CONTINUOUS EMOTIONAL INTENSITY CONTROLLABLE SPEECH SYNTHESIS USING SEMI-SUPERVISED LEARNING

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ABSTRACT

With the rapid development of the speech synthesis system, recent text-to-speech models have reached the level of generating natural speech similar to what humans say. But there still have limitations in terms of expressiveness. In particular, the existing emotional speech synthesis models have shown controllability using interpolated features with scaling parameters in emotional latent space. However, the emotional latent space generated from the existing models is difficult to control the continuous emotional intensity because of the entanglement of features like emotions, speakers, etc. In this paper, we propose a novel method to control the continuous intensity of emotions using semi-supervised learning. The model learns emotions of intermediate intensity using pseudo-labels generated from phoneme-level sequences of speech information. An embedding space built from the proposed model satisfies the uniform grid geometry with an emotional basis. In addition, to improve the naturalness of intermediate emotional speech, a discriminator is applied to the generation of low-level elements like duration, pitch and energy. The experimental results showed that the proposed method was superior to control the categorical emotion

1. INTRODUCTION

Recent advances in deep learning (DL) have significantly improved the performance of speech synthesis systems, and the synthesized speech from DL-based text-to-speech (TTS) models \textsuperscript{[1]-[4]} have already shown excellent performance about naturalness. It is suitable and sufficient for general information delivery purposes to apply a speech synthesis system to real-world applications. However, speech synthesis with conveying diverse emotions and prosody differs significantly from actual human voices. Because it is difficult to synthesize expressive speech including paralinguistic characteristics such as pitch, stress, tone, and rhythm.

Expressive speech models are increasingly necessary, so emotional TTS research is being aggressively pursued. There are several works \textsuperscript{[4]-[6],[8],[9],[10],[11],[12]} related to emotional speech synthesis model. First, some studies \textsuperscript{[4]-[6]} proposed methods to extract emotional information from reference speech. Global style token (GST) \textsuperscript{[4]} demonstrated a style encoder trained by unsupervised learning to extract style embedding vector from reference speech and then exploited it to synthesize emotional speech. Other studies \textsuperscript{[5],[6]} used a speech emotion recognition (SER) model to learn a speech emotion embedding space. Authors \textsuperscript{[7],[8]} fine-tuned a pretrained speech synthesis model \textsuperscript{[8]} to utilize categorical emotion labels. Specifically, Lee et al \textsuperscript{[7]} applied the emotion labels to the attention RNN to enable emotional speech synthesis. Tits et al \textsuperscript{[8]} fine-tuned a pretrained speech synthesis model with a small set of emotional dataset. Unfortunately, speech synthesized by the previous methods \textsuperscript{[4]-[6],[8]} provided only a coarse-grained expression because the entire sentence has been adjusted with one global information. Therefore, it is difficult to reflect the user’s requirements for fine-grained control in the emotional TTS model. To improve fine-grained expression, there are attempts to control an emotion intensity \textsuperscript{[9],[10],[11],[12]}, not the categorical emotion of speech. \textsuperscript{[9],[10]} introduced models to reflect detailed emotional expression by adjusting emotion strength with controllable parameter. \textsuperscript{[11]} proposed a method to control the intensity of emotions using non-linear interpolation from categorical emotion embedding space. \textsuperscript{[12]} controlled fine-grained emotion intensity by conducting distance-based intensity quantization.

Even though authors \textsuperscript{[9],[10],[11],[12]} have proposed controllable emotional intensity models, there are two limitations. First, it is difficult to synthesize speech by controlling the emotion space as desired. Conventional emotional TTS models find the emotion embedding vector for discretized intervals and utilize the vector to synthesize emotion speech. As shown in Fig. \textsuperscript{1}(a), an embedding space is entangled not only with various emotions but also with other features, like speaker identity, pitch or linguistic information. Accordingly, the grid geometry from the perspective of the emotional basis may form a valley-shaped grid as shown in Fig. \textsuperscript{1}(a). Due to the valley-shaped grid in the embedding space, linearity for emotions cannot be guaranteed, and it is hard to control emotions as desired. For example, suppose you want to find an intermediate emotion (see the yellow point in Fig. \textsuperscript{1}) from two certain emotions (see red points in
Contributions in this study are as follows.

