Controllable Emotion Transfer For End-to-End Speech Synthesis

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Abstract

Emotion embedding space learned from references is a straightforward approach for emotion transfer in encoder-decoder structured emotional text to speech (TTS) systems. However, the transferred emotion in the synthetic speech is not accurate and expressive enough with emotion category confusions. Moreover, it is hard to select an appropriate reference to deliver desired emotion strength. To solve these problems, we propose a novel approach based on Tacotron. First, we plug two emotion classifiers – one after the reference encoder, one after the decoder output – to enhance the emotion-discriminative ability of the emotion embedding and the predicted mel-spectrum. Second, we adopt style loss to measure the difference between the generated and reference mel-spectrum. The emotion strength in the synthetic speech can be controlled by adjusting the value of the emotion embedding as the emotion embedding can be viewed as the feature map of the mel-spectrum. Experiments on emotion transfer and strength control have shown that the synthetic speech of the proposed method is more accurate and expressive with less emotion category confusions and the control of emotion strength is more salient to listeners.

Index Terms: speech synthesis, emotion transfer, emotion strength control, style loss

1. Introduction

The naturalness of speech synthesis has been dramatically advanced with the proliferation of sequence-to-sequence (seq2seq) based neural approaches [1–5]. As natural sound can be reasonably produced by current seq2seq-based models learned from a typical corpus with consistently neutral speaking style, there has been increasing interest in how to deliver expressive speech with these seq2seq models [6–10]. Human speech is expressive in nature and delivering accurate and controllable expressive speech from text is highly desired with substantial applications in human-computer interaction and audio content generation. Proper expression rendering affects overall speech perception, which is important for applications such as audiobooks and newsreaders. In particular, emotional speech synthesis, which focuses on emotion expression rendering, has evolved a plenty of work in this direction lately [29], such as Global Style Tokens (GST) [7, 15], Variational Autoencoder (VAE) [8, 30] and their variants and updates [31, 32]. However, the transferred emotion in the synthetic audio is often over-averaged and it is hard to select a proper reference to deliver the desired emotion strength as well.

To solve the two problems – deliver emotion accurately and control emotion strength flexibly, we propose a reference-based emotion speech synthesis approach based on the Tacotron framework. Specifically, similar to [6, 7], we adopt a reference by the synthetic speech should be perceived easily by the listeners without confusions. Second, controlling the emotion delivery in a flexible way. The emotion expressions embedded in human speech are subtle with different strengths. Thus we desire an emotional TTS to flexibly deliver emotional speech with preferred strength. For example, we should manage to synthesize 'very happy' and 'a little bit happy' through synthetic speech.

There has been a long history for tackling the first problem, which can trace back to the era of conventional Hidden Markov Model (HMM) based statistical parametric speech synthesis [16–19]. A straightforward way to conduct emotional speech synthesis is to use categorized emotional data to train a model [20]. When emotional data is limited with only a few samples, model adaptation [21–23] is often adopted on the average or neutral voice model that has been trained beforehand using a sizable set of data. With the wide use of deep neural networks [5,12,24], besides the above adaptation method, emotional speech synthesis has evolved to multiple solutions, such as code/embedding-based [13,25,26] input and multi-head network [7]. However, these studies only can learn an averaged emotion distribution over the training data, lacking the ability for fine-grained control. Another raised problem is emotion confusion, i.e., synthetic emotional speech samples always have confusion over different emotion categories.

To the best of our knowledge, there are few studies addressing the second problem due to the difficulties on how to label and quantize emotion strength given an emotion speech corpus. A recent study has managed to approach this problem by learning a ranking function on emotional speech samples using relative attributes in an unsupervised manner [27, 28]. Thus the learned ranking function can designate each sample a strength that is subsequently used as a label to train a Tacotron-based TTS model.

With the fast development of the seq2seq modeling architecture, particularly the Tacotron family [1,2], reference-based style transfer has emerged as another solution with great potential to solving the two problems simultaneously. By learning a style embedding space through expressive samples in an unsupervised manner and conditioning Tacotron on it, synthetic audio that matches the prosody of the reference audio can be generated even when the reference and synthesis speakers are different. Following the principle of 'say it like this' [6], there has evolved a plenty of work in this direction lately [29], such as Global Style Tokens (GST) [7, 15], Variational Autoencoder (VAE) [8, 30] and their variants and updates [31, 32]. However, the transferred emotion in the synthetic audio is often over-averaged and it is hard to select a proper reference to deliver the desired emotion strength as well.

