A STUDY OF EXTENSION NEURAL BANDWIDTH OF TELEPHONE SPEECH FOR ENHANCED SPEAKER RECOGNITION

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ABSTRACT: In this paper presents previous work on training the recognition system of mixed bandwidth (BW) speakers by predicting misplaced material in the upper band (UB) of sampled telephone communication. Mixed BW assembly's connotation narrowband (NB) and wideband (WB) vocal corpus voice using NB basic voice sampling with the low pass filter interpolator, subsequent in damage of material in the innovative WB voice. In this article, we discover the use of a convolutional deep convolutional neural network (CNN) and a long-term bidirectional memory network (BLSTM) together with a before suggested deep neural network (DNN) for bandwidth extension (BWE).) of telephone announcement NB Loudspeaker gratitude arrangements consummate of stretched bandwidth purposes must established exhibition related to the common basic BW and NB structures. In terms of cost detection function (DCF), the CNN-BWE system improved by 10.78% and 15.96% (relative) in the Chatterers In the Wild (SITW) assessment core and in the multi provision conditions - speaker correspondingly w.r.t the baseline NB; and developed by 3.21% and 4.13% by burden on the mixed baseline BW.

Keywords: Bandwidth allowance, speaker recognition, deep residual CNN, BLSTM, assignment learning

1. INTRODUCTION

Consider the situation of the formation of speaker recognition schemes in which we must admission to data marked by dual changed dominions: telephone and microphone. The voice of the phone is sampled at 8 KHz, while the voice of the microphone is sampled at 16 KHz. From nowadays on, we resolve call 8 KHz data as narrow band (NB) and 16 KHz data as wide band (WB) and the band between 4-8 KHz as upper band (UB). The conventional way of joining data sets with a changed sampling frequency is to reduce the sample at all to the lowest sampling frequency, in our case from 16 KHz to 8 KHz. This outcomes in the damage of material popular the upper band (UB) of 16 KHz data. The microphone voice sampled together with the telephone voice is recycled to train the speaker acknowledgement classification. This technique works quite well after the assessment dataset is also vocal. Though, it is not optimum when the assessment data are balanced as the lost UB also encloses discriminating information from the rapporteur. Additional selection is to train the scheme only on the accessible WB corpus, avoiding the need for top-down sampling. But this approach would lead to poor consequences when the accessible statistics after the World Bank is scarce. This is a self-same mutual situation in speaker acknowledgment investigation, largely driven by NIST speaker acknowledgment valuations, where NB telephone speech is obtainable in abundance, but data labelled WB is scarce.

In [1], “we proposed to up sample the NB data using a simple low-pass filter interpolator and then combine it with the WB corpus to train a mixed-BW x-vector [2] speaker recognition system”. “Hence, no information loss is incurred how- ever; this basic up sampling does not predict any information in the UB of the NB corpus”. “In this work, we investigate several neural architectures to predict the missing information in the UB of the up sampled data”. “We will refer to this pro- cess as Bandwidth extension (BWE) throughout the paper”. “We are mainly interested in using this BWE to improve speaker recognition performance in microphone speech”. “In this paper, we did not focus on actually recovering the waveform and evaluating the quality of the up sampled signals, which would involve organizing human perceptual tests”.

“There are few works dealing with this problem in the field of automatic speech recognition (ASR). The authors in [3]”, “propose to jointly train a feed forward deep neural network (DNN) for BWE and ASR system on both NB and WB data. Authors in [4, 5] train a DNN on log-power spectrogram (LPS) features for BWE and then train ASR on bandwidth extended NB data”. “They also showed that predicting the en- tire WB is better than just predicting the missing UB, which leads to discontinuities between the NB and the UB spectrum”. “The authors in [6] proposed mixed-BW training where the NB filter-bank was zero padded to match the dimension of the WB filter-bank when training the ASR system”.

In this work, “we compare several neural architectures for BWE in terms of speaker recognition performance we experimented with a feed forward DNN, a deep residual full-CNN and a BLSTM”. “The CNN architecture was inspired by the work done in [7] for image style transfer and single image super resolution”.

