker similarity of the converted speech \cite{1, 2}. PPG is a sequence of frame-level linguistic information representation obtained from the speaker-independent automatic speech recognition (SI-ASR) system. The PPGs based VC frameworks mainly have two key components: the conversion model and the vocoder. The conversion model converts PPGs extracted from the source speech into acoustic features of the target speaker. Then the vocoder uses these converted features to synthesize the speech waveform of the target speaker. However, we observe two limitations with existing works \cite{3, 4}.

Firstly, earlier works \cite{3, 4} mainly utilized acoustic features (e.g., the pitch, voiced/unvoiced flag, aperiodicity) of the source speech to control the prosody of generated waveform. However, the prosody is related with many factors, such as the intonation, stress and rhythm. It is a challenging task to perfectly describe the prosody through acoustic features. The same problem exists in Text-To-Speech (TTS). To avoid this problem in TTS, recent approaches learn to model prosody that do not require explicit annotations \cite{5}. They use neural networks to learn prosody embeddings from reference speech in an unsupervised manner. These approaches have demonstrated their ability to generate speech with expressive styles. Inspired by the power of prosody embeddings, we also utilize prosody embeddings in VC.

Secondly, vocoders influence the quality of converted speech. Prior works utilized parametric vocoders (such as STRAIGHT \cite{6} and WORLD \cite{7}). However, these vocoders limit the quality of generated speech. To improve the speech quality, researches focus on WaveNet \cite{8}. However, because WaveNet relies on sequential generation of one audio sample at a time, it is hard to deploy in a real-time production setting. Recently, an efficient neural vocoder called LPCNet \cite{9} is proposed. The LPCNet inference runs faster than real time on a standard CPU while producing a high quality speech output. Therefore, we choose LPCNet for speech generation.

In this paper, we propose a VC framework based on prosody embeddings and LPCNet. The main contributions of the paper lie in two aspects: 1) To better control the prosody of converted speech, we extract prosody embeddings from the source speech. 2) To synthesize speech with close to natural quality in real time, we utilize LPCNet for speech generation. To the best of our knowledge, it is the first time that prosody embeddings are utilized to control of the prosody of generated speech for non-parallel VC.

2. BASELINE SYSTEM

2.1. Linear Prediction Coding Net (LPCNet)

LPCNet \cite{9} is a WaveRNN \cite{10} variant that uses the neural networks to generate speech samples from Bark-Frequency Cepstral Coefficients (BFCCs) \cite{11}, pitch and pitch correlation parameters. In this work, we use the code published by
the Mozilla team [9] with some modifications. The original LPCNet vocoder can only generate 16 kHz signals. To generate 24kHz signals, we increase 18-dimensional BFCCs to 30-dimensional BFCCs. Meanwhile, we utilize OpenBLAS to accelerate the LPCNet inference.

2.2. Framework Overview

In the training stage (Fig. 1(a)), we extract the acoustic features \( Y \in \mathbb{R}^{T \times D_a} \), PPGs \( L \in \mathbb{R}^{T \times D_p} \), pitch \( f_0 \in \mathbb{R}^{T \times 1} \) and voiced/unvoiced flag (vuv) \( f_{\text{vuv}} \in \mathbb{R}^{T \times 1} \) from the given speech data of the target speaker, where \( T \) is the number of frames. \( D_a \) and \( D_p \) represent the feature dimension of the acoustic features and PPGs, respectively. To control the prosody of generated speech, we form the input features by concatenating the pitch, vuv and PPGs, denoted as \( F = [L; f_0; f_{\text{vuv}}] \). Then a CBHG [12] conversion model is trained to map the input \( F \) to the output acoustic features.

In the conversion stage (Fig. 1(b)), we first extract the PPGs, pitch and vuv features from the source speech. As the feature mismatch exists between the source speaker’s pitch and the target speaker’s pitch, a linear conversion is applied:

\[
f_{0_y} = \exp(\log(f_{0_x}) - \mu_y) \frac{\sigma_y}{\sigma_x} + \mu_y
\]

where \( f_{0_x} \) is the source speech’s pitch and \( f_{0_y} \) is the converted pitch. \( \mu_x \) (or \( \mu_y \)) and \( \sigma_x \) (or \( \sigma_y \)) represent the mean and the standard variance of the source speech’s (or target speech’s) \( f_0 \) in logarithmic scale, respectively.

