CTA-RNN: Channel and Temporal-wise Attention RNN Leveraging Pre-trained ASR Embeddings for Speech Emotion Recognition

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Abstract

Previous research has looked into ways to improve speech emotion recognition (SER) by utilizing both acoustic and linguistic cues of speech. However, the potential association between state-of-the-art ASR models and the SER task has yet to be investigated. In this paper, we propose a novel channel and temporal-wise attention RNN (CTA-RNN) architecture based on the intermediate representations of pre-trained ASR models. Specifically, the embeddings of a large-scale pre-trained end-to-end ASR encoder contain both acoustic and linguistic information, as well as the ability to generalize to different speakers, making them well suited for downstream SER task. To further exploit the embeddings from different layers of the ASR encoder, we propose a novel CTA-RNN architecture to capture the emotional salient parts of embeddings in both the channel and temporal directions. We evaluate our approach on two popular benchmark datasets, IEMOCAP and MSP-IMPROV, using both within-corpus and cross-corpus settings. Experimental results show that our proposed method can achieve excellent performance in terms of accuracy and robustness.

Index Terms: speech emotion recognition, transfer learning, representation learning, information fusion

1. Introduction

Speech emotion recognition (SER), which aims to recognize the emotional characteristics of human speech and classify the utterance into one of a pre-defined set of emotion categories, has become a hot topic in the speech research field [1]. SER plays an important role in a variety of applications, including intelligent customer service and personal voice assistants. To make human–machine interaction more natural and harmonic, it is vital for machines to capture the emotional changes of humans and respond in a proper way [2].

In the era of deep learning, deep neural networks, such as convolutional neural networks (CNNs) [3], recurrent neural networks (RNNs) [4], and, more recently, self-attention mechanisms [5], have been widely used for SER. However, existing SER models are still far from human-level performance. While low-level acoustic features, such as prosody, pitch, or tensity, can influence the preliminary perception of emotion, high-level semantics of speech aid in further confirming the speaker’s real emotional state. To take full advantage of these aspects, researchers have proposed utilizing audio and text data simultaneously to recognize emotions from speech. Specifically, the text modality could benefit from the large-scale pre-trained models (e.g., GloVe [6] or BERT [7]) from the NLP area, resulting in more robust and accurate models. For example, Yoon et al. [8] combined the high-level representations via concatenation and set up a baseline for bi-modal SER. Pan et al. [9] utilized a multi-modal attention sub-network to model inter-modality interactions before late fusion. Nevertheless, the majority of existing works assumed that the human transcriptions of speech were available from the start. In practice, the available transcriptions are derived from the output of an automatic speech recognition (ASR) module. Hence, the computational complexity of the ASR module and potential errors in the transcriptions may represent a bottleneck in a deployment pipeline.

To solve this problem, several studies have explored how to incorporate linguistic information into the high-level representations of speech without explicit text input. For example, Cai et al. [10] proposed a multi-task learning framework that performed ASR and SER at the same time to encode the linguistic information into the intermediate representations. Feng et al. [11] used the output of an ASR decoder as an alternative to the text features and combined it along with the conventional SER module. However, most previous works only used rudimentary ASR models as an auxiliary part of their frameworks and failed to fully develop the capabilities of ASR models. To date, there has been little research into the potential correlation between state-of-the-art ASR models and the SER task.

In this paper, we look into the viability of exploiting a large-scale pre-trained end-to-end ASR model, specifically, the Conformer model, for downstream SER task and compare the impact of ASR performance on SER. Further, we propose a novel Channel and Temporal-wise Attention RNN (CTA-RNN) architecture to leverage the pattern discrepancy of embeddings from diverse blocks of the Conformer encoder. Experimental results show that our proposed approach can achieve state-of-the-art performance on IEMOCAP and MSP-IMPROV. Moreover, the cross-corpus evaluations demonstrate a significant performance gain over the existing works.

