Key-Sparse Transformer with Cascaded Cross-Attention Block for Multimodal Speech Emotion Recognition

Weidong Chen, Xiaofeng Xing, Xiangmin Xu, Jichen Yang

1School of Electronic and Information Engineering, South China University of Technology, China

eewdchen@mail.scut.edu.cn, xfxing@scut.edu.cn, xmxu@scut.edu.cn, nisonyoung@gmail.com

Abstract

Speech emotion recognition is a challenging and important research topic that plays a critical role in human-computer interaction. Multimodal inputs can improve the performance as more emotional information is used for recognition. However, existing studies learnt all the information in the sample while only a small portion of it is about emotion. Moreover, under the multimodal framework, the interaction between different modalities is shallow and insufficient. In this paper, a key-sparse Transformer is proposed for efficient SER by only focusing on emotion related information. Furthermore, a cascaded cross-attention block, which is specially designed for multimodal framework, is introduced to achieve deep interaction between different modalities. The proposed method is evaluated by IEMOCAP corpus and the experimental results show that the proposed method gives better performance than the state-of-the-art approaches.

Index Terms: speech emotion recognition, sparse network, modality interaction

1. Introduction

In recent years, speech emotion recognition (SER) is fast becoming a key instrument in human-computer interaction (HCI) [1,2]. Whether the system can accurately capturing the user’s emotions or not deeply affects the user’s experience. SER also sheds new light on autism and the elderly care and so on, which are collectively referred to healthcare [3]. For example, the people who suffer from severe speech and language disorder have difficulty expressing their emotions. An emotion recognition system can help to treat the patients and improve their emotional communication skills. Speech is multimodal as it contains text information by its nature [5]. Some studies only consider the single modality like audio or text and can not make the best use of it. Latest researches have also proved that multimodal methods outperform the single modal methods while the former take more emotional information when recognizing [6,8]. In this regard, we use both audio and text for SER in this paper.

Multimodal SER has been a hot research topic for decades. For example, Krishna et al. [8] used raw audio waveform as audio features and GloVe word embedding as text features for multimodal learning. In the same way, Lian et al. [10] used openSMILE toolkit to extract acoustic features, including energy, spectral, MFCCs and their statistics (such as mean, root quadratic mean, variance) and utilized ELMo word embeddings as lexical features for emotion classification.

Pre-trained Self Supervised Learning (SSL) has made great success in many fields such as Natural Language Processing (NLP) [11,12,13], computer vision [14,15,16] and speech recognition [17,18,19]. Meanwhile, recent works that used pre-trained SSL model have obtained promising results in SER [20,21,22]. Benefited from SSL technique, wav2vec [18] is the most commonly used pre-trained model in speech community, which can solve multiple downstream tasks successfully by fine-tuning with a few task-specific data. BERT [11] and its successors [12,13] are dedicated to extracting the universal representation of word. Thus, in this paper, pre-trained SSL models wav2vec and RoBERTa [12] are used to extract audio and text embeddings, respectively.

Inspired by the attention mechanism, Transformer [23], which is outstanding in modeling long sequence, was proposed and has achieved great success in NLP. Ju et al. [24] designed a Transformer based discriminative decoding module for multi-label emotion detection. In addition, Siriwardhana et al. [20] presented a Transformer block to extract appropriate features and achieved better performance. Powered by the Transformer, several Transformer based architectures have been introduced for SER. Tarantino et al. [25] used global windowing system in Transformer to capture deep relationships within the utterance. Moreover, Huang et al. [20] used Transformer to fuse different modalities for emotion recognition.

However, few works have paid attention to that not all the information in audio or text is related to emotion. For example, considering a text “Okay, look it’s a beautiful day. Why are we arguing?” in IEMOCAP corpus [27], the attention weights are shown in Figure 1. Words “beautiful” and “arguing” contain the majority of emotional information in this sentence but the attention mechanism in vanilla Transformer takes note of all the words. However, the words that are not related to emotion such as “it”, “a” and “look”, are unnecessary and become noises. To address this issue, we propose a novel method, named key-sparse Transformer (KS-Transformer), to judge the importance of each word or speech frame and help the model focus on the emotion related information better. In addition, since the emotional information between different modalities is often complementary [8], we design a cascaded cross-attention block (CCAB) to fuse audio and text with high efficiency. Moreover, recent studies in multimodal SER showed that interacting information between audio and text only once is shallow and insufficient [20,23]. Therefore, we use a special module, which consists of several CCABs, to learn interactive information multiple times and implement deep interaction.

