Incorporating VAD into ASR System by Multi-task Learning

Meng Li¹, Yan Xia¹, Feng Lin¹
¹Megatronix(Beijing) Technology Co., Ltd.

Abstract

When we use End-to-end automatic speech recognition (E2E-ASR) system for real-world applications, a voice activity detection (VAD) system is usually needed to improve the performance and to reduce the computational cost by discarding non-speech parts in the audio. Usually ASR and VAD systems are trained and utilized independently to each other. In this paper, we present a novel multi-task learning (MTL) framework that incorporates VAD into the ASR system. The proposed system learns ASR and VAD jointly in the training stage. With the assistance of VAD, the ASR performance improves as its connectionist temporal classification (CTC) loss function can leverage the VAD alignment information. In the inference stage, the proposed system removes non-speech parts at low computational cost and recognizes speech parts with high robustness. Experimental results on segmented speech data show that by utilizing VAD information, the proposed method outperforms the baseline ASR system on both English and Chinese datasets. On unsegmented speech data, we find that the system outperforms the ASR systems that build an extra GMM-based or DNN-based voice activity detector.

Index Terms: online speech recognition, end-to-end, voice activity detection, multi-task learning, wav2vec 2.0

1. Introduction

In recent years, there has been a growing trend in probing into end-to-end automatic speech recognition (E2E-ASR) system, which directly maps audio waves into text. The most popular E2E-ASR approaches include the connectionist temporal classification (CTC) [1, 2], the recurrent neural network transducer (RNN-T) [3, 4] and attention-based encoder-decoder architectures [5]. E2E-ASR models show advantages over traditional methods in simplicity and outperform conventional ASR systems when trained on enough training data [6]. However, most of the methods are based on the assumption that the input audio has been processed into short speech segments. The mismatch between the assumption and the real-world scene makes it difficult to transcribe unsegmented long audios and to recognize speech in real time by directly using E2E-ASR systems. To approach the problem, a voice activity detection (VAD) [7, 8] system is often built to detect the speech segments and to discard the non-speech segments in the input audio.

A number of techniques can be used for VAD. Unsupervised approaches include building VAD systems based on energy [9], zero crossing rate [10], the periodicity measure [11]. Supervised VAD systems include support vector machines [12], Gaussian mixture models (GMM) [13], deep neural networks (DNN) [14, 15, 16]. In recent years, DNN-based VAD systems have attracted much attention because they can extract more information from the input feature and achieve better performance than conventional VAD systems. However, it takes extra effort and additional memory resources to build a DNN-based VAD model. A viable solution is integrating ASR and VAD into one model.

Recently, attempts have been made to integrate ASR and VAD into an E2E Neural Network. In Yoshimura et al.’s study [17], VAD is integrated into a CTC-based E2E-ASR model, in which blank labels from the CTC softmax output are regarded as the non-speech region. In Tao and Busso’s study [18], a multi-task learning (MTL) framework, which has two classification layers on the top of the network, is proposed to perform both audiovisual ASR and audiovisual VAD tasks. In the above-mentioned studies, VAD and ASR share the same network architecture. However, compared with ASR, VAD is less complicated and needs fewer computational resources, which means that using the same model structure for VAD and ASR is not computationally efficient.

In this work, we attempt to incorporate VAD into an E2E ASR system by leveraging multi-task learning approach. In the training stage, the model is firstly pre-trained with wav2vec 2.0 [19] framework, a self-supervised framework for speech representation learning, which has shown its advantage of helping convergence and improving the performance in ASR. In this paper, we build the model based on wav2vec 2.0 to get high performance in both ASR and VAD tasks. Then, ASR and VAD tasks are jointly trained with a MTL technique. With the help of MTL, the model learns representations that are discriminative for all tasks and obtains the better generalization than models trained by single task learning (STL). Experimental results show that our MTL approach outperforms STL approach in both ASR and VAD tasks. To reduce the computational cost of VAD, we only use the output features from the bottom feature extraction module of the network architecture to perform the VAD task. This design is more consistent with human cognition process and infants’ language learning process: In Jusczyk’s study [20], infants firstly have the ability to detect the language sound patterns before they recognize words. And to help the ASR system make better use of the information learned from VAD task, we propose a cross-task attention module to learn interactive information between ASR and VAD. To support online speech recognition, we use a chunk-hopping mechanism, which enables the model to encode on segmented frame chunks one after another [21]. And to eliminate unnecessary computational cost in the inference stage, we propose an online VAD&ASR inference algorithm with high robustness. Experimental results show that when we transcribe unsegmented long audios with the online VAD&ASR joint inference algorithm, the performance is nearly as good as what is achieved by transcribing short speech segments processed through human efforts.