* Lei Xie is the corresponding author. This work was supported by the National Key Research and Development Program of China under Grant 2017YFB1002102.
encoder to learn an emotion embedding space and Tacotron is conditioned on the emotion embedding for emotion transfer. But differently, in order to transfer emotion accurately and expressively, we use an emotion classifier connected to the reference encoder to enhance the emotion-discriminative ability of the emotion space. Moreover, we use another reference encoder with an emotion classifier after the decoder output to further strengthen the emotion-discriminative ability of the predicted mel-spectrum. Importantly, we further use style loss [14, 33] to measure the style difference between the generated and reference mel-spectrum. In detail, we calculate the Gram matrices of the above embeddings and then minimize the L2 distance between them. The emotion strength in the synthetic speech can be controlled easily by adjusting the value of the emotion embedding. Our model is thus learned with the integration of four losses: the basic Tacotron MSE loss, two emotion classification losses and the style loss. Experiments on emotion transfer and strength control have validated the effectiveness of our approach: synthetic speech is more accurate and expressive with less emotion category confusions; the control of emotion strength is more salient to subjective listeners.

2. The proposed model

The proposed model is shown in Figure 1, which is built on the modified Tacotron2 [2] with an emotion embedding learning network, an auxiliary learning network and a specifically designed style loss.

2.1. The modified Tacotron2

We use a slightly modified version of Tacotron2 which empirically shows better performance. First, we convert the input Chinese text into a character sequence. The encoder is composed of a pre-net of two fully connected layers and a CBHG [34] (1-D convolution bank + highway network + bidirectional GRU [35]) module. The CBHG module converts the pre-net output into the final encoder representation, followed by GMM attention. The decoder is an autoregressive recurrent neural network (RNN) in which a stack of GRUs with vertical residual connections generating attention queries at each decoder time step. Finally, we use a CBHG-based post-net to transform the mel-scale spectrogram into a linear spectrogram for reconstructing waveform by a multi-band WaveRNN [4].

2.2. Emotion embedding network

The emotion embedding network is shown on the top left of Figure 1, which is comprised of a reference encoder and an emotion classifier. We design this network to construct an emotion embedding space, which learns from reference audio samples and performs emotion transfer during inference. It also can be adjusted via a continuous scalar to control the strength of emotion transferred.

The reference encoder. The reference encoder follows the structure proposed by Skerry-Ryan et al. [6], which consists of six 2D convolutional layers and a GRU [35] layer, and the last GRU state passes through a fully connected layer (FC) to generate a 128-dimensional reference embedding.

Emotion classifier. Different from [6], we plug an emotion classifier to the reference encoder, which aims to learn more discriminative emotion embedding that can better distinguish different emotion types. In detail, the classifier has a 128-unit input layer and two 256-unit fully connected (FC) layers, both with ReLu activation. The final softmax layer outputs the probability of seven emotion types, i.e., neutral, happy, surprise, angry, disgust, fear and sad. We use the second hidden layer output as the emotion embedding and the Tacotron2 encoder output takes it as a condition.

2.3. Auxiliary network

We use another auxiliary emotion classifier along with the decoder to further make the predicted mel-spectrogram more discriminative to emotion types. As shown on the top right of Figure 1, the structure of this classification network is same as that of the emotion embedding network, but the input is the predicted mel-spectrogram from the decoder. The second hidden layer output is also used as the emotion representation of the synthesized speech.

2.4. Style loss

Style loss [14] was first proposed in computer vision to capture the artistic style of an image using the Gram matrix of features maps generated by a CNN, where the Gram matrix computes patch-level appearance statistics, such as texture, in a location-invariant manner. Recently, the Gram matrix has been adopted to measure mel-spectrogram of audio signals [31], aiming to capture local statistics of an audio signal in the frequency-time domain. It is believed that the Gram matrix is able to represent low-level characteristics of speech, e.g. loudness, stress, speed, pitch, etc, which are highly related to emotion expressions.

The emotion embedding in our proposed model is a collection of CNN output sequences, which can be naturally seen as the feature map of mel-spectrogram. Each value of feature map from the convolution of a specific filter at a target location, and the essence is the extraction and quantification of features, so each value can be seen as the strength of emotion-related features. Our goal is to synthesize speech with a certain target emotion category (such as surprise), while flexibly controlling the strength of the emotion transferred to the target. To achieve this, the emotion style difference between the generated speech and the reference speech can be measured using style loss. Specifically, given the emotion embedding (feature map) of reference and synthesized speech R and S, their corresponding gram matrices G and I are calculated by inner-product as:
where $N$ and $M$ are the number of rows and columns of the matrix respectively. Finally, the total loss of the proposed model becomes:

$$L_{tot} = L_{tac} + L_{sty} + L_{cls,src} + L_{cls,tgt},$$

(3)

where $L_{tac}$ is the typical Tacotron MSE loss, $L_{sty}$ is the style loss in Eq. (2), and $L_{cls,src}$ and $L_{cls,tgt}$ are classification loss of the emotion embedding network and the auxiliary classifier network, respectively.

