Waveform-based Voice Activity Detection Exploiting Fully Convolutional networks with Multi-Branched Encoders

Cheng Yu1, Kuo-Hsuan Hung1, I-Fan Lin1, Szu-Wei Fu1, Yu Tsao1, Jeih-wei Hung2

1Research Center for Information Technology Innovation, Academia Sinica, Taiwan
2Department of Electrical Engineering, National Chi Nan University, Taiwan

r06943106@g.ntu.edu.tw, yu.tsao@citi.sinica.edu.tw

Abstract

In this study, we propose an encoder-decoder structured system with fully convolutional networks to implement voice activity detection (VAD) directly on the time-domain waveform. The proposed system processes the input waveform to identify its segments to be either speech or non-speech. This novel waveform-based VAD algorithm, with a short-hand notation “WVAD”, has two main particularities. First, as compared to most conventional VAD systems that use spectral features, raw-waveforms employed in WVAD contain more comprehensive information and thus are supposed to facilitate more accurate speech/non-speech predictions. Second, based on the multi-branched architecture, WVAD can be extended by using an ensemble of encoders, referred to as WEVAD, that incorporate multiple attribute information in utterances, and thus can yield better VAD performance for specified acoustic conditions. We evaluated the presented WVAD and WEVAD for the VAD task in two datasets: First, the experiments conducted on AURORA2 reveal that WVAD outperforms many state-of-the-art VAD algorithms. Next, the TMHINT task confirms that through combining multiple attributes in utterances, WEVAD behaves even better than WVAD.

Index Terms: voice activity detection, fully convolutional network, ensemble, waveform utterances

1. Introduction

Voice activity detection (VAD) aims to detect speech segments from audio streams and has been widely applied as a fundamental yet crucial front-end unit in various speech-related applications, such as automatic speech recognition (ASR) [1, 2], communication systems [3, 4], speaker recognition systems [5, 6], and speech enhancement (SE) [7, 8]. Conventional VAD methods are designed based on assumptions of speech and noise characteristics. One class of VAD identifies speech segments based on energy levels. Some notable examples are [9, 10, 11, 12, 13]. Although the energy-level-based approaches can perform well in clean conditions, their detection precision is usually dropped when background noises are significant. Another class of VAD is usually served as the core unit in the VAD systems and achieved remarkable improvements over conventional approaches. As for the ML-based VAD approaches, the support vector machine (SVM) is usually served as the core module. Notable examples are [14, 15, 16]. In contrast, Some VAD algorithms are based on a Gaussian mixture model (GMM) framework. For example, in [17] Ying proposed a sequential Gaussian mixture model using expectation-maximization (EM) for initialization to achieve VAD. Compared with the ML-based methods that usually use hand-crafted features, the DL-based methods can exploit more extensive and versatile feature representations dwelled in the latent spaces (layers) of the employed deep neural network, such as recurrent neural networks (RNNs) [21, 22] and long-short term memory (LSTM) [23, 24]. For example, in [25] Zhang proposed a fusion of multiple features using a deep belief network (DBF) that outperforms several past state-of-the-art works with a compact framework. Nevertheless, the respective VAD accuracy is not necessarily satisfactory when tested under some challenging noise situations.

In light of the progress of VAD algorithms mentioned earlier, multiple features seem to be a better choice than a single feature to achieve superior speech/non-speech classification. In addition, adopting a deep-learning model in a VAD process has been one of the most favorable ways that can assure acceptable VAD accuracy and exhibit robustness against challenging noise environments. Therefore, in this study, we aim to design a novel VAD scenario that adopts multiple speech attributes and leverages a DL-based ensemble framework. Preliminary experiments have shown that this new waveform-based VAD method outperforms some state-of-the-art VAD algorithms for the Aurora2 dataset [26], and we have also shown that employing more speech attributes as the input to this new system benefits the VAD performance for the TMHINT database [27].

2. Related Works

This section briefly introduces some VAD algorithms that motivate us to develop the new VAD scenario.