2. Proposed Methods

In this section, we will introduce our proposed approach, which combines VAD with ASR through MTL technique and is pre-trained with wav2vec 2.0 framework [19].
As is shown in Figure 1, the proposed model architecture is built on the base structure of wav2vec2.0, which is composed of two parts: a multi-layer convolutional feature encoder and a context network which follows the Transformer architecture [22, 23]. The convolutional feature encoder maps the raw audio input \( X \) into latent representations, \( Z = (z_1, ..., z_T) \). Then the context network takes the latent representations as input to build contextualized representations, \( C = (c_1, ..., c_T) \).

Based on the architecture of wav2vec2.0, we perform ASR and VAD on different layers. For VAD task, to provide temporal information, we add a single group 1-D convolutional layer that is applied directly on the output embeddings of the feature encoder. Then we add an FC layer, which takes latent representations as input and outputs class representations of speech and non-speech, on the 1-D convolutional layer.

For ASR task, to better utilize the alignment information learned from VAD, we propose adding a Cross-task Attention Layer after the context network (Transformer). Derivate from Self-Attention[22], The Cross-task Attention Layer has three inputs: a pair of Key-Value vectors learned from VAD, we propose adding an Cross-task Attention layer to contextualized vector \( c_t \) and send these through a prediction head.

As depicted in Figure 1, The Cross-task Attention Layer extracts features \( G = (g_1, ..., g_T) \) from \( Q, K \) and \( V \) as follows:

\[
g_t = c_t + f_g(q_{\text{asr}}, k_{\text{vad}}, v_{\text{vad}}(\theta_g)) \tag{1}
\]

where \( f_g \) is the function played by Cross-task attention layer with parameter set \( \theta_g \).

2.2. Chunk-hopping Mechanism

To support online speech recognition, a chunk-hopping mechanism proposed in [21] is implemented. The chunk-hopping mechanism is illustrated in Figure 2. Specifically, the complete utterance of a sentence is firstly segmented into several non-overlapping chunks. For each chunk, we splice a left chunk \( L \) before the chunk as historical context and a right chunk \( R \) after it as future context. Spliced chunks only serve as contexts and generate no output. For the first chunk in the utterance, only a right chunk is spliced. And for the last chunk in the utterance, only a left chunk is spliced.

2.3. Multi-Task Learning

For ASR task, we use a CTC loss [1, 2] to optimize the model. CTC predicts the posterior probability of \( p(Y|X) \), where \( Y = \{y_t \in \mathcal{V} | t = 1, ..., L\} \) is the output sequence and \( X = \{x_t \in \mathbb{R} | t = 1, ..., T\} \) the input sequence, by introducing a frame-wise alignment \( A = \{a_t \in \mathcal{V} \cup \{< b >| t = 1, ..., T\} \) with an additional blank symbol \( < b > \). The joint probability of \( Y \) given \( X \) can be written as follows:

\[
p_{\text{CTC}}(Y|X) = \sum_A p(Y|A)p(A|X) \tag{2}
\]

The learning objective of a CTC-based model is defined as follows:

\[
\mathcal{L}_{\text{CTC}} = \log p_{\text{CTC}}(Y|X) \tag{3}
\]

For VAD task, we use cross-entropy as the loss function, which is defined as follows:

\[
\mathcal{L}_{\text{CE}} = y \log \hat{y} + (1 - y) \log (1 - \hat{y}) \tag{4}
\]

where \( y \) is the ground truth of VAD task, \( \hat{y} \) is the prediction of VAD task.