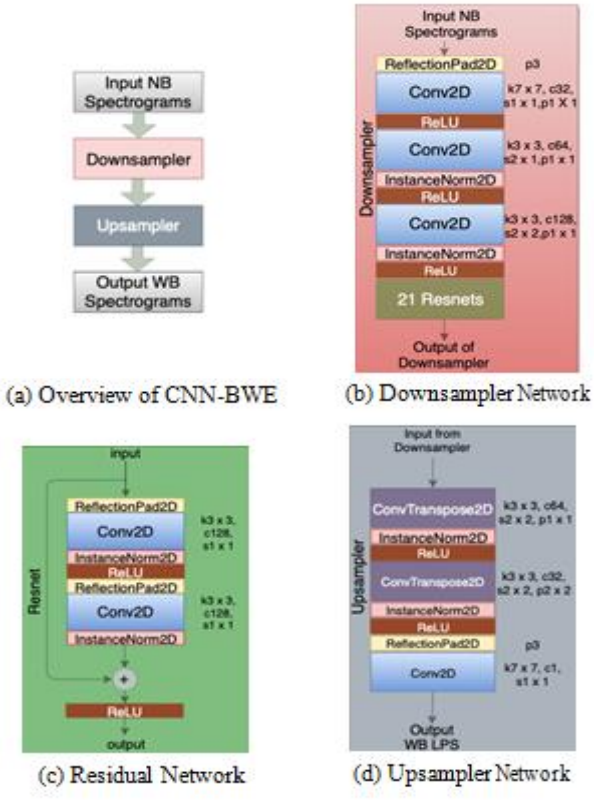


Fig. 1. Individual building blocks of CNN-BWE (k-kernel, s-strides, c-filters, p-padding)

"The rest of the paper is organized as follows in Section 2, we explain the architectures of DNN-BWE, CNN-BWE and BLSTM-BWE systems". "Section 3 gives details of datasets used in this work and the training details of those systems". "In Section 4, we explain the baseline speaker recognition systems used in this work and the BWE-speaker recognition systems we conclude with a summary of the work in Section 5".

2. BWE SYSTEMS – ARCHITECTURES

In this segment, we label the network buildings of the BWE structures used in this work.

2.1. DNN-BWE Network

The feed forward "DNN that we used for BWE was similar to our previous work [1] and was originally proposed by [5]". "The DNN-BWE had 3 hidden layers with 2048 neurons in each hidden layer 5 past and future frames were appended to the current frame at the input". "Rectified linear unit (ReLU) nonlinearity was used in each layer except the output layer where linear activation was used".

2.2. CNN-BWE Network

Our "CNN-BWE network architecture was comparable to the fully- convolutional network used by [7] for image style transfer and single image super resolution the network consisted of two major building blocks: a down sampler network and an up sampler network, which essentially work as an encoder- decoder network". "An overview of CNN-BWE network is shown in Fig. 1(a) the down sampler network consisted of three 2D convolutional layers followed by several residual blocks [8]"."The purpose of the down sampler is to reduce the dimension of the feature maps to a low-dimensional manifold which preserves the properties of speech". "It performs in-network down sampling with strides greater than 1, which is computationally efficient since it reduces the number of convolutions by reducing the feature map dimensions". "The number of residual blocks was set to 21 for the details of kernel sizes, strides, number of filters and padding dimension in each layer of the down sampler network and the residual network refer to Fig 1(b) and Fig 1(c) respectively".

The up technician network contained of two deconvolutional layers monitored by a convolution layer. "The commission of the up- technician is to decode the low-dimensional illustration into the log-power spectrogram (LPS) of WB speech the deconvolutional layers increase the feature dimension by a factor of 2 by applying strides of 1/2 while decreasing the number of filters by a factor of 2 for the details of kernel sizes, strides, number of filters and padding dimension in each layer of the up sampler refer to Fig. 1(d)".

The entire complex contained of individual convolutional and deconvolutional layers. "No pooling or fully connected layers were included. Hence the network is termed as deep residual fully-convolutional neural network". "The fact that it is fully convolutional allows the network to process variable length sequences without increasing the number of parameters".

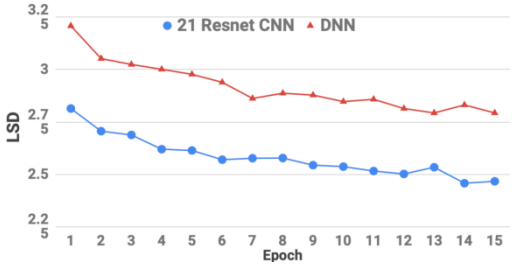
2.3. BLSTM-BWE Network

We also investigated with a "BLSTM with two 512 dimension hidden layers the nonlinear activation used was ReLU". "The output of the BLSTM was fed to an affine layer, which made the network output dimension to match the required WB features dimension".

