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Investigating Very Deep Highway Networks for Parametric Speech Synthesis

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Abstract

The depth of the neural network is a vital factor that affects its performance. Recently a new architecture called highway network was proposed. This network facilitates the training process of a very deep neural network by using gate units to control a information highway over the conventional hidden layer. For the speech synthesis task, we investigate the performance of highway networks with up to 40 hidden layers. The results suggest that a highway network with 14 non-linear transformation layers is the best choice on our speech corpus and this highway network achieves better performance than a feed-forward network with 14 hidden layers. On the basis of these results, we further investigate a multi-stream highway network where separate highway networks are used to predict different kinds of acoustic features such as the spectral and F0 features. Results of the experiments suggest that the multi-stream highway network can achieve better objective results than the single network that predicts all the acoustic features. Analysis on the output of highway gate units also supports the assumption for the multi-stream network that different hidden representation may be necessary to predict spectral and F0 features.

Index Terms: speech synthesis, deep neural network

1. Introduction

Parametric speech synthesis aims at predicting speech acoustic features such as spectral and F0 features based on the input linguistic specification of text (in the case of Text-to-Speech) or conceptual representation of a potential sentence (in the case of Concept-to-Speech) [1]. This parametric method has achieved great performance by leveraging statistical models such as the hidden Markov model (HMM) [2].

Recently, this HMM-based framework was complemented or replaced by various methods using the neural network [3][4]. The claimed advantage of a neural network is its ability to extract structural features from the input data when the network is deep enough [5]. However, for speech synthesis, the comparison between HMM and deep feed-forward neural networks (DNN) with up to 5 hidden layers showed that increasing the depth of the network did not promise better performance for all kinds of acoustic features, especially, for the F0 features [3]. These results may be due to the difficulty in training the deep network since the authors showed later that a DNN with 7 hidden layers achieved consistently better performance than previous systems when the rectifier linear activation function (ReLU) [6] was utilized to facilitate the training process [7].

Thus, we can infer that, if the difficulty of training DNN can be further alleviated, deeper neural network may be more efficient than 'shallow' models. Although recent research showed that a DNN with 5 hidden layers could extract phonemic information from the input spectral features for speech recognition [8], whether a similar network is sufficient to extract linguistic features from the text for speech synthesis is unknown. Additionally, the neural network for speech synthesis computes a single hidden representation and then transforms it into spectral and F0 features at the output layer. Considering the differences between spectral and F0 features, we wonder whether sharing the same hidden representation is the best strategy.

In this paper, we investigate the above questions using a neural network called *highway network* [9]. The highway network utilizes trainable gate units to merge the output of a conventional non-linear transformation layer with its input. It allows the input information to flow directly to the output without non-linear transformation. Similarly, gradients can also be propagated backwards through the highway without attenuation, which eases the gradient vanishing problem. For image classification, a very deep highway network with more than 100 hidden layers has achieved excellent performance [10]. Another reason to leverage the highway network is that the gate units can be used to inspect the usefulness of the hidden layers. Typically, the gate units will favor the information on highway if the hidden layer is 'useless'.

On the depth of the neural network, our experiments show that a highway network deep enough (with 14 non-linear transformation layers) but not deeper could improve the accuracy of predicted acoustic features than the relatively shallow networks. On the basis of the result, we present a *multi-stream highway network*, where multiple highway networks sharing a common input hidden vector are used to predict spectral and F0 features separately. The analysis on the output of the highway gate units suggests that the spectral and F0 features may not necessarily share the same hidden representation in the neural network. Experimental results also show that the multi-stream highway network performs better than the single-stream highway network and DNN that predict all the acoustic features.

Section 2 of this paper discusses the highway network and Section 3 presents the multi-stream highway network. Section 4 show the experiments, including the influence of the depth on the performance of the highway network, analysis on the gate unit and the performance of the multi-stream highway network.

2. Highway Network

A neural network with a single hidden layer can be easily trained by the random initialization and back-propagation algorithm. However, the same strategy does not guarantee a well-trained network when the number of hidden layer increases. This difficulty can be alleviated by several approaches, including pre-training with generative models [5][11].

