Formant Tracking Using Dilated Convolutional Networks Through Dense Connection with Gating Mechanism

Wang Dai¹, Jinsong Zhang¹, Yingming Gao², Wei Wei¹, Dengfeng Ke³, Binghuai Lin⁴, Yanlu Xie¹

¹School of Information Science, Beijing Language and Culture University, China
²Institute of Acoustics and Speech Communication, Technische Universität Dresden, Germany
³National Laboratory of Pattern Recognition, Institute of Automation, Chinese Academy of Sciences, China
⁴MIG, Tencent Science and Technology Ltd., Beijing, China
daiwang.ai@163.com, {jinsong.zhang, xieyanlu}@blcu.edu.cn, yingming.gao@mailbox.tu-dresden.de, wwei906@163.com, dengfeng.ke@nlpr.ia.ac.cn, binghuailin@tencent.com

Abstract

Formant tracking is one of the most fundamental problems in speech processing. Traditionally, formants are estimated using signal processing methods. Recent studies showed that generic convolutional architectures can outperform recurrent networks on temporal tasks such as speech synthesis and machine translation. In this paper, we explored the use of Temporal Convolutional Network (TCN) for formant tracking. In addition to the conventional implementation, we modified the architecture from three aspects. First, we turned off the "causal" mode of dilated convolution, making the dilated convolution see the future speech frames. Second, each hidden layer reused the output information from all the previous layers through dense connection. Third, we also adopted a gating mechanism to alleviate the problem of gradient disappearance by selectively forgetting unimportant information. The model was validated on the open access formant database VTR. The experiment showed that our proposed model was easy to converge and achieved an overall mean absolute percent error (MAPE) of 8.2% on speech-labeled frames, compared to three competitive baselines of 9.4% (LSTM), 9.1% (Bi-LSTM) and 8.9% (TCN).

Index Terms: formant tracking, convolutional architecture

1. Introduction

Formants are considered to be resonances of the vocal tract during speech production. An accurate estimation of formant frequencies in spontaneous speech is often desired in many phonological experiments of laboratory phonology, sociolinguistics, and bilingualism [1][2]. They also play a key role in the perception of speech and are useful in the coding, synthesis and enhancement of speech, and are useful in the coding, synthesis and enhancement of speech and are useful in the coding, synthesis and enhancement of speech and are useful in the coding, synthesis and enhancement of speech. Motivated by this idea, Deng et al. released a handpicked VTR/Formants corpus in 2006 [3]. It was subsequently adopted by some researchers as benchmark dataset to develop and evaluate new algorithms for formant tracking. For example, Mehta et al. evaluated their proposed Kalman-based autoregressive moving average modeling methods on this database [4]. Inspired by the great success of deep learning in many application areas, Dissen et al. employed Long Short-Term Memory (LSTM) networks to train a supervised regression model between LPC coefficients plus Pitch-Synchronous Cepstrum Coefficients (named PSCCs) and hand-corrected formant frequencies for every speech frame [5]. Later, Dissen et al. [6] explored the potential of using sparse programs (55 × 50 PSCCs) for formant tracking with Convolutions LSTM networks [7] and found that incorporating the PSCCs and LPCs achieved the better general performance than using them separately.

Recent studies showed that generic convolutional architectures can outperform recurrent networks on tasks such as speech synthesis and machine translation [21][22]. In particular, the Temporal Convolutional Network (TCN) for sequence modeling was proposed [23], which was composed of dilated causal convolutional networks with residual connection. Stacking convolutional layers with different dilation factors can capture the long-range dependence of the sequence. Integrating different hidden features through residual connection makes model more robust. In this work, therefore, we explored whether such advantages of TCN are beneficial for formant tracking. In addition to the application of the conventional TCN model, we modified its architecture from three aspects: 1) we turned off the "causal" mode of dilated convolution, making sure the dilated convolution see the future speech frames; 2) all the dilated convolutions are closely connected, thus effectively reusing the shallow features; 3) we adopted a gating mechanism to automatically select forgetting unimportant information during training. In terms of quantitative error analysis, we compared our proposed approach with other five methods for formant tracking on the VTR test set, including WaveSurfer [7], Praat [8], LSTM model, Bi-LSTM model and TCN based model.
2. Model Description

The architecture of proposed model for formant tracking is shown in Figure 1, our framework mainly consists of three components: (1) dilated convolutions, (2) dense connections and (3) gated linear units, all of which are described in subsequent sections.

