PHONEIX: ACOUSTIC FEATURE PROCESSING STRATEGY FOR ENHANCED SINGING PRONUNCIATION WITH PHONEME DISTRIBUTION PREDICTOR

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ABSTRACT

Singing voice synthesis (SVS), as a specific task for generating the vocal singing voice from a music score, has drawn much attention in recent years. SVS faces the challenge that the singing has various pronunciation flexibility conditioned on the same music score. Most of the previous works of SVS can not well handle the misalignment between the music score and actual singing. In this paper, we propose an acoustic feature processing strategy, named *PHONEix*, with a phoneme distribution predictor, to alleviate the gap between the music score and the singing voice, which can be easily adopted in different SVS systems. Extensive experiments in various settings demonstrate the effectiveness of our *PHONEix* in both objective and subjective evaluations.

Index Terms— singing voice synthesis, feature processing, duration prediction

1. INTRODUCTION

SVS aims to generate a singing voice from a music score that contains pitch and duration information organized by notes with corresponding lyrics [1]. Different from the similar task of text-tospeech (TTS), it is difficult to obtain large public singing datasets for SVS [2-4], due to the copyright restrictions and the strict recording environment requirements. Moreover, singing has higher variability than spoken language, as singers have the flexibility to make changes to scores, making singing more natural and pleasing. For example, the pronunciation of the same word can vary significantly due to pitch and tempo changes in singing. Therefore, it is challenging to learn the pronunciation of lyrics and make the singing match the melodic changes in the music score, especially on smallscale SVS corpora. Recently, a work [5] trains a singing-data-free SVS model on speech datasets to imitate the voice of a singing template. Nevertheless, a common practice in current score-based SVS systems is to adopt acoustic feature processing (AFP) strategies in the acoustic model to enhance the learning of singing pronunciation based on limited SVS data.

Current AFP strategies for SVS acoustic models can be roughly categorized into two types. 1) *Type 1* AFP strategy is to use the original note pitch and whole note duration from the music score (i.e., Fig. 1 (a)) as the pitch and duration input, with no distinction between vowels and consonants. To further distinguish vowels and consonants, a duration predictor is built to produce fine-grained

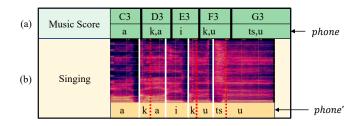


Fig. 1. (a) Music score input. Black bold vertical lines denote note splits. (b) Manually labeled phoneme time sequence. White bold lines indicate syllable splits and red dotted lines indicate phoneme splits in each syllable.

phoneme-level duration, which is trained based on supervision calculated by force-alignment [6-11], heuristics [12-15] etc. The advantage of this type of feature processing strategy is that the input phoneme and pitch sequence are strictly aligned at the note level based on the music score. However, as illustrated in Fig. 1, there is a gap between the Type 1 music score and the actual singing voice in phoneme duration distribution. Acoustic models are not able to adapt the distribution with only music scores. 2) Type 2 AFP strategy is to use a labeled phoneme duration sequence (i.e. Fig. 1 (b)) and the note sequence from the music score (i.e. Fig. 1 (a)) as input [16–26]. The labeled phoneme duration sequence provides a supervision signal for duration predictor to predict the actual duration of phonemes and notes given Type 1 phoneme and note duration from the music score. The disadvantage is that the labeled phoneme duration sequence is annotated based on the singing voice and it is not exactly aligned with the music score. This misalignment will lead to redundant phonemes and missing phonemes, which will hurt the generation from the actual singing voice. Moreover, different from the training phase, the actual phoneme duration is unavailable during inference, such discrepancy between training and inference adversely leads to a great restriction of application scenarios for SVS. Overall, the divergence between music score and actual singing cannot be well solved in the acoustic model by these two types of strategies.

To mitigate the gap between the music score and actual singing, we propose a new AFP strategy, named *PHONEix*, for the SVS acoustic model. Specifically, the acoustic model accepts the music score as input, and then the proposed **phoneme distribution predictor** learns the phoneme durations, adapting to the actual pronunciation. Finally, the aligned *Type 1* score features (phoneme, pitch, phoneme duration) are encoded and then length regulated under the guidance of the actual phoneme duration to address the gap (illus-

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AFP Strategy		Type 1	Type 2	PHONEix	
Raw Data		あかいくつ はいてた	C3	あかいくつ はいてた	
Feats. Input	Frame Level	C3 D3 E3 F3 G3 a k,a i k,u ts,u	C3 D3 E3 F3 G3 a k a i k u ts u	C3 D3 E3 F3 G3 a k a i k u ts u	
	Phone Level	[C3, D3, D3, E3, F3, F3, G3, G3] [a, k, a, i, k, u, ts, u]	[C3, C3, D3, D3, E3, F3, G3, G3, G3] [a, k, k, a, i, u, u, ts, u]	[C3, D3, D3, E3, F3, F3, G3, G3] [a, k, a, i, k, u, ts, u]	
Length Regulator	GT Input	a k a i k u ts u obtained by HMM-based forced alignment	a k¦a i k'u ts¦u guided by annotation	a k¦a i k'u ts¦u guided by annotation	