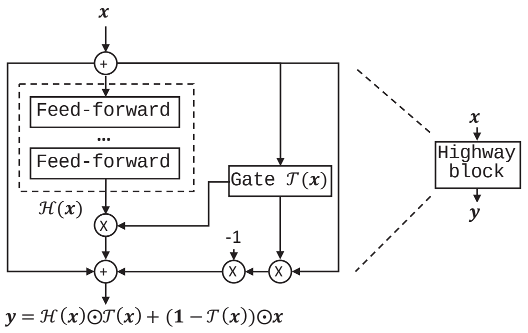


Figure 1: Computation flow in one highway block

Recently, researchers have proposed a new neural network architecture called *highway network* [9]. This new type of network is based on the classical feed-forward neural network. Similarly, each hidden layer in the highway network will transform the input vector $\boldsymbol{x}$ as

$$\mathcal{H}(\boldsymbol{x}) = f(\boldsymbol{W}_H\boldsymbol{x} + \boldsymbol{b}_H), \tag{1}$$

where $f(.)$ is the non-linear activation function, $\boldsymbol{W}_H$ is the transformation matrix and $\boldsymbol{b}_H$ is the bias vector. However, the highway network incorporates a new type of nodes called gate unit to compute a control vector

$$\mathcal{T}(\boldsymbol{x}) = \sigma(\boldsymbol{W}_T\boldsymbol{x} + \boldsymbol{b}_T). \tag{2}$$

The activation function here is the sigmoid function $\sigma(x) = \frac{1}{1+e^{(-x)}}$. Then, the gate merges the output of the hidden layer $\mathcal{H}(\boldsymbol{x})$ with the input $\boldsymbol{x}$ as

$$\boldsymbol{y} = \mathcal{H}(\boldsymbol{x}) \odot \mathcal{T}(\boldsymbol{x}) + (\boldsymbol{1} - \mathcal{T}(\boldsymbol{x})) \odot \boldsymbol{x}. \tag{3}$$

Here, the $\odot$ denotes the element-wise multiplication. This transformation from $\boldsymbol{x}$ into $\boldsymbol{y}$ is conducted in a single highway block, as Figure 1 shows.

The parameters in the gate are trainable. When the output of the gate approaches zero, $\boldsymbol{x}$ can be directly propagated forwards ($\boldsymbol{y} \approx \boldsymbol{x}$). In this case, the gradient can also be propagated backwards without attenuation introduced by the hidden layer. Thus, very deep network can be trained without special training strategy. The highway block can be more complex by introducing another gate $\mathcal{C}(\boldsymbol{x})$ to replace $(\boldsymbol{1} - \mathcal{T}(\boldsymbol{x}))$ in Equation 3. It can also be simplified by eliminating all the gates and directly computing the output as $\boldsymbol{y} = \mathcal{H}(\boldsymbol{x}) + \boldsymbol{x}$. This simplified residual network have been used in an image classification task [10].

Note that, $\mathcal{H}(\boldsymbol{x})$ can be the non-linear transformation conducted by multiple hidden layers. Besides, the dimension of $\mathcal{H}(\boldsymbol{x})$ should be identical to $\mathcal{T}(\boldsymbol{x})$ and $\boldsymbol{x}$. If the dimension doesn't match, additional transformation can be incorporated to change the dimension of $\boldsymbol{x}$.

3. Multi-stream Highway Network for the Speech Synthesis Task

3.1. Motivation

Similar to the application in image classification, a highway network can be directly utilized for the speech synthesis task. This network will transform the input linguistic specification by highway blocks and then map the transformed hidden representation into spectral and F0 features as Figure 2 shows. Because all the acoustic features are predicted by a single network, we call it a *single-stream* network.