2.1. VAD using multiple features

Some ML/DL-based VAD approaches shed light on the advantage of utilizing multiple acoustic features, like the work in [28]. To further yield advantages from multiple features, a deep ensemble framework with acoustic environment detection (AEC) is proposed in [29] that aims to explore benefits for VAD from multiple environmental features. Dey proposed an ensemble
framework based on SVM [31] that shows huge improvements compared to a single SVM for VAD. Zhang proposed an ensemble of classifiers (multi-resolution stack, MRS) [32] based on their proposed bDNN model. Noticeably, the MRS outperforms other VAD approaches by great margins in the area under curve (AUC) metric. However, these approaches generally use segmented spectral magnitude features, or power magnitude features from time-frequency analyses, where the phase information is not taken into consideration.

2.2. VAD based on time-domain or phase-aware scheme

Recently, phase features from time-frequency analyses have been shown to be unignorable for an effective VAD, according to what Wang proposed in their phase-aware framework [33]. To integrate the advantages of the aforementioned approaches totally different neural network structures, can sometimes be great since it requires the integration of three forms other VAD approaches by great margins in the area under curve (AUC) metric. However, these approaches generally use segmented spectral magnitude features, or power magnitude features from time-frequency analyses, where the phase information is not taken into consideration.

2.2. VAD based on time-domain or phase-aware scheme

Recently, phase features from time-frequency analyses have been shown to be unignorable for an effective VAD, according to what Wang proposed in their phase-aware framework [33]. For even better use of full information from speech signal, Zazo proposed a CLDNN framework [34] that directly performs VAD on segmented waveform utterances. The convolutional blocks in CLDNN dissolve time-domain features as filter banks, and feeds the extracted features to a LSTM-DNN block for finalization of detection. However, the model complexity of CLDNN can sometimes be great since it requires the integration of three totally different neural network structures.

3. Proposed Method

To integrate the advantages of the aforementioned approaches while maintaining a compact structure, we propose a waveform-based VAD framework using an encoder-decoder structure consisting of fully convolutional network, and we further improve this framework by integrating multiple speech attributes through an ensemble of encoders.

3.1. Encoder-Decoder FCN framework

Partially inspired by our previous works [35], this newly presented scenario primarily adopts an encoder-decoder (ED) scheme, which resorts to a fully convolutional network (FCN) to implement VAD directly on the time-domain speech waveforms. This novel waveform-based VAD algorithm, with a short-hand notation “WVAD”, is depicted in Figure 1(a), consists of an encoder of four convolutional blocks, a framing block, and a decoder of three convolutional blocks, which detailed arrangements are shown in Figure 1(b).

Briefly speaking, WVAD converts the input waveform \( x(t) \) to a series of frame-wise VAD output, \( \tilde{y} = [y_1[\tau], y_{ns}[\tau]] \), where \( y_1[\tau] \) and \( y_{ns}[\tau] \) refers to the scores for speech channel and non-speech channel, respectively, and \( \tau \) is the frame index. For any specific frame \( \tau \) in \( x(t) \), if \( y_1[\tau] \geq y_{ns}[\tau] \), it is predicted as a speech frame; otherwise it is predicted as non-speech. In the following sub-sections, we detail each portion of WVAD.

3.1.1. Encoder Framework

Each of the four encoder blocks (EBs) shown in Figure 1(a) consists of a one-dimensional convolutional layer followed by a leaky-ReLU activation function, as depicted in the upper part of Figure 1(b). These four EBs are stacked in an inverted-triangular fashion as in Figure 1(b) (by decreasing the number of channels) to downscale the feature map into two channels, denoted by \( s \).

3.1.2. Framing Block (FB) framework

Since the VAD targets are labeled on the frames and stride half of frame points each label (that is, the speech/non-speech labeling is frame-based and the neighboring frames have a 50% overlap), we thus implement a framing block (FB) which adopts a one-dimensional layer with the same stride as the VAD labeling. As shown in the middle part of Figure 1(b), the FB consists of a convolution layer, which receives the feature map \( s \) from the preceding encoder framework, and a sigmoid activation layer. Briefly speaking, here the FB serves as a primitive speech-non-speech classifier, in which the two channels in the convolutional layer attempt to reflect the speech and non-speech frames, respectively.

