Diverse and Controllable Speech Synthesis with GMM-Based Phone-Level Prosody Modelling

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Abstract—Generating natural speech with diverse and smooth prosody pattern is a challenging task. Although random sampling with phone-level prosody distribution has been investigated to generate different prosody patterns, the diversity of the generated speech is still very limited and far from what can be achieved by human. This is largely due to the use of uni-modal distribution, such as single Gaussian, in the prior works of phone-level prosody modelling. In this work, we propose a novel approach that models phone-level prosodies with a GMM-based mixture density network and then extend it for multi-speaker TTS using speaker adaptation transforms of Gaussian means and variances. Furthermore, we show that we can clone the prosodies from a reference speech by sampling prosodies from the Gaussian components that produce the reference prosodies. Our experiments on LJSpeech and LibriTTS dataset show that the proposed GMM-based method not only achieves significantly better diversity than using a single Gaussian in both single-speaker and multi-speaker TTS, but also provides better naturalness. The prosody cloning experiments demonstrate that the prosody similarity of the proposed GMM-based method is comparable to recent proposed fine-grained VAE while the target speaker similarity is better.

Keywords—speech synthesis, prosody modelling, prosody cloning, mixture density network

I. INTRODUCTION

TEXT-TO-SPEECH (TTS) synthesis is a process that transforms a transcript into its corresponding speech. Traditional statistical parametric speech synthesis (SPSS) [1], [2] typically contains multiple components, such as a text front-end, a duration model and an acoustic model. In recent years, end-to-end speech synthesis that directly synthesizes speech from text is widely explored based on deep learning. For example, sequence-to-sequence models, such as tacotron2 [3] and transformer TTS [4], are able to generate highly natural speech that is comparable to human speech. Besides, non-autoregressive TTS models are also investigated for stability and fast generation, including FastSpeech2 [5] and parallel tacotron2 [6].

Besides the linguistic content, speech contains a lot of non-linguistic or para-linguistic information such as speaker identity and prosody. Typically, prosody refers to intonation, speed, intensity, and etc [7], which significantly affects the naturalness of speech. Prosody has a top-down hierarchical structure [8], [9], [10], including discourse, phrase, utterance, word, syllable and phone. In traditional TTS systems, prosodic features, especially pitch and duration, are exhaustively investigated for generating naturally sounding speech. [11] proposes a rule-based prosody prediction method while [12] generates the prosody with a weighted finite-state transducer (WFST). [13] applies the restriction of natural pitch range to the unit selection synthesizer and improves the intonation naturalness. There are also researches exploiting prosodic features for emotional speech synthesis [14], [15].

In recent end-to-end speech synthesis, literatures mainly focus on utterance-level [16], [17], [18] and phone-level [19], [20], [21] prosody, where the prosody representations are extracted by neural networks. Prosody modelling is important for generating diverse speech corresponding to the same input text. Given the distribution of prosody representations, we can sample various prosodies from the distribution to guide the speech synthesis. Compared with utterance-level prosody modelling, phone-level prosody is more fine-grained to precisely control synthesised speech. Hence, we focus on phone-level prosody modelling in this work.

Additionally, prosody cloning and prosody transfer are two downstream tasks that controls the prosody with a reference in synthesizing speech of a target speaker. In most cases, the training corpus is in the form of text audio pairs without prosody labelling. Therefore, we often describe the prosody with a reference speech and try to imitate the reference prosody in speech synthesis. There are two different cases: a) the reference speech is constrained to share the same linguistic content with the input text [16], [22], [23], b) no constraint is imposed [17], [18]. To avoid confusion, we refer to the two cases as prosody cloning and prosody transfer respectively. In this work, we only focus on the prosody cloning task. One of the recent popular methods for prosody cloning is fine-grained variational auto-encoder (VAE) [22], [23] which extracts prosody representations from the reference speech with a fine-grained VAE architecture for guiding the synthesis.

Despite the success of the prior works for phone-level prosody modelling, it is still challenging to generate highly diverse speech. This is largely due to the use of uni-modal distribution, such as single Gaussian. Actually, phone-level prosodies are highly diverse even for the same context, hence it is natural to apply multi-modal distribution. In traditional automatic speech recognition (ASR) systems, one of the most dominant techniques is HMM-GMM [24], [25], [26], in which the distribution of acoustic features for each HMM state is modeled with a GMM. Similarly, GMM is also used to model acoustic features in traditional SPSS [27], [28] and has improved voice quality.