• By using a novel low-level data mixer to generate intermediate emotion points, the proposed model trained with semi-supervised learning can generate emotional speech with a continuous intensity value.

• By applying a discriminator to the variance adaptor, the mel-spectrogram can be generated well without prediction loss.

2. METHOD

The overall architecture of the proposed model is shown in Fig. 2. Fastspeech2 [3] is used to generate a mel-spectrogram from the phoneme sequence. We propose a speech mixer M to generate pseudo-labels \( \hat{x} \) reflecting intermediate emotion intensities in a variance adapter. The speech mixer \( M \) generates an intermediate low-level elements like pitch \( p \), duration \( d \), and energy \( e \). Also, discriminator \( D \) is applied to the predicted elements for improving naturalness.

2.1. Speech Mixer

A speech mixer \( M \) generates interpolated pseudo-labels \( \hat{x} \) for intermediate emotion intensities. In order to interpolate any two emotions \( (emo_i, emo_j) \), emission speech pair \( (S_{emo_i}, S_{emo_j}) \) should be sampled from different emotion categories \( \mathbb{E} = \{emo_0, emo_1, ..., emo_K\} \) where \( K \) denotes the number of emotions. In this paper, we used \( K = 5 \) and categorical emotions include neutral, happy, sad, angry, and surprise. Its sampling function \( F \) can be represented by

\[
S_{emo_j} = F(S_{emo_i}).
\]

The emotion speech pair are sampled as follows

\[
(emo_i = neutral, emo_j \in \mathbb{E} \setminus \{neutral\}),
\]

resp. \( (emo_i \in \mathbb{E} \setminus \{neutral\}, emo_j = neutral) \).

To generate a pseudo-label \( \hat{x} \), sampled pair \( (S_{emo_i}, S_{emo_j}) \) is converted into phoneme-level averaged values, so that the same sentences have the same length of pitch \( (p_{emo_i}, p_{emo_j}) \), duration \( (d_{emo_i}, d_{emo_j}) \) and energy \( (e_{emo_i}, e_{emo_j}) \). Then speech mixer \( M \) generates pseudo-labels \( \hat{x}_{\lambda}^{emo_i,emo_j} \) for intermediate intensity of emotional speech, given by

\[
M(x_{emo_i}, x_{emo_j}, \lambda) = g(\lambda x_{emo_i} + (1-\lambda) x_{emo_j})
\]

\[
= \hat{x}_{\lambda}^{emo_i,emo_j},
\]

where \( x_{emo} \in \{p_{emo}, d_{emo}, e_{emo}\} \) and \( \lambda \) denotes an interpolation weight. \( g(\cdot) \) denotes floor function if \( x_{emo} = d_{emo} \) else identity function. Specifically, the interpolation weight \( \lambda \) is randomly selected from beta distribution \( \beta(0.5, 0.5) \). For notation simplicity, we denote \( x_{emo} = x \) and \( \hat{x}_{\lambda}^{emo_i,emo_j} = \hat{x} \).
2.2. Generator

As shown in Fig. 2(a), we use FastSpeech2 [3], which consists of a variance adapter, phoneme-encoder, and decoder. The phoneme encoder receives a phoneme sequence as an input and outputs an embedding vector. After adding a positional encoding to the embedding vector, the encoder produces a hidden phoneme embedding \( \mathcal{H}_{\text{phon}} \).

Speaker and emotion Look-Up Tables (LUTs) are introduced to extend the existing variance adapter to a multi-speaker setting like Fig. 2(b). The speaker LUT is assigned to each speaker and trained to suit the speaker. The emotion LUTs also are optimized according to the emotion labels. To optimize the hidden phoneme embedding \( \mathcal{H}_{\text{phon}} \), the speaker and the emotion LUTs, loss functions for training each low-level element are described as follows.