2. Related work

2.1. Conformer encoder

Recently, the Conformer model [12] has been proposed for end-to-end ASR and achieved state-of-the-art performance. As shown in Figure 1, the Conformer encoder consists of N stacked Conformer blocks, where each block contains four modules arranged in a sandwich-like way: the Feed-Forward module (FFN), the Multi-Head Self-Attention module (MHSAs), the Convolution module (Conv), and another Feed-Forward module. This architecture combines the advantages of Transformer models [13] and CNNs organically, being capable of capturing the long-term context and the local context dependencies.

\hspace{1cm}This work is partially supported by the National Key Research and Development Program of China (No. 2021YFC3320103).
2.2. RNN with multi-head self-attention

The architecture, RNN with multi-head self-attention (RNN-MHSA), has been widely used as a strong baseline in the task of SER [9][11][14]. RNN is a prominent tool in modeling sequential data and works well at storing and accessing context information over a sequence. An RNN module is first applied on the spectrogram of speech to derive the state of hidden units \( H \in \mathbb{R}^{n \times d_h} \), where \( n \) is variable depending on the input length. The self-attention module can capture the emotional salient parts of \( H \) in the temporal direction and output a fixed-length vector. Further, the multi-head structure can focus on different subspaces of the input representations at the same time. The output vectors from different heads are concatenated to construct a final vector before sent into the emotion classifier.

3. Methodology

3.1. ASR embeddings

As demonstrated in Figure 1(a), a conventional bi-modal SER pipeline requires a well-trained ASR model to generate speech transcriptions first. The high-level representations of audio and text are then extracted, before being sent into a carefully built fusion module. Differently, we propose using the ASR encoder’s embeddings directly, as depicted in Figure 1(b). The motivation stems from two aspects. On the one hand, the state-of-the-art end-to-end ASR models [15][16] integrate the acoustic model and language model into a single framework. Intuitively, the intermediate representations of a well-trained ASR model are capable of encoding both acoustic and latent linguistic information. On the other hand, the available datasets for ASR pre-training are large enough to ensure the robustness of ASR embeddings across different speakers, which may relieve the problem of present SER models’ poor generality [17][18].

Considering that fine-tuning the ASR models with the SER datasets can distort the pre-trained features and underperform them out-of-distribution, we fix the weights of a pre-trained ASR encoder and use it as a front-end feature extractor. In this work, we focus on the encoder of the state-of-the-art Conformer models pre-trained on large-scale ASR datasets. Given an input spectrogram \( A = [a_1, a_2, ..., a_n] \in \mathbb{R}^{n \times d_a} \), the ASR embeddings of the \( i \)-th Conformer block can be denoted as \( E^v(i) = [e_1, e_2, ..., e_m] \in \mathbb{R}^{m \times d_v} \). Hence, the problem can be formulated as how to map \( E^v(i) \) into a fixed-length vector that is discriminative for SER, where \( i \in \{1, 2, ..., N\} \).

3.2. CTA-RNN architecture

Previous research has shown that combining the embeddings from multiple layers of a pre-trained model can result in a more accurate and robust downstream model, owing to the fact that the pattern learned by each layer differs [19][20]. A widely used strategy is to start with a trainable fully connected layer, and then utilize the weighted average of embeddings from different layers for the subsequent models. Hence, the learnt weights can be regarded as the empirical importance of each layer. However, the best weight distribution for distinct utterances may differ.

Inspired by the advantage of RNN-MHSA, we propose an RNN-based architecture for attending to the emotional salient parts of \( E \in \mathbb{R}^{N \times m \times d_e} \) in both the channel and temporal directions, dubbed CTA-RNN. Given the embeddings \( E \in \mathbb{R}^{N \times m \times d_e} \), we first applied \( N \) independent RNN modules to model the sequential data of each channel, the combined state of hidden units is denoted as \( H \in \mathbb{R}^{N \times m \times d_h} \). An intuitive way to achieve both the channel and temporal-wise attention is to reshape the features into \( H' \in \mathbb{R}^{(N \times m) \times d_e} \) and applied a global self-attention. However, the computation complexity will grow exponentially as \( N \) increases.