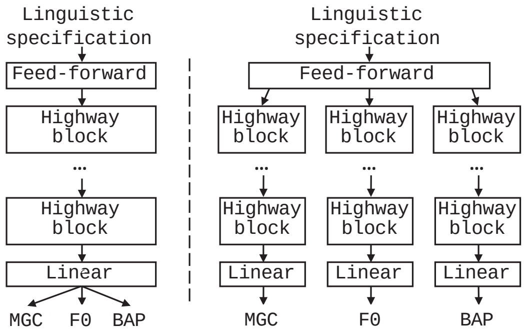


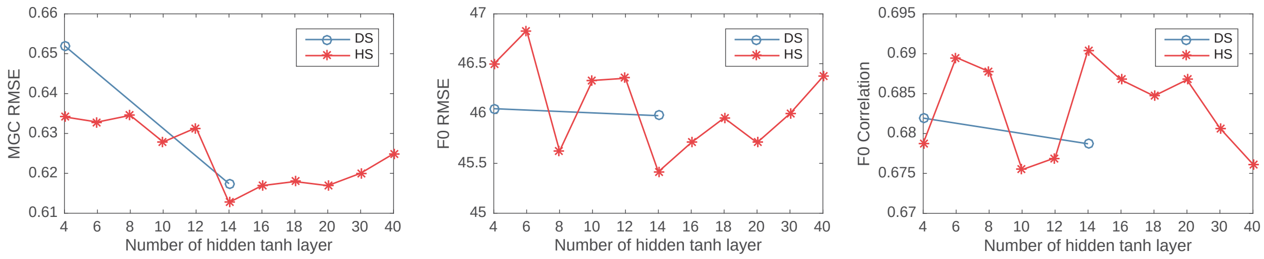
Figure 2: The single-stream (left) and multi-stream (right) highway network for speech synthesis. MGC and BAP denote mel-generalized cepstral coefficients and band aperodicity, respectively.

A drawback of the single-stream structure is the unbalanced dimension of spectral and F0 features [12]. Another drawback is that the same hidden representation is utilized to predict the spectral and F0 features. Training this single-stream network with spectral and F0 features as targets is a Multitask Learning (MTL) task [13]. Although the theory of MTL argues that shared representation can improve the generalization ability of the model for every task involved, a prerequisite for this advantage is that those tasks should be related with each other. For example, MTL is beneficial when the system predicts perception-based spectral features and normal spectral features simultaneously [14]. For Text-to-Speech (TTS), the spectral features are highly correlated with the identity of segmental units in the input text. However, the F0 features are not only influenced by the segmental units (e.g. lexical stress) but also by supra-segmental aspect such as the syntactic structure and discourse context of the text [15]. While the identity of segmental units can be easily retrieved from the input linguistic specification, linguistic information related to F0 prediction is not directly accessible. Thus, complex computation may be required to extract the useful information from the text. Besides, TTS systems usually provide the speech synthesizer with so-called prosodic features. These automatically inferred noisy features may also require additional transformation. Thus, different hidden representations may be necessary to predict F0 and spectral features.

3.2. The structure of a multi-stream network

To examine the above argument, we present a multi-stream highway network shown in Figure 2. Near the input end, a linear projection layer transforms the input vector into another vector of a certain dimension. Then, multiple highway networks predict spectral and F0 features separately.

By separating the highway network for each data stream, the influence of the unbalanced dimension can be alleviated. Besides, the multi-stream structure disentangles the non-linear transformation for spectral and F0 streams. Because the gate units are trainable, the number of non-linear transformation layers for each feature stream can be dynamically adjusted in a data-driven approach. Thus, it's more flexible than the single-stream structure. Because the activation of the hidden layer is controlled by the gate units, analysis on the output of these gate units can tell whether F0 and spectral features must share similar hidden representation.



(a) (b) (c)

Figure 3: Results of the preliminary test on single-stream feed-forward network (*DS*) and highway network (*HS*) on the test set. Each highway block in *HS* contains two hidden transformation layers with $tanh$ activation function.

4. Experiments

4.1. Corpus preparation and system notation

The speech database for experiments contains 12072 English utterances (16 hours) recorded by a female speaker in a neutral news reading style. Both the test and validation set contained 500 randomly selected utterances. Mel-generalized cepstral coefficients (MGC) of order 60, a one-dimensional continuous F0 trajectory, the voiced/unvoiced (V/U) condition, and band aperiodicity of order 25 were extracted for each speech frame by the STRAIGHT vocoder [16]. The delta and delta-delta components of the acoustic features except the voiced/unvoiced condition were also extracted. The Flite toolkit [17] was used for all the systems to conduct the grapheme-to-phoneme conversion and prosodic prediction for both the training and test sets. These phonemic, syntactic and prosodic feature were encoded into a vector of 382 dimension as the input to the neural network.

Three kinds of systems listed in Table 1 were involved in experiments. The toolkit for training the neural network was modified on the basis of the CURRENNT library [18]. Pretraining was not used in experiments.

