MAXIMIZING MUTUAL INFORMATION FOR TACOTRON

Peng Liu†, Xixin Wu‡, Shiyin Kang†, Guangzi Li†, Dan Su†, Dong Yu†

† Tencent AI Lab
‡ Department of Systems Engineering and Engineering Management,
The Chinese University of Hong Kong, China
{feanorliu, shiyinkang, guangzhilei, dansu, dyu}@tencent.com
wuxx@se.cuhk.edu.hk

ABSTRACT
End-to-end speech synthesis methods already achieve close-to-human quality performance. However compared to HMM-based
and NN-based frame-to-frame regression methods, they are prone to
some synthesis errors, such as missing or repeating words and
incomplete synthesis. We attribute the comparatively high utterance
to error rate to the local information preference of conditional autore-
gressive models, and the ill-posed training objective of the model,
which describes mostly the training status of the autoregressive
module, but rarely that of the condition module. Inspired by Info-
GAN, we propose to maximize the mutual information between the
text condition and the predicted acoustic features to strengthen the
dependency between them for CAR speech synthesis model, which
would alleviate the local information preference issue and reduce the
utterance error rate. The training objective of maximizing mutual in-
fornation can be considered as a metric of the dependency between
the autoregressive module and the condition module. Experiment
results show that our method can reduce the utterance error rate.

Index Terms— speech synthesis, end-to-end, mutual informa-
tion, Tacotron, conditional autoregressive model

1. INTRODUCTION
Tacotron [1] and Tacotron2 [2] are conditional autoregressive (CAR)
models trained with teacher forcing [3]. The condition is summar-
ized from the input text with attention mechanism [4]. Transformer-
TTS [5] can be considered as another instance of CAR model, with
effective utilization of self-attention mechanism [6]. Such architec-
ture can be trained in an end-to-end way, so it has a much shorter
pipeline and needs less expert knowledge and human labor. It is
flexible enough to adapt for speaking style [7,8] and multi-speaker
[9,10]. In addition, it is easy to be combined with neural vocoder
[11,12,13] to enhance the synthesized waveform quality.

Training with teacher forcing induces a mismatch between the
training period and the inference period, usually known as exposure
bias [14]. Even worse, it strengthens the local information prefer-
ence [15] for the CAR model. We explain the local information
preference intuitively first. At each time step during training, the
CAR model receives a teacher forcing input and a conditional input.
The teacher forcing input is one previous time step from the tar-
get. The conditional input is the text to be synthesized. If the CAR
model learns to copy the teacher forcing input, or to predict the target
totally depending on teacher forcing input without using the condi-
tional information, it still gets small training root mean square error
(RMSE). Finally the model, which achieves small RMSE, may not
learn to depend on the condition at all. So at the inference period,
the CAR model generates results that have nothing to do with the
condition. Note that local information preference still exists even if
teacher forcing is not used. When a random variable \( x \) admits au-
toregressive dependency over a conditional random variable \( z \), i.e.
\( p(x|z) = \prod_{i} p(x_i|x_{<i},z) \), an universal function approximator, such
as RNNs used in the CAR model, can in theory represent the distri-
bution without condition on \( z \) [15].

The local information preference weakens the dependency be-
 tween the predicted acoustic features and the text condition when
training a CAR speech synthesis model. In most cases, the CAR
speech synthesis model learns to depend on the text condition to
predict the acoustic features. However they are prone to bad cases.
We argue that this is caused by the local information preference of
the model. Since the model prefers predicting the acoustic features
from the teacher forcing input at training stage, it does not model the
dependency between the text condition and the predicted acoustic
features sufficiently. If we can strengthen the dependency, we may
reduce the bad-case rate.

In [16], the authors propose a information-theoretic regularization
for generative adversarial networks (GAN) [17] to learn a set of
disentangled latent codes. The authors separate GAN’s input noise
vector into incompressible noise and latent codes with factorized dis-
bution. But the generator of GAN is free to ignore the additional
latent codes and predicts observations only conditioning on the in-
compressible noise. To eliminate such trivial solutions, the authors
maximize the mutual information between the latent codes and the
observations for GAN. This leads to the InfoGAN model. The idea
is straightforward. Since the the mutual dependency between two
variables can be measured by mutual information, maximizing mu-
tual information (MMI) would strengthen the dependency between
the latent codes and the observations, and hence eliminate the trivial
solutions that the GAN’s generator models the observations without
depending on the latent codes. Inspired by InfoGAN, we propose to
maximize the mutual information between the text condition and the
predicted acoustic features to strengthen the dependency for CAR
speech synthesis models. This would alleviate the local information
preference problem and reduce the rate of bad cases.