The contributions of this paper can be summarized as follows:
• We propose KS-Transformer to judge the importance of each speech frame or word that helps the model focus on the emotion related information better.
• We design CCAB to fuse different modalities and learn interactive information multiple times instead of once. To the best of our knowledge, this is the first work that considers multiple interactions for SER.
• We evaluate the proposed method on the public benchmark IEMOCAP corpus and demonstrate that it achieves better results than the existing state-of-the-art multimodal approaches.

2. Proposed Method

The proposed model, as shown in Figure 2, mainly consists of three modules. In which, feature extraction module is used to learn the input feature, modality interaction module is used for learning interactive information and deep fusion module aims to further combine the information from audio and text. In addition, average pooling, concatenation and classifier are applied to predict the emotions. The dimension of the text embedding is 1024 while that of audio embedding is 512. More details will be introduced in the following subsections.

Figure 2: Overview structure of the proposed model.

2.1. Vanilla Transformer

2.1.1. Transformer structure

Vanilla Transformer consists of encoder and decoder originally. In this paper, we use Transformer to represent the encoder part, since it is the one needed for the implementation of our proposed architecture. The inputs of Transformer are divided into \( Q, K \) and \( V \), which consist of Query, Key and Value vectors, respectively. Same as the original paper [23], we use sine and cosine functions of different frequencies as positional encoding. Position-wise feed-forward network with a ReLU activation [31] is utilized for providing nonlinear transformation. Dropout [31] and LayerNorm [32] are applied before and after the skip connection, respectively. Multi-head attention mechanism is the core of Transformer, which will be described next.

2.1.2. Multi-head attention mechanism

Attention mechanism is fundamental to Transformer, whose main idea is to find the most relevant part in \( V \) for each Query vector by multiplying \( Q \) and \( K \) and produce a weight matrix \( W \). It is depicted in Equation (1)

\[
W = \text{softmax}(\frac{QK^T}{\sqrt{d_Q}})
\]

where \( d_Q \) is the dimension of the Query vector.

Multiply \( W \) and \( V \) to generate the attention output \( \text{attn} \). The computation is shown in Equation (2). Each vector in \( \text{attn} \) is the weighted sum of Value vectors in \( V \) with different attention weights.

\[
\text{attn} = W \times V
\]

For multi-head attention, we combine the attention outputs from all the heads using concatenation and feed them into a linear projection layer. Assuming \( \text{attn}_i \) is the attention output from \( i^{th} \) head and the number of head is \( M \), the multi-head attention mechanism is defined as follow:

\[
A = \text{concat}(\text{attn}_1, \text{attn}_2, \text{attn}_3...\text{attn}_M)W_0
\]

2.2. Key-Sparse Transformer

For emotion recognition task, we can only focus on the words that contain emotional information and the others can be seen as noises which are no need to pay attention to. Same as audio modality where we focus on a short duration in an utterance is enough and more efficient. The question is how to find the emotional information automatically. Assume the number of Query vectors in \( Q \) is \( i \) while that of Key vectors in \( K \) is \( j \), the key-sparse attention mechanism is illustrated in Figure 3. It should be noted that \( K \) and \( V \) are always the same in Transformer.

Figure 3: The key-sparse attention in KS-Transformer. In which, softmax and summation are performed on each row and column, respectively. In addition, \( \odot \) and \( \otimes \) represent position-wise multiplication and matrix multiplication, respectively.