4.2. Preliminary test on the depth of the highway network

This experiment tested *HS* systems with 2 to 20 highway blocks. Every block had 2 hidden transformation layers with $tanh$ activation function. Thus, the deepest *HS* included 40 transformation layers in total. Layer size of the transformation and gate layers was set to 382 in order to avoid the transformation on the dimension of the input data. Bias of the gate was initialised as -1.5 while other parameters were randomly initialized.

Objective results on the test set are shown in Figure 3. The comparison among *HS* groups shows that the RMSE on the MGC generally decreased with the increasing number of highway blocks. However, the RMSE gradually increased after the number of highway blocks was larger than 14. This result suggests that, although deeper network is helpful in spectral acoustic features modelling, the depth can not be increased infinitely without over-fitting to the data.

As reference systems, *DS* systems with 4 and 14 hidden layers were trained. The layer size of the shallow *DS* was set to 512 following our previous experiments while that of the deep *DS* was set to 382. The results demonstrates that *DS* with 14 hidden layers achieved similar performance as the best *HS*. Note that *DS* with 14 hidden layers was trained based on the initialization strategy in [19]. Thus, it can be inferred that either a better initialization strategy or a carefully designed network such as the highway network can help the training process of deep networks, at least for the spectral modelling of the speech synthesis task.

Table 1: Experimental systems involved in experiments.

Notation	Definition
HS	Single-stream highway network
HM	Multi-stream highway network
DS	Single-stream deep feed-forward network

On F0 prediction, *HS* with 14 transformation layers performed better than other networks. But generally the improvement was not consistent with the depth of the network. Particularly, highway networks with 14 to 20 non-linear transformation layers can be worse than the *DS* system with only 4 hidden layers. This gap is quite different from that in the MGC prediction.

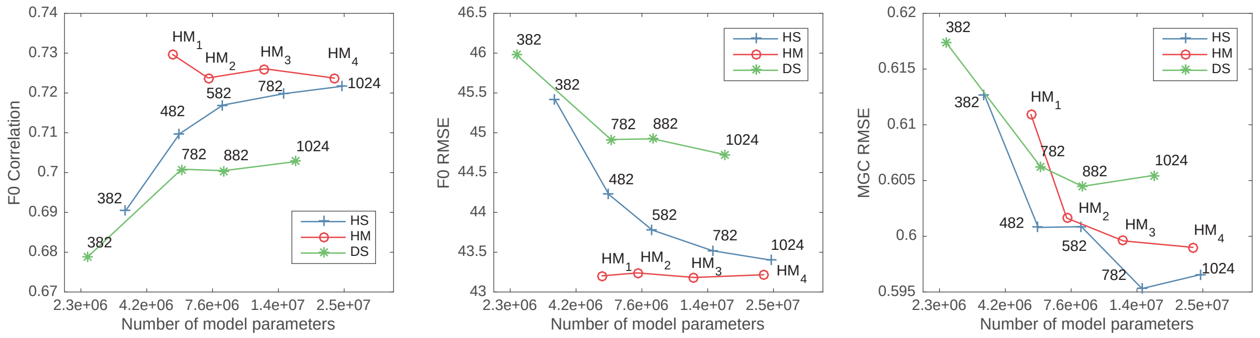
4.3. Experiments on multi-stream highway networks

Based on the results of the preliminary experiment, we tested the performance the multi-stream structure *HM* against *HS* and *DS* when the number of hidden transformation layer for all systems was fixed as 14. Following the argument in Section 3, *HM* adopted three highway networks for MGC, F0 and BAP features. To compare the performance, experimental systems with different sizes of the hidden (and gate) layer were trained. Because *HM* adopted multiple sub-networks, the layer size of each sub-network can be adjusted more flexibly. Thus, as shown in Table 2, *HM* systems with different configurations of layer size were trained .

The results are shown in in Figure 4. The comparison between *DS* and *HS* indicates that the highway network can perform better than the traditional feed-forward network when the number of model parameters is comparable. Interestingly, the RMSE on MGC increased when the layer size of *DS* and *HS* was increased to 1024. But the performance on F0 prediction did not degrade.

Compared with *HS*, *HM* achieved better performance on F0. This result can partially supports that F0 prediction in the single-stream structure may be affected by the unbalanced dimension of spectral and F0 features. However, *HM*'s performance on MGC stream can not surpass *HS* when the total number of parameters is comparable. One possible reason is that the size of the network for MGC stream in *HM* is always smaller than the size of *HS*. If *HS* devotes most of the model capacity to model MGC features, its performance on MGC prediction is expected to be better than *HM*. Note that, a fair comparison on MGC prediction is impossible because the exact number of hidden units devoted by *HS* for MGC modelling is unknown.