Then we concatenate the PPGs, converted pitch and vuv features together. These representations are used as the input to the conversion model to predict the converted acoustic features. Finally, we use LPCNet for speech generation.

2.3. Limitations

Despite the good performance of the baseline system, it still has some limitations. Firstly, the pitch detection algorithms face challenges in some challenging situations (e.g., singing conditions [13]). Secondly, the prosody is related with many factors, including the intonation, stress, rhythm and pitch. However, in the baseline system, we only utilize the pitch to control the prosody of the generated speech.

3. PROPOSED METHOD

To overcome above limitations, we utilize the reference encoder [5] to learn prosody embeddings from the input speech. The reference encoder is plugged into the baseline system and trained without any other supervision except for the VC’s reconstruction error.

3.1. Framework Overview

During training (Fig. 2(a)), different from the baseline system, we also learn prosody embeddings \( P \in \mathbb{R}^{T \times D_e} \) from the reference encoder, where \( D_e \) represents the feature dimension of prosody embeddings. To control the prosody of converted speech, we form the input features by concatenating the pitch, vuv, PPGs and prosody embeddings, denoted as \( F = [L; f_0; f_{\text{vuv}}; P] \), where \( F \in \mathbb{R}^{T \times (D_p + D_e + 2)} \). Then, a CBHG [12] conversion model is trained to map the input \( F \) to the output acoustic features.

At run-time (Fig. 2(b)), we first extract the pitch, vuv, PPGs and prosody embeddings for an arbitrary source speech. Then we transform the pitch of the source speaker into that of the target speaker by the linear conversion in Eq. (1). We concatenate these representations as the input, and transform the input to acoustic features by the conversion model. Finally, we use LPCNet for speech generation.

3.2. Reference Encoder

Speech is encoded to prosody embeddings using the reference encoder. Earlier works focused on fixed-length prosody embeddings regardless of the length of the input speech [5]. These prosody embeddings lose the temporal information of the input speech. However, the temporal information is
Fig. 2. The framework of the proposed system.

Fig. 3. The prosody reference encoder module. A 6-layer stack of 2D convolutions with ReLU activations, followed by a single-layer GRU with 1 unit and a $tanh$ activation.

As shown in Fig. 3, the reference encoder takes a mel-spectrogram $I \in \mathbb{R}^{T \times D_m}$ as the input, where $T$ is the length of the mel-spectrogram and $D_m$ is the feature dimension. This network contains 6-layer 2D-convolutional layers. Each layer is composed of $3 \times 3$ filters with $1 \times 2$ stride, SAME padding and ReLU activation. The number of filters in each layer are $[32, 32, 64, 64, 128, 128]$. The outputs of the last convolutional layer is fed to a uni-directional Gated Recurrent Unit (GRU) [14] with one unit and a $tanh$ activation. The outputs of the GRU at every timestep form the variable-length prosody embeddings $P \in \mathbb{R}^{T \times D_e}$.

In this paper, we also test the following modifications in the reference encoder: 1) CoordConv [15] can augment the positional information to the input. As the positional information is useful to encode prosody sequentially [16], we use CoordConv for the first convolutional layer. 2) Bi-directional GRU can get the information from frames occurring before and after itself in the mel-spectrogram. As the contextual information is useful to encode prosody, we replace uni-directional GRU with bi-directional GRU. However, we do not observe performance improvement with these modifications. Therefore, we utilize the reference encoder in Fig. 3 to extract variable-length prosody embeddings.

4. EXPERIMENTS AND DISCUSSION

Speech samples from the following experiments are available online at https://zeroqiaoba.github.io/voice-conversion.

4.1. Database and Feature Extraction

The voice conversion experiments are conducted on our Mandarin corpus recorded by professional speakers. For training, we choose 1 female speaker (TS) as the target speaker. This speaker has 15000 utterances. To increase the amount of training samples, we perform data augmentation by means of speed perturbation. Speech perturbation is a technique of changing speech speed without the tone changed. It is performed on original signals with speed factor 0.4, 0.6, 0.8, 1.0 and 1.2. For testing, we select 1 female speaker (MY) and 1 male speaker (YYX), with 20 utterances from each speaker. To verify the effectiveness of our method in challenging situations, we also choose 20 songs from a male speaker (Song).