To address this issue, we propose splitting the attention into two directions. We first applied channel and temporal-wise mean pooling to obtain two anchor features, denoted as \( \overline{H}_c \in \mathbb{R}^{m \times d_h} \) and \( H_t \in \mathbb{R}^{N \times d_h} \), respectively. Afterwards, the MHSA modules are utilized to calculate the attention weights in the two directions. Mathematically, the attention vector of \( j \)-th head can be computed as:

\[
\alpha_{c,j} = \text{SoftMax} \left( \frac{W^Q_{c,j}(W^K_{c,j}H'_t)^T}{\sqrt{d_k}} \right) \tag{1}
\]

\[
\alpha_{t,j} = \text{SoftMax} \left( \frac{W^Q_{t,j}(W^K_{t,j}H'_c)^T}{\sqrt{d_k}} \right) \tag{2}
\]

where \( W^K_{c,j}, W^K_{t,j} \in \mathbb{R}^{1 \times d_k} \) and \( W^Q_{c,j}, W^Q_{t,j} \in \mathbb{R}^{d_v \times d_k} \) are learnable parameters, while \( \alpha_{c,j} \in \mathbb{R}^{1 \times N} \) and \( \alpha_{t,j} \in \mathbb{R}^{1 \times m} \) are the scaled attention probability vectors. Different from the conventional MHSA, we propose applying these attention vectors on the original \( H \in \mathbb{R}^{N \times m \times d_h} \). Specifically, the output \( v_j \) of the \( j \)-th head can be calculated as:

\[
M_j = \alpha_{c,j}^T \alpha_{t,j} \tag{3}
\]

\[
v_j = \left( W^j_{v} H' \right) \odot M_j \tag{4}
\]
where $W_{j}^{V} \in \mathbb{R}^{d_{\alpha} \times d_{h}}$ is trainable. $W_{j}^{V}H^{T} \in \mathbb{R}^{d_{\alpha} \times m \times N}$ represents the transformed ‘value feature’, while $M_{j} \in \mathbb{R}^{m \times N}$ is the attention matrix considering both directions. We calculate the Hadamard product (denoted as $\odot$) of $M_{j}$ and the $d_{h}$ sub-matrices of $W_{j}^{V}H^{T}$, respectively, and sum up each weighted matrices to derive the output $v_{t} \in \mathbb{R}^{d_{\alpha}}$. The final vector $v_{t} \in \mathbb{R}^{d_{\alpha} \times d_{h}}$ is obtained by concatenating the outputs from $n_{a}$ heads.

4. Experiments

4.1. Datasets

We use two popular benchmark datasets in English to evaluate the proposed approach.

**IEMOCAP**: The IEMOCAP dataset [21] contains approximately 12 hours of audio-visual data from 10 actors. The dataset contains 5 sessions and each session is performed by one female and male actor in scripted and improvised scenarios, and the ground truth transcripts of speech are provided. To be consistent with the previous works, we merge the utterances labeled ‘excited’ into the ‘happy’ class, and the distribution of utterances used in the experiments is [happy: 1636, sad: 1084, angry: 1103, neutral: 1708].

**MSP-IMPROV**: The MSP-IMPROV dataset [22] contains 6 sessions of dyadic interactions between pairs of male-female actors. 15 target sentences are used to collect the recordings. For each target sentence, 4 emotional scenarios were created to elicit happy, angry, sad and neutral responses. To make the emotion natural, two actors interacted with each other in improvised scenarios, and one person uttered the target sentences. The distribution of utterances used in the experiments is {happy: 2644, sad: 885, angry: 792, neutral: 3477}. Compared with IEMOCAP, MSP-IMPROV contains more natural and spontaneous speech. Moreover, the emotion distribution of MSP-IMPROV is more unbalanced, making it a more challenging SER dataset.

4.2. Experimental setup

4.2.1. Implementation details

We first resampled the speech signal at 16 kHz and extracted the 80-dimensional Log Mel-scale Filter Bank (LMFB) with 25 ms frame size and 10 ms frame shift. The LMFB was used as the input to a pre-trained Conformer model to derive the embeddings of the encoder. In this work, we refer to the WeNet toolkit [23] for the ASR training recipe of Conformer models. Specifically, the Conformer encoder consisted of 12 blocks and the embeddings were 512-dimensional. In order to study the influence of ASR performance on downstream SER task, we compare the Conformer models pre-trained on a 960-hour subset of Librispeech [24] and a 10,000-hour subset of Gigaspeech [25]. For a fair comparison, we also performed ASRs on both SER datasets using the Conformer models to obtain speech transcriptions, which were further transformed into 1024-dimensional text features (denoted as $T$) via a pre-trained BERT model. Table 1 displays the evaluation results of ASR performance.