However, the performance of *HM* on MGC prediction can be improved by increasing the layer size of the MGC subnetwork, which is shown by comparison between HM_1 and HM_2. Increasing the layer size from HM_2 to HM_3 resulted in



(a) (b) (c)

Figure 4: Performance of the multi-stream highway network (*HM*) against the single-stream highway (*HS*) and feed-forward network (*DS*) on the test set. All systems contained 14 hidden transformations layers. The number associated with every *HS* and *DS* system is the layer size of the network. Definition of HM_1 to HM_4 is listed in Table 1. For reference, the number of parameter of the *DS* with 4 hidden layers and 512 units per layer is 1.1e+06.

Table 2: The network structure of *HM* systems in Figure 4.

	Layer size of the sub-network		
Notation	MGC stream	F0 stream	BAP stream
HM_1	256	256	256
HM_2	382	256	256
HM_3	512	382	256
HM_4	768	512	256

in further improvement. However, when the layer size of F0 sub-network was increased to 512, HM_4's performance on the F0 prediction degraded, which may suggest the layer size below 512 is sufficient for F0 modelling on the utilized corpus. In general, the network structure of *HM* can be adjusted in a flexible way. If the layer size is carefully chosen, *HM* can achieve better overall performance than *HS*. Subjective evaluation on the experimental systems can not be conducted on time. However, synthetic samples can be accessed online [1].

4.4. Interpreting the results using the highway networks

To interpret the performance of the *HM* systems, we plotted and analyzed the output of the gate units in HM_1 for the test set. Figure 5 shows the results for all the data frames corresponding to phoneme /a/. Figure 5(a)-(b) shows the output of the gate units in the sub-network for MGC. Because the bias of the gates was set to -1.5 and model parameters were randomly initialized, the output of the gate units were around 0.2 ($\approx \frac{1}{1+exp(1.5)}$) before the training process began. After the 1st training epoch, as Figure 5(a) shows, the output of the gate was still about 0.2. Note that the variance of the gate output in block 1 was large because the input to that block was not bound by the shared linear projection layer. After the last training epoch, the gate output in the block 1 approximated a binomial distribution, which indicates that the first highway block may derive sparse representation for the MGC stream.

This binomial distribution can observed in the second highway block. In the following blocks, the gate output approximated the distribution of a bell shape. This trend indicates that the highway blocks near the output of the network conduct a complex transformation based on the weighted sum of the input and output of the non-linear transformation layers. Note that, the gross histograms for different phonemes are similar. But the distribution in each dimension of the gate output was different.

The distribution of gates' output in the F0 sub-network, as Figure 5(c)-(d) shows, was different from that in the MGC sub-network. In block 1, only a few dimensions of the gates' output approached 1.0. In the following highway blocks, the gate output was dominated by the mode near 0.2, and the bias of those highway blocks after model training was still similar to the initial value. These results indicated that the highway blocks were only slightly tuned. But this 'lazy' network seemed to be more effective for F0 modelling than the single-stream highway and normal feed-forward network. Thus, these results suggest that the different hidden representations may be beneficial to model these different kinds of acoustic features.

An inspection on the gate output of *HS* is shown in Figure 6. Although we can not differentiate the hidden representation for spectral and F0 streams, the distribution of gate output resembled that of the spectral stream in Figure 5(b). Because the dimension of the spectral features, including MGC and BAP, was much larger than that of the F0 features, this observation may support the assumption that the hidden representation for the spectral features dominate the single-stream structure.