To achieve more accurate and controllable prosody representation, we propose a novel approach that models phone-level prosodies with a GMM-based mixture density network (MDN) [29]. We use a prosody extractor to extract phone-level prosody embeddings from ground-truth mel-spectrograms and use a prosody predictor of MDN to predict the GMM
distribution of the embeddings. In inference stage, the prosody of each phone is randomly sampled from the predicted GMM distribution for generating speech with diverse prosodies. Furthermore, we extend the GMM-based prosody modelling for multi-speaker TTS. For each GMM distribution, the speaker-independent means and variances of all Gaussian components are nonlinearly transformed to speaker-dependent ones with a same group of parameters. Our experiments are performed on single-speaker LJSpeech [30] and multi-speaker LibriTTS [31] dataset respectively. The proposed GMM-based phone-level prosody modelling not only achieves better diversity than using a single Gaussian in both single-speaker and multi-speaker tasks, but also provides better naturalness.

Furthermore, in GMM-based prosody modelling, phone-level prosodies are clustered into Gaussian components. In other words, the Gaussian component index represents a certain type of prosody. Hence we can control the prosodies of synthetic speech by sampling phone-level prosody embeddings from the specified components. Therefore, it is natural to clone the reference prosody by synthesizing speech with specific components that produce the reference prosody embeddings. Our experiments show that the prosody similarity of the proposed GMM-based cloning method is comparable to the fine-grained VAE while the target speaker similarity is better.

The main contributions of this work are as follows:

- We propose a novel approach that utilizes a GMM-based mixture density network for phone-level prosody modelling in end-to-end speech synthesis, which significantly improves the diversity of generated prosody without losing naturalness.
- We propose speaker adaptation with nonlinear transformations of Gaussian means and variances to effectively apply GMM-based phone-level prosody modelling for multi-speaker TTS.
- We propose a GMM-based prosody cloning method, which achieves better target speaker similarity than prior works.

In the rest of this paper, prior works of prosody modelling and cloning are reviewed in Section II. Then we introduce the proposed GMM-based prosody modelling method for single-speaker TTS in Section III and for multi-speaker TTS in Section IV. GMM-based prosody cloning scheme is described in Section V. Section VI and VII gives experiments setup and results, and finally Section VIII concludes the paper.

II. RELATED WORK

A. Prosody modelling

Utterance-level prosody modelling in TTS is first investigated in [16], in which a global (utterance-level) prosody embedding is extracted from a reference speech for controlling the prosody of TTS output. [17] factorizes the prosody embedding with several global style tokens (GST), each of which represents a certain speaking style, whose weighted sum specifies the prosody. Variational auto-encoder (VAE) is also used for prosody modelling in [18]. However, all of the above methods can only describe prosodies at utterance-level, while phone-level prosodies can control the generated speech more precisely. Hence, in this work, we only focus on phone-level prosody modelling.

Phone-level prosody modelling is analyzed in several recent works. [32] tries to use an attention module to align the reference frame-level prosodies with each phone. [19] finds the instability problem in this method, so it directly extracts phone-level prosody from the segment of acoustic features corresponding to each phone, and models the posterior distribution of the extracted prosody with a single Gaussian in a VAE architecture. In inference stage, the prosodies of phones are independently sampled from the prior distribution $\mathcal{N}(0, I)$. [20] auto-regressively predicts the phone-level prosody distribution for each phone, and conditions the prediction on the history of phone-level prosodies with an LSTM. This can be formulated as

$$p(e_k; \epsilon < k, X) = \mathcal{N}(e_k; \mu_k, \sigma^2_k)$$

where $e_k$ represents the prosody of the $k$-th phone and $X$ represents the input phone sequence. [21] proposes hierarchical VAE for phone-level prosody modelling, which tries to obtain an interpretable latent space.

However, most of the prior works for phone-level prosody modelling assumes that the distribution of prosody embeddings is a single Gaussian, which does not have sufficient complexity to model rich prosodies. This leads to limited prosody diversity of generated speech.