The hyper-parameters for training kept the same in all experiments. The basic RNN-MHSA model consisted of a 2-layer Bi-GRU with 256 hidden units in each layer and a 8-head self-attention module with 64 nodes in each head. The dropout of each Bi-GRU layer is 0.3. The batch size was set to 32, and the max training epochs were set to 50. An Adam optimizer with an initial learning rate of $10^{-3}$ was applied to optimize the model parameters, and the learning rate was halved if the validation loss did not decrease for a consecutive 10 epochs.

| ASR-PT   | IEMOCAP | MSP-IMPROV |
|----------|---------|------------|
|          | WER(%)  | CER(%)     |
|          | WER(%)  | CER(%)     |
| Librispeech | 31.88   | 22.28      |
| Gigaspeech | 16.43   | 12.90      | 18.68      | 13.85      |

4.2.2. Baseline models

We denote the pre-processed sequential features used in the following experiments as $A \in \mathbb{R}^{n \times 80}$, $T \in \mathbb{R}^{w \times 1024}$, and $E^{(G)} \in \mathbb{R}^{m \times 512}$.

**RNN**: It represents the baseline approach that directly uses $A$, $T$ or $E^{(G)}$ as the input to an RNN-MHSA model.

**WF-RNN**: A trainable fully connected layer is first applied to compute the weighted average of embeddings from different blocks, dubbed weighted fusion (WF). The result $E'$ will be sent into an RNN-MHSA model.

**EF-RNN**: The ASR embeddings from different blocks are first stacked in the dimensional direction to construct $E' \in \mathbb{R}^{m \times 6144}$, dubbed early fusion (EF). The result $E'$ will be sent into an RNN-MHSA model.

**LF-RNN**: Several independent RNN-MHSA models are deployed to convert each sequential data into a fixed-length vector, respectively, dubbed late fusion (LF). The vectors are concatenated before being sent into an RNN-MHSA model. This approach also proves to be effective in conventional bi-modal SER with the ability to handle time-asynchronous data streams.

4.2.3. Evaluation settings

To evaluate the generalization of the models, we performed both within-corpus (denoted as IEM and MSP) and cross-corpus (denoted as IEM2MSP and MSP2IEM) experiments. For within-corpus SER, we applied cross-validation (CV) to avoid the impact of limited data. Take IEMOCAP for example, a 10-fold leave-one-speaker-out CV was conducted, i.e., 4 sessions from 8 speakers were used for training, while utterances from the two speakers in the left session were used for validating and testing, respectively. Similarly, a 12-fold leave-one-speaker-out CV was conducted on MSP-IMPROV. While for cross-corpus SER, we directly evaluated the best models trained from the within-corpus experiments on the other dataset. For instance, we used all the data from MSP-IMPROV to evaluate the best models trained on IEMOCAP and averaged the results, and vice versa. Since the two datasets are unbalanced, we utilize the officially recommended metric, named unweighted average recall (UAR). UAR is insensitive to the impact of class imbalance and averages the sum of each class recall by the number of classes.