Key-sparse attention mechanism, which is used in KS-Transformer, is capable of judging the importance of each speech frame or word. As shown in Figure 4 the weight matrix \( W \) is obtained by multiplying \( Q \) and \( K \), and each row in \( W \) are the weights of Value vectors in \( V \). As a Value vector represents a frame in audio or a word in text, we add up all the weights of the same Value vector and the summation is used as a discriminator for the importance of the speech frame or word in the sample. We select \( k \) Value vectors with top-\( k \) largest summation and keep their attention weights in weight matrix unchanged while the others are reset to zero. This operation makes
the weight matrix from dense to sparse and reduces the redundancy, that’s why we call the Transformer as KS-Transformer. The top-k mask is calculated by Equation 4:

\[ M_t = \begin{cases} 
0 & \text{if } s_k < \text{threshold} \\
1 & \text{if } s_k \geq \text{threshold} 
\end{cases} \tag{4} \]

where threshold is the \( k \)-th largest summation and \( z \in [1, j] \).

### 2.3. Feature extraction module

The feature extraction module is used to learn the input features, which are extracted from pre-trained SSL models, aims to obtain suitable features for SER task. For modeling rich contexts, this module usually consists of a stack of vanilla Transformers, wherein the later Transformer takes the output of the former Transformer as input. \( Q, K \) and \( V \) inputs here are the same, which is known as self-attention [23].

### 2.4. Modality interaction module

The details of CCAB and modality interaction module are shown in Figure 4. CCAB is a cascade of two KS-Transformers, in which, the first KS-Transformer creates \( Q \) from modality \( A \) and \( K, V \) from modality \( B \). With this special input method, the key-sparse attention mechanism will find out the most relevant part in \( B \) for \( A \) and produce an output which has combined \( A \) with \( B \) information. Since the emotional information between different modalities is often complementary, neither \( A \) nor \( B \) can represent the accurate emotion. Therefore, the second KS-Transformer takes the fused features as input and considers the information from both audio and text when applying key-sparse self-attention. Benefited from CCAB, \( A \) and \( B \) are fused more comprehensively and accurately.

![Figure 4: The details of CCAB (left) and modality interaction module (right).](image)

As shown in the right part of Figure 4, modality interaction module consists of a stack of CCABs, wherein the later CCAB takes the output of the former CCAB as \( Q \) input while \( K \) and \( V \) are always from modality \( B \). That the information from \( B \) goes through one CCAB is regarded as one interaction because the information from \( B \) had flowed into \( A \) by the key-sparse attention mechanism. More than one CCAB are applied for multiple times interactions. A skip connection is utilized for the features’ stability.

### 2.5. Deep fusion module

Most researches took the fused features to predict emotions after the interaction [21, 33, 34, 35]. However, we argue that the fused features maybe not the best and can be deep fused to improve the performance. Since the outputs of this module are used for emotion classification, we apply KS-Transformer rather than vanilla Transformer to focus on the emotional information better. As shown in Figure 5, this module consists of several KS-Transformers, in which, they take the fused features as input and utilize key-sparse attention to enhance the interaction between audio and text and implement deep fusion.

![Figure 5: The details of deep fusion module](image)

### 3. Experiments

#### 3.1. Database introduction

IEMOCAP corpus is used to evaluate the proposed method. It contains five sessions, every of which has one male and one female speaker, respectively. To stay consistent with the previous works [9, 28, 29], we select the most commonly used four emotion categories of Angry (1103), Neutral (1708), Happy (& Excited) (1636) and Sad (1084). We conduct 5-fold cross-validation and repeat 10 times with varied weight initializations. The final accuracy is the average of all test sessions.

#### 3.2. Experimental setup

In order to make the embeddings in same modality have the same length, cropping or padding operation is used. As a result, the length of audio and text embeddings are fixed as 460 and 20, respectively. To learn the features, we use five vanilla Transformers in feature extraction module and two KS-Transformers in deep fusion module. The number of CCABs used in modality interaction module will be discussed later. Eight attention heads are used in multi-head attention mechanism. Adam optimizer [36] with learning rate of \( 5 \times 10^{-4} \) and 50% decay in every 30 epochs is applied to optimize the model. Dropout with \( p = 0.5 \) is utilized to alleviate over-fitting. 50% attention weights are forced to zero in each KS-Transformer.

#### 3.3. Experimental Results and analysis

##### 3.3.1. Benefits of multimodal

We only use audio information to investigate the performance of uni-modal method and compare its confusion matrix with our proposed multimodal approach in Figure 6. We can observe that the angry emotion, which is easily expressed in audio, has highest recall rate in uni-modal method, while the recall rates for
neutral and happy are very low. Meanwhile, it should be noted that the uni-modal modal, there is a problem of prediction bias for the angry class. These problems are alleviated by utilizing text information together as seen from Figure 6(b). This result demonstrates the ambiguity in audio modality and confirms the benefit of combining the complementary information from text.