3.1.3. Decoder Framework

Here the decoder framework is to further polish up the output of the FB in order to achieve a superior VAD performance. This decoder framework is created through stacking decoder blocks (DBs), each consisting of a two-channel convolutional

![Figure 1: The architecture of the proposed WVAD.](image-url)
layer and a sigmoid activation layer, as shown in the lower part of Figure 2(b). Similar to the encoder framework, here these DBs are stacked in an inverted triangular fashion. In these DBs (denoted by DB1, DB2, and DB3) each convolutional layer resolves time-frequency representations in the channels of feature maps, while the shrinking kernel sizes involve in the convolutional layers can be expressed by
\[ \tilde{z}_j,0 = \sigma(F_j^T, \odot b_1, m) \] (1)
\[ \tilde{z}_j,m = \sigma(F_j^T, \odot z_{j-1}(\tau) + b_2, m) \] (2)
where \( F_j \in \mathbb{R}^{t \times I} \) and \( b_1, m \) denote the filter (kernel) and bias for channel \( j \) in a convolutional layer of DB_m respectively, \( \tau \) denotes segment time index in each channel, \( z_j,0(\tau) \) denotes the feature map of channel \( j \) from DB_m, \( m = 1, 2, 3 \), and \( z_j,0(\tau) \) is the feature map of channel \( j \) from the FB framework. Thus, given the input speech waveform \( x(t) \), we have the following outputs in turn:
\[ s(t) = [s_1(t); s_2(t)] = \text{Encoder}(x(t)), \] (3)
\[ \tilde{z}_0(\tau) = [z_1,0(\tau); z_2,0(\tau)] = \text{FB}(s(t)), \] (4)
\[ \hat{y}(\tau) = [z_1,3(\tau); z_2,3(\tau)] = \text{DB}_1(\text{DB}_2(\text{DB}_3(\tilde{z}_0(\tau)))) \] (5)
where \( z_1,0(\tau) \) and \( z_2,3(\tau) \) correspond to the speech channel and non-speech channel, respectively, in the predicted VAD label vector \( \hat{y}(\tau) \).

3.2. Encoders with Utterance-Level Attribute Tree (UAT)

Here, we further propose to refine WVAD by exploiting multiple encoders by means of an utterance-level attribute tree (UAT). According to our recent study [36], a UAT divides the utterances in the training set into several subsets according to different attributes. For example, let a UAT adopt two levels of attribute, namely gender and signal-to-noise ratio (SNR). The first level consists two nodes corresponding to two genders: male and female, which subsequently makes four nodes in the second level, namely male and high-SNR, female and high-SNR, male and low-SNR, and female and low-SNR. As a result, an extension of WVAD that adopts an ensemble of attributes, abbreviated as WEVAD, can be created and operated with the following procedures:

Step 1: We use a UAT to split the training data into several subsets, each subset belonging to a particular attribute or the intersection of several attributes. Then for each subset, an WVAD model is trained, as shown in Fig. 2(a).

Step 2: The encoder part of all UAT-guided attribute-wise WVAD models is collected and arranged in parallel to be an ensemble of encoders, which outputs are concatenated and then fed to a frame block (FB) network and a decoder network in turn, as depicted in Fig. 2(b). This new framework is trained using the whole training set, while only the parameters in the FB and decoder frameworks are learned and the encoder ensemble is frozen.

Step 3: In the test phase, an arbitrary test utterance \( x \) is first fed to the encoder ensemble to produce multiple feature maps, which are concatenated as follows:
\[ \hat{s} = [\text{Encoder}_1(x), \text{Encoder}_2(x), ..., \text{Encoder}_n(x)] \] (6)
where \( n \) is the number of encoders in the ensemble. Finally, the feature map ensemble \( \hat{s} \) is passed through the subsequent FB and decoder frameworks to obtain the predicted VAD label sequence \( \hat{y}(\tau) \), as described in Eq. (5).