2.5. Emotion strength control

Since the emotion embedding can be viewed as the feature map of the mel spectrogram, representing the strength of emotion-related features, the emotion strength in the synthetic speech can be controlled easily by adjusting the value of emotion embedding. In this work, we use an emotion scalar to multiply the emotion embedding to control emotion transfer strength at the inference stage, as shown in Figure 1. This is similar to the degree control in image style transfer [14]. Note that this scalar always equals to 1 during the training process.

3. Experiments

We evaluate the performance of our proposed model in emotion transfer and emotion strength control through subjective evaluations and sample analysis. Twenty (gender balanced) native Mandarin listeners are invited to participate in the evaluation.

3.1. Experimental setup

We use the same dataset as in [27]: a high-quality emotional speech corpus containing 14-hour of recordings by a professional Chinese actress. She imitates a little girl to speak with seven categories of emotion (neutral, happy, angry, disgust, fear, surprise and sadness). There are 60 000 sentences in the neutral emotion category, and 620 sentences in each of the remaining emotion categories. During model training, all the recordings are down-sampled from 44 kHz to 16 kHz. We randomly select 10 sentences from each emotion data as the subjective listening test set.

During inference, we randomly select one sentence from each emotion test set as the emotion reference audio. We conduct experiments on both emotion transfer and emotion strength control. For the latter experiments, although the emotion scalar can be controlled continuously to represent emotion strength in each emotion category, we set it to 0.5, 1.5 and 2.5 to represent three typical emotion strengths – weak, medium and strong, respectively. Even though the scalar means the stronger emotion strength, the scalar cannot be infinite. We find that when the strength scalar is greater than 3, it will lead to the excessive transfer of emotion. For example, the generated speech with anger emotion will have a very fast speaking rate which affects intelligibility. In particular, when the emotion scalar is as low as 0.1, the target emotion will change to neutral speech. As a result, in the emotion strength control experiments, each test sentence will be synthesized to 18 samples, including 6 kinds of emotions (without neutral) and each has three emotion strengths.

3.2. Emotion transfer

3.2.1. Ablation studies

We first conduct ablation studies on emotion transfer to validate the effectiveness of different structures with different losses. Specifically, we conduct a subjective emotion classification test on 10 synthetic samples for each emotion where the sentences are chosen form the neutral test set in order to let the listeners focus on the emotion expression delivered by audio instead of the text. The emotion scalar is set to 1 as we do not evaluate the strength control in this experiment.

Table 1: Accuracy of subjective emotion category classification based on the ablation study of our proposed model.

| Loss | $L_{tac}$ | +$L_{cls,tgt}$ | +$L_{cls,src}$ | +$L_{cls,src}$ +$L_{cls,tgt}$ | $L_{tot}$ |
|------|-----------|----------------|---------------|---------------------|--------|
| fear | 0.71      | 0.76           | 0.91          | 0.95                | 0.97   |
| disgust | 0.67   | 0.73           | 0.75          | 0.79                | 0.85   |
| angry | 0.81     | 0.94           | 0.92          | 0.96                | 0.98   |
| sadness | 0.95  | 0.93           | 0.96          | 0.98                | 0.97   |
| happy | 0.66      | 0.70           | 0.72          | 0.75                | 0.84   |
| surprise | 0.62  | 0.67           | 0.75          | 0.78                | 0.82   |

Classification accuracy is shown in Table 1. Note that there are 200 listening samples for each emotion category and listeners are asked to select one from the 6 emotion categories for each testing sample. We can see from Table 1 that the
This paper proposes a controllable emotion speech synthesis approach based on emotion embedding space learned from references. In order to deliver the emotion more accurately and expressively with strength control, we modify the Prosody-Tacotron structure with two emotion classifiers to enhance the emotion-discriminative ability of the emotion embedding and the predicted mel-spectrum. Moreover, we adopt a style loss to measure the difference between the generated and reference mel-spectrum. During inference, the strength of the synthetic speech can be easily controlled by adjusting a scalar to the emotion embedding. Comparative experiments with other methods show that the synthetic speech of the proposed method is more accurate and expressively with less emotion confusions and the emotion strength control is more salient to subjective listeners. Samples can be found from https://silyfox.github.io/tscslp-98-demo/.
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