Figure 6: Normalised confusion matrices of single modal method and the proposed multimodal method.

3.3.2. Key-sparse attention analysis

To demonstrate the effectiveness of the key-sparse attention, we compare the attention weights in vanilla Transformer and KS-Transformer by visualization. As shown in Figure 7, the vanilla Transformer takes note of the noisy words and trends to overfitting. However, the KS-Transformer makes the connections from dense to sparse, which is able to ignore most of the noises and focus on the emotional information better.

Figure 7: Visualization of the attention weights.

3.3.3. The role of Modality interaction module playing

Here, we will investigate the role of modality interaction module (MIM) playing from the experimental results. To do so, we change the number of CCABs used from zero to three, where zero means that the whole module is removed, and the results are shown in Table 1. Weighted accuracy (WA) and unweighted accuracy (UA) are used as criteria.

From Table 1 we show that the interaction is insufficient when one CCAB is applied. Meanwhile, we observe that the WA and UA can be improved when the number of CCABs increases from one to three and the best results can be obtained when the number is three, which demonstrates the necessity of multiple interactions and the effectiveness of this module. Next, in the same way, we will investigate the roles of feature extraction module (FEM) and deep fusion module (DFM) playing.

Table 1: Performances of different number of CCABs in modality interaction module on IEMOCAP.

| Amount | WA  | UA  |
|--------|-----|-----|
| 0      | 0.726 | 0.734 |
| 1      | 0.724 | 0.735 |
| 2      | 0.731 | 0.740 |
| 3      | 0.743 | 0.753 |

3.3.4. The roles of FEM and DFM playing

To investigate the roles of FEM and DFM playing, we further perform an ablation experiments on them and the corresponding results are reported in Table 2.

From Table 2 it can be seen that the absence of FEM causes a significant drop in performance, which means it is essential to learn the features extracted from pre-trained SSL models. The performance is further improved by using DFM and the proposed FEM+MIM+DFM can give the best performance.

3.3.5. Comparison with some known systems

Here, Table 3 gives the performance comparison among the proposed method with some known systems on IEMOCAP, in which all the four systems apply audio and text as the inputs.

From Table 3 it can be observed that our method gives better performance than the existing state-of-the-art systems, which means that the proposed KS-Transformer with CCAB is effective for SER.

Table 3: Performance comparison among the proposed method and some known system on IEMOCAP in terms of WA and UA.

| Methods      | WA  | UA  |
|--------------|-----|-----|
| STSER (Chen et al., 2020) | 0.711 | 0.721 |
| GBAN (Liu et al., 2020) | 0.724 | 0.701 |
| CMA (D N et al., 2020) | - | 0.728 |
| Ours | 0.743 | 0.753 |

4. Conclusion

In this paper, KS-Transformer, using a novel key-sparse attention mechanism has been proposed. Only the emotion related speech frames in audio or words in text can be noticed and assigned with attention weights. In addition, we present cascaded cross-attention block to fuse the complementary information from audio and text. Meanwhile, a stack of CCABs are utilized to achieve deep interaction. The experimental results on IEMOCAP show that the proposed method can give better performance than the state-of-the-art approaches. In the future, we will further explore the optimal sparsity in KS-Transformer for SER task. Furthermore, we will try to combine more modalities to improve the system performance.
5. References

[1] R. Cowie, E. Douglas-Cowie, N. Tsatspolious, G. Votsis, S. Kollias, W. Fellenz, and J. G. Taylor, “Emotion recognition in human-computer interaction,” IEEE Signal Processing Magazine, vol. 18, no. 1, pp. 32–80, 2001.

[2] S. Ramakrishnan and J. M. Emary, “Speech emotion recognition approaches in human computer interaction,” vol. 52, no. 3, pp. 1467–1478, 2013.