4. Experimental Setup and Results

Here, we first examine the presented WVAD by comparing it with several state-of-the-art VAD algorithms in terms of Accuracy and AUC. This comparison is implemented on the AURORA2 corpus [28] with the VAD labeling in [39], which contains 8,440 and 60,000 utterances at a sampling rate of 8kHz for multi-condition training and testing, respectively. Next, we use the Taiwan Mandarin version of the hearing in noise test (TMHINT) [29] corpus to evaluate WVAD, by varying the settings of the attribute in the used UAT. MHINT contains 36,000 training utterances that are artificially corrupted with 100 noise types at 31 different SNRs (from -10dB to 20dB). For TMHINT, the target frame-based VAD labels are created by applying the rVAD [17] algorithm to clean noise-free utterances. Note that the VAD label of each frame is organized as a vector of two channels. The non-speech frame is labeled as [1, 0], while the speech frame is labeled as [0, 1].

In addition, with the TMHINT dataset, two versions of WEVAD, WEVAD(2) and WEVAD(6), are evaluated and compared, in which WEVAD(2) corresponds to 2 gender nodes of encoders (male and female) and WEVAD(6) is associated with 6 nodes of encoders (male, male high-SNR, male low-SNR, female, female high-SNR, and female low-SNR).

Notably, we report the VAD results in two metrics: ACC(%) and AUC(%). ACC indicates the VAD accuracy, calculated as the ratio of the number of correctly predicted frames to the number of total frames, and AUC is the abbreviation of “area under the curve”, which involves the receiver operating characteristic (ROC) curve with the x-axis for false-positive rate (FPR) and the y-axis for the true-positive rate (TPR).

4.1. Effects and performances of WVAD on AURORA2

At the outset, Tables 1 and 2 list the ACC and AUC scores, respectively, for the presented WVAD and several state-of-the-art VAD algorithms for the AURORA2 corpus. It is clearly shown in Table 1 that WVAD provides the optimal ACC scores for almost all noise types and levels (except for the train noise at -5 dB and 0 dB SNR) among the eight methods. In addition, from Table 2 WVAD achieves significantly higher AUC scores than the other four algorithms at all SNR levels. These results demonstrate that WVAD behave quite excellent as well as robust for the VAD task under a wide range of noise environments. Next, Figure 4(a) and (b) shows the output histograms of three decoder blocks (DB1, DB2, and DB3) of WVAD shown in Figure 1(a) for the test set with babble noise at -5 dB SNR, where the blue bars and orange bars refer to the non-speech channel and speech channel, respectively. From Figure 4(a) to (c), we find that the histogram for the speech channel (with orange color) gradually concentrates into two groups with low and high values, indicating its increasing discriminative ability.

Finally, Figures 4(a) and (b) show the histograms with respect to true-negative (TN) and true-positive (TP) cases of the final output \( \hat{y} \) for the same test set as Figure 4(c). The two figures evidently show that the proposed WVAD can help establish more distinctive numerical distribution from the speech channel (with orange color) than the non-speech channel (with blue color).

4.2. Results for the TMHINT corpus

In this section, we examine the performances of WEVAD, WEVAD(2) and WEVAD(6) for the TMHINT task. Considering the fact that the sampling rate of the utterances in TMHINT is 16 kHz, different from that of AURORA2, we slightly adjust
Table 1: Accuracy (%) of WVAD and several state-of-the-art approaches at 4 noise types (Restaurant, Street, Airport, Train), 1 channel mismatch noise type (Subway) at four SNR levels in AURORA2.