Loss of duration \( \mathcal{L}_d \) consists of mean-square error (MSE) of logarithm function such that

\[
\mathcal{L}_d = \mathbb{E}[\log(d + 1) - \hat{d}]^2, \tag{1}
\]

where \( d \) and \( \hat{d} \) are a phoneme-level duration and its predicted value from a duration predictor, respectively. Similar to loss of duration \( \mathcal{L}_d \), loss functions of pitch \( \mathcal{L}_p \) and energy \( \mathcal{L}_e \) are formulated as MSE, given by

\[
\mathcal{L}_p = \mathbb{E}[|p - \hat{p}|^2], \tag{2}
\]

\[
\mathcal{L}_e = \mathbb{E}[|e - \hat{e}|^2], \tag{3}
\]

where \( p \) and \( e \) are labels of pitch and energy, respectively. \( \hat{p} \) and \( \hat{e} \) denote predicted values from pitch and energy predictors. For Eqs. (1), (2), and (3), labels \( x \in \{d, \hat{d}, p, \hat{p}, e, \hat{e}\} \) can be replaced with pseudolabels \( \tilde{x} \in \{d, \hat{d}, p, \hat{p}, e, \hat{e}\} \).

2.3. Discriminator

Low-level elements generated by the speech mixer do not exist a corresponding speech ground-truth, so it is difficult to guarantee naturalness. Adversarial training scheme is conducted to help the variance adpoter generate more realistic pitch, duration and energy sequences. We adopt the least squares GAN [14] loss for training our proposed model. Discriminators are shown as D in Fig. 2(a), which are trained adversarially on the predicted pitch \( \hat{p} \), duration \( \hat{d} \), and energy \( \hat{e} \) from the variance adapter. The adversarial loss \( \mathcal{L}_{\text{adv}} \) is as follows:

\[
\mathcal{L}_{\text{adv}} = \mathbb{E}[(x - 1)^2] + \mathbb{E}[(\tilde{x})^2] \tag{4}
\]

2.4. Training Objectives

Network training consists of two phases: (1) learning categorical emotion using the original dataset \( x \), (2) learning intermediate emotion using pseudo-label data \( \tilde{x} \) generated from a speech mixer \( M \). First, when the model is trained with a categorical dataset \( x \), Eqs. (1), (2), and (3) are used, and mean-average error (MAE) loss is also computed between a ground-truth mel-spectrogram \( y \) and predicted mel-spectrogram \( \hat{y} \), given by

\[
\mathcal{L}_{\text{mel}} = \mathbb{E}[|y - \hat{y}|]. \tag{5}
\]

So, categorical loss is defined as

\[
\mathcal{L}_{\text{categorical}} = \mathcal{L}_{\text{mel}} + \mathcal{L}_p + \mathcal{L}_d + \mathcal{L}_e. \tag{6}
\]

Second, when the network is trained with intermediate emotion \( \tilde{x} \) generated from a speech mixer \( M \), MSE losses are used similarly to a categorical loss \( \mathcal{L}_{\text{categorical}} \). However, the adversarial loss is additionally applied to each pseudo-label \( \tilde{x} \), instead of Eq. (5), given by

\[
\mathcal{L}_{\text{adv}} = \mathcal{L}_{\text{adv}}^{\text{pitch}} + \mathcal{L}_{\text{adv}}^{\text{duration}} + \mathcal{L}_{\text{adv}}^{\text{energy}}. \tag{7}
\]

So, intermediate loss is defined as

\[
\mathcal{L}_{\text{intermediate}} = \mathcal{L}_{\text{adv}} + \mathcal{L}_p + \mathcal{L}_d + \mathcal{L}_e. \tag{8}
\]

Finally, total training loss consists of categorical loss and intermediate loss as follows

\[
\mathcal{L}_{\text{total}} = \mathcal{L}_{\text{categorical}} + \mathcal{L}_{\text{intermediate}} \tag{9}
\]

3. EXPERIMENTS AND RESULTS

3.1. Dataset

We used Emotional Speech Database (ESD) [15] for multi-speaker models. The ESD covers five emotions (neutral, happy, angry, sad and surprise) and comprises of 350 parallel utterances from 10 native English speakers and 10 native Chinese speakers. We only used the English dataset with all emotions for training and evaluation.

