EmotionNAS: Two-stream Architecture Search for Speech Emotion Recognition

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Abstract

Speech emotion recognition (SER) is a crucial research topic in human-computer interactions. Existing works are mainly based on manually designed models. Despite their great success, these methods heavily rely on historical experience, which are time-consuming but cannot exhaust all possible structures. To address this problem, we propose a neural architecture search (NAS) based framework for SER, called “EmotionNAS”. We take spectrogram and wav2vec features as the inputs, followed with NAS to optimize the network structure for these features separately. We further incorporate complementary information in these features through decision-level fusion. Experimental results on IEMOCAP demonstrate that our method succeeds over existing state-of-the-art strategies on SER.

Index Terms: speech emotion recognition (SER), neural architecture search (NAS), two-stream framework.

1. Introduction

Speech emotion recognition (SER) has received increasing attention due to its contribution to human-computer interactions \cite{1, 2, 3}. It aims to understand how humans express emotions, and then identify their emotional states from speech cues \cite{4, 5}.

In the past few decades, deep neural networks have achieved promising results in SER \cite{6, 7, 8}. Despite their great success, these manually designed models heavily rely on expert knowledge and empirical evaluations \cite{9, 10, 11}. Researchers tend to speculate on historical experiences but cannot exhaust all possible situations. Therefore, how to design networks more intelligently has been brought into focus. To this end, we explore the use of neural