| Noise type | SNR | G.729B(37) | Zhang13(27) | RamirezbD(2) | Yu(38) | MK-SVM(21) | AEC(30) | WV AD |
|------------|-----|-------------|-------------|-------------|--------|-------------|---------|------|
| Restaurant | 0dB | 65.31       | 64.38       | 64.56       | 64.51  | 75.71       | 75.68   | 89.57 |
|            | 5dB | 69.67       | 66.03       | 69.59       | 68.10  | 83.25       | 83.59   | 93.01 |
| Street     | -5dB| 57.45       | 54.58       | 55.25       | 54.58  | 61.38       | 67.41   | 81.50 |
|            | 0dB | 65.71       | 57.43       | 58.28       | 57.59  | 73.35       | 73.76   | 89.57 |
| Airport    | -5dB| 57.00       | 56.94       | 57.18       | 57.53  | 65.86       | 66.35   | 86.89 |
|            | 0dB | 65.54       | 61.32       | 62.22       | 62.29  | 75.59       | 76.66   | 91.33 |
| Train      | -5dB| 51.35       | 59.84       | 61.17       | 59.95  | 76.31       | 76.95   | 93.42 |
|            | 0dB | 67.91       | 59.48       | 61.17       | 59.95  | 76.31       | 76.95   | 93.42 |
| Subway     | -5dB| 49.25       | 68.23       | 68.15       | 68.25  | 75.90       | 75.70   | 94.96 |
|            | 0dB | 55.20       | 68.15       | 68.16       | 68.18  | 82.38       | 83.29   | 94.96 |

Table 2: Accuracy (%) averaged over 7 noise types at six SNR levels in AURORA2.

| Methods                  | ACC(%) | AUC(%) |
|-------------------------|--------|--------|
| MRCSG-SVM(21)           | 95.33  | 95.50  |
| ZhangbD(27)             | 95.93  | 95.77  |
| bDN(32)                 | 96.09  | 95.86  |
| MK-SVM(32)              | 96.56  | 96.15  |
| WV AD                   | 99.45  | 98.80  |
| WEVAD(2)                | 99.22  | 97.62  |
| WEVAD(6)                | 99.25  | 97.69  |

Figure 3: The output histograms of the two channels for (a) DB1, (b) DB2, and (c) DB3 in log scale (y-axis), with the -5dB-SNR babble test set in AURORA2.

Figure 4: The histograms of two channels with respect to (a) true-negative (TN) and (b) true-positive (TP) cases of the final output y in log scale (y-axis), with the -5dB-SNR babble test set in AURORA2.

Figure 5: The average accuracy and AUC in TMHINT over 4 noise types at 6 SNR levels using WVAD, WEVAD(2) and WEVAD(6).

5. Conclusion

In this study, we present novel waveform-based VAD scenarios that leverage an encoder-decoder structure consisting of fully convolutional networks. Furthermore, by virtue of the utterance-level attribute tree (UAT) algorithm, we can create an ensemble of attribute-wise encoders in the leading part of the whole VAD system, which is believed to capture more beneficial VAD information than a single encoder. Experiments conducted on the AURORA2 dataset reveals that the presented WVAD behaves significantly better than many state-of-the-art VAD algorithms, and through the TMHINT evaluation results we further validate that the encoder-ensemble version of WVAD, viz. WEVAD, can further promote the VAD performance in terms of ACC and AUC metric scores. We conclude that the newly presented methods can provide accurate VAD results for utterances distorted by noise of various types and SNR levels.
6. References

[1] J. Ramirez, J. M. Gómez, and J. C. Segura, “Voice activity detection: fundamentals and speech recognition system robustness,” Robust speech recognition and understanding, vol. 6, no. 9, pp. 1–22, 2007.

[2] J. Ramirez, J. C. Segura, C. Benítez, L. García, and A. Rubio, “Statistical voice activity detection using a multiple observation likelihood ratio test,” IEEE Signal Processing Letters, vol. 12, no. 10, pp. 689–692, 2005.

[3] F. Beritelli, S. Casale, and A. Cavallaro, “A robust voice activity detector for wireless communications using soft computing,” IEEE Journal on Selected Areas in Communications, vol. 16, no. 9, pp. 1818–1829, 1998.