Viewing from another perspective, the reconstruction error only
reflects the training status of the autoregressive module since we can
get small reconstruction error even if the model generates random
human-voice-like acoustic features. The mutual information objec-
tive can remedy the weakness of the original training objective.

In the following, we begin with explaining the local information
preference formally for CAR speech synthesis models and re-
view the existing designs in Tacotron which prevent the model from predicting the target totally depending on teacher forcing input in section 2. Then we explain our method and provide the experiment results in section 3 and 4. Finally, we conclude our work in section 5.

2. WHY CAR TTS MODEL TENDS TO IGNORE THE TEXT CONDITION

In this section we first explain local information preference for CAR model formally. Then we explain why Tacotron still works though it tends to ignore the text condition.

2.1. Variational encoder-decoder perspective of CAR model

Usually we perform maximum likelihood estimation (MLE) to train a CAR speech synthesis model. And the model communicates information form the text to the acoustic features through the time-aligned latent variables. Such latent variables exist in various speech recognition and synthesis systems, such as the hidden state in the HMM-based speech synthesis system, the forward-backward search matrix in the CTC recognizer, and the attention variables in Tacotron. We can formalize the CAR speech synthesis model as a variational encoder-decoder (VED) [18]. We use \( x \) and \( \theta \) to represent a text and its corresponding acoustic features in the training set. Since it is a CAR model, the conditional likelihood can be written as

\[
\log p_{\theta}(x|t) = \sum_{i=1}^{N} \log p_{\theta}(x_i|x_{<i}, t),
\]

where \( N \) is the number of acoustic frames in \( x \). For simplicity, we suppose the distribution of the time-aligned latent variables, \( c \), is factorizable, i.e.

\[
\log p_{\phi}(c|x, t) = \sum_{i=1}^{N} \log p_{\phi}(c_i|x_{<i}, t).
\]

At least this is true for the ad hoc treatment of the attention variables in Tacotron [19]. Then

\[
\log p_{\theta}(x|t) = \log \int_{c} p_{\phi}(c|x, t) \, dc = \sum_{i=1}^{N} \log \int_{c_i} p(x_i|c_i|x_{<i}, t) \, dc_i.
\]

The training objective is to maximize the sum of the conditional likelihood of each \( t \), \( x \) pair in the training set. For a training pair at time step \( i \):

\[
\log p_{\theta}(x_i|x_{<i}, t) = D_{KL}(q_{\phi}(c_i|x_{<i}, t)||p_{\phi}(c_i|x_{<i})) + \mathcal{L}(\theta, \phi, x, t) \tag{1}
\]

The first RHS term is the KL divergence of the encoder approximation from the model posterior (it is the posterior because it has access to the current \( x_i \)). The second RHS term is the variational lower bound. Since the KL-divergence term is always non-negative:

\[
\log p_{\theta}(x_i|x_{<i}, t) \geq \mathcal{L}(\theta, \phi, x, t)
\]

\[
= E_{q_{\phi}(c_i|x_{<i}, t)}[-\log q_{\phi}(c_i|x_{<i}, t) + \log p_{\phi}(x_i, c_i|x_{<i}, t)]
\]

\[
= -D_{KL}(q_{\phi}(c_i|x_{<i}, t)||p_{\phi}(c_i|x_{<i})) + E_{q_{\phi}(c_i|x_{<i}, t)}[\log p_{\phi}(x_i|x_{<i}, c_i)]
\]

\[
= \log p_{\theta}(x_i|x_{<i}, t) - D_{KL}(q_{\phi}(c_i|x_{<i}, t)||p_{\phi}(c_i|x_{<i})) \tag{2}
\]

\[
= \log p_{\theta}(x_i|x_{<i}, t) - \int D_{KL}(q_{\phi}(c_i|x_{<i}, t)||p_{\phi}(c_i|x_{<i})) \, dc_i \tag{3}
\]