![Fig. 1: Prosody cloning pipeline with fine-grained VAE.](image)

B. Prosody cloning

Apart from sampling diverse prosodies for speech synthesis, prosody cloning is another important task. It clones the prosody of a source speech to the synthetic speech of a target speaker with a same linguistic content. [16] extracts an utterance-level prosody embedding from the reference speech for the synthesis. [22], [23] utilizes a fine-grained VAE for prosody cloning, whose pipeline is shown in Figure 1. In the training stage, the reference speech is exactly the same as the training target. The posterior of latent variables are calculated by a prosody extractor. Then the prosody representations are
obtained from the posterior and then concatenated to the encoder output together with the speaker embedding. In the inference stage, the synthesis is conditioned on the target speaker embedding and the prosody representations of the source speech.

However, the prosody representations often suffer from speaker identity interference. Although [23] introduces a normalization convolutional layer and a bottleneck layer to alleviate the problem, the model structure and training strategy still need to be carefully designed and the problem still occurs in some situations.

In this work, we model the prosodies with GMMs and then clone the prosodies from a reference speech by sampling prosodies from the Gaussian components that produce the reference prosodies, which fundamentally avoids the speaker identity interference.

III. GMM-BASED PHONE-LEVEL PROSODY MODELLING FOR SINGLE- SPEAKER TTS

A. Mixture Density Network

Mixture density network (MDN) is defined as the combined structure of a neural network and a mixture-of-expert model. We focus on GMM-based MDN in this work to predict the parameters of the GMM distribution, including means $\mu_i$, variances $\sigma_i^2$, and mixture weights $w_i$. It should be noted that the sum of the mixture weights is constrained to 1, which can be achieved by applying a Softmax function, formalized as

$$w_i = \frac{\exp (\alpha_i)}{\sum_{j=1}^{M} \exp (\alpha_j)} \quad (2)$$

where $M$ is the number of Gaussian components and $\alpha_i$ is the corresponding neural network output. The mean and variance of Gaussian components are presented as

$$\mu_i = m_i \quad (3)$$
$$\sigma_i^2 = \exp (v_i) \quad (4)$$

where $m_i$ and $v_i$ are the neural network outputs corresponding to the mean and variance of the $i$-th Gaussian component. Equation (10) constrains the $\sigma_i^2$ to be positive.

The criterion for training MDN is the negative log-likelihood of the observation $y$ given its input $x$. Here we can formulate the loss function as

$$L_{MDN} = -\log p(y; x)$$
$$= -\log \left( \sum_{i=1}^{M} w_i N(y; \mu_i, \sigma_i^2) \right) \quad (5)$$

Therefore, given the input $x$, the mixture density network is optimized to predict GMM parameters $w_i$, $\mu_i$ and $\sigma_i$ that maximize the likelihood of $y$.

B. Overall architecture

The overall architecture of the proposed system is shown in Figure 2(a). The TTS model in this paper is based on the recent proposed FastSpeech2[5], where the input phone sequence is first converted into a hidden state sequence $h$ by the encoder and then passed through a variance adaptor and a decoder for predicting the output mel-spectrogram. Compared with the original FastSpeech [33], FastSpeech2
is optimized to minimize the mean square error (MSE) $L_{\text{MEL}}$ between the predicted and the ground-truth mel-spectrograms, instead of applying a teacher-student training. Moreover, the duration target is not extracted from the attention map of an autoregressive teacher model, but from the forced alignment of speech and text. Moreover, [5] condition the prediction of mel-spectrogram on the variance information such as pitch and energy with a variance adaptor. The adaptor is trained to predict the variance information with an MSE loss $L_{\text{VAR}}$.

In this work, we introduce a prosody extractor and a prosody predictor in the FastSpeech2-based TTS system. In the training stage, the prosody embeddings
\[ e = [e_1, e_2, ..., e_K] \]  
(6)
are extracted for all the $K$ phones by the prosody extractor from the corresponding mel-spectrogram segment. It is then projected and added to the corresponding hidden state sequence $h$ in order to better reconstruct the mel-spectrogram. The output of the prosody extractor, $e_k$, represents the prosody embedding for the $k$-th phone and is used as the target to train the prosody predictor during training. The distribution of $e_k$ is assumed to be a GMM whose parameters are predicted by an MDN. Here, the MDN is the prosody predictor. The prosody predictor autoregressively predicts the GMM distributions of the prosody embeddings. In inference stage, we sample the $\tilde{e}_k$ from the predicted distribution for each phone.