[4] E. D. Lee, H. P. Stern, and S. Mahmoud, “A voice activity detection algorithm for communication systems with dynamically varying background acoustic noise,” in Proc. VTC, vol. 2. IEEE, 1998, pp. 1214–1218.

[5] J. Alam, P. Kenny, P. Ouellet, T. Stafylakis, and P. Droushnel, “Supervised/unsupervised voice activity detectors for text-dependent speaker recognition on the rsr2015 corpus,” in Proc. Odyssey, Workshop, 2014, pp. 123–130.

[6] M.-W. Mak and H.-B. Yu, “A study of voice activity detection techniques for nist speaker recognition evaluations,” Computer Speech & Language, vol. 28, no. 1, pp. 295–313, 2014.

[7] S. Boll, “Suppression of acoustic noise in speech using spectral subtraction,” IEEE Transactions on acoustics, speech, and signal processing, vol. 27, no. 2, pp. 113–120, 1979.

[8] Y. Lu and P. C. Loizou, “A geometric approach to spectral subtraction,” Speech communication, vol. 50, no. 6, pp. 453–466, 2008.

[9] J. Haigh and J. Mason, “Robust voice activity detection using cepstral features,” in Proc. TENCON, vol. 3. IEEE, 1993, pp. 321–324.

[10] S. G. Tanyer and H. Ozier, “Voice activity detection in nonstationary noise,” IEEE Transactions on speech and audio processing, vol. 8, no. 4, pp. 478–482, 2000.

[11] K.-H. Woo, T.-Y. Yang, K.-J. Park, and C. Lee, “Robust voice activity detection algorithm for estimating noise spectrum,” Electronics Letters, vol. 36, no. 2, pp. 180–181, 2000.

[12] D. Enqiang, L. Guizhong, Z. Yatong, and C. Yu, “Voice activity detection based on short-time energy and noise spectrum adaptation,” in Proc. ICOSP, vol. 1. IEEE, 2002, pp. 464–467.

[13] C.-C. Hsu, K.-M. Cheong, T.-S. Chi, and Y. Tsao, “Robust voice activity detection algorithm based on feature of frequency modulation of harmonics and its dop implementation,” IIEC Transactions on Information and Systems, vol. 99, no. 10, pp. 1808–1817, 2015.

[14] J. Sohn, N. S. Kim, and W. Sung, “A statistical model-based voice activity detection,” IEEE signal processing letters, vol. 6, no. 1, pp. 1–3, 1999.

[15] E. Nemer, R. Goubran, and S. Mahmoud, “Robust voice activity detection using higher-order statistics in the ipc residual domain,” IEEE Transactions on Speech and Audio Processing, vol. 9, no. 3, pp. 217–231, 2001.

[16] J.-H. Chang, N. S. Kim, and S. K. Mitra, “Voice activity detection based on multiple statistical models,” IEEE Transactions on Signal Processing, vol. 54, no. 6, pp. 1965–1976, 2006.

[17] Z.-H. Tan, N. Dehak et al., “rvad: An unsupervised segment-based robust voice activity detection method,” Computer Speech & Language, vol. 59, pp. 1–21, 2020.

[18] D. Enqiang, L. Guizhong, Z. Yatong, and Z. Xiaodi, “Applying support vector machines to voice activity detection,” in Proc. ICSP-6, vol. 2. IEEE, 2002, pp. 1124–1127.

[19] Q.-H. Jo, J.-H. Chang, J. Shin, and N. Kim, “Statistical model-based voice activity detection using support vector machines,” IET Signal Processing, vol. 3, no. 3, pp. 205–210, 2009.

[20] J. W. Shin, J.-H. Chang, and N. S. Kim, “Voice activity detection based on statistical models and machine learning approaches,” Computer Speech & Language, vol. 24, no. 3, pp. 515–530, 2010.

[21] J. Wu and X.-L. Zhang, “Efficient multiple kernel support vector machine based voice activity detection,” IEEE Signal Processing Letters, vol. 18, no. 8, pp. 466–469, 2011.