In the above equations, \( \phi \) is the attention encoder parameters and \( \theta \) is the autoregressive decoder parameters for a CAR speech synthesis model. Since we suppose the text communicates information to the acoustic features only through the time-aligned latent variables, by Bayes rule, we have

\[
p(x_i, c_i|x_{<i}, t) = p(x_i|x_{<i}, c_i)p(c_i|x_{<i}, t)
\]

used in Eq 2. Note that the variational encoder-decoder formalization is a bit different from the original VAE. From Eq 1 we can see that \( q_{\phi}(c_i|x_{<i}, t) \) is used to approximate the model posterior distribution, \( p_{\phi}(c_i|x_{<i}, t) \). However, it does not use information from the current \( x_i \), because \( x_i \) is the acoustic feature frame to predict at inference time step \( i \), we cannot use it as the input to the encoder. We can use \( q_{\phi}(c_i|x_{<i}, t) \) as the prior distribution, \( p_{\phi}(c_i|x_{<i}, t) \), then the KL-divergence term becomes 0 in Eq 2. If we use a deterministic function to calculate \( c_i \), Eq 2 becomes the training objective of Tacotron. In Eq 3 the KL-divergence term is 0 only when \( x_i \) and \( c_i \) are conditionally independent. In such case, the time-aligned latent variables, \( c_i \), are meaningless. If the model learns meaningful time-aligned latent variables, the KL-divergence term is positive. When trained to maximize \( \log p_{\theta}(x_i|x_{<i}, t) \), the model would not learn meaningful time-aligned latent variables to avoid the extra cost if \( x_{<i} \) contains enough information to predict \( x_i \). Since the time-aligned latent variables are the bridges that communicate information from text to acoustic features, the model cannot exploit the text efficiently without the latent variables. we arrive at a similar conclusion as variational lossy autoencoder (VLAEM): information can be modeled locally by the CAR model will be modeled locally without using information from the time-aligned latent variables, only the remainder will be modeled using them [15]. We argue that this is one of the possible reasons why attention mechanism cannot learn alignment under some bad configurations [20].

2.2. Why Tacotron learns to condition on text

We argue that Tacotron learns to condition on the text mainly because of several designs: the reduction window, the large frame shift and the dropout in the decoder prenet. Reduction window is a frame dropout mechanism like the word dropout used in VAE language model (VAELM) [21] to weaken the connection between autoregressive steps. Setting reduction factor to 5 [1] can be considered as dropping 80% frames at equal intervals. This is a bit different from dropping words randomly to a certain percentage in VAELM, but they work in a similar way.

We can use the Euclidean distance (ED) between the teacher forcing input and the acoustic target as a metric for information locality (ED relates to the RMSE used at training). If the ED is smaller, it is easier for the CAR model to predict the target only based on the teacher forcing input without using text information. We list the frame averaged ED of mean-std normalized log mel wrapped short-time Fourier transform (STFT) magnitude for different configurations for the LJSpeech dataset [22] in Table 1. If a reduction window is used, we repeat the teacher forcing input reduction factor times to make the number of frames consistent with that of the target. From Table 1 we can see that using larger reduction factor and frame shift could increase the ED between the teacher forcing input and the acoustic target, which indicates that the connection between them is weakened. To achieve smaller training RMSE, the model has to depend more on the text. In [23], the authors point out that the decoder prenet dropout in Tacotron could make the model condition more on the input text. Intuitively, the dropout makes the teacher forcing input incomplete, so the model has to condition more on the text to reconstruct the target. It is reported in [2] that significantly more pronunciation issues are observed when using 5ms frame shift. In [24], the authors report that a narrower prenet bottleneck is critical in picking up attention during training. Decreasing the prenet bottleneck size would compress the teacher forcing input and increase the information gap. In conclusion, increasing the information gap between the teacher forcing input and target is vital for Tacotron to achieve acceptable performance. Also dropping teacher forcing input frames randomly to a certain percentage is a cheap trick to make the model more robust, which is not applied to Tacotron in previous works.
Table 1. Euclidean distance (ED) between the teacher forcing input and the acoustic target for different reduction factor and frame shift (frame length is 4 times of frame shift) configurations for LJSpeech.

| Reduction factor | Frame shift (ms) | ED 5 | ED 12.5 |
|------------------|------------------|------|---------|
| 1                | 0.289            | 0.374|         |
| 2                | 0.367            | 0.507|         |
| 5                | 0.516            | 0.751|         |