Fig. 2. Different AFP strategy. Details of *Type 1* and *Type 2* are introduced in Sec. 1 and *PHONEix* are in 2.2. Blocks of different colors represent phoneme duration. The green blocks are from the music score and the yellow blocks are from annotation. The gray block is obtained by HMM-based forced alignment. The orange block is predicted by the phoneme distribution predictor. In column *Type 2* strategy and the red lines are division of vowels and consonants. The red phonemes in phone-level feature input are redundant phonemes and missing phonemes caused by misalignments between notes and annotation.

trated in Fig. 2). In summary, the contributions of this work include:

- We propose a new AFP strategy *PHONEix* for SVS, which narrows the gap between the music score and the singing voice by feeding *Type 1* duration and actual duration successively into the acoustic model. *PHONEix* can be easily migrated to different SVS systems.
- We evaluate the proposed strategy on different SVS models.
 Extensive objective and subjective experiments demonstrate the effectiveness of *PHONEix*, which brings significant improvement.

The rest of this article is organized as follows. Section 2 presents the proposed AFP strategy and phoneme distribution predictor. Section 3 presents our experimental setup, results, and discussion. Finally, Section 4 concludes the paper.

2. METHODOLOGY

This section introduces our proposed AFP strategy *PHONEix* and its integration with the SVS framework.

2.1. Overall Framework

As illustrated in Fig. 3, the whole system accepts inputs of the music score at note level and learns phoneme duration information guided by annotations. There are five steps in the application of the acoustic model: 1) A *Prior Encoder* is attached before the major encoder-decoder-based structure. It consumes music scores and generates hidden representations of the music score at the note level. 2) A proposed *Phoneme Distribution Predictor* is integrated to predict the proportion of phonemes in each syllable-note pair according to the *Type 1* score features. 3) Then, an *Acoustic Encoder* converts the predicted duration with its corresponding phoneme and pitch into musical features at the phoneme level. 4) A *Duration Predictor* forecasts the acoustic frame lengths for each phoneme and passes the value to the *Length Regulator* for expansion. 5) Finally, the *Decoder* transfers the frame-level features to the spectrum.

2.2. Acoustic Feature Processing Strategy

Fig. 2 illustrates the difference between **PHONEix** and other AFP strategies. Some of the previous works calculate acoustic features based solely on time sequence from the music score without referencing actual singing (Fig. 1 (a)). Others input the actual phoneme time sequence for training, which varies from the inference Type 1 input. To bridge the gap between the music score and the actual singing voice (illustrated in Fig. 3), we employ a new AFP strategy PHONEix. The input of the Acoustic Encoder consists of the Type 1 note-level score features, i.e., phoneme, pitch, and note duration. Then, the final output of the Acoustic Encoder is expanded to fit the actual duration under the guidance of an annotated phoneme time sequence. Nevertheless, the duration distributions of vowels and consonants vary sensibly. It is difficult for the duration predictor to provide an accurate frame expansion length with the same duration input among all phonemes in each note. In order to obtain a more precise phoneme pronunciation duration, a Prior Encoder is introduced to help learn the proportion of phoneme pronunciation. The pronunciation of lyrics varies with pitch and note duration and is influenced by the context of the song. Hence, we utilize a Bi-LSTM or Transformer-based encoder instead of just analyzing linguistic features and providing predictions syllable by syllable. The *Prior Encoder* can share the same networks as the *Acoustic* Encoder, which can be easily adapted to various encoder-decoderbased acoustic models.

2.3. Phoneme Distribution Predictor

As discussed in Sec. 2.1, we propose a learned phoneme duration for the following parts of the model, instead of using the same note duration for vowels and consonants or fixed phoneme duration (i.e. phoneme annotation). The learned phoneme duration is predicted by a proposed *Phoneme Distribution Predictor* to distinguish vowels and consonants. To be specific, the predictor employs a series of 1-D convolutional layers to extract context information from the musical score features generated by the *Prior Encoder*. The predictor gives a n-dimension probability distribution $\mathbf{p} = (p_1, p_2, \ldots, p_n)$, where n is the maximum number of phonemes in a syllable-note pair, which is determined by a syllable-phoneme lexicon. After that,