All acoustic features are extracted with 10 ms window shift. WORLD [7] is used to extract 1-dimensional pitch and 1-dimensional vuv features. LPCNet [9] is utilized to extract 32-dimensional acoustic features, including 30-dimensional BFCCs, 1-dimensional pitch and 1-dimensional pitch correction parameter. The librosa toolkit [17] is used to extract 80-dimensional mel-spectrograms. The 512-dimensional PPGs are extracted from the acoustic model in the SI-ASR system. The SI-ASR system is implemented using the Kaldi toolkit [18] and trained on our 20,000 hours Mandarin corpus.
4.2. Experimental Setup

The CBHG [12] conversion model consists of a bank of 1-D convolutional filters, followed by highway networks (4 layers with 64 hidden units) and a bidirectional GRU (64 units for each GRU component). Concretely, it has \( K = 16 \) sets of 1-D convolutional filters, where the \( k \)-th set contains 128 filters of width \( k (k \in [1, K]) \). Because variable-length prosody embeddings have a large enough capacity to copy the input speech, we have to use a very small dimension of bottleneck size. In this paper, we use 1-dimensional prosody embeddings. To optimize parameters, we use the Adam optimizer with a learning rate of 0.001. We train our models for at least 100k steps with a batch size of 32. Gradient clipping is also utilized for regularization with a norm set to 1.

Five systems are evaluated in the experiments. In addition to the baseline system (Baseline) and the proposed system (Proposed), three comparison systems are also implemented to verify the effectiveness of our proposed method. Comparison system 1 (C1): It comes from the baseline system, but ignoring \( f_0 \). Specifically, we do not use any acoustic features of the source speech to control the prosody of converted speech. Meanwhile, WORLD vocoder is used for speech generation. Comparison system 2 (C2): We use the same setting as C1, while LPCNet vocoder is used for speech generation. Comparison system 3 (C3): It comes from the baseline system. Besides the pitch and vuv features, we also use the aperiodicity coefficient to control the prosody.

4.3. Subjective Evaluation

We build VC systems for the female speaker (TS). Subjective listing tests for three types of conversion are conducted: Song-to-TS, MY-to-TS and YYX-to-TS. The Mean Opinion Score (MOS) tests are conducted to assess speech quality. In the MOS tests, listeners are asked to rate the converted speech on a 5-point scale, ranging from 1 (completely unnatural) and 5 (completely natural). Meanwhile, we conduct the Same/Different paradigm to assess speaker similarity. In this test, the listeners are asked to compare and select whether the converted samples are uttered by the same target speaker. 12 native Chinese speakers participate in all tests.

MOS test results for three conversion tasks are shown in Fig. 4. As can be seen, C1 achieves worse performance than C2 in all cases. These results suggest that the speech quality of LPCNet significantly outperforms that of WORLD. In three conversion tasks, we observe that the proposed method outperforms other baseline systems, especially for the Song-to-TS task. It indicates that VCs, especially for singing conversions, clearly benefit from prosody embeddings, as they enable fine-grained control the prosody of generated speech. Furthermore, experimental results show C3 and Baseline outperform C2. Acoustic features of the source speech can control the prosody of generated waveform. Augmenting these acoustic features can achieve good performance in naturalness.

Similarity test results for three conversion tasks are shown in Fig. 5. We notice that C1 achieves worse performance than C2 in all cases. These results suggest that speaker similarity of LPCNet significantly outperforms that of WORLD. In the Song-to-TS task, the proposed method significantly outperforms C1, C2, C3 and Baseline in terms of speaker similarity. However, in the MY-to-TS task, we observe the converted speech of our proposed method achieves slightly worse performance than that of C3 regarding to the speaker similarity, though the difference is not significant. The feature mismatch exists between the source speaker’s prosody embeddings and the target speaker’s prosody embeddings. Future investigations include a detailed analysis of the speaker normalization techniques for prosody embeddings.

5. CONCLUSIONS

In this paper, we propose a voice conversion framework based on prosody embeddings and LPCNet. The prosody embeddings enable fine-grained control of the prosody of generated speech. LPCNet can synthesize speech with close to natural quality while running in real time on a standard CPU. Subjective evaluations show that the proposed method can achieve both high naturalness and high speaker similarity in challenging situations, such as the source speech is a singing song.
6. REFERENCES

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