3. MAXIMIZING MUTUAL INFORMATION (MMI) FOR TACOTRON

Although the previous mentioned designs in Tacotron alleviate the local information preference, they weaken the autoregressive decoder and decrease the model’s performance. A model using reduction factor 2 generates better perceptual results than one using reduction factor 5 \[1\]. This indicates that the more the autoregressive model is weakened, the more drop in performance is induced. Even worse, Tacotron make mistakes, such as repeating words, omitting words and incomplete sentences, which seldomly appear in HMM-based methods \[25\] or NN-based frame-to-frame regression methods \[26\]-\[28\]. The dependency between the predicted acoustic features and the text input in Tacotron is not sufficiently modeled. If the dependency is sufficiently modeled and the model is penalized heavily when it makes mistakes during training, the generated acoustic features should strictly follow the text. So we take the InfoGAN approach that maximize the mutual information between the predicted acoustic features and the text input during training to strengthen the dependency between them.

3.1. MMI with an auxiliary recognizer

The mutual information between the input text, \(t\), and the predicted acoustic features, \(\tilde{x}\), is

\[
I(\tilde{x}; t) = H(t) - H(t|\tilde{x})
\]

where \(H(t)\) is the entropy of the input text, \(H(t|\tilde{x})\) is the conditional entropy of the input text given the predicted acoustic features, and \(I(\tilde{x}; t)\) is the mutual information between the input text and the predicted acoustic features.

The mutual information term to the training objective in Eq 1 can penalize the model if it ignores the dependency between the predicted acoustic features and the text. When this penalty is stronger than the KL-divergence term in Eq 3, the model learns meaningful time-aligned latent variables to exploit the text.

3.2. CTC recognizer for Tacotron

To keep the end-to-end property, we use a simple CTC recognizer as the auxiliary recognizer. The CTC recognizer uses the same convolution stack + bidirectional LSTM \[30\] layer structure as the Tacotron2’s text encoder for simplicity except that the former has an extra CTC loss layer. Lack of a language model is usually considered as a drawback of the CTC recognizer \[31\]. However, this quite meets our demand, since we do not want a language model to remedy the detected errors. Minimizing the CTC loss could strengthen the dependency between the predicted acoustic features and the input text during training.

The final loss function is:

\[
\mathcal{L} = |x_{\text{mel}} - \tilde{x}_{\text{mel}}| + |x_{\text{linear}} - \tilde{x}_{\text{linear}}| + CELoss(x_{\text{stop}}, \tilde{x}_{\text{stop}}) + \lambda \text{CTCLoss}(t, \tilde{x}_{\text{mel}})
\]

4. EXPERIMENTS

We show that maximizing the mutual information between the predicted acoustic features and the text to be synthesized can reduce the rate of bad case.

4.1. Experiment setup

We use LJSpeech for English and Databaker Chinese Standard Mandarin Speech Corpus (db-CSMSC) for Mandarin Chinese in our experiments. LJSpeech contains 13,100 audio clips of a single female speaker. We process the transcriptions with Festival \[32\] to get the phoneme sequences. db-CSMSC contains 10,000 Mandarin sentences recorded by a single female native speaker and recorded in a professional recording studio. The dataset contains the Chinese character and pinyin transcriptions and hand-crafted time intervals. In our experiments, we only use the pinyin transcription and transfer the pinyin sequence to a pinyin scheme which contains initials and sub-finals. Our pinyin scheme contains much less units than the initial-final pinyin scheme. It can alleviate the out-of-vocabulary and data sparsity problems.

All the waveforms are downsampled to 16k Hz in our experiments. We extract 2048-point STFT magnitudes with Hanning window and wrap the features with Mel filter to 80-band Mel spectrum. We use 12.5ms/50ms window shift for our experiments. Then a log operation is applied to linear spectrum and Mel spectrum. We use repeat padding for the training samples of different lengths in a batch since zero padding would affect the batch normalization statistics. We use the Adam optimzier with \(\beta_1 = 0.9, \beta_2 = 0.999\) and \(\epsilon = 10^{-8}\). The initial learning rate is 0.002 and starts to decay by a factor of \(\sqrt{4000}/\text{step}\) from 4000 step \[34\]. The gradient is clipped to maximum global norm of 1.0 \[35\]. We use Tacotron2 for our

\[\text{https://www.data-baker.com/open_source.html}\]
Table 2: Utterance error rate (UER) for different configurations. (RF is short for reduction factor and DFR is short for drop frame rate).