**C. Prosody extractor and prosody predictor**

The detailed architecture of the prosody extractor is shown in Figure 2(b). It contains 2 layers of 2D convolution, each followed by a batch normalization layer and a ReLU activation function. A bidirectional GRU is designed after the above modules. The concatenated forward and backward states from the GRU layer is the output of the prosody extractor, which is referred to as the prosody embedding of the phone.

Figure 2(c) demonstrates the detailed architecture of the prosody predictor. The hidden state $h$ of the input phone sequence is passed through 2 layers of 1D convolution, each followed by a ReLU, layer normalization and dropout layer. The output of the above modules is then concatenated with the previous prosody embedding and sent to a GRU. The GRU is designed to condition the prediction of the current prosody distribution on the previous prosodies. Then we project the GRU output to obtain $w_{k,i}$, $m_{k,i}$ and $v_{k,i}$, which is then transformed to the GMM parameters according to Equation (2) - (10).

Equation (5) formulates the training criterion for an MDN, which is the negative log-likelihood of the observations. Here, the observations are the prosody embeddings $e$, so we obtain the loss function for training the prosody predictor
\[ L_{\text{PP}} = \sum_{k=1}^{K} \log p(e_k; e_{<k}, h) \]
\[ = \sum_{k=1}^{K} \log \left( \sum_{i=1}^{M} w_{k,i} \mathcal{N}(e_k; \mu_{k,i}, \sigma_{k,i}^2) \right) \]  
(7)
where $w_{k,i}$, $\mu_{k,i}$, and $\sigma_{k,i}$ are the GMM parameters of the $i^{th}$ component of phone $k$. They are predicted given $h$ and $e_{<k}$.

**D. Training criterion**

The prosody extractor and the prosody predictor are both jointly trained with the FastSpeech2 architecture. The overall architecture is optimized with the loss function
\[ L = \beta L_{\text{PP}} + L_{\text{FastSpeech2}} \]
\[ = \beta L_{\text{PP}} + (L_{\text{MEL}} + L_{\text{VAR}}) \]  
(8)
where $L_{\text{PP}}$ is defined in Equation (7), $L_{\text{FastSpeech2}}$ is the loss function of FastSpeech2 which is the sum of variance prediction loss $L_{\text{VAR}}$ and mel-spectrogram reconstruction loss $L_{\text{MEL}}$ as described in [5], and $\beta$ is the relative weight between the two terms. It should be noted that we use a stop gradient operation on $e$ in calculating the $L_{\text{PP}}$, so the prosody extractor is not optimized with $L_{\text{PP}}$ directly.

**IV. Speaker Adaptation of GMM for Multi-Speaker TTS**

In Section III, we propose a GMM-based prosody modelling method for single-speaker TTS, in which phone-level prosodies are clustered into $M$ Gaussian components. In multi-speaker TTS, the speaker embedding is selected from a look up table and added to the speaker-independent(SI) encoder output $h_{si}$, yielding the speaker-dependent(SD) hidden sequence $h_{sd}$. We hope that each Gaussian component represents the same type of prosody across different speakers, so that speaker identity and prosody type are disentangled and we can control the prosodies with Gaussian indices across speakers.

There is a trivial method that directly predicts the SD means $m_{k,i}$ and log-variances $v_{k,i}$ with $h_{sd}$. However, in this case, there is no constraint that ensures same types of prosodies are clustered in same Gaussian components across speakers. Actually, we do find in our experiments that this strategy often leads to the unstable result across speakers, especially across genders.

Therefore, in this work, we propose a novel method that first predicts the SI means $m_{k,i}$ and log-variances $v_{k,i}$ and then non-linearly transforms them to the corresponding SD ones $m_{k,i}^{(s)}$ and $v_{k,i}^{(s)}$. Due to the speaker independence of SI parameters, only the prosody is clustered first, which determines the prosody type of each component. The SD parameters transformed from the SI ones contain additional speaker information but inherit the clustering results. Hence, in this case, each Gaussian component represents a same type of prosody across different speakers. The transformation method is detailed below.

We extend the single-speaker TTS in Section III to multi-speaker TTS, as is shown in Figure 3(a). Both $h_{si}$ and $h_{sd}$ are sent to the prosody predictor.