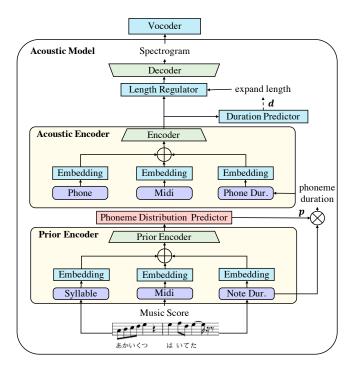


Fig. 3. The SVS system architecture with **PHONEix** AFP strategy. Details are introduced in Sec. 2.1. The green blocks can be adjusted to accommodate different acoustic models.

we utilize the distribution to split the note duration d^{note} extracted from the music score. The proportion for the i^{th} phoneme is p_i and the annotated phoneme duration d^{ph}_i is conform to actual phoneme distribution. A mean square error serves as an additional loss term to fit the predicted proportion to the real proportion in the actual singing pronunciation:

$$\mathcal{L}_{ph} = \|d^{\text{note}} \times \boldsymbol{p} - \boldsymbol{d}^{\text{ph}}\|_{2}. \tag{1}$$

In some fast-speed songs, the phoneme duration can be too short to be passed by the acoustic frame resolution. To ensure integrity of phonemes, we assign a minimum duration to these short phonemes. Therefore, in inference, the phoneme duration in acoustic framelevel is defined as follows:

$$\widehat{d}_i^{\text{ph}} = \text{rint}[\max(d^{\text{note}} \times p_i, 1)] \quad (i = 1, \dots, k), \tag{2}$$

where rint is a rounding function that maps the duration to the closest integer.

3. EXPERIMENTS

3.1. Dataset

We conduct our experiments on two datasets in two different languages. Every song is sampled at 24 kHz. We extract 80-dimensional Mel spectrograms with a window length of 1200 samples and a shifting size of 300 samples. The spectrograms normalized with global mean and variance from the train set are used as the ground truth for acoustic model outputs.

Ofuton: an open male singing corpus, consisting of 56 Japanese songs [27]. We divide the dataset by songs, resulting in a training

set (51), a valid set (5), and a testing set (5), respectively. The annotation information of the dataset includes manually labeled phoneme duration and music scores in MusicXML format. The segments of songs are separated by the <sil>, <pau>, and
br> silence marks, which align with segmentations of rest notes and breath marks in MusicXML.

Opencpop: a public Chinese female singing corpus of 100 songs in total [29]. The annotation of phoneme duration and music score are organized in Textgrids. We follow the segmentations of the official release.

3.2. Experimental Settings

The experiments are conducted using the music processing toolkit Muskits [28], which is adapted from ESPnet [30]. More details about the codes can be found on github ².

Model architectures: We verify the proposed AFP strategy on two acoustic models. Both models adopt the encoder-decoder structure and the duration predictor proposed in FastSpeech [31]. The models also share the configuration of the embedding layers. To be specific, we utilize 384-dimensional embedding layers for lyrics, notes, and note durations. The encoder and decoder of the first model are both three-layer 256-dimensional bidirectional Long-Short Term Memory units (Bi-LSTM) following [2]. The second network utilizes a Transformer structure from [14]. Apart from the additional loss for phoneme distribution predictor, we apply the same loss functions as [2] and [14]. We use the same HiFi-GAN vocoder [32] to convert the predicted acoustic features into waveforms.

Training: For both models, we utilize the Adam optimizer with a learning rate of 0.001 without schedulers. The batch size is 16. In all experiments, we select the model checkpoints with the best validation losses for further evaluation.

Evaluation metric: We follow the objective and subjective evaluations in [2]. For objective evaluation, we utilize Mel-cepstral distortion (MCD), voiced/unvoiced error rate (VUV_E), and semitone accuracy (SA). For subjective evaluation, we randomly select 30 singing segments from the test set and invite 40 judges to score the quality of each segment on a scale of 1 to 5. We report the mean opinion scores (MOS) with a 95% confidence interval.

3.3. Comparison with baselines

We compare the proposed strategy with the *Type 1* and *Type 2* processing strategies described in Sec. 1. Table 1 presents the evaluation scores of the proposed acoustic processing strategy and the two baselines. All strategies are conducted with LSTM and Transformer-based encoder-decoder acoustic model structures on the Ofuton and Opencpop datasets, respectively.

Type 1: The AFP strategy of music score does not involve actual phoneme time sequence in the acoustic model. We apply the processing pipelines in Xiaoice [14]. It accepts score features at note level and expands frame lengths according to the phoneme duration produced by HMM-based forced-alignment [33, 34].

Type 2: The other way of processing acoustic features is to use the annotated phoneme time sequence as acoustic encoder input and length expansion ground truth for the length regulator. We analyze the acoustic feature following [2]. The training stage has been tuned to fit the actual singing. However, the music score input in inference differs from the annotated ones in training as described in Sec. 1.