2.1. Dilated convolutions

The generic TCN architecture uses dilated 1D causal convolution where the convolution filter is applied over an area larger than its length by skipping certain input values \([d=1, 2, 4] \). Compared with LSTM, the dilated causal convolution needs less nonlinear operations, making the model converge easier. The receptive field can be set to an arbitrary large size by increasing dilation factor. A major disadvantage of dilated causal convolution is the “causal” mode when handling the context-dependent sequence tasks. It can only look back at history information because the output at time \( T \) is convolved only with elements from earlier to current time step. In speech formant tracking, formants of each frame will be affected by future frames, so we turned off the “causal” mode of dilated convolution, making the dilated convolution see the future information. A general practice is to use a dilation factor sequence of form \( \{1, 2, 4, 8, \ldots \} \). When \( d = 1 \), a dilated convolution reduces to a regular convolution. Using larger dilation factor yields an top level output which can capture a wider range of inputs. We provide an illustration in Figure 2(b). In this work, there are 9 1D convolutions stacked with the dilation factors \( \{1, 2, 4, 1, 2, 4, 1, 2, 4\} \) to obtain long context dependence, as shown in Figure 1. Every dilated convolution layer has 64 filters with a size of 3.

2.2. Dense connections

The depth of the neural network model is important for learning advanced representations, but it is also accompanied with the challenge of gradient disappearance. Residual training [24] is considered to be an effective way to address this problem. Using this connection mode, TCN can build a very deep network. Densely connected networks were recently proposed in [23]. They can be regarded as a natural evolution version of [24] where the inputs to a given layer in the network are a concatenation of the outputs from all the previous layers. This way avoids the vanishing gradient problem in depth model. Another advantage is that each layer reused output from all previous layers, such that different level features are fused to improve the robustness of the model. Inspired by the effectiveness of dense connection, we adopted it in our model. A slight difference from [24] is that all the dilated convolutions are closely connected to capture more fine-grained features as shown in the densely connected arcs of Figure 1.

2.3. Gated linear units

There are several Gating mechanisms that had been explored in modern convolutional architectures for sequential modeling [26, 27, 28]. Parallel to our work, [27] has shown the form of \((X \times W + b) \otimes \sigma(X \times V + c)\) is more effective than others for language modeling. Coupling linear units to the gates, referred to as gated linear units, reduce the vanishing gradient problem. This retains the non-linear capabilities of the layer while allowing the gradient to propagate through the linear unit without scaling. Similarly, in this work, after applying the linearity to the Batch Normalization output of every dilated 1D convolution, we attenuated it with a sigmoid gate (shown in Figure 2(a)). Moreover, we used SpatialDropout1D [29] at the back of each gated linear unit to sparse the output dimensions (channels) information, thus improving the robustness of the model.

3. Experiment

3.1. Dataset

VTR corpus [19] was used in this work to evaluate our model and baselines. It contains 538 SX or SI utterances, selected as a representative subset of TIMIT corpus. Here, SX de-
notes phonetically compact utterances and SI denotes phonetically diverse utterances. The training set consists of 346, out of which 324 utterances have handpicked VTR. These 346 utterances cover 173 speakers with one SX and one SI utterance from each speaker. The test set consists of 192 utterances covering 24 speakers, and each speaker has 5 SX utterances and 3 SI utterances. Both training and test sets were first annotated by an automatic formant tracking algorithm [11], and subsequently hand-corrected for every 10 ms frame by a group of phonologists based on visual inspection of the first three formants in the spectrogram. We further set aside 24 utterances from 12 speakers (fecd0, mgrl0, falk0, mjrh1, fpaf0, mtrt0, fcdr1, mwsh0, fbcz0, msjk0, fjrp1, mdlc1) from the training set as the validation set.