[22] D. Ying, Y. Yan, J. Dang, and F. K. Soong, “Voice activity detection based on unsupervised learning framework,” IEEE Transactions on Audio, Speech, and Language Processing, vol. 19, no. 8, pp. 2624–2633, 2011.

[23] T. Hughes and K. Mierle, “Recurrent neural networks for voice activity detection,” in Proc. ICASSP. IEEE, 2013, pp. 7378–7382.

[24] F. Tao and C. Busso, “Bimodal recurrent neural network for audio-visual voice activity detection,” in Proc. Interspeech, 2017, pp. 1938–1942.

[25] F. Eyben, F. Weninger, S. Squartini, and B. Schuller, “Real-life voice activity detection with lstm recurrent neural networks and an application to hollywood movies,” in Proc. ICASSP. IEEE, 2013, pp. 483–487.

[26] J. Kim and M. Hahn, “Voice activity detection using an adaptive context attention model,” IEEE Signal Processing Letters, vol. 25, no. 8, pp. 1181–1185, 2018.

[27] X.-L. Zhang and J. Wu, “Deep belief networks based voice activity detection,” IEEE Transactions on Audio, Speech, and Language Processing, vol. 21, no. 4, pp. 697–710, 2012.

[28] H.-G. Hirsch and D. Pearce, “The aurora experimental framework for the performance evaluation of speech recognition systems under noisy conditions,” in Proc. ISCA ITRW ASR2000, 2000.

[29] M. Huang, “Development of taiwan mandarin hearing in noise test,” Department of speech language pathology and audiology, National Taipei University of Nursing and Health Science, 2005.

[30] J. Hwang, H.-M. Park, and J.-H. Chang, “Ensemble of deep neural networks using acoustic environment classification for statistical model-based voice activity detection,” Computer Speech & Language, vol. 38, pp. 1–12, 2016.

[31] J. Dey, M. S. B. Hossain, and M. A. Haque, “An ensemble svm-based approach for voice activity detection,” in Proc. IICCE. IEEE, 2018, pp. 297–300.

[32] X.-L. Zhang and D. Wang, “Boosting contextual information for deep neural network based voice activity detection,” IEEE/ACM Transactions on Audio, Speech, and Language Processing, vol. 24, no. 2, pp. 252–264, 2015.

[33] L. Wang, K. Phapatanaburi, Z. Go, S. Nakagawa, M. Iwashashi, and J. Dang, “Phase aware deep neural network for noisy robust voice activity detection,” in Proc. ICME. IEEE, 2017, pp. 1087–1092.

[34] R. Zazo, T. N. Sainath, G. Simko, and C. Parada, “Feature learning with raw-waveform cldns for voice activity detection,” Proc. Interspeech, pp. 3668–3672, 2016.

[35] S.-W. Fu, T.-W. Wang, Y. Tsao, X. Lu, and H. Kawai, “End-to-end waveform utterance enhancement for direct evaluation metrics optimization by fully convolutional neural networks,” IEEE/ACM Transactions on Audio, Speech, and Language Processing, vol. 26, no. 9, pp. 1570–1584, 2018.

[36] C. Yu, R. E. Zearario, J.Sherman, Y.-Y. Hsieh, X. Lu, H.-M. Wang, and Y. Tsao, “Speech enhancement based on denoising autoencoder with multi-branchied encoders,” arXiv preprint arXiv:2001.01538, 2020.

[37] A. Bu, “silence compression scheme for g. 729 optimized for terminals conforming to recommendation v.70,” ITU-T Recommendation G.729, 1996.

[38] T. Yu and J. H. Hansen, “Discriminative training for multiple observation likelihood ratio based voice activity detection,” IEEE Signal Processing Letters, vol. 17, no. 11, pp. 897–900, 2010.

[39] Z.-H. Tan and B. Lindberg, “Low-complexity variable frame rate analysis for speech recognition and voice activity detection,” IEEE Journal of Selected Topics in Signal Processing, vol. 4, no. 5, pp. 798–807, 2010.