¹Since there is no official split of the data, we instead use the same split as in the previous work [28].

²https://github.com/A-Quarter-Mile/PHONEix

Table 1. Comparison of the proposed AFP strategy, **PHONEix**, with baselines (i.e., **Type 1** and **Type 2**). It is evaluated with Bi-LSTM or Transformer based encoder-decoder structures on Ofuton and Opencpop. Evaluations include three objective metrics (**MCD**, **VUV_E**, and **SA**) and a subjective metric (**MOS**) are described in Sec. 3.2. The details of models and datasets are discussed in Sec. 3.1.

Dataset	Model	Method	MCD ↓	VUV E↓	SA ↑	MOS ↑
	LSTM	Type 1	6.74	2.49%	56.65%	2.54 ± 0.05
		Type 2	6.34	2.53%	57.58%	2.58 ± 0.05
		PHONEix	6.28	2.41%	61.17%	3.03 ± 0.06
Ofuton	Transformer	Type 1	6.95	1.93%	61.09%	2.60 ± 0.05
		Type 2	6.78	1.71%	58.44%	2.26 ± 0.05
		PHONEix	6.52	2.15%	62.47%	3.01 ± 0.06
		Ground Truth	-	-	-	4.47 ± 0.04
		Type 1	9.33	6.79%	46.92%	2.09 ± 0.05
	LSTM	Type 2	8.62	11.32%	56.65% 57.58% 61.17% 61.09% 58.44% 62.47 %	2.48 ± 0.05
		PHONEix	7.90	6.05%	60.97%	3.56 ± 0.06
Opencpop		Type 1	8.77	6.19%	52.16%	2.52 ± 0.05
	Transformer	Type 2	9.05	10.59%	52.90%	1.89 ± 0.04
		PHONEix	8.42	5.97%	60.47%	3.03 ± 0.05
		Ground Truth	-	-	-	4.72 ± 0.03

Table 2. Objective evaluations of the ablation study on learned phoneme duration. Detailed discussions can be found in Sec. 3.4.

Duration Source	MCD↓	VUV_E↓	SA ↑
PHONEix	6.28	2.41%	61.17%
Annotation	6.46	2.51%	61.23%
Statistical Rule	6.39	2.59%	60.49%
Music Score	6.73	2.69%	59.03%
Music Score (Note)	6.79	2.74%	58.39%

The results in Table 1 show significant improvements in both subjective and objective metrics in our SVS system equipped with an AFP strategy. The cases of corresponding results are shown in Fig. 4. The result of Fig. 4 shows that the *PHONEix* obtains the best estimation of duration of phonemes among all method, which further confirms the effectiveness of our proposed *PHONEix*.

3.4. Ablation study

In this subsection, we test the effectiveness of learnable phoneme duration input for the acoustic encoder and the validity of the proposed phoneme distribution predictor.

In order to prove the effectiveness of learned phoneme duration, we compare it with other fixed duration sources for the acoustic encoder: 1) annotation (i.e., annotated phoneme duration). 2) statistical rule where the duration is derived from the statistical calculation of the corresponding dataset. 3) music score where the duration is obtained from the note duration. We use the same ground truth phoneme duration (annotated phoneme duration) in the *Length Regulator* for the above three settings. The results show that the learned phoneme duration from *PHONEix* gets a higher score in MCD and VUV_E and comparable semitone accuracy to the annual annotation. The learned phoneme duration indicates the precise division of vowels and consonants in each note, which leads to ample pronunciation in singing. In addition, we train the SVS system that

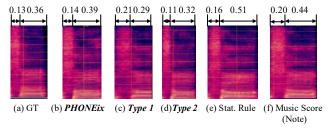


Fig. 4. The cases of various methods. The number above the picture indicates the duration of the phoneme (in seconds).

direct optimized over acoustic features at the syllable-note level (i.e. Music Score (Note) in Table 2) and expand frame length by note time sequence. The note-level feature gets worse performances that it cannot generate the representation needed for good pronunciation without phoneme division (see Fig. 4 (f)).

4. CONCLUSION AND FUTURE WORK

In this work, we introduce for the first time an improved AFP strategy *PHONEix* to an SVS system. It helps narrow the gap between theoretical music score input and actual singing. In it, a novel **phoneme distribution predictor** is integrated to give phoneme proportions in each note. Therefore, the phoneme duration becomes a learnable feature to fit the complex pronunciation in singing. The prior encoder module can be quickly adapted to different acoustic models. If given a large SVS dataset, it would be promising work to pre-train a phoneme distribution predictor to annotate phoneme time sequences in raw datasets.

5. ACKNOWLEDGEMENT

This work was supported by the National Natural Science Foundation of China (No. 62072462) and the National Key R&D Program of China (No. 2020AAA0108600).

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