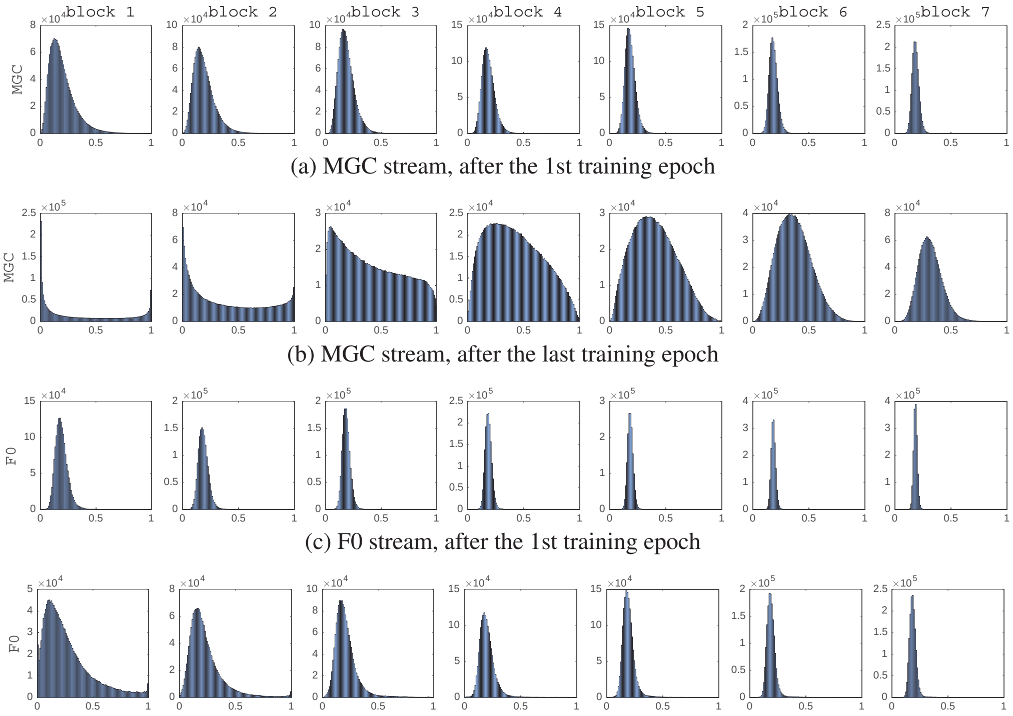
5. Conclusion

By leveraging gate units that control information flow over the conventional hidden transformation layer, the highway network provides a good way for training a deep neural network. In this paper, we investigated the use of the highway network for the speech synthesis task. Experimental results show that a highway network with 14 non-linear transformation layers can achieve better performance than a feed-forward network with 4 to 5 hidden layers.

The highway network can also be utilized to analysis the performance of the neural network. Typically, the distribution of the gate output in the highway network indicates that different non-linear transformations may be preferred to derive hidden representation for spectral and F0 prediction. Accordingly, a multi-stream highway network, in which separate highway networks are utilized for predicting spectral and F0 features, can achieve better performance for F0 modelling while yield similar performance on the spectral part.

It is not surprising that different representations are required to predict spectral and F0 features. For the future work, the

[1] Synthetic samples, scripts and CURRENNT for highway network training can be found on http://tonywangx.github.io/.



(a) MGC stream, after the 1st training epoch

(b) MGC stream, after the last training epoch

(c) F0 stream, after the 1st training epoch

(d) F0 stream, after the last training epoch

Figure 5: Histogram of the output of gates units in highway blocks of the multi-stream highway network HM_1 (7 highway blocks). (a)-(b) show the gates in the sub-network for MGC; (c)-(d) for F0. block 1 is near the input layer while block 7 is linked to the output. The data were generated given all the input data of phoneme /a/ in the test set.

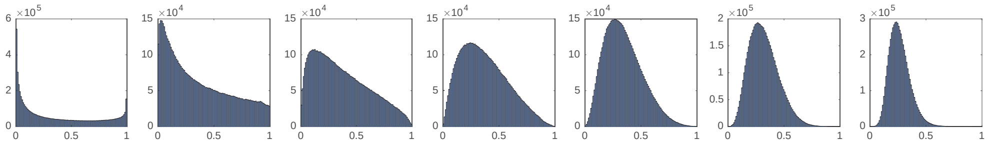


Figure 6: Histogram of the gates output $\mathcal{T}(\boldsymbol{x})$ of network *HS* with 14 hidden layers and 1024 layer size after the last training epoch. The data were generated for all the frames of phoneme /a/ in the test set .

sensitivity measure defined in [20] may tell what kind of information contributes to spectral and F0 modelling. Fine analysis on the contribution of different input information to spectral and F0 modelling is also interesting [8]. Besides the normal feed-forward network, it is also possible to combine highway pass with recurrent neural network as what Zhang et al. did for speech recognition task [21].

6. Acknowledgements

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7. References

[1] P. Taylor, *Text-to-Speech Synthesis*. Cambridge University Press, 2009.