In this paper, we use MTL to jointly train ASR and VAD tasks. The joint loss, \( \mathcal{L}_{\text{MTL}} \), is given as:

\[
\mathcal{L}_{\text{MTL}} = \mathcal{L}_{\text{cts}} + \mathcal{L}_{\text{CE}} \tag{5}
\]

2.4. Online VAD&ASR Inference Algorithm

In the inference stage, to support online speech recognition and achieve robust performance, we propose an online VAD&ASR Inference algorithm which supports ASR in a pseudo-streaming form. The online VAD&ASR Inference algorithm is shown in Algorithm 1. The inputs and variables that need to be initialized include:

- The streaming audio input: \( x = (x_1, ..., x_T) \)
- The threshold of VAD above which the current frame is classified as speech: \( \theta_{vad} \)
- The threshold of minimum speech length: \( C \)
- The threshold of minimum silence length: \( B \)
- The ASR chunk \( \Omega_t \), which is implemented as a queue of maxsize \( l \) that receives speech data, is initialized as empty queue
• The count of current frames that need to be processed, \( c \), is initialized as 0
• The count of current continuous frames that are silience, \( b \), is initialized as 0
• The current status \( S \), which denotes speaking if set to True and non-speaking if set to False, is initialized as False

### Algorithm 1 Online VAD&ASR

**Input:** \( x = (x_1, ..., x_t, ..., x_T) \), \( \theta_{vad}, C, B, \ell \)

**Initialize:** \( \Omega_t \leftarrow \emptyset, c = 0, b = 0, S = \text{FALSE} \)

**Output:** \( y = (y_1, ..., y_t, ..., y_s) \)

1: for \( t = 1, ..., T \) do
2: \( \theta_t = \text{VAD}(x_t) \)
3: \( c \leftarrow + \)
4: if \( \theta_t >= \theta_{vad} \) then
5: \( b = 0 \)
6: else
7: \( b \leftarrow + \)
8: end if
9: \( S = \text{TRUE} \) if \( c - b >= C \)
10: \( S = \text{FALSE} \) if \( b > B \)
11: if \( (c - b >= l) \) \( \land (b > B) \) \&\& \( S \) then
12: \( \text{ENQUEUE}((\Omega_t, (x_{t-l-1}, ..., x_{t-l})) \)
13: \( y_t = \text{ASR}(\Omega_t) \)
14: \( \ell \leftarrow 0 \)
15: \( c \leftarrow 0 \)
16: end if
17: end for
18: return \( y = (y_1, ..., y_t, ..., y_s) \)

During the online VAD&ASR process, the proposed system continuously outputs \( y_t \), which is the recognition result of ASR chunk \( \Omega_t \). In lines 2-8, we predict the VAD score and make count for \( c \) & \( b \) at current frame. In lines 9-10, the current status \( S \) is determined by \( c \) & \( b \); if \( c - b > C \) which means that there are more than \( C \) frames before the continuous silence frames, \( S \) is set to True. And if \( b > B \), which means that there are more than \( B \) continuous silence frames at current time, \( S \) is set to False. In lines 11-16, the middle result is computed at current time \( t \) if the following conditions are met:

I. \( c - b >= l \), which means that there are more than \( l \) frames before the continuous silence frames.

II. \( (b > B) \) \&\& \( S \), which implies the end of an utterance.

Everytime we get the ASR result from \( \Omega_t \), \( \ell \) and \( c \) are reset to 0 and 0 respectively.