| corpus      | RF 2   | RF 0.2 | RF 0.0 |
|-------------|--------|--------|--------|
| LJSpeech    | no MMI | 16%    | 15%    | 10%    |
|             | MMI    | 10%    | 5%     | -      |
| db-CSMSC    | no MMI | 17%    | 12%    | 7%     |
|             | MMI    | 5%     | 4%     | -      |

Table 3: Mean opinion score (MOS) with 95% confidence intervals for different configurations.

|         | DFR 0.0 | DFR 0.2 | MMI + DFR 0.0 | MMI + DFR 0.2 |
|---------|---------|---------|---------------|---------------|
| MOS     | 3.84±0.16 | 3.92±0.17 | 3.83±0.14 | 3.87±0.15 |

4.2. UER and MOS for Tacotron-MMI

In Tacotron2, the attention context is concatenated to the LSTM output and projected by a linear transform to predict the Mel spectrum. This means the predicated Mel spectrum contains linear components of the text information. If we use this Mel spectrum as the input to the CTC recognizer, the text information is too easily accessible for the recognizer. This may cause the text information to be encoded in a pathological way in the Mel spectrum and lead to a strict diagonal alignment map (one acoustic frame output for one phoneme input) combined with location-sensitive attention. So before the linear transform operation, we add an extra LSTM layer to mix the text input) combined with location-sensitive attention. So before the linear transform operation, we add an extra LSTM layer to mix the text information and acoustic information.

4.3. Discussion

Many previous works focus on improving Tacotron’s reliability. In [23], professor forcing is adopted to mitigate the exposure bias induced by training with teacher forcing. The authors use diagonal attention penalty to enforce that the alignment between the acoustic features and the text is approximately diagonal in [37]. In [38], the authors propose to use the alignment information form hand-crafted labels or from an HMM-based system to guide the attention for Tacotron. Since a large body of legacy corpus and HMM-based systems exist, this is an efficient way to improve Tacotron. However, it is not trained in an end-to-end way. The implicit duration model of Tacotron uses alignment information that is not self-contained. Transformer-TTS adopts self-attention structure to improve the training and inference efficiency and to shorten the long range dependency path between any two inputs at different time steps [5].

In the speech-to-speech translation task [24], experiment results demonstrated that the multi-task recognition loss worked, but without proper explanation. It can be explained by Eq. 5 where minimizing the multi-task recognition loss can be interpreted as maximizing the mutual information between the learned hidden representation and the corresponding text in that task. When training with the multi-task recognition loss, the learned hidden representation encodes more linguistic information rather than acoustic information only, results in a better fit for the speech translation task.

5. Conclusion

In this paper we analyze why Tacotron is prone to synthesis errors. In short, modeling the correlation between the text and the acoustic features sufficiently is important to avoid the bad cases. To gain this objective, we propose to maximize the mutual information between the text and the predicted acoustic features with an auxiliary CTC recognizer. Experiment results show that our method can reduce the rate of bad cases. Besides our method can be trained in an end-to-end manner. It keeps the short pipeline of the original method.
6. REFERENCES