3.2. Data preprocessing
Following the study [19], we used the same acoustic features (LPCCs + PSCCs). A new frame of 30 ms consisted of three order 30-dim LPCCs (total 300-dim). We first removed the DC component and applied a pre-emphasis filter \((H(z) = 1 - 0.97z^{-1})\) to the input speech signal. Then the input signal was divided into frames, and the acoustic features were extracted from each frame. The frame shift was 10 ms, and frames were overlapping with Hamming windows of 30 ms. The 50-dim Pitch-Synchronous Cepstrum Coefficients was directly extracted from Dissen’s open source code [19].

3.3. Loss function
Dissen et al. [19] used a fully connected layer with 3 neurons as the output layer to predict F1, F2 and F3 of each speech frame. The high level features, i.e., the output of the last hidden layer, were shared by each formant but not specific. In fact, there is an inner relationship between formants, each of which has a specific frequency band. Inspired by the success of multitask learning models including the baselines. The deep learning tool used in this work is Keras. The loss function to minimize was mean absolute error, and we used Adam [31] as the optimizer. The initial learning rate of optimizer was set to 0.001 and decreased by 0.0005 after training 50 epochs. All configurations were trained for maximum 100 epochs with a batch size of 4 spoken utterances. The model which had the smallest loss on validation set was selected. Silent segments at both end of utterances were not trained and evaluated. We fixed a maximum length of 710 frames on VTR dataset. Short utterances were padded zero if they were shorter than the fixed maximal length.

During training and testing, we used the Masking layer of Keras to locate the zero time step to be skipped.

3.5. Baselines
The LSTM tracking model was trained using the same model configuration from [19] except for the previously mentioned optimizer and loss function. On this basis, we trained the Bi-LSTM tracking model by replacing the LSTM layers with Bi-directional LSTM layers. We also trained the TCN based tracking model using the same model parameter settings for our proposed model. In addition to the three neural network formant tracking models, we also extracted formants using WaveSurfer and Praat. The two widely used speech analysis tools are set to the same data preprocessing configuration.

3.6. Metrics
Two quality measures were calculated to quantify the distance of formant tracker output to the annotation reference:

- **MAE**: mean absolute error between reference and formant tracker output calculated over speech frames.
- **MAPE**: mean absolute percent error between reference and formant tracker output calculated over speech frames.

The smaller the value is, the more the formant tracker output matches the reference.

4. Results and Discussion
Figure 3 shows the training (dashed lines) and validation (solid lines) loss for different neural network models. Although they follow the same trend in the beginning stage, the LSTM based models (curves with obvious fluctuations as shown in Figure 3) appear to be more difficult to converge than other models after the first 20 epochs, even over-fitting happened to the Bi-LSTM model. With a faster convergence speed, Our model achieved even better performance than the “TCN” model.

![Figure 3: Training and validation loss for different neural network models.](image-url)
Table 1: MAE(\text{Hz}) and MAPE(\%) on whole VTR test utterances.

| Speech & Model | MAE (Hz) | MAPE (%) | LSTM | Bi-LSTM | TCN | Our |
|---------------|----------|----------|------|---------|-----|-----|
| F1            | 111.3    | 20.4     | 232.2 | 55.0    | 89.4 | 16.9 | 86.1 | 16.6 | 82.7 | 15.2 | 75.1 |
| F2            | 160.3    | 11.1     | 301.2 | 21.6    | 94.6 | 6.6  | 89.1 | 6.1  | 88.5 | 5.7  | 80.5 |
| F3            | 255.4    | 10.6     | 368.5 | 15.6    | 119.4 | 4.8  | 115.5 | 4.6  | 111.4 | 4.2  | 98.0 |
| Overall       | 176.4    | 16.1     | 300.2 | 30.7    | 101.2 | 9.4  | 97.0 | 9.1  | 94.0 | 8.9  | 84.0 |

Table 2: MAE(\text{Hz}) on broad phone classes.