### 3. Experimental Setup

#### 3.1. Training Strategy

We use a two-stage training strategy to train the model. To guarantee the performance of the primary task, i.e. ASR, we train a single task ASR model by finetuning the wav2vec 2.0 pretrained model in the first stage. In the second stage, we train our multi-task model by finetuning the ASR model from the first stage. The chunk-hopping mechanism described in Section 2.2 is used in the second training stage. To adapt to different real-time demands, the sizes of chunks are randomly set from 0.5 second to 3 seconds and the spliced chunks are all fixed to 0.5 second.

To obtain the labels of VAD, we use the silero-vad[24] toolkit to generate annotations from speech.

#### 3.2. Dataset and Configuration

The proposed system is experimented with the fairseq toolkit [25] on the HKUST Mandarin Chinese conversational telephone speech recognition (HKUST)[26] corpus and the Librispeech[27] dataset. Librispeech dataset contains 1000h of training data split into “clean-100h”, “clean-360h” and “other-500h” subsets and also contains development and test sets that are split into simple (“clean”) and harder (“other”) subsets. To reduce the experiment cost, we only train the model with the “clean-100h” part of the training data. HKUST consists of long conversations with speech and non-speech parts. To recognize the long-form audios, non-speech parts need to be removed before speech parts are sent to ASR. Therefore, HKUST dataset can be used to examine the overall effect of VAD and ASR. As for the ASR modeling units, Chinese characters are used for HKUST dataset and letters are used for Librispeech dataset.

We use publicly released pre-trained wav2vec2.0 base model, which is composed of a seven-block CNN feature extractor and a 12-layer transformer encoder. In the finetuning stage, we follow the settings described in [19], i.e. Adam optimizer, learning rate of 2e-5, total batchsize of 1600sec and a tri-stage rate scheduler where the learning rate is warmed up for the first 8000 steps, held constant for the next 32000 steps and then linearly decayed for 40000 steps. Settings are the same for both HKUST dataset and Librispeech 100h dataset.

In the inference stage, hyperparameters for VAD segmentation and ASR decoding are set by tuning on the development set. For HKUST, we randomly select 1000 utterances from the original training set as the development set. We use the beam-search decoder of [28] for ASR decoding. The LM weight and the word insertion score of a 4-gram language model (LM), which is trained on the transcript of the training set, are set to 0.46 and 0.52 respectively. The beamsize is set to 20. The threshold of VAD, \( \theta_{vad} \), is set to 0.45. The threshold of minimum speech length, \( C \), is set to 0.1 second. The threshold of minimum silence length, \( B \), is set to 0.6 second. The size of spliced chunks described in Section 2.2 is set to 0.64 second. For Librispeech, we only experiment on segmented audios and simply use the Verterbi decoder without an language model for ASR. All the experiments are performed on 4 GeForce RTX 2080 Ti GPUs.

### 4. Experimental Results

#### 4.1. VAD&ASR Multi-task Learning

In this section, we aim to investigate the effect of VAD&ASR Multi-task Learning (MTL) on each task. Firstly, to verify the effect of MTL on ASR task, on HKUST dataset we compare the proposed MTL method with the vanilla wav2vec 2.0 Single-task Learning (STL) system and a high-performance Transformer+CTC system on the ESPnet toolkit [29], and on Librispeech we only compare the proposed method with the vanilla wav2vec2.0 model. The results on HKUST dataset are shown in Table 1. Character error rate (CER) is used as the evaluation metric because CER is widely used for the Chinese ASR evaluation due to its ambiguous word boundary. The results on Librispeech dataset are shown in Table 2.

As can be seen from Table 1, the baseline wav2vec 2.0 STL system achieves a very high performance on HKUST dataset: it works better than the Transformer+CTC ASR system, where the CER is reduced from 23.5% to 22.0%. And with the aid from the proposed MTL approach, the performance further improves by 7.3% relative CER (from 22.0% to 20.4%).
Table 1: CER(%) comparison on HKUST dataset

| System                                      | CER |
|---------------------------------------------|-----|
| Transformer+CTC (speed perturb+RNNLM)       | 23.5|
| Wav2vec2.0 + 4-gram LM                     | 22.0|
| Proposed + 4-gram LM                       | 20.4|

