Long-Running Speech Recognizer: An End-to-End Multi-Task Learning Framework for Online ASR and VAD

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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. This paper presents a novel end-to-end (E2E), multi-task learning (MTL) framework that integrates ASR and VAD into one model. The proposed system, which we refer to as Long-Running Speech Recognizer (LR-SR), learns ASR and VAD jointly from two separate task-specific datasets in the training stage. With the assistance of VAD, the ASR performance improves as their connectionist temporal classification (CTC) loss function can leverage the VAD alignment information. In the inference stage, the LR-SR system removes non-speech parts at low computational cost and recognizes speech parts with high robustness. Experimental results on segmented speech data show that the proposed MTL framework outperforms the baseline single-task learning (STL) framework in ASR task. On unsegmented speech data, we find that the LR-SR system outperforms the baseline 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 integrate ASR and VAD into an E2E multi-task system which can be used in long-running speech recognition scenarios. In the training stage, the model is firstly pre-trained with wav2vec 2.0 [19] framework, a recently proposed 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 layers 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. To determine the loss weight of each task, instead of being tuned by hand, the model automatically weighs between the loss of each task by using the uncertainty weighting loss [21]. To support online speech recognition, we use a chunk-hopping mechanism, which enables the model to encode on segmented frame chunks one after another [22]. 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. Long-Running Speech Recognizer

In this section, we will introduce the Long-Running Speech Recognizer (LR-SR), which combines VAD with ASR through MTL technique and is pre-trained with wav2vec 2.0 framework

2.1. Architecture

As is shown in Figure 1, the LR-SR model is built on the base structure of wav2vec 2.0, which is composed of two parts: a multi-layer convolutional feature encoder and a context network which follows the Transformer architecture [23, 24]. 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, \( \tilde{C} = (c_1, ..., c_T) \).

Based on the architecture of wav2vec 2.0, we perform ASR and VAD on different layers. For VAD task, we simply add an FC layer, which takes latent representations as input and outputs class representations of speech and non-speech, on the convolutional feature encoder. For ASR task, to better utilize the alignment information learned from VAD, we propose adding an Integration Layer after the context network (Transformer). Then an FC layer is implemented to extract integrated features, \( g = (g_1, ..., g_T) \) from \( Z \) and \( \tilde{C} \) as follows:

\[
g_t = z_t + \text{ReLU}(f_g(c_t, z_t|\theta_g))
\]

where \( f(x|\theta) \) is the FNN with parameter set \( \theta \). \( c_t \) and \( z_t \) are firstly concatenated and then projected by \( f_g \). A ReLU activation function is added after \( f_g \). The Integration Layer is an optional layer, without which the FC layer for ASR can also be implemented on the top of the context network.

2.2. Chunk-hopping Mechanism

To support online speech recognition, a chunk-hopping mechanism proposed in [22] 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. To apply contextual information, 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 utterence, only a right chunk is spliced. And for the last chunk in the utterence, only a left chunk is spliced.

Figure 1: The model architecture of LR-SR.

Figure 2: Chunk hopping mechanism.

2.3. MTL with Task Uncertainty Loss

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 \( X = \{x_t \in \mathbb{R} | t = 1, ..., T \} \) is 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:

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

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

\[
L_{\text{CTC}} = \log p_{\text{CTC}}(Y|X)
\]

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

\[
L_{\text{CE}} = y \log \hat{y} + (1 - y) \log (1 - \hat{y})
\]

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. To determine the loss weight of each task, instead of being tuned by hand, a method proposed by Kendall et al. [21] is used to let the model automatically weighs between the loss of each task by learning the task observation noise parameter \( \sigma_t \), where \( t \) refers to a specific task. For LR-SR, the MTL joint loss, \( L_{\text{MTL}} \), is given as:

\[
L_{\text{MTL}} = \frac{1}{\sigma_{\text{ASR}}} L_{\text{CTC}} + \frac{1}{\sigma_{\text{VAD}}} L_{\text{CE}} + \log \sigma_{\text{ASR}} + \log \sigma_{\text{VAD}}
\]

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: \( x = (x_1, ..., x_t, ..., x_T) \)
- The threshold of VAD above which the current frame is classified as speech: \( \theta_{\text{ad}} \)
- 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 silence, \( b \), 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: \( x = (x_1, \ldots, x_t, \ldots, x_T), \theta_{\text{asr}}, C, B, l; \)

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

Output: \( y = (y_1, \ldots, y_{l-1}, y_l) \):

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

During the online VAD&ASR process, LR-SR 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. \( c - b \geq C \), 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 \( \Omega_t \), we check if \( S \) is True. In lines 11-16, the middle result is computed at current time \( t \) if the following conditions are met:

3. Experimental Setup

3.1. Training Strategy

We use a two-stage training strategy to train the LR-SR. To guarantee the performance of the primary task, i.e. ASR, we train a single task ASR model by finetuning the wav2vec 2.0 pre-trained 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.