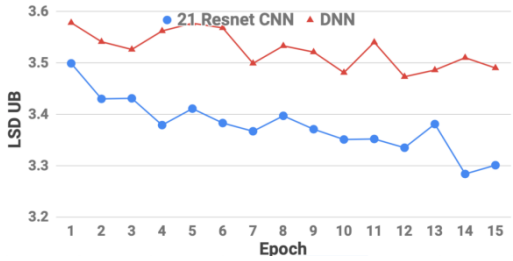
3. BWE SYSTEMS - TRAINING SETUP

3.1. Datasets

"WB data used in this work comprises of microphone recordings from Mixer6, SRE08 microphone speech and Vox- Celeb [9] data sets". "In total, WB data consisted of 30974 utterances from 1871 speakers all the BWE systems were trained on parallel NB-WB data obtained by down sampling the WB data to 8 kHz the WB microphone data was split into 90%-10% training and validation without speaker overlap."



(a) LSD



(b) LSD-UB

Fig. 2. LSD and LSD-UB comparison of CNN-BWE and DNN-BWE Systems

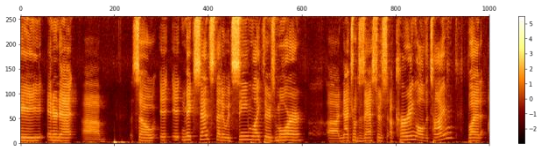
3.2. Training Details

BWE systems were implemented using PyTorch [10]. As in [4], the BWE systems were trained to predict the entire WB. The input was 129 dimension NB LPS while the output was 257 dimension WB LPS, similar to [4]". "Mean squared error (MSE) objective was used all the networks were trained for a maximum of 50 epochs, where an epoch is completed when we have observed a sample from each utterance". "Dropout [11] was used as regularizer (except for CNN-BWE) with 0.4 drop probability".

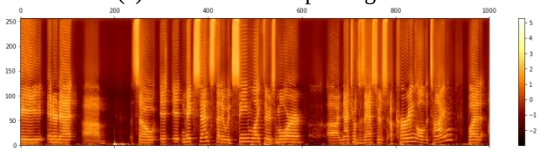
Used for the"DNN-BWE, for each utterance in the mini-batch we selected 64 frames we used a context of 5 past and future frames to predict each WB frame". "For the CNN-BWE systems, the input was arranged as four dimensional tensor of size n × C × F × D, with mini-batch size n = 1, chan- nel size C = 1, sequence length F and feature dimension D = 129". We conduct experiment training with different sequence lengths F = 129, 257.

Figure 2 compares the junction of "DNN-BWE and CNN-BWE system trained on sequences of length 129 the performance was measured on the validation data in terms of log-spectral distortion (LSD) and LSD of UB (LSD-UB) at the end of every epoch". "LSD measures the reconstruction quality of individual frequencies in LPS domain".

$$\mathrm{LSD}(X,\hat{X}) = \frac{1}{L}\sum_{l=1}^{L}\sqrt{\frac{1}{K}\sum_{k=1}^{K}(X(l,k)-\hat{X}(l,k))^2} \quad (1)$$



(a) Reference WB spectrogram



(b) Predicted WB spectrogram by CNN-BWE

Fig. 3. Comparison of reference and predicted spectrograms by CNN-BWE system.

The CNN-BWE structure achieved lower "LSD and LSD- UB compared to DNN-BWE since we used 21 residual blocks in CNN-BWE network it had, in total, 46 convolutional layers and two deconvolutional layers". " In spite of the network depth, the number of parameters of CNN-BWE is less than that of the DNN-BWE. The CNN-BWE network has 6M parameters compared to 16M for DNN-BWE network". "Figure 3 shows comparison of spectrograms of original WB utterance from validation set and corresponding predicted WB utterances from a CNN-BWE system".

To compare the presentation of "CNN-BWE with a recurrent neural network model, we trained a BLSTM-BWE on sequence of lengths of 505 frames". "The comparison of BWE systems on speaker recognition performance is given in next section".

4. BWE-SPEAKER RECOGNITION SYSTEMS

We measured the heavens of the BWE approaches for speaker recognition using x-vector speaker acknowledgment schemes. Presentation was restrained on the SITW assessment set on core- core (single speaker) and assist-multi (multiple speakers in enrol and test) environments.