The prosody predictor for multi-speaker TTS is demonstrated in Figure 3(b). The SI output, including SI means $m_{k,i}$ and log-variances $v_{k,i}$, are obtained from $h_{si}$, while the SD output, including transformation parameters $A_{k,i}^{(s)}$, $b_{k,i}^{(s)}$, $C_{k,i}^{(s)}$, $d_{k}^{(s)}$ and the logits of Gaussian components $\alpha_{k,i}^{(s)}$, are obtained...
from $h_{sd}$. The architecture for predicting the SD output is the same as in the single speaker system, and an additional bi-directional GRU and a linear projection layer is added for predicting the SI output. In order to calculate SD means $m_{k,i}^{(s)}$ and log-variances $v_{k,i}^{(s)}$, we apply a non-linear speaker-dependent transformation to the SI $m_{k,i}$ and $v_{k,i}$, which can be formulated as

$$m_{k,i}^{(s)} = \text{Linear} \left( \tanh \left( A_k^{(s)} m_{k,i} + b_k^{(s)} \right) \right) \quad (9)$$

$$v_{k,i}^{(s)} = \text{Linear} \left( \tanh \left( C_k^{(s)} v_{k,i} + d_k^{(s)} \right) \right) \quad (10)$$

It should be noted that all the $M$ Gaussian components are transformed with a same group of parameters $A_k^{(s)}$, $b_k^{(s)}$ and $C_k^{(s)}$, $d_k^{(s)}$. For simplicity, we restrict the $A_k^{(s)}$ and $C_k^{(s)}$ to be diagonal.

V. GMM-BASED PROSODY CLONING

In Section IV, we propose a GMM-based prosody modelling method for multi-speaker TTS, in which phone-level prosodies are clustered into $M$ Gaussian components. In other words, the Gaussian component index represents a certain type of prosody, which means we can control the prosodies of synthetic speech by sampling phone-level prosody embeddings from the specified components. Therefore, it is natural to clone the reference prosody by synthesizing speech with specific components that produces the reference prosody embeddings.

The pipeline of prosody cloning is demonstrated in Figure 4. First, we train a multi-speaker TTS system with GMM prosody modelling as described in Section IV. Then we extract source prosody embeddings $e_{(src)}$ from the reference speech, predict the Gaussian mixture parameters of the source speaker with the prosody predictor, and then calculate the posterior probability that $e_{k}^{(src)}$ comes from the $j$-th Gaussian component. According to the Bayes’ Theorem, the posterior probability is

$$P \left( j | e_{k}^{(src)} \right) = \frac{P \left( j \right) P \left( e_{k}^{(src)} | j \right)}{P \left( e_{k}^{(src)} \right)} \quad (11)$$

The Gaussian component that produces $e_{k}^{(src)}$ is the one that maximizes the posterior probability, that is

$$i_k = \arg \max_j P \left( j | e_{k}^{(src)} \right)$$

$$= \arg \max_j w_{k,j}^{(src)} \mathcal{N} \left( e_k^{(src)} ; \mu_{k,j}^{(src)} , \sigma_{k,j}^{(src)} \right) \quad (12)$$

When $k$ indexes over all $K$ phonemes, the indices of the Gaussian components that produce $e_{k}^{(src)}$ generate a sequence

$$i = [i_1, i_2, ..., i_K] \quad (13)$$
Fig. 4: Speech Synthesis with cloned phone-level prosodies from a reference speech.

according to Equation (12). Then we predict the Gaussian mixture parameters of the target speaker and sample the prosody embedding from the \( \hat{e}_k^{(tgt)} \) for the \( k \)-th phone in speech synthesis, which can be denoted as

\[
\hat{e}_k^{(tgt)} \sim N(\mu_{k,i_k}, \sigma_{k,i_k}^2)
\]

(14)

Thus, the phone-level prosody embeddings \( \hat{e}_k^{(tgt)} \) from the specified Gaussian indices precisely clone the reference prosodies. Further, the GMM parameters for the target speaker are purely predicted with the target speaker embedding, so source speaker interference cannot occur in our prosody cloning.

VI. EXPERIMENTAL SETUP

A. Dataset

1) Single-speaker dataset: LJSpeech is an English dataset, containing about 24 hours speech recorded by a female speaker. We randomly leave out 250 utterances for testing.

2) Multi-speaker dataset: LibriTTS is a multi-speaker English dataset, which consists of 3 parts – “train-clean-100”, “train-clean-360” and “train-other-500”. We only use the combination of the two clean parts “train-clean-100” and “train-clean-360” in this work, which is called “train-clean-460”. It contains about 245 hours speech and 1151 speakers. We randomly leave out 378 utterances for testing.