[2] K. Tokuda, Y. Nankaku, T. Toda, H. Zen, J. Yamagishi, and K. Oura, "Speech synthesis based on hidden Markov models," *Proceedings of the IEEE*, vol. 101, no. 5, pp. 1234–1252, 2013.

[3] H. Zen, A. Senior, and M. Schuster, "Statistical parametric speech synthesis using deep neural networks," in *ICASSP-2013*, 2013, pp. 7962–7966.

[4] Z. H. Ling, S. Y. Kang, H. Zen, A. Senior, M. Schuster, X. J. Qian, H. M. Meng, and L. Deng, "Deep learning for acoustic modeling in parametric speech generation: A systematic review of existing techniques and future trends," *IEEE Signal Processing Magazine*, vol. 32, no. 3, pp. 35–52, 2015.

[5] Y. Bengio, "Learning deep architectures for ai," *Found. Trends Mach. Learn.*, vol. 2, no. 1, pp. 1–127, Jan. 2009. [Online]. Available: http://dx.doi.org/10.1561/2200000006

[6] X. Glorot, A. Bordes, and Y. Bengio, "Deep sparse rectifier neural networks," in *International Conference on Artificial Intelligence and Statistics*, 2011, pp. 315–323.

[7] H. Zen and A. Senior, "Deep mixture density networks for acoustic modeling in statistical parametric speech synthesis," in *ICASSP-2014*. IEEE, 2014, pp. 3844–3848.

[8] T. Nagamine, M. L. Seltzer, and N. Mesgarani, "Exploring how deep neural networks form phonemic categories," in *INTERSPEECH-2015*, 2015.

[9] R. K. Srivastava, K. Greff, and J. Schmidhuber, "Highway networks," *CoRR*, vol. abs/1505.00387, 2015. [Online]. Available: http://arxiv.org/abs/1505.00387

[10] K. He, X. Zhang, S. Ren, and J. Sun, "Deep residual learning for image recognition," *CoRR*, vol. abs/1512.03385, 2015. [Online]. Available: http://arxiv.org/abs/1512.03385

[11] G. E. Hinton and R. Salakhutdinov, "Reducing the dimensionality of data with neural networks," *Science 28*, vol. 313, no. 5786, pp. 504–507, 2006.

[12] S. Kang and H. M. Meng, "Statistical parametric speech synthesis using weighted multi-distribution deep belief network," in *INTERSPEECH-2014*, 2014, pp. 1959–1963.

[13] R. Caruana, "Multitask learning," *Machine learning*, vol. 28, no. 1, pp. 41–75, 1997.

[14] Z. Wu, C. Valentini-Botinhao, O. Watts, and S. King, "Deep neural networks employing multi-task learning and stacked bottleneck features for speech synthesis," in *ICASSP-2015*. IEEE, 2015, pp. 4460–4464.

[15] J. Cole, "Prosody in context: a review," *Language, Cognition and Neuroscience*, vol. 30, no. 1-2, pp. 1–31, 2015.

[16] H. Kawahara, I. Masuda-Katsuse, and A. Cheveigne, "Restructuring speech representations using a pitch-adaptive time-frequency smoothing and an instantaneous-frequency-based F0 extraction: Possible role of a repetitive structure in sounds," *Speech Communication*, vol. 27, pp. 187–207, 1999.

[17] HTS Working Group, "The English TTS System "Flite+hts_engine"," 2014. [Online]. Available: http://hts-engine.sourceforge.net/

[18] F. Weninger, J. Bergmann, and B. Schuller, "Introducing CURRENT: The Munich open-source CUDA recurrent neural network toolkit," *The Journal of Machine Learning Research*, vol. 16, no. 1, pp. 547–551, 2015.

[19] X. Glorot and Y. Bengio, "Understanding the difficulty of training deep feedforward neural networks," in *International conference on artificial intelligence and statistics*, 2010, pp. 249–256.

[20] K. C. Sim, "On constructing and analysing an interpretable brain model for the dnn based on hidden activity patterns," in *ASRU-2015*, 2015, pp. 22–29.

[21] Y. Zhang, G. Chen, D. Yu, K. Yao, S. Khudanpur, and J. Glass, "Highway long short-term memory rnns for distant speech recognition," in *ICASSP-2016*. IEEE, 2016, pp. 5755–5759.