Table 2: WER(%) comparison on Librispeech-100h dataset

| model                  | dev clean | dev other | test clean | test other |
|------------------------|-----------|-----------|------------|------------|
| Wav2vec2.0 w/o LM      | 6.12      | 13.56     | 6.07       | 13.36      |
| Proposed w/o LM        | 5.59      | 13.39     | 5.65       | 12.87      |

And as shown in Table 2, compared with the wav2vec 2.0 model trained on the clean 100 hour subset of Librispeech, the proposed method achieves WER 5.59/13.39 on dev-clean/other with a relative reduction of 8.7%/1.3% and achieves WER 5.65/12.87 on test-clean/other with a relative WER reduction of 6.9%/3.7%.

Furthermore, to explore performance of the proposed method on VAD task, we compare the proposed MTL method with the VAD system trained with the same CNN architecture in the proposed model architecture. We use three metrics to evaluate the performance of VAD: detection error rate (DetER), false alarm rate (FA) and missed detection rate (Miss). The DetER measures the fraction of time that is not attributed correctly to speech or to non-speech and is computed as:

\[
\text{DetER} = \frac{N_{\text{falsealarm}} + N_{\text{miss}}}{N_{\text{total}}} \quad (6)
\]

where \(N_{\text{falsealarm}}\) is the number of false positive speech predictions, \(N_{\text{miss}}\) is the number of false negative speech predictions and \(N_{\text{total}}\) is the total number of predictions.

As is shown in Table 3, the false alarm of the proposed MTL approach is slightly higher than the STL approach. In terms of the detection error rate and missed detection, the MTL method outperforms the STL method by 23.6% and 32.8% relative improvements respectively.

4.2. Online VAD&ASR Inference

In this section, to explore the combined effect of VAD and ASR, all experiments are conducted on unsegmented long audios from HKUST dataset. Firstly, to investigate the performance of the random chunk-hopping training strategy described in Section 3.1, we set the ASR chunk to different lengths in the proposed online VAD&ASR inference process.

Results are shown in Table 4, where \(L_{\text{asr}}\) refers to the length of the ASR chunk. Obviously, the performance gets better as \(L_{\text{asr}}\) increases just as it should be. The point is that it shows robustness to \(L_{\text{asr}}\) in some range. When we decrease \(L_{\text{asr}}\) from 5 seconds to 3 seconds, the CER only increases relatively by 1%. But when we decrease \(L_{\text{asr}}\) from 3 seconds to 0.64 second, the CER increase relatively by 9%.

Next, we compare the proposed system with the following methods:

- **Oracle**: The audio input was segmented according to the manual annotations provided by the dataset.
- **Base1**: The audio input was segmented by the GMM-based VAD system, which is implemented on the WebRTC-vad toolkit.
- **Base2**: The audio input was segmented by the domain-adversarial DNN-based VAD system[30], which is robust to domain mismatch. We use the publicly released pipeline implemented on the pyannote.audio toolkit[31].

As is shown in Table 5, Base2 outperforms Base1, which indicates the effectiveness of DNN-based VAD method. And the proposed system further outperforms Base2, where the improvement mainly comes from the decrease of substitution error. The possible reason might be that the proposed MTL method helps the model leverage linguistic information provided by ASR task. There is only a 0.25% CER gap between the proposed method and the Oracle method.

5. Conclusions

This study proposed a novel end-to-end online ASR framework that integrate VAD by multi-task learning. The CTC-based ASR and VAD are complementary to each other so that the proposed method improved the performance on both tasks. Moreover, the proposed method used simple architecture in the bottom layers of the network to train VAD task, which resulted in a lower computational cost of VAD. The whole system was trained based on the wav2vec2.0 self-supervised pre-training method, thus reduced the reliance on labeled training data. Our experimental results showed the advantages of the proposed method over other conventional methods that implement ASR after VAD segmentation. Future work includes combining more tasks into the system and improving the inference speed.