| Speech & Model | MAE (Hz) | MAPE (%) | LSTM | Bi-LSTM | TCN | Our |
|---------------|----------|----------|------|---------|-----|-----|
| F1            | 52.4     | 135.6    | 101.2 | 158.2   | 219.0 | 61.6 | 65.9 | 95.5 | 60.6 | 68.9 | 92.6 | 52.5 | 58.8 | 86.0 |
| F2            | 67.4     | 119.2    | 120.5 | 243.5   | 309.7 | 76.3 | 86.4 | 134.2 | 74.1 | 80.4 | 128.8 | 69.1 | 86.3 | 125.8 | 60.2 | 72.0 | 108.4 |
| F3            | 102.5    | 324.8    | 191.4 | 406.4   | 366.3 | 71.1 | 153.2 | 142.2 | 69.2 | 139.2 | 136.2 | 67.2 | 152.2 | 126.2 | 60.5 | 133.2 | 108.2 |
| Overall       | 287.6    | 330.7    | 779.5 | 551.6   | 607.2 | 180.1 | 159.2 | 178.2 | 169.2 | 135.2 | 174.2 | 168.2 | 140.2 | 174.2 | 161.2 | 143.2 |

Table 3: MAPE(\%) on broad phone classes.

| Speech & Model | MAE (Hz) | MAPE (%) | LSTM | Bi-LSTM | TCN | Our |
|---------------|----------|----------|------|---------|-----|-----|
| F1            | 10.2     | 62.6     | 22.3 | 11.0     | 9.5 | 11.3 | 4.4 | 3.8 | 11.1 | 4.5 | 3.9 | 9.8 | 3.9 | 3.6 | 8.9 | 3.7 | 3.2 |
| F2            | 14.9     | 9.7     | 27.5 | 23.1     | 14.4 | 14.8 | 7.7 | 5.7 | 14.5 | 6.7 | 5.3 | 13.7 | 7.8 | 5.4 | 12.4 | 6.4 | 4.6 |
| F3            | 24.4     | 11.5     | 48.3 | 30.9     | 15.2 | 15.5 | 11.2 | 5.6 | 15.1 | 9.8 | 5.4 | 15.0 | 11.3 | 5.0 | 13.8 | 9.7 | 4.3 |
| Overall       | 65.5     | 19.7     | 138.2 | 42.6     | 29.7 | 27.9 | 9.0 | 5.7 | 27.5 | 7.6 | 5.1 | 27.4 | 8.5 | 5.6 | 26.7 | 7.2 | 4.8 |
| F1            | 75.0     | 14.4     | 190.4 | 30.9     | 23.9 | 32.8 | 8.5 | 6.6 | 31.8 | 7.3 | 6.5 | 31.3 | 7.6 | 6.6 | 32.6 | 7.7 | 6.1 |
| F2            | 56.0     | 11.2     | 65.1 | 20.8     | 17.1 | 24.3 | 7.9 | 5.8 | 23.6 | 6.8 | 5.3 | 23.6 | 7.5 | 6.1 | 22.7 | 6.7 | 5.1 |

Table 4: MAE(\text{Hz}) on CV transitions and VC transitions.

| Speech & Model | MAE (Hz) | LSTM | Bi-LSTM | TCN | Our |
|---------------|----------|------|---------|-----|-----|
| CV transitions | 253.1    | 316.4 | 538.6 | 562.7 | 731.0 | 113.2 | 151.6 | 157.4 | 110.2 | 139.2 | 147.4 | 112.4 | 153.3 | 162.4 | 101.4 | 133.4 | 140.4 |
| VC transitions | 245.2    | 291.4 | 523.5 | 526.7 | 703.1 | 110.2 | 145.1 | 152.4 | 108.2 | 134.2 | 143.4 | 110.2 | 146.1 | 157.4 | 99.2 | 127.3 | 135.3 |

5. Conclusions

In this paper, we proposed a novel temporal convolutional network unit upon the conventional TCN model for formant tracking. The “causal” mode of dilated convolution was turned off to capture the impact of speech context. Each layer reused the output from all previous layers through the dense connection. With the gating mechanism, the model selectively forgets unimportant information. The approach was validated on an open access dataset. The experiment showed that our model achieved the best performance on almost all broad phone classes and transitions, compared to LSTM based models and TCN model.

6. References

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