B. Data preparation

All the speech data in this work is resampled to 16kHz for simplicity. The mel-spectrograms are extracted with 50ms window, 12.5ms frame shift, 1024 FFT points and 320 mel-bins. Before training TTS, we compute the phone alignment of the training data with an HMM-GMM ASR model trained on Librispeech [34], and then extract the duration of each phone from the alignment for TTS training.

C. Acoustic model

The acoustic model in this work is based on FastSpeech2 [5]. It consists of a phone embedding layer, an encoder, a variance adaptor and a decoder. The phone embedding layer contains a lookup table which is trained together with the TTS system. It transforms the input one-hot phone sequence to a 512 dimensional phone embedding sequence. The encoder consists of 6 layers of Transformer whose output is a 512 dimensional hidden sequence. Two variance adaptors are applied in our system for pitch and energy respectively. They both use 2 layers of 1D CNN with a kernel size of 3 and a linear projection layer that outputs the predicted pitch and energy. The decoder contains 6 layers of Transformer and a linear projection layer that outputs the mel-spectrogram. In the multi-speaker TTS, we add a 128 dimensional speaker embedding to the output of the encoder, controlling the speaker identity of the synthetic speech.

The \( \beta \) in Equation (8) is set to 0.02. An Adam optimizer [35] is used for TTS training in conjunction with a noam learning rate scheduler [36]. The output mel-spectrogram is converted to the waveform with a MelGAN [37] vocoder, which is trained on the same training set.
D. Prosody modelling

In this section, we describe the configurations of the proposed GMM-based phone-level prosody modelling PLP-GMM and two other prosody modelling methods ULP and PLP-SG. We build three TTS systems with the three prosody modelling methods respectively and they all share the same acoustic model configurations described in Section VI-C.

1) ULP: A popular approach for utterance-level prosody (ULP) modelling is conditioning the synthesis on a latent variable from VAE [18]. The dimensionality of the latent variable is set to 128. In the training stage, the latent variable is sampled from the posterior for each utterance. In the inference stage, the latent variable is sampled from the prior distribution, which is a standard Gaussian $\mathcal{N}(0,I)$.

2) PLP-SG: For precise prosody modelling, we apply phone-level prosodies (PLP) in this work. One basic method of PLP modelling is to use a single Gaussian [19], [20]. As shown in Figure 2, we introduce a prosody extractor and a prosody predictor to extract and predict prosody representations for the phones. In the prosody extractor, the 2 CNN layers with 8 channels and $3 \times 3$ kernel size is followed by a 64 dimensional bi-directional GRU layer. The prosody predictor contains 2 layers of CNN with kernel size 3 and a 512 dimensional GRU followed by a linear projection layer that outputs the parameters of a single Gaussian. In multi-speaker TTS, as demonstrated in Figure 3, the prosody predictor passes the speaker independent hidden sequence $\mathbf{h}_{si}$ through a 32 dimensional bi-directional GRU followed by a linear projection layer that outputs speaker independent means and log-variances.

3) PLP-GMM: As is described in Section III and IV, the proposed system models the phone-level prosodies with GMM, which means the output of the prosody predictor is the parameters of GMMs. The other configurations of PLP-GMM are the same as PLP-SG.

E. Prosody cloning

We use LibriTTS dataset in our experiments on prosody cloning. The data preparation and acoustic model configurations are exactly the same as described in Section VI-B and VI-C. We select two speakers, one male and one female speaker, as the target speakers. The speech of the test set is synthesized with the two target speakers respectively, where the prosodies are cloned from the ground-truth speech of source speakers. For simplicity, instead of sampling from the specified Gaussian component as in Equation 14, we directly select the mean as the prosody embedding of target speaker.
We build two systems in our experiments for prosody cloning: 1) the proposed GMM-based model and 2) the fine-grained VAE model [22], [23]. The architecture of the fine-grained VAE model is reviewed in Section II-B, which extracts fine-grained latent variables from the reference speech with a VAE to guide the synthesis. The latent variable in the experiment is 128 dimensional, which is the same as the prosody embeddings in PLP-GMM for fair comparison. To alleviate the speaker identity interference, [23] introduces an instance norm layer in its prosody extractor and a bottleneck layer that downsamples the prosody representations with a factor $\tau$. In our experiments, we set the $\tau$ to 10.