[3] A. Arruti, I. Cearreta, A. Álvarez, E. Lazkano, and B. Sierra, “Feature Selection for Speech Emotion Recognition in Spanish and Basque: On the Use of Machine Learning to Improve Human-Computer Interaction,” PLoS ONE, vol. 9, no. 10, pp. 1–23, 2014.

[4] S. Tokuno, G. Tumatori, S. Shono, E. Takei, T. Yamamoto, G. Suzuki, S. Minatoya, and M. Shimura, “Usage of emotion recognition in military health care,” in Defense Science Research Conference and Expo (DSR), 2011, pp. 1–5.

[5] G. Shen, R. Lai, R. Chen, Y. Zhang, K. Zhang, Q. Han, and H. Song, “WISE: Word-Level Interaction-Based Multimodal Fusion for Speech Emotion Recognition,” in Proc. Interspeech 2020, pp. 369–373.

[6] P. Tzirakis, G. Trigeorgis, M. A. Nicolaou, B. W. Schuller, and S. Zafeiriou, “End-to-end multimodal emotion recognition using deep neural networks,” IEEE Journal of Selected Topics in Signal Processing, vol. 11, no. 8, pp. 1301–1309, 2017.

[7] D. Nguyen, K. Nguyen, S. Sridharan, A. Ghasemi, D. Dean, and C. Fookes, “Deep spatio-temporal features for multimodal emotion recognition,” in IEEE Winter Conference on Applications of Computer Vision (WACV), 2017, pp. 1215–1223.

[8] Z. Pan, Z. Luo, J. Yang, and H. Li, “Multi-Modal Attention for Speech Emotion Recognition,” in Proc. Interspeech 2020, pp. 364–368.

[9] K. D. N. and A. Patil, “Multimodal Emotion Recognition Using Cross-Modal Attention and 3D Convolutional Neural Networks,” in Proc. Interspeech 2020, pp. 4243–4247.

[10] Z. Lian, J. Tao, B. Liu, J. Huang, Z. Yang, and R. Li, “Context-dependent domain adversarial neural network for multimodal emotion recognition,” Proc. Interspeech 2020, pp. 394–398.

[11] J. Devlin, M.-W. Chang, K. Lee, and K. Toutanova, “BERT: Pre-training of Deep Bidirectional Transformers for Language Understanding,” arXiv preprint arXiv:1810.04805, 2018.

[12] Y. Liu, M. Ott, N. Goyal, J. Du, M. Joshi, O. Levy, M. Lewis, L. Zettlemoyer, and V. Stoyanov, “RoBERTa: A Robustly Optimized BERT Pretraining Approach,” arXiv preprint arXiv:1907.11692, 2019.

[13] Z. Lan, M. Chen, S. Goodman, K. Gimpel, P. Sharma, and R. Soricut, “ALBERT: A Lite BERT for Self-supervised Learning of Language Representations,” arXiv preprint arXiv:1909.11942, 2019.

[14] I. Misra and L. d. v. Maaten, “Self-supervised learning of pretext-invariant representations,” in Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition (CVPR), June 2020.

[15] P. Sermanet, C. Lynch, Y. Chebotar, J. Huo, E. Jung, S. Schaal, S. Levine, and G. Brain, “Time-contrastive networks: Self-supervised learning from video,” in IEEE International Conference on Robotics and Automation (ICRA), 2018, pp. 1134–1141.

[16] J. Lu, D. Batra, D. Parikh, and S. Lee, “Vilbert: Pre-training task-agnostic visiolinguistic representations for vision-and-language tasks,” in Advances in Neural Information Processing Systems, 2019, pp. 13–23.

[17] M. Ravanelli, J. Zhong, S. Pascual, P. Swietojanski, J. Monteiro, J. Trmal, and Y. Bengio, “Multi-task self-supervised learning for robust speech recognition,” in IEEE International Conference on Acoustics, Speech and Signal Processing (ICASSP), 2020, pp. 6989–6993.

[18] S. Schneider, A. Baevski, R. Collobert, and M. Auli, “wav2vec: Unsupervised pre-training for speech recognition,” in Proc. Interspeech 2019, pp. 3465–3469.

[19] A. Baevski, S. Schneider, and M. Auli, “vq-wav2vec: Self-supervised learning of discrete speech representations,” in International Conference on Learning Representations, 2020.