4.1. Baseline Systems

We experimented with three baseline x-vector systems: " a NB baseline system, a WB baseline system and a mixed-BW baseline system the NB baseline used 23 MFCC features based on 23 filters Mel filter-bank". "The rest of systems used 23 MFCC with 30 filters Mel filter-bank". "Features were and silence frames were removed. The x-vector system was built using Kaldi [12]". "Full rank probabilistic discriminant analysis [13] was used for scoring"." PLDA scores were normalized using adaptive symmetric norm (S-Norm) [14]".

NB baseline schemes describe the predictable technique of training speaker recognition systems. "Training data com- prised of NB telephone data including SRE04-10, Mixer6, Switchboard Phases 1,2 and 3 (91224 utterances from 7001 speakers) and down sampled WB microphone data including Mixer6, SRE08 microphone speech and VoxCeleb (30974 utterances from 1871 speakers)". "No data augmentation was used. WB baseline system was trained only on the available WB microphone data". "Thus, this system was trained on much less speakers than NB baseline". 'The NB baseline system has the disadvantage that the in- formation in the UB of the WB training and evaluation data is lost". No material loss occurs in the "WB baseline system but the training data is much smaller,

since we have not used NB data to overcome these two disadvantages, in our previous work [1], we proposed a mixed-BW system where the NB telephone data were up sampled with a low-pass filter interpolator and the WB microphone training and evaluation data were used without any modification". "The MFCC configuration used to train this system is similar to the WB base- line system the mixed-BW system was trained on the same datasets as the NB system".

4.2. BWE-Speaker recognition Systems

The mixed-BW starting point up examples the "NB data but do not estimate the spectrum in the upper-band, which is assumed to be null"."The systems in this section used the neural BWE systems to predict the UB spectrum when up sampling. Apart from that, these systems are similar to the mixed-BW base- line". "They use the same training datasets and feature the total pipeline for training the BWE speaker recognition systems is as follows". "LPS features are extracted from the NB telephone speech and utterance level means variance normalization is applied". "Then, the BWE networks convert NB LPS features into WB LPS features". "WB LPS are then converted into MFCC. Finally, the MFCC of the WB data and the BWE MFCC of the NB data are pooled to train the x-vector system". "The experiments with these systems will allow knowing whether the BWE networks are able to add speaker discriminant information to the predicted upper-band of the spectrum".

4.3. BWE-Speaker recognition Results

"Table 1 summarizes the results of the baseline and BWE- speaker recognition systems. The mixed-BW baseline system performed the best among the baselines all the BWE systems improved over the baseline systems in terms of both EER and DCF". "CNN-BWE system trained on sequences of length 257 performed the best in terms of DCF over all". "However, the relative difference in terms of EER between the CNN-BWE and BLSTM-BWE system was not very significant (5.71 and 5.74 respectively)". In relations of virtual

Table 1. Speaker ID results on SITW (F - sequence length)

	SITW Core			SITW Assist-Multi		
	EER	**DCF(1E-2)**	**DCF(1E-3)**	**EER**	**DCF(1E-2)**	**DCF(1E-3)**
Baseline						
NB	6.01	0.5111	0.7105	8.88	0.5569	0.7351
WB	8.02	0.5538	0.7505	8.54	0.5049	0.6880
mixed-BW	5.93	0.4711	0.6713	7.62	0.4890	0.6667
BWE-speaker ID results						
DNN-BWE	**5.55**	0.4705	0.6516	7.10	0.4812	0.6481
CNN-BWE (F-129)	5.74	0.4737	0.6630	**7.08**	0.4737	0.6671
CNN-BWE (F-257)	5.71	**0.4560**	**0.6480**	7.29	**0.4680**	**0.6475**
BLSTM-BWE (F-505)	5.74	0.4621	0.6523	7.35	0.4717	0.6510

Enhancement of DCF at preceding 0.01, the CNN-BWE enhanced by 10.78% and 15.96% for core and assist-multi-speaker "SITW conditions respectively over the NB baseline compared to the mixed-BW system, the relative improvements were 3.21% and 4.13% for core and assist-multi-speaker conditions, which justifies our attempt to predict information in the UB for telephone speech for speaker recognition".