VII. EXPERIMENTAL RESULTS AND ANALYSIS

A. The necessity of using phone-level prosodies

Firstly, we verify whether using the extracted ground-truth phone-level prosodies (PLP) $e$ is better than using utterance-level prosodies (ULP) in reconstruction. Here, we reconstruct the test set with PLP-GMM and ULP, which is guided by the extracted ground-truth PLP $e$ and by the ULP sampled from the posterior respectively.

Mel-cepstral distortion (MCD) [38] is an objective measure of the distance between two sequences of mel-cepstral coefficients. We extract 25 dimensional mel-cepstral coefficients with 5ms frame shift [39] from both the synthetic speech and the corresponding ground-truth speech on the test set for computing the MCD. The results are demonstrated in Table I, where a lower MCD represents a better reconstruction performance. In both single-speaker and multi-speaker systems, using the extracted phone-level prosodies (PLP) $e$ achieves lower MCD than the utterance-level baselines. This is natural because phone-level prosody representations contain much more information about how each phone is pronounced than an utterance-level representation. Therefore, it is necessary to use phone-level prosodies in TTS systems for precise prosody controlling.

| Prosody Condition | Single-speaker TTS | Multi-speaker TTS |
|-------------------|-------------------|-------------------|
| ULP               | 5.22              | 5.31              |
| PLP               | 3.38              | 3.46              |

B. The number of Gaussian components for phone-level prosody modelling

In this section, we try to figure out how many Gaussian components are needed to model the distribution of the extracted phone-level prosodies $e$. We plot the log-likelihood curves on both the training set and the test set with several different numbers of Gaussian components in Figure 5. The observations in both the single-speaker and multi-speaker systems are similar. We can find that the log-likelihood gap between the training and test set in the single Gaussian model is larger than that in the Gaussian mixture models. Moreover, the log-likelihood curves of Gaussian mixture models are much higher than the single Gaussian model in both the training and test set. Therefore, we can conclude that the distribution of phone-level prosodies is multimodal and it should be modeled with Gaussian mixtures.

Additionally, increasing the number of components also provides higher log-likelihood, because the more components enable the model to simulate more complicated distribution. However, when we double the number of the components from 10 to 20, the improvement is very limited. Therefore, we do not further increase the number of components, and use 20 components in the following GMM-based systems.

C. Prosody diversity

According to the investigation above, we train the proposed system PLP-GMM with 20 Gaussian components. In the inference stage, the Gaussian mixture distributions of phone-level prosodies are predicted, from which the phone-level prosodies $\hat{e}$ are sampled. The synthesis is then guided by the sampled prosodies $\hat{e}$.\(^1\)

We compare PLP-GMM with two baseline systems ULP and PLP-SG in terms of prosody diversity. We synthesize the utterances in the test set 3 times with various sampled prosodies. We perform AB preference tests where two groups of synthetic speech from two different TTS systems are presented and the listeners need to select the better one in terms of prosody diversity. 10 test cases are randomly selected from the test set for each listener. Figure 6(a) and Figure 6(b) show the results in single-speaker and multi-speaker respectively. We can find that PLP-GMM provides better prosody diversity in the synthetic speech than both ULP and PLP-SG. This can

\(^1\)Audio examples are available here https://cpdu.github.io/gmm_prosody_modelling_examples.
Fig. 7: MUSHRA test in terms of naturalness.

be easily explained by the fact that a sequence of phone-level embeddings depicts the prosody more precisely than an utterance-level embedding and the fact that Gaussian mixtures can better model the phone-level prosody embeddings than a single Gaussian.

D. Naturalness

We also evaluate the naturalness of the above systems with a MUSHRA test, in which the listeners are asked to rate each utterance on a scale of 0 to 100. The speech converted back from the ground-truth mel-spectrogram with the vocoder is also rated in the test, which is denoted as GT. The results are reported in Figure 7. It can be observed that PLP-GMM synthesizes speech with better naturalness compared with PLP-SG because of the better phone-level prosody modelling. The MUSHRA score of PLP-GMM is 23.1% and 8.6% higher than PLP-SG on single-speaker and multi-speaker task respectively with p-value < 0.05. We can also find that ULP generates speech with similar naturalness as PLP-GMM, which can also be easily explained. In ULP, no phone-level prosody is explicitly considered. Hence, the synthetic speech contains an averaged phone-level prosodies, whose naturalness is comparable to the sampled phone-level prosodies in PLP-GMM. However, both the naturalness of PLP-GMM and ULP are slightly lower than GT.