[20] S. Siriwardhana, T. Kalabarachchi, M. Billingshurst, and S. Nanayakkara, “Multimodal emotion recognition with transformer-based self supervised feature fusion,” IEEE Access, vol. 8, pp. 176274–176285, 2020.

[21] S. Siriwardhana, A. Reis, R. Weerasekera, and S. Nanayakkara, “Jointly Fine-Tuning “BERT-Like” Self Supervised Models to Improve Multimodal Speech Emotion Recognition,” in Proc. Interspeech 2020, pp. 3755–3759.

[22] J. Liu, Z. Liu, L. Wang, Y. Gao, L. Guo, and J. Dang, “Temporal Attention Convolutional Network for Speech Emotion Recognition with Latent Representation,” in Proc. Interspeech 2020, pp. 2337–2341.

[23] A. Vssawani, N. Shazeer, N. Parmar, J. Uszkoreit, L. Jones, A. N. Gomez, U. Kaiser, and I. Polosukhin, “Attention is all you need,” in Proceedings of the 31st International Conference on Neural Information Processing Systems, 2017, pp. 5998–6008.

[24] X. Ju, D. Zhang, J. Li, and G. Zhou, Transformer-Based Label Set Generation for Multi-Modal Multi-Label Emotion Detection. New York, NY, USA: Association for Computing Machinery, 2020, p. 512–520.

[25] L. Tarantino, P. N. Garner, and A. Lazaridis, “Self-Attention for Speech Emotion Recognition,” in Proc. Interspeech 2019, pp. 2578–2582.

[26] J. Huang, J. Tao, B. Liu, Z. Lian, and M. Niu, “Multimodal transformer fusion for continuous emotion recognition,” in IEEE International Conference on Acoustics, Speech and Signal Processing (ICASSP), 2020, pp. 3507–3511.

[27] C. Busso, M. Bulut, C.-C. Lee, A. Kazemzadeh, E. Mower, S. Kim, J. N. Chang, S. Lee, and S. N. Narayanan, “lemocap: interactive emotional dyadic motion capture database,” Language Resources and Evaluation, vol. 42, no. 4, pp. 335–359, 2008.

[28] P. Liu, K. Li, and H. Meng, “Group Gated Fusion on Attention-Based Bidirectional Alignment for Multimodal Emotion Recognition,” in Proc. Interspeech 2020, pp. 379–383.

[29] M. Chen and X. Zhao, “A Multi-Scale Fusion Framework for Bi-modal Speech Emotion Recognition,” in Proc. Interspeech 2020, pp. 374–378.

[30] X. Glorot, A. Bordes, and Y. Bengio, “Deep sparse rectifier neural networks,” in Proceedings of the Fourteenth International Conference on Artificial Intelligence and Statistics, 2011, pp. 315–323.

[31] N. Srivastava, G. Hinton, A. Krizhevsky, I. Sutskever, and R. Salakhutdinov, “Dropout: a simple way to prevent neural networks from overfitting,” The journal of machine learning research, vol. 15, no. 1, pp. 1929–1958, 2014.

[32] J. Lei Ba, J. R. Kiros, and G. E. Hinton, “Layer Normalization,” arXiv preprint arXiv:1607.06450, 2016.

[33] J. Qiu, X. Li, and K. Hu, “Correlated attention networks for multimodal emotion recognition,” in IEEE International Conference on Biometrics and Biomedicine (BIBM), 2018, pp. 2656–2660.

[34] D. Hazarika, S. Gorantla, S. Poria, and R. Zimmermann, “Self-attentive feature-level fusion for multimodal emotion detection,” in IEEE Conference on Multimedia Information Processing and Retrieval (MIPR), 2018, pp. 196–201.

[35] T. Mittal, U. Bhattacharya, R. Chandra, A. Bera, and D. Manocha, “M3er: Multiplicative multimodal emotion recognition using facial, textual, and speech cues,” Proceedings of the AAAI Conference on Artificial Intelligence, vol. 34, no. 02, pp. 1359–1367, Apr. 2020.

[36] D. P. Kingma and J. Ba, “Adam: A Method for Stochastic Optimization,” arXiv preprint arXiv:1412.6980, 2014.