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, 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 [28]. The results on HKUST dataset are shown in Table 3. 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.

As can be seen from Table 3, the baseline wav2vec 2.0 STL

| hyperparameters | value |
|----------------|-------|
| max tokens (batch size) | 9,600,000 |
| max update steps | 80,000 |
| optimizer | Adam |
| learning rate (lr) | 2e-05 |
| warmup steps | 8,000 |
| hold steps | 32,000 |
| decay steps | 40,000 |
| mask prob | 0.65 |
| mask channel prob | 0.5 |
| mask channel length | 64 |

Considering the difficulty in obtaining a dataset with the annotations of both ASR and VAD, we use a multi-dataset sampler, which samples from different task-specific datasets with a pre-defined probability \( p_t \), where \( t \in \{ \text{asr, vad} \} \). In practice, \( p_{\text{asr}} = 0.75 \) and \( p_{\text{vad}} = 0.25 \).

3.2. Dataset and Configuration

The LR-SR system is experimented with the fairseq toolkit [25] on the HKUST Mandarin Chinese conversational telephone speech recognition (HKUST) [26] corpus. The main reason for choosing HKUST is that it consists of long conversations with speech and non-speech parts. Therefore, VAD is an essential part before ASR to remove non-speech parts and to extract speech parts in the long audio. We use the Chinese character as the modeling unit.

We use publicly released pre-trained wav2vec2.0 base model, which is composed of a seven-block CNN feature extractor and a 24-layer transformer encoder, and follow the same experimental hyperparameters as listed in Table 1.

In the fine-tuning 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 beamsearch decoder of [27] 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 respectively. The beamsize is set to 20. The threshold of VAD, \( \theta_{\text{asr}} \), 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.

All the experiments are performed with the Tesla K80 GPU.

Table 1: Common hyperparameters in the finetuning stage
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 6.8% relative CER (from 22.0% to 20.5%). If we remove the Integration Layer described in Section 2.1, the CER drops to 21.0%, which indicates the effectiveness of the Integration Layer.

Furthermore, to explore the effect of MTL 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:

\[
\text{DetER} = \frac{N_{\text{false alarm}} + N_{\text{miss}}}{N_{\text{total}}}
\]

where \(N_{\text{false alarm}}\) 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. By removing the Intergration Layer, the detection error rate increases from 17.8% to 18.2% and the missed detection increases from 12.5% to 13.0%, which proves the positive effect of the Intergration Layer on VAD.

### 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. 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 10 seconds to 3 seconds, the CER only increases relatively by 1.9%. But when we decrease \(L_{\text{asr}}\) from 3 seconds to 0.64 second, the CER increase relatively by 8.5%, where the increased error mainly comes from the deletion error and the substitution error.

Next, we compare the proposed LR-SR 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, which is robust to domain mismatch. We use the publicly released pipeline implemented on the pyannote.audio toolkit.

As is shown in Table 5, **Base2** outperforms **Base1**, which indicates the effectiveness of DNN-based VAD method. And the proposed LR-SR 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 LR-SR leverage linguistic information provided by ASR task. There is only a 0.3% CER gap between the LR-SR and the **Oracle** method.

### 5. Conclusions

This study proposed a novel end-to-end online ASR framework to integrate ASR and 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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**Table 2: CER(%) comparison on HKUST dataset**

| System | CER (%) |
|--------|---------|
| Transformer+CTC (speed perturb+RNNLM) | 23.5 |
| Wav2vec2.0 (STL) + 4-gram LM | 22.0 |
| LR-SR (MTL) + 4-gram LM | 20.5 |

**Table 3: VAD performance comparison on HKUST dataset**

| System | DetER (%) | FA (%) | Miss (%) |
|--------|-----------|--------|----------|
| STL    | 18.8      | 5.3    | 12.5     |
| MTL w/o Integration Layer | 18.2 | 5.2 | 13.0 |

**Table 4: Effect of ASR chunk size**

| \(L_{\text{asr}}(s)\) | CER (%) | Sub (%) | Del (%) | Ins (%) |
|------------------------|---------|---------|---------|---------|
| 4.06                  | 14.3    | 6.8     | 1.9     |
| 2                     | 14.1    | 6.6     | 1.9     |
| 2                     | 13.7    | 6.0     | 2.0     |
| 2                     | 13.5    | 5.7     | 2.0     |
| 2                     | 13.3    | 5.6     | 1.9     |
| 2                     | 13.3    | 5.7     | 1.8     |

**Table 5: Performance comparison on HKUST long audio**

| Method | CER (%) | Sub (%) | Del (%) | Ins (%) |
|--------|---------|---------|---------|---------|
| Oracle | 20.5    | 13.5    | 5.2     | 1.8     |
| Base1  | 22.6    | 14.3    | 6.6     | 1.7     |
| Base2  | 22.0    | 14.2    | 6.0     | 1.8     |
| LR-SR  | 20.8    | 13.3    | 5.7     | 1.8     |

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