4.3. Experimental results and discussion

4.3.1. Feasibility analysis of ASR embeddings

We first compare the performance of three types of models using different features as input: (1) $E^{(G)}$ models: RNN models using $E^{(G)}$ as input; (2) $A$ models: RNN models using $A$ as input; (3) $A + T$ models: LF-RNN models using both $A$ and $T$ as inputs. In this subsection, we will focus on the $E^{(G)}$ models where $i \in \{2, 4, 6, 8, 10, 12\}$. As demonstrated in Figure 2, the $E^{(G)}$ models (plotted in solid lines) can consistently outperform the $A$ models (plotted at block 0). When the block number $i$ in-
To further investigate the pattern discrepancy of different blocks, we performed experiments on $A + E^{(1)}$ and $T + E^{(1)}$ models, constructed in a similar way as $A + T$ models. Three representative $E^{(i)}$ models were selected for comparison. The experimental results are reported in Table 2. Compared with the $E^{(1)}$ baseline models, integrating $T$ features can further boost the performance, whereas incorporating $A$ features can achieve little performance gain, indicating that the majority of acoustic emotional cues have been preserved in $E^{(1)}$. Another finding is that the $A + E^{(i)}$ models can achieve better results than the $T + E^{(i)}$ models, which is in opposite to the cases of $E^{(1)}$ models and $A + E^{(1)}$ models. One probable explanation is that the ASR embeddings at the top of encoder can learn more abstract linguistic information than those at the bottom of encoder, whereas low-level acoustic patterns can be partially lost at the top of encoder. As a result, the ASR embeddings at the middle blocks can be regarded as a compromise between acoustic and linguistic information, providing a more accurate and robust representation for downstream SER.

Table 3: Performance comparison of our proposed CTA-RNN and the baseline models. State-of-the-art results of previous approaches are also presented for reference.

| Method                  | Within-corpus UAR(%) | Cross-corpus UAR(%) |
|-------------------------|----------------------|---------------------|
|                          | IEM                  | MSP                |
| IEM Baseline            |                      |                    |
| Ahn et al. [27]         | 73.1                 | 54.0               |
| Abdel et al. [26]       | 69.7                 | -                  |
| Yoon et al. [8]*        | 73.1                 | 54.0               |
| Feng et al. [11]        | 69.7                 | -                  |
| Latif et al. [18]       | 64.1                 | 56.2               |
| Latif et al. [18]       | 64.1                 | 56.2               |
| WF-RNN                  | 72.8                 | 61.1               |
| EF-RNN                  | 74.4                 | 61.9               |
| LF-RNN                  | 75.3                 | 62.8               |
| CTA w/o RNN             | 75.6                 | 62.4               |
| CTA-RNN                 | 76.1                 | 63.5               |

* indicates results of reproduction with the experimental setup in this paper.

Figure 2: Within-corpus and cross-corpus experimental results using the Conformer models pre-trained on Librispeech (left) and Gigaspeech (right). Dashed lines represent the baseline models for bi-modal SER. Solid lines represent the models based on ASR embeddings from different blocks, where block 0 represents the original LMFB.

4.3.2. Fusion of ASR embeddings

In Table 3, we present the experimental results of different fusion approaches to take full advantage of $E^{(i)}$, where $i \in \{1, 2, \ldots, 12\}$. Comparing the baseline models, we find that late fusion (LF) performs better in within-corpus experiments, whereas early fusion (EF) performs better in cross-corpus evaluation. Overall, our proposed CTA-RNN models demonstrate the best performance in all experimental settings. We also perform experiments that applied CTA directly on the embeddings without RNN modules. A slight performance degradation can be observed as a result of this change. In return, the overall computation complexity and training time can be lowered by a large margin. Compared with existing state-of-the-art approaches [8][11][18][26][27], our proposed CTA-RNN architecture can significantly improve the performance of SER in both within-corpus and cross-corpus experiments. Differently, the unlabeled target datasets were not available in advance for the cross-corpus experiments described in this paper, making it a more challenging setup. The excellent robustness of our approach mainly benefits from the large-scale ASR datasets for pre-training.

5. Conclusions

In this paper, we investigate the viability of leveraging the embeddings of a large-scale pre-trained Conformer encoder for downstream SER. Empirically, the embeddings from the middle blocks of a well pre-trained ASR encoder may contain adequate acoustic and linguistic information, making them more suited for SER. Additionally, improving the ASR performance of pre-trained models can benefit for downstream SER. Further, we propose a CTA-RNN architecture to effectively fuse the ASR embeddings from different blocks. The experimental results show that our proposed methodology can achieve state-of-the-art performance on IEMOCAP and MSP-IMPROV without explicit text as input. Moreover, the cross-corpus evaluations demonstrate the robustness of large-scale pre-trained ASR embeddings across different speakers and domains. In future work, we intend to explore the correlation of emotional speech in several languages and expand on our work to multi-lingual SER.
6. References

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