NEURAL SEQUENCE-TO-SEQUENCE SPEECH SYNTHESIS USING A HIDDEN SEMI-MARKOV MODEL BASED STRUCTURED ATTENTION MECHANISM

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ABSTRACT

This paper proposes a novel Sequence-to-Sequence (Seq2Seq) model integrating the structure of Hidden Semi-Markov Models (HSMMs) into its attention mechanism. In speech synthesis, it has been shown that methods based on Seq2Seq models using deep neural networks can synthesize high quality speech under the appropriate conditions. However, several essential problems still have remained, i.e., requiring large amounts of training data due to an excessive degree for freedom in alignment (mapping function between two sequences), and the difficulty in handling duration due to the lack of explicit duration modeling. The proposed method defines a generative model to realize the simultaneous optimization of alignments and model parameters based on the Variational Auto-Encoder (VAE) framework, and provides monotonic alignments and explicit duration modeling based on the structure of HSMM. The proposed method can be regarded as an integration of Hidden Markov Model (HMM) based speech synthesis and deep learning based speech synthesis using Seq2Seq models, incorporating both the benefits. Subjective evaluation experiments showed that the proposed method obtained higher mean opinion scores than Tacotron 2 on relatively small amount of training data.

Index Terms—Speech Synthesis, Deep Neural Networks, Attention Mechanism, Hidden Semi-Markov Models, Sequence-to-Sequence Models

1. INTRODUCTION

There has been much recent research on end-to-end text-to-speech synthesis based on neural networks. In essence, text-to-speech synthesis is a sequence transform generating a sequence of acoustic features from a sequence of characters. Therefore, it is well-suited to using a Sequence-to-Sequence (Seq2Seq) model with an attention mechanism that infers the relationship (alignment) between the sequences [1]. Although it has been shown that methods based on Seq2Seq models can synthesize high quality speech under the appropriate conditions, critical problems still have remained, i.e., requiring large amounts of training data due to an excessive degree for freedom in alignment obtained from the attention mechanism, and the difficulty in handling duration because explicit alignment information cannot be obtained. To overcome these problems, some improved techniques have been proposed recently, e.g., applying constraints to attention which tends to yield monotonic alignment [2,3], and incorporating explicit alignment and/or duration to Seq2Seq models [4-6]. However, no method has yet been established that can perform overall optimization of both alignment and model parameters while also considering duration.

An important fact to be noticed is that above mentioned problems were appropriately solved in the conventional speech synthesis based on hidden Markov models (HMM-based speech synthesis). HMM-based speech synthesis uses a hidden semi-Markov model (HSMM), which is an HMM incorporating a state duration model, with state sequence as a latent variable representing alignment, and performing simultaneous optimization while also considering duration. In this paper, we propose a speech synthesis technique based on a Seq2Seq model with attention mechanism incorporating an HSMM structure. The proposed method is composed of a generative model based on a variational auto-encoder (VAE) [7], in which the alignment between input and output sequences is represented as latent variables as HSMM. The proposed method can also be interpreted as one of forms of structured attention [8] using HSMM. The alignment obtained by the proposed method is monotonic and consistent over an entire sequence, therefore it is expected to be able to build high quality systems using less training data than the conventional Seq2Seq models. Moreover, since duration is handled explicitly in the proposed model, it can be controlled in speech synthesis. The proposed method can be regarded as an integration of previous HMM-based speech synthesis and recent deep learning based speech synthesis using Seq2Seq models, incorporating both the benefits.

2. RELATED WORK

2.1. Seq2Seq models with an attention mechanism

Sequence-to-Sequence models using an attention mechanism [9] can learn the time correspondence relationship between
two sequences of different lengths, and have been used in end-to-end speech synthesis models such as Tacotron 2 [1]. These models are composed of three main elements: an encoder, a decoder, and an attention mechanism. The attention mechanism probabilistically selects an encoder hidden state for each decoder time step, which enables it to obtain suitable latent representations for sequences of various lengths. The context vector \( c_i \), obtained by the attention mechanism for time \( i \) is represented by a weighted sum of encoder hidden states \( h_j \) as follows.

\[
c_i = \sum_{j=1}^{N} \alpha_{ij} h_j
\]

where \( \sum_{j} \alpha_{ij} = 1 \), \( N \) is the input sequence length, and \( \alpha_{ij} \) are probabilities representing the degree of attention on the \( j \)th hidden state \( h_j \) in the encoder, computed from \( h_j \) and the \( i+1 \)th state in the decoder. Attention corresponds to the alignment between linguistic and acoustic feature sequences in speech synthesis, and can be obtained automatically through training. However, the above mentioned attention mechanism has excessive degree of freedom in matching function between two sequence and requires suitable constraints to keep monotonic alignment in speech synthesis. Moreover, estimating matching function does not take into account of the duration of units in linguistic feature sequences, e.g., phones.

### 2.2. DNN-HSMM

A hidden semi-Markov models (HSMM) is a HMM incorporating a duration model, and its likelihood function is given as follows.

\[
p(o \mid l, \lambda_{\text{HSMM}}) = \sum_z p(o, z \mid l) \quad (2)
\]

\[
= \sum_z \left\{ \prod_{t=1}^{T} p(o_t \mid z_t, l) \prod_{k=1}^{K} p(d_k \mid l) \right\} \quad (3)
\]

where \( o = (o_1, o_2, \ldots, o_T) \), and \( l = (l_1, l_2, \ldots, l_K) \) represent acoustic and linguistic feature values respectively, and \( z \) represents the state sequence for alignment. State duration, \( d_k \) represents the duration of each state, \( k \) in \( z \).

\[
z = (z_1, z_2, \ldots, z_T)
\]

\[
= (S_1, S_2, \ldots, S_2, \ldots, S_2, \ldots, S_K) \quad (5)
\]

Usually the parameters of HSMM are optimized by the expectation-maximization (EM) algorithm for the maximum likelihood estimates. The algorithm iteratively updates the the posterior probability distribution \( p(z \mid o, l) \) and model parameters \( \lambda_{\text{HSMM}} \), and the posterior probability can be efficiently computed using a generalized forward-backward algorithm [11]. A DNN-HSMM [10] has been proposed as a statistical model for incorporating the qualities of an HSMM, i.e., handling duration appropriately, into a neural network. In the DNN-HSMM, the neural network takes linguistic features as input and generates HSMM model parameters. Taking both output and duration probabilities as Gaussian distributions, this yields:

\[
p(o_t \mid z_t = k, l) = \mathcal{N}(o_t \mid \mu_k, \sigma_k^2) \quad (6)
\]

\[
p(d_k \mid l) = \mathcal{N}(d_k \mid \xi_k, \eta_k^2) \quad (7)
\]

\[
\{\mu_k, \sigma_k^2, \xi_k, \eta_k^2\} = \text{DNN}(l_k) \quad (8)
\]

This achieves a more flexible mapping from linguistic features to model parameters than the decision-tree-based clustering used in HMM-based speech synthesis, while duration and alignment can be appropriately handled within the framework of statistical generative models. However, due to the limitation that final acoustic features \( o \) are generated by the HSMM, quality is somewhat inferior compared with recent Seq2Seq models.

### 3. PROPOSED METHOD

#### 3.1. HSMM based structured attention

This paper proposes a novel Seq2Seq model based on an attention mechanism integrating the structure of HSMM. The method defines a generative model based on a variational auto-encoder (VAE) [7] framework, in which the alignment between acoustic feature and linguistic feature sequences is represented by the discrete latent variable sequence corresponding to HSMM states. An overview of the method is shown in Figure 1. We first define an evidence lower bound (ELBO) based on the likelihood function \( p(o \mid l) \):

\[
\log p(o \mid l) = \sum_z p(o, z \mid l) \quad (9)
\]

\[
\geq \sum_z q(z) \log \frac{p(o, z \mid l)}{q(z)} \quad (10)
\]

\[
= \sum_z q(z) \log p(o \mid z, l) + \sum_z q(z) \log p(z \mid l) - \sum_z q(z) \log q(z) \quad (11)
\]

\[
= \mathcal{L}_{\text{ELBO}} \quad (12)
\]

![Fig. 1. VAE based structured attention](image-url)
where $q(z)$ and $p(o \mid z, l)$ are the encoder and decoder respectively, composed of separate neural networks. Usually, prior distribution $p(z \mid l)$ is set to a particular distribution beforehand, e.g., a normal distribution. In the proposed method, we assume it consists of a neural network that will be trained.

The VAE optimizes the neural network by maximizing the evidence lower bound $\mathcal{L}_{\text{ELBO}}$. In the proposed model, latent variable $z$ represents a discrete state sequence similarly to an HSMM, and the approximate posterior distribution $q(z)$ represented by the encoder is assumed to be composed of a DNN-HSMM:

$$q(z) = p(z \mid o, \lambda_{\text{HSMM}})$$  \hspace{1cm} (13)

$$\lambda_{\text{HSMM}} = \text{DNN-HSMM}(l)$$  \hspace{1cm} (14)

In other words, the proposed method uses the HSMM as an estimator for state posterior probability $q(z)$ while the conventional DNN-HSMM uses it as a generator of outputs acoustic features $o$. Normally, to calculate the ELBO (equation (12)), sampling the latent variables from the posterior distribution is used in VAEs. However, since $z$ is a discrete variable sequence in the proposed method, the following expectation is used to propagates encoder information to the decoder

$$\gamma_k(t) = p(z_t = k \mid o, l) = \sum_z q(z) \delta(z_t, k)$$  \hspace{1cm} (15)

It can be clearly seen that $\gamma_k(t)$ is the attention itself, that is, $\gamma_k(t)$ represents the degree of attention on linguistic feature $l_k$ when generating the frame for time $t$. Even though the calculation of $\gamma_k(t)$ requires counting all possible state sequences, it can be efficiently calculated using a generalized forward-backward algorithm as in DNN-HSMM. This enables the proposed method to estimate attention based on consistent alignment over the entire sequences representing monotonic alignment.

From the definition of ELBO, the decoder can be defined as a neural network with any structure whose inputs are $z$ and $l$, and output is $o$. However, as mentioned above, assuming expectation $\gamma = \{\gamma_k(t) \mid k = 1, \ldots, K, t = 1, \ldots, T\}$ instead of $z$ is passed from the encoder, it means that the decoder has the following approximation.

$$\sum_z q(z) \log p(o \mid z, l) \approx \log p(o \mid \gamma, l)$$  \hspace{1cm} (16)

Moreover, by applying the structure similar to a conventional attention mechanism, the exact same form as the decoder in Seq2Seq models:

$$\log p(o \mid l) = \log p(o \mid \{l_t\})$$  \hspace{1cm} (17)

$$\{l_t\} = \{l_1, l_2, \ldots, l_T\}$$  \hspace{1cm} (18)

$$\gamma_k(t) = \sum_{k=1}^{K} \gamma_k(t) f(l_k)$$  \hspace{1cm} (19)

where $f(\cdot)$ is the decoder PreNet (corresponding to the en-
terms were conducted using speech data from a single male speaker. The speech database consists of 503 Japanese sentences; 450 sentences were used as training data, and remaining 53 sentences were used as test data. The sampling rate of the speech data was 48 kHz. Three methods in addition to the proposed method (PROPOSED) were compared: DNN-HSMM (DNN-HSMM), Tacotron 2 (TACO), and a frame-unit acoustic model (FRAME). The target acoustic features to be modeled included a 50-dimensional mel-cepstrum coefficient vector extracted by STRAIGHT analysis [12], the log-fundamental frequency, V/UV, and a 25-dimensional aperiodicity features. For DNN-HSMM and PROPOSED, acoustic features with their dynamic features were assumed to be generated from the HSMM. The HSMMs had five states, structured left-to-right with no skips. As an input feature vector, a 386-dimensional phoneme-unit linguistic feature was used for TACO, and a 388-dimensional state-unit linguistic feature with a phoneme internal state index was used for DNN-HSMM and PROPOSED. For FRAME, we used a 394-dimensional frame-unit linguistic feature consisting of the state-unit linguistic feature, using DNN-HSMM for alignment and adding items including a position number within the state segment and duration context. During synthesis in FRAME, the duration estimated by DNN-HSMM was used. The model structure for DNN-HSMM is similar to the encoder part of the proposed method (Figure 2), and trained based on the maximizing likelihood criterion. The model structure of TACO was adopted from the reference [1], replacing the embedding layer with a linear transform and adding guided attention loss ($g = 0.2$) [3] for training. The reduction factor of 3 was used, and only monophone labels were enabled in the initial stage of training. The decoder in the FRAME was the same as for the proposed method (Figure 2), and training was conducted with the frame-unit linguistic feature as input to the PreNet($\cdot$). From preliminary test results, the prior distribution and encoder duration model were shared in PROPOSED. In the training procedure for PROPOSED, initial training of the decoder was performed with setting the trained DNN-HSMM to the encoder and then an overall optimization was conducted. Adam [13] was used as the optimization algorithm for all training in all methods.

4.2. Subjective Evaluation

The naturalness of synthesized speech was evaluated using Mean Opinion Score (MOS) tests. For each of ten subjects, 15 sentences from the test data were selected at random and evaluated in 5-scale scores. The results of subjective evaluation are shown in Figure 3. The figure shows that the PROPOSED received the highest score for naturalness, confirming that the method is effective. In particular, PROPOSED obtained a higher score than FRAME using the same decoder structure. This suggests that the simultaneous optimization of alignment and model parameters was effective in the pro-

4.1. Experimental Conditions

To show the effectiveness of the proposed method, experiments were conducted using speech data from a single male speaker. The speech database consists of 503 Japanese sentences; 450 sentences were used as training data, and remaining 53 sentences were used as test data. The sampling rate of the speech data was 48 kHz. Three methods in addition to the proposed method (PROPOSED) were compared: DNN-HSMM (DNN-HSMM), Tacotron 2 (TACO), and a frame-unit acoustic model (FRAME). The target acoustic features to be modeled included a 50-dimensional mel-cepstrum coefficient vector extracted by STRAIGHT analysis [12], the log-fundamental frequency, V/UV, and a 25-dimensional aperiodicity features. For DNN-HSMM and PROPOSED, acoustic features with their dynamic features were assumed to be generated from the HSMM. The HSMMs had five states, structured left-to-right with no skips. As an input feature vector, a 386-dimensional phoneme-unit linguistic feature was used for TACO, and a 388-dimensional state-unit linguistic feature with a phoneme internal state index was used for DNN-HSMM and PROPOSED. For FRAME, we used a 394-dimensional frame-unit linguistic feature consisting of the state-unit linguistic feature, using DNN-HSMM for alignment and adding items including a position number within the state segment and duration context. During synthesis in FRAME, the duration estimated by DNN-HSMM was used. The model structure for DNN-HSMM is similar to the encoder part of the proposed method (Figure 2), and trained based on the maximizing likelihood criterion. The model structure of TACO was adopted from the reference [1], replacing the embedding layer with a linear transform and adding guided attention loss ($g = 0.2$) [3] for training. The reduction factor of 3 was used, and only monophone labels were enabled in the initial stage of training. The decoder in the FRAME was the same as for the proposed method (Figure 2), and training was conducted with the frame-unit linguistic feature as input to the PreNet($\cdot$). From preliminary test results, the prior distribution and encoder duration model were shared in PROPOSED. In the training procedure for PROPOSED, initial training of the decoder was performed with setting the trained DNN-HSMM to the encoder and then an overall optimization was conducted. Adam [13] was used as the optimization algorithm for all training in all methods.

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posed method. Comparing PROPOSED and DNN-HSMM, a clear improvement of PROPOSED suggests that the flexible autoregressive decoder structure contributed significantly to improving naturalness. Because of the relatively small amount of training data, TACO obtained poor alignment accuracy due to its over degree of freedom in attention, and the proposed method was able to achieve suitable alignment due to the suitable structured attention.

5. CONCLUSION

This paper proposed a method for Seq2Seq modeling using structured attention based on HMM. The proposed method is formulated based on a VAE framework, and can be regarded as an integration form of the conventional HMM speech synthesis and a neural network based Seq2Seq model. Experimental results showed improvement in naturalness of synthesized speech due to the simultaneous optimization of alignment and model parameters based on VAE framework. The robust alignment estimation based on the appropriate structure constraint using HMM also contributes to the quality of synthesized speech especially on the small amount of training data. Future work includes evaluation using larger speech database and application to fully end-to-end speech synthesis and to multiple speaker models.

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