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1. https://github.com/wiseman/py-webrtcvad
6. References

[1] A. Graves, S. Fernández, F. Gomez, and J. Schmidhuber, “Connectionist temporal classification: labelling unsegmented sequence data with recurrent neural networks,” in ICML 06, 2006.

[2] A. Graves and N. Jaitly, “Towards end-to-end speech recognition with recurrent neural networks,” in ICML, 2014.

[3] A. Graves, “Sequence transduction with recurrent neural networks,” ArXiv, vol. abs/1211.3711, 2012.

[4] K. Rao, H. Sak, and R. Prabhavalkar, “Exploring architectures, data and units for streaming end-to-end speech recognition with rnn-transducer,” 2017 IEEE Automatic Speech Recognition and Understanding Workshop (ASRU), pp. 193–199, 2017.

[5] D. Bahdanau, K. Cho, and Y. Bengio, “Neural machine translation by jointly learning to align and translate,” CoRR, vol. abs/1409.0473, 2015.

[6] C. C. Chiu, T. N. Sainath, Y. Wu, R. Prabhavalkar, P. Nguyen, Z. Chen, A. Kannan, R. J. Weiss, K. Rao, and E. a. Gonna, “State-of-the-art speech recognition with sequence-to-sequence models,” in ICASSP 2018 - 2018 IEEE International Conference on Acoustics, Speech and Signal Processing (ICASSP), 2017.

[7] B. Atal and L. Rabiner, “A pattern recognition approach to voiced-unvoiced-silence classification with applications to speech recognition,” IEEE Transactions on Acoustics, Speech, and Signal Processing, vol. 24, pp. 201–212, 1976.

[8] J. Ramirez, J. M. Górriz, and J. C. Segura, “Voice activity detection, fundamentals and speech recognition system robustness,” 2007.

[9] 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, pp. 180–181, 2000.

[10] J. Junqua, B. Reaves, and B. K. Mak, “A study of endpoint detection algorithms in adverse conditions: incidence on a dtw and hmm recognizer,” in EUROSPEECH, 1991.

[11] R. Tucker, “Voice activity detection using a periodicity measure,” 1992.

[12] N. Mesgarani, M. Slaney, and S. Shamma, “Discrimination of speech from nonspeech based on multiscale spectro-temporal modulations,” IEEE Transactions on Audio, Speech, and Language Processing, vol. 14, pp. 920–930, 2006.

[13] A. Lee, K. Nakamura, R. Nisimura, H. Sato, and K. Shikano, “Noise robust real world spoken dialogue system using gmm based rejection of unintended inputs,” in INTERSPEECH, 2004.

[14] X. Zhang and J. Wu, “Deep belief networks based voice activity detection,” IEEE Transactions on Audio, Speech, and Language Processing, vol. 21, pp. 697–710, 2013.

[15] N. Ryant, M. Liberman, and J. Yuan, “Speech activity detection on youtube using deep neural networks,” in INTERSPEECH, 2013.

[16] T. Hughes and K. Mierle, “Recurrent neural networks for voice activity detection,” 2013 IEEE International Conference on Acoustics, Speech and Signal Processing, pp. 7378–7382, 2013.

[17] T. Yoshimura, T. Hayashi, K. Takeda, and S. Watanabe, “End-to-end automatic speech recognition integrated with ctc-based voice activity detection,” ICASSP 2020 - 2020 IEEE International Conference on Acoustics, Speech and Signal Processing (ICASSP), pp. 6999–7003, 2020.

[18] F. Tao and C. Busso, “End-to-end audiovisual speech recognition system with multitask learning,” IEEE Transactions on Multimedia, vol. 23, pp. 1–11, 2021.

[19] A. Baevski, H. Zhou, A. rahan Mohamed, and M. Auli, “wav2vec 2.0: A framework for self-supervised learning of speech representations,” ArXiv, vol. abs/2006.11477, 2020.

[20] P. Jusczyk, “How infants begin to extract words from speech,” Trends in Cognitive Sciences, vol. 3, pp. 323–328, 1999.