3.2. Model Performance

To evaluate the emotion intensity recognition of the proposed model, a preference test was conducted. We used a crowd-sourced platform (Amazon Mechanical Turk) for the listening test, and 11 sentences were randomly sampled for each emotion. A total of 220 people
participated in the experiment. First, the raters listen to the same speaker and speech uttered with a neutral emotion, and speech uttered with a specific emotion as a reference. Then, two sentences uttered with different intensities are given, and among the two sentences, raters should select the one with the stronger emotion. A specific emotion is one of four emotions like happy, sad, angry, or surprise, and 4 intensity types were tested. There are 4 types such as (0.0 vs 0.25), (0.25 vs 0.5), (0.5 vs 0.75), and (0.75 vs 1.0). For speech quality evaluation, mean opinion score (MOS) [16] was measured through a questionnaire to verify the speech naturalness. For categorical emotional speech, mel cepstral distortion (MCD) [17] and F0 root mean square error (F0 RMSE) were computed for quantitative evaluation. Conventional method [11] controls emotion intensity through non-linear interpolation based on GST [4]. As shown in Table 2, the proposed method outperforms the conventional model [11] in all metrics. Specifically, Table 2(i) shows that our proposed method achieves the best accuracy for all intensity types. This indicates that the proposed model can synthesize speech well according to the given intensity scale. In addition, in the case of speech quality evaluation, the proposed method showed better performance than the conventional model [11] in all emotions as shown in Table 2(ii).

### 3.3. Ablation Study

We conducted an ablation study to validate the effectiveness of the discriminator. In the proposed model w/o discriminator at Table 2(a), all types of emotion intensity accuracy decreased compared to the model w/ discriminator when λ distribution is beta (see Table 2(i)). However, for the F0 RMSE metric as shown in Table 2(ii), the model w/o discriminator represented better performance than w/ discriminator since the model w/o discriminator was only optimized to minimize regression losses related to labels and pseudo-labels.

In addition, another ablation study was conducted for different interpolation weight distributions of speech mixer $M$. We compared discrete and uniform distributions as interpolation weight $\lambda$. Discrete distribution means that the mixing ratio $\lambda$ is randomly sampled from among 0, 0.5, and 1.0. And uniform means that the ratio $\lambda$ is sampled from the uniform distribution $U(0, 1)$. The proposed model trained with the speech mixer using beta distribution $\beta(0.5, 0.5)$ shows the best performance of the emotion intensity recognition as shown in Table 2(a)(i). However, the model with discrete distribution achieved the best MCD and F0 RMSE scores except w/o discriminator (see Table 2(b)(ii)). The model trained with the discrete distribution can frequently encounter categorical labels and be optimized, thus the quantitative metrics are minimized.

### 3.4. Plotting pitch contours of samples

Synthesized speech samples of the proposed model and conventional model [11] were analyzed. The pitch contour was plotted for the same speaker and sentence as shown in Fig. 3. The pitch contour of the proposed model dynamically changed according to the emotional intensity $\lambda$. However, the conventional model [11] showed similar pitch contours despite the intensity $\lambda$ being modified from 0.25 to 0.75. In particular, the proposed model can synthesize the speech at any emotional intensity (see the dashed line in Fig. 3(b)) although the conventional model [11] cannot (see Fig. 3(a)). It means that the pitch sequences can be controlled by selecting the desired intensity with any continuous value. Thus, we confirmed that our proposed model can dynamically adjust the intensity of emotions.

### 4. CONCLUSION

Improving expression in the domain of speech synthesis is very important but challenging task. In particular, for supervised learning, labeling a dataset that can control the emotions of speech is a laborious and difficult task. Therefore, we proposed a model that can control the emotional intensity with continuous value using semi-supervised learning. Intermediate low-level elements are generated for a categorical emotional speech dataset, and it is used as a pseudo-label for network learning. Also, the ground-truth mel-spectrogram does not exist in the pseudo-labels, so a discriminator is used to supplement it. The proposed model through experiments showed superior performance in emotional intensity control and naturalness.
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