5. CONCLUSION

This work examined the impact of expecting the misplaced statistics in the UB of telephone communication on speaker recognition presentation. "We experimented with a DNN, a deep residual fully-convolutional network (CNN) and a BLSTM network for BWE". "Individual x-vector based speaker recognition systems were trained on bandwidth

extended features obtained from each of these three systems". "The performance of BWE speaker recognition systems was compared to three baseline systems–NB, WB and mixed-BW". "All the BWE speaker recognition systems improved in performance com- pared to all three baselines". "The best performer in terms of DCF was the CNN-BWE system trained on sequence lengths of 257 in terms of DCF, the CNN-BWE system" showed relative improvement of 10.78% and 15.96% in the SITW eval core and assist-multi-speaker condition respectively w.r.t. the "NB baseline and improved by 3.21% and 4.13% w.r.t. to the mixed-BW baseline, which up samples NB speech just using a low-pass filter interpolator". "In terms of number of parameters, the CNN-BWE model with 21 presents is the lightest weight with ∼ 6M parameters compared to DNN-BWE with ∼ 16M parameters and BLSTM-BWE with ∼ 18M parameters". "As future work, we will explore joint model training of BWE system and speaker recognition system with alternate feature representations like filter banks and raw waveform. We will also look into unsupervised BWE using adversarial learning".

REFERENCES

[1] Phani Sankar Nidadavolu, Cheng-I Lai, Jess Villalba, and Najim Dehak, "Investigation on bandwidth exten- sion for speaker recognition," in Proc. Interspeech 2018, 2018, pp. 1111–1115.

[2] David Snyder, Daniel Garcia-Romero, Gregory Sell, Daniel Povey, and Sanjeev Khudanpur, "X-vectors: Ro- bust dnn embeddings for speaker recognition," Submit- ted to ICASSP, 2018.

[3] Jianqing Gao, Jun Du, Changqing Kong, Huaifang Lu, Enhong Chen, and Chin-Hui Lee, "An experimental study on joint modeling of mixed-bandwidth data via deep neural networks for robust speech recognition," in Neural Networks (IJCNN), 2016 International Joint Conference on. IEEE, 2016, pp. 588–594.

[4] Kehuang Li, Zhen Huang, Yong Xu, and Chin-Hui Lee, "Dnn-based speech bandwidth expansion and its appli- cation to adding high-frequency missing features for automatic speech recognition of narrowband speech," in Sixteenth Annual Conference of the International Speech Communication Association, 2015.

[5] Kehuang Li and Chin-Hui Lee, "A deep neural network approach to speech bandwidth expansion," in Acoustics, Speech and Signal Processing (ICASSP), 2015 IEEE In- ternational Conference on. IEEE, 2015, pp. 4395–4399.

[6] Jinyu Li, Dong Yu, Jui-Ting Huang, and Yifan Gong, "Improving wideband speech recognition using mixed- bandwidth training data in cd-dnn-hmm," in Spo- ken Language Technology Workshop (SLT), 2012 IEEE. IEEE, 2012, pp. 131–136.

[7] Justin Johnson, Alexandre Alahi, and Li Fei-Fei, "Per- ceptual losses for real-time style transfer and super-resolution," in European Conference on Computer Vi- sion. Springer, 2016, pp. 694–711.

[8] Kaiming He, Xiangyu Zhang, Shaoqing Ren, and Jian Sun, "Deep residual learning for image recognition," in Proceedings of the IEEE conference on computer vision and pattern recognition, 2016, pp. 770–778.

[9] Arsha Nagrani, Joon Son Chung, and Andrew Zisser- man, "Voxceleb: a large-scale speaker identification dataset," arXiv preprint arXiv:1706.08612, 2017.

[10] Adam Paszke, Sam Gross, Soumith Chintala, and Gre- gory Chanan, "Pytorch: Tensors and dynamic neural networks in python with strong gpu acceleration," 2017.

[11] Nitish Srivastava, Geoffrey Hinton, Alex Krizhevsky, Ilya Sutskever, and Ruslan Salakhutdinov, "Dropout: a simple way to prevent neural networks from overfit- ting," The Journal of Machine Learning Research, vol. 15, no. 1, pp. 1929–1958, 2014.

[12] Daniel Povey, Arnab Ghoshal, Gilles Boulianne, Lukas Burget, Ondrej Glembek, Nagendra Goel, Mirko Han- nemann, Petr Motlicek, Yanmin Qian, Petr Schwarz, et al., "The kaldi speech recognition toolkit," in IEEE2011 workshop on automatic speech recognition and understanding. IEEE Signal Processing Society, 2011, number EPFL-CONF-192584.

[13] Niko Bru¨ mmer and Edward De Villiers, "The speaker partitioning problem.," in Odyssey, 2010, p. 34.

[14] Niko Bru¨ mmer and Albert Strasheim, "Agnitios speaker recognition system for evalita 2009," in The 11th Con- ference of the Italian Association for Artificial Intelli- gence. Citeseer, 2009