E. The controllability of Gaussian component index

In GMM-based prosody cloning, we precisely control the synthesized phone-level prosodies with specified Gaussian indices. In this section, we explore whether Gaussian index could control the prosody. Figure 8 illustrates 3 synthetic mel-spectrograms of the male target speaker, where only the prosody of phone EY1 is sampled from 3 different Gaussian components while the prosodies of other phones are cloned from the specified components. In the figure, the segments of the phone EY1 are between the red lines, where three different prosodies can be observed. Furthermore, the prosodies of other phones are almost the same, because they are all cloned from the reference speech. These results clearly show that the phone-level prosodies can be controlled by the Gaussian component indices.

F. Pitch contour in GMM-based prosody cloning

To visualize the GMM-based prosody cloning, we plot the pitch contour in this section, which is one of the most conspicuous factors of prosody. We extract pitch features with
Fig. 9: An example of pitch contours of the reference speech (REF), the synthetic speech with cloned prosody (PLP-GMM-CP) and the synthetic speech with randomly sampled prosody (PLP-GMM-SP). Here the reference speaker is female and the target speaker is male.

Kaldi\cite{40} command compute-kaldi-pitch-feats for the reference speech (REF), the synthetic speech with cloned prosody (PLP-GMM-CP) and the synthetic speech with randomly sampled prosody (PLP-GMM-SP). Figure 9 illustrates an example where the reference speaker is female and the target speaker is male. We can observe that although the absolute pitch value of the female reference speaker is much higher than the target male speaker, the shape of the pitch contour is similar between PLP-GMM-CP and REF. The absolute pitch value of PLP-GMM-CP and PLP-GMM-SP is similar, because they are both the synthetic speech of the target male speaker, while the shapes of the pitch contour are quite different, because the prosody of PLP-GMM-SP is randomly sampled and is different from the reference.

**G. Subjective evaluation of prosody cloning**

In order to evaluate the prosody similarity between the synthetic speech and the reference speech, we consider using a MUSHRA test in which the listeners are asked to rate the prosody similarity on a scale of 0 to 100. In addition to PLP-GMM-CP and fine-grained VAE that applies prosody cloning, we also present PLP-GMM-SP and the reference speech in the test\footnote{Audio examples are available here \url{https://cpdu.github.io/gmm_prosody_cloning_examples}.}. The test results are depicted in Figure 10. As is expected, both PLP-GMM-CP and fine-grained VAE significantly improves the mean score by 64.9\% and 68.1\% respectively over PLP-GMM-SP that randomly samples the prosody, which demonstrate the effectiveness of prosody cloning. Furthermore, the performance of PLP-GMM-CP and fine-grained VAE is comparable and the mean score of fine-grained VAE is slightly higher. However, the reference still performs the best over both the prosody cloning methods.

In prosody cloning, we hope to synthesize speech without the speaker identity interference from the reference. Hence, we evaluate the speaker similarity with a MUSHRA test again and illustrate the results in Figure 11. It can be observed that the score of PLP-GMM-CP and PLP-GMM-SP is comparable. PLP-GMM-CP outperforms the fine-grained VAE with statistical significance ($p < 0.05$) and improves the mean score by 15.2\%. This is as expected because the prosody representations in fine-grained VAE may suffer from speaker identity interference.

**VIII. CONCLUSION**

In this paper, we propose a novel approach that utilizes a GMM-based mixture density network for phone-level prosody
modelling in end-to-end speech synthesis. Then we further extend the GMM-based model for multi-speaker TTS with nonlinear transformations of Gaussian means and variances. Finally, we apply the GMM-based prosody modelling to prosody cloning task. Our experiments on LJSpeech and LibriTTS dataset show that the proposed GMM-based method not only achieves significantly better diversity than using a single Gaussian in both single-speaker and multi-speaker TTS, but also provides better naturalness. The prosody cloning experiments demonstrate that the prosody similarity of the proposed GMM-based method is comparable to recent proposed fine-grained VAE while the target speaker similarity is better.

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