[1] Y. Wang et al, “Tacotron: A fully end-to-end text-to-speech synthesis model,” CoRR, vol. abs/1703.10135, 2017.
[2] J. Shen et al, “Natural TTS synthesis by conditioning wavenet on MEL spectrogram predictions,” in ICASSP, 2018, pp. 4779–4783.
[3] R. J. Williams and D. Zipser, “A learning algorithm for continuously running fully recurrent neural networks,” Neural Computation, vol. 1, no. 2, pp. 270–280, 1989.
[4] D. Bahdanau, K. Cho and Y. Bengio, “Neural machine translation by jointly learning to align and translate,” in ICLR, 2015.
[5] N. Li et al, “Close to human quality TTS with transformer,” CoRR, vol. abs/1809.08895, 2018.
[6] A. Vaswani et al, “Attention is all you need,” in NIPS, 2017, pp. 6000–6010.
[7] R. J. Skerry-Ryan et al, “Towards end-to-end prosody transfer for expressive speech synthesis with tacotron,” in ICML, 2018, pp. 4700–4709.
[8] Y. Wang et al, “Style tokens: Unsupervised style modeling, control and transfer in end-to-end speech synthesis,” in ICML, 2018, pp. 5167–5176.
[9] A. Gibiansky et al, “Deep voice 2: Multi-speaker neural text-to-speech,” in NIPS, 2017, pp. 2966–2974.
[10] Y. Jia et al, “Transfer learning from speaker verification to multispeaker text-to-speech synthesis,” in NeurIPS, 2018, pp. 4485–4495.
[11] N. Kalchbrenner et al, “Efficient neural audio synthesis,” in ICML, 2018, pp. 2415–2424.
[12] A. van den Oord et al, “Wavenet: A generative model for raw audio,” in ISCA, 2016, p. 125.
[13] A. van den Oord et al, “Parallel wavenet: Fast high-fidelity speech synthesis,” in ICML, 2018, pp. 3915–3923.
[14] M. Ranzato et al, “Sequence level training with recurrent neural networks,” in ICLR, 2016.
[15] X. Chen et al, “Variational lossy autoencoder,” in ICLR, 2017.
[16] X. Chen et al, “Infogan: Interpretable representation learning by information maximizing generative adversarial nets,” in NIPS, 2016, pp. 2172–2180.
[17] I. J. Goodfellow et al, “Generative adversarial networks,” CoRR, vol. abs/1406.2661, 2014.
[18] C. Zhou and G. Neubig, “Multi-space variational encoder-decoders for semi-supervised labeled sequence transduction,” in ACL, 2017, pp. 310–320.
[19] S. Shankar and S. Sarawagi, “Posterior attention models for sequence to sequence learning,” in International Conference on Learning Representations, 2019.
[20] X. Wu et al, “Attention-based recurrent generator with gaussian tolerance for statistical parametric speech synthesis,” in ASMMC, 2017.
[21] S. R. Bowman et al, “Generating sentences from a continuous space,” in SIGNLL, 2016, pp. 10–21.
[22] K. Ito, “The lj speech dataset,” https://keithito.com/LJ-Speech-Dataset/, 2017.
[23] H. Guo et al, “A new gan-based end-to-end tts training algorithm,” CoRR, vol.abs/1904.04775, 2019.
[24] Y. Jia et al, “Direct speech-to-speech translation with a sequence-to-sequence model,” CoRR, vol.abs/1904.06037, 2019.
[25] M. Coto-Jiménez and J. G. Close, “Speech synthesis based on hidden markov models and deep learning,” Research in Computing Science, vol. 112, pp. 19–28, 2016.
[26] Y. Fan et al, “TTS synthesis with bidirectional LSTM based recurrent neural networks,” in INTERSPEECH, 2014, pp. 1964–1968.
[27] S. Kang and H. M. Meng, “Statistical parametric speech synthesis using weighted multi-distribution deep belief network,” in INTERSPEECH, 2014, pp. 1959–1963.
[28] H. Zen, A. W. Senior and M. Schuster, “Statistical parametric speech synthesis using deep neural networks,” in ICASSP, 2013, pp. 7962–7966.
[29] D. Barber and F. V. Agakov, “The IM algorithm: A variational approach to information maximization,” in NIPS, 2003, pp. 201–208.
[30] S. Hochreiter and J. Schmidhuber, “Long short-term memory,” Neural Computation, vol. 9, no. 8, pp. 1735–1780, 1997.
[31] A. Graves, “Sequence transduction with recurrent neural networks,” CoRR, vol.abs/1211.3711, 2012.
[32] P. Taylor, A. W. Black and R. Caley, “The architecture of the festival speech synthesis system,” in ESCA/COCOSDA, 1998, pp. 147–152.
[33] D. P. Kingma and J. Ba, “Adam: A method for stochastic optimization,” in ICLR, 2015.
[34] A. Vaswani et al, “Tensor2tensor for neural machine translation,” in AMTA, 2018, pp. 193–199.
[35] R. Pascanu, T. Mikolov and Y. Bengio, “On the difficulty of training recurrent neural networks,” in ICML, 2013, pp. 1310–1318.
[36] J. Kominek and A. W. Black, “The CMU arctic speech databases,” in ISCA ITRW on Speech Synthesis, 2004, pp. 223–224.
[37] H. Tachibana, K. Uenoyama and S. Aihara, “Efficiently trainable text-to-speech system based on deep convolutional networks with guided attention,” in ICASSP, 2018, pp. 4784–4788.
[38] X. Zhu et al, “Pre-alignment guided attention for improving training efficiency and model stability in end-to-end speech synthesis,” IEEE Access, pp. 1–1, 2019.