AN AUTOREGRESSIVE RECURRENT MIXTURE DENSITY NETWORK FOR PARAMETRIC SPEECH SYNTHESIS

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ABSTRACT

Neural-network-based generative models, such as mixture density networks, are potential solutions for speech synthesis. In this paper we follow this path and propose a recurrent mixture density network that incorporates a trainable autoregressive model. An advantage of incorporating an autoregressive model is that the time dependency within acoustic feature trajectories can be modeled without using the conventional dynamic features. More interestingly, experiments show that this autoregressive model learns to be a filter that emphasizes the high frequency components of the target acoustic feature trajectories in the training stage. In the synthesis stage, it boosts the low frequency components of the generated feature trajectories and hence increases their global variance. Experimental results show that the proposed model achieved higher likelihood on the training data and generated speech with better quality than other models when dynamic features were not used in any model.

Index Terms— Speech synthesis, Autoregressive model, Mixture density network, Recurrent neural network

1. INTRODUCTION

Parametric speech synthesis aims at generating speech based on textual information. It uses an acoustic model, such as a hidden Markov model (HMM), to generate the acoustic features from textual information and then a vocoder to convert the generated features into the speech waveform [1]. Recently, various neural-network-based models have been proposed to better map the textual features into acoustic ones [2, 3]. There are also neural networks that directly model spectral features to avoid artifacts in vocoding [4, 5].

This paper proposes a recurrent mixture density network that incorporates an autoregressive model. This proposed model first uses a recurrent neural network (RNN) to extract a hidden representation from the input linguistic features. Then, it transforms the output of the RNN as the model parameter of a mixture density network (MDN) that depicts the distribution of the target acoustic features [6]. This RNN-based MDN is called the recurrent mixture density network (RMDN) in this paper. Based on the RMDN, the proposed model further assumes that the mean of the target feature distribution is dependent on the observed features of previous steps, and this cross-time dependency can be modelled using an autoregressive (AR) model [7]. The entire model, including the AR model and RMDN, can be trained using the back-propagation algorithm with the maximum likelihood criterion.

By modeling the cross-time dependency using an AR model, the proposed model does not require the conventional dynamic features nor the classical speech parameter generation method [1]. Therefore, it is similar to the Autoregressive HMM for speech synthesis [8, 9]. However, experiments on the proposed model show more interesting results. Specifically, the AR model in the training stage learns to be a filter that emphasizes high frequency components of the training feature trajectories while it attenuates their low frequency components, thus, increasing the entire model’s likelihood on the training data. In the synthesis stage, the trained AR model compensates the low frequency components of the generated trajectories and increases their global variance (GV) [10]. Subjective evaluation shows that the proposed model is better than the RNN and plain RMDN when dynamic features are not used in any model.

In Section 2, we introduce the RNN and MDN. In Section 3, we present the proposed model. Then, we show the experiments in Section 4, and discuss the future work and draw the conclusion in Section 5 and Section 6, respectively.

2. NEURAL NETWORKS FOR SPEECH SYNTHESIS

2.1. Recurrent Neural Network

The basic task of a hidden layer in an RNN is to transform the input \( x_t \) and previously extracted hidden state \( h_{t-1} \) into a new vector \( h_t \):

\[
h_t = \mathcal{F}(W_x x_t + W_h h_{t-1} + b).
\]

Here, \( \mathcal{F} \) is a non-linear function; \( W_x \) is the transformation matrix and \( b \) is the bias. A vanilla RNN based on this operation is difficult to train because of the gradient vanishing and exploding problem. As a solution, the long short term memory (LSTM) unit, where trainable gates control the input, output and the state of the memory cell [11], has been proposed to replace the simple \( \mathcal{F}() \).

An RNN network with LSTM units and deep bi-directional time dependency (DBLSTM-RNN) has been reported for speech synthesis [3]. This RNN derives \( h_t \) based on \( x_t \) that encodes the textual information. Then, it transforms \( h_t \) into the acoustic feature vector \( o_t \), based on which speech can be constructed.

2.2. Mixture Density Network

Different from neural networks that only give a point estimation for the target data, an MDN predicts the value of a parameter set based on which probability density function (PDF) of the target variable can be specified [6]. An MDN may use the Gaussian mixture model (GMM) as the PDF of the acoustic feature vector \( o_t \):

\[
p(o_t; \mathcal{M}) = \sum_{m=1}^{M} \omega_m N(o_t; \mu_m, \Sigma_m).
\]
In Equation 2, $M$ is the number of mixture components and $\mathcal{M}_t = \{\omega_1^t, \ldots, \omega_M^t, \mu_1^t, \ldots, \mu_M^t, \Sigma_1^t, \ldots, \Sigma_M^t\}$ is the parameter set whose value is predicted by the neural network that takes $x_t$ as input. For simplicity, the dependency of $\mathcal{M}_t$ on $x_t$ is omitted in this paper. Also note that $\Sigma_M^t$ is usually assumed to be diagonal [6].

As a generative model, an MDN can be trained using the back-propagation algorithm under the maximum likelihood criterion. An MDN based on a feedforward neural network architecture has been proposed [12] for speech synthesis. An MDN can also be constructed based on an RNN, which results in an RMDN [13].

3. AUTOREGRESSIVE RECURRENT MIXTURE DENSITY NETWORK

3.1. Definition

Our proposed model is based on the RMDN, yet it is assumed that the observations $o_{t-K:t-1} = [o_{t-K}^t, \ldots, o_{t-1}^t]^{-1}$ in the past $K$ time steps affect the mean value of the GMM at the current time $t$. Accordingly, it defines the PDF of the target feature as

$$p(o_t|o_{t-K:t-1}; M_t) = \sum_{m=1}^{M} \omega_m^t N(o_t; \mu_m^t, \Sigma_m^t),$$

where $o_t \in \mathbb{R}^D$ is the bias and $a_k \in \mathbb{R}^D$ is a vector that scales $o_{t-k}$ by element-wise production $\odot$. Note that $o_t = 0, \forall t \in (-\infty, 0]$.

As the proposed model defines a PDF similar to that of the Autoregressive HMM [8], we refer to it as Autoregressive RMDN (AR-RMDN). An AR-RMDN with $K=2$ is plotted in Figure 1. The context-dependent $M_t$ in the AR-RMDN is predicted by the RNN that takes linguistic feature vectors as input. Although $a_k$ and $b$ can also be context-dependent, our experiments suggest that a better approach is to set $a_k$ and $b$ as context-independent (or time-invariant). In the training stage, the weights of RNN and $\{a_k, b\}$ can be trained using the back-propagation algorithm under the maximum likelihood criterion.

3.2. Interpretation

As the AR-RMDN uses the AR model to depict the cross-time dependency of the target feature, it is similar to the Autoregressive HMM [8]. Compared with the HMM-based or neural-network-based models using dynamic features or trajectory models [14, 15], the AR model assumes the distribution of the current time step is affected only by the past observations, which makes the model both efficient in computation and consistent in the statistical sense [8].

Instead of only explaining the AR-RMDN as a probabilistic model [16], we interpret it further based on the signal and filter theory. Given training data $o_{1:T} = [o_1^t, \ldots, o_T^t]^{-1}$, where $o_t \in \mathbb{R}^D, \forall t \in [1, T]$, the model’s likelihood can be calculated as

$$p(o_{1:T}; M_{1:T}) = \prod_{t=1}^{T} p(o_t|o_{t-K:t-1}; M_t) = \prod_{t=1}^{T} p(o_t; M_t),$$

where

$$p(c_t; M_t) = \sum_{m=1}^{M} \omega_m^t \prod_{d=1}^{D} \frac{1}{\sqrt{2\pi \sigma_d^m}} \exp\left(-\frac{c_t,d - \mu_m^t,d}{2\sigma_d^m}\right),$$

and

$$c_t,d = a_t,d - \sum_{k=1}^{K} a_k,d o_{t-k,d}.$$
4. EXPERIMENTS AND RESULTS

4.1. Corpus and Systems

Experiments used the Blizzard Challenge 2011 Nancy corpus that has 12072 English utterances [18]. Both the test and validation set contained 500 randomly selected utterances. Mel-generalized cepstral coefficients (MGCs) of order 60, continuous F0 trajectory, voiced/unvoiced (V/U) condition, and band aperiodicity (BAP) of order 25 were extracted for each speech frame by using the STRAIGHT vocoder [19]. The Flite toolkit [20] conducted the text-analysis for the entire corpus. The output of Flite were converted into a vector of order 382 as the input \( x_t \) to the neural network.

Experimental systems are listed in Table 1. Similar to the configuration in [3], RNN and RNN+MLPG included 2 feedforward layers with 512 nodes, 2 DBLSTM layers with 256 nodes, and a linear output layer. RMDN and AR-RMDN contained the same hidden RNN part. For RMDN and AR-RMDN, the MDN layer included a binomial distribution for the V/U condition, three GMMs for the MGC, F0, and BAP with the number of mixture components as 2, 2, 1, respectively. Using two mixture components instead of a single one for MGC and F0 makes the model less affected by the outliers. AR-RMDN set the autoregressive parameter \( K = 1 \) for RMDN and \( K = 0 \) for BAP. By then, we only implemented the model with \( K = 1 \), and found that either choice achieved a similar performance for MGC and F0. Additional test showed that it was unnecessary to use AR model for BAP.

The RNN and RNN+MLPG systems were trained first. Then, the weights of RNN, except the output layer, were used to initialize RMDN. Finally, the weights of AR-RMDN were initialized using RMDN, and \((a, b)\) was initialized as zero. In the generation stage, RNN+MLPG used the maximum likelihood parameter generation (MLPG) method [1] while RNN directly output the trajectories. RMDN and AR-RMDN used the mean of the most probable mixture component as the output of each frame.  

4.2. Analysis of Trained Model

As Figure 2 shows, the likelihood of AR-RMDN is higher than RMDN. From the perspective of model assumption, AR-RMDN is expected to be better as it takes the cross-time dependency into consideration. From the perspective of the signal and filter, AR-RMDN’s performance may be due to the filtering conducted by \( A(z) \). For the spectral part, the trajectory of the \( d\)-th order MGC, where \( d \in [1, 60] \), is processed by \( A^d(z) = 1 - a_d z^{-1} \). As Figure 3 shows, \( a_d \) in \( A^d(z) \) is not the white noise but a feature trajectory that can be generated by the neural network given input textual features. Similar results can be observed in F0 modeling.

4.3. Analysis of Generated Feature Trajectories

In the synthesis stage, \( H(z) = \frac{1}{1 - z^{-1}} \) in AR-RMDN compensates the low-frequency components of the feature trajectories generated by the RMDN part and de-emphasizes their high-frequency components. The generated MGC trajectories of one sample utterance (BC2011_nancy_APDC2-166-00) are shown in Figure 5. Interestingly, while all systems failed to generate the high frequency change in the trajectory of the 30th-order MGC, AR-RMDN generated a trajectory that had a similar dynamic range as the natural one. On the F0, AR-RMDN generated a more dynamic trajectory and a more accurate high pitch accent near the 120th frame.

For further analysis, GV is used to measure the dynamic range of generated feature trajectories. The results are shown in Figure 6. For low order MGCs, all systems generated trajectories with a similar GV to the natural data. However, for the high order MGCs, only AR-RMDN maintained the GV level of the generated trajectories. Similarly, AR-RMDN generated the F0 with larger GV than the other systems. Because the local maximum and minimum of the F0 trajectory is crucial in realization of the pitch accent [23], the over-smoothed F0 trajectory may fail to convey the pitch accent specified by the input of the neural network. The interesting point is that, instead of explicitly incorporating the GV criterion in

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1The toolkit modified based on CURRENNT [21], implementation details of AR-RMDN and speech samples can be found at http://tonywangle.github.io
the synthesis stage. AR-RMDN increased the GV of the generated trajectories using a filter \( \frac{1}{\tau_{\text{const}}} \) trained from the data.

A subjective evaluation based on MUSHRA method [24] with 10 paid native English listeners was conducted at the University of Edinburgh. The results are shown in Figure 4. Although statistically insignificant, AR-RMDN achieved a higher score than RNN+MLPG \( (p = 0.35 \text{ in t-test}) \) even though AR-RMDN didn’t use dynamic features or MLPG for trajectory generation. What’s more, while the difference between RNN+MLPG and RMDN is not significant \( (p = 0.135) \), AR-RMDN is significantly better than RMDN \( (p = 0.02) \) and RNN \( (p = 0.00) \). Although AR-RMDN alleviates the over-smoothing problem, it cannot be significantly better than RNN+MLPG because the generated feature trajectories, particularly the F0, may not be smooth enough since the AR model only models the cross-time dependency locally. The discontinuity of the generated F0 by AR-RMDN can be observed near the 80th frame in Figure 5. At last, RMDN’s better performance than RNN is related to the use of two mixture components for MGC and F0 since two mixture components may be robust to the outliers in the data [25, 26].

5. DISCUSSION

As the proposed model increased the GV of the generated feature trajectories, we also compared it with another RMDN system with a postfilter on the modulation spectrum (MS) [27]. The results showed that both methods increased the GV and generated synthetic speech better than the plain RMDN. The difference is that the MS postfilter manipulates the feature trajectory in the modulation spectrum domain while the proposed model works in ‘time’ domain.

Although the AR-RMDN achieved high likelihood, random samples from the AR-RMDN were less natural than generating the mean trajectory. One reason may be that the AR model is still weak in modeling the time dependency of the feature trajectory.

6. CONCLUSION

We introduced the autoregressive model into the recurrent mixture density network for speech synthesis. Experimental results showed that the trainable autoregressive model amplifies the high-frequency components and attenuates the low-frequency part of the target acoustic feature trajectories in the training stage. In the synthesis stage, it compensates the low-frequency components and de-emphasizes the high-frequency components of raw trajectories generated by the neural network. Further analysis has shown that, even through the explicit global variance criterion is not used, the proposed model increases the level of the global variance of the generated feature trajectories because of the AR model in the synthesis stage. Our proposed model has achieved higher likelihood on the training and validation data, and better quality of synthetic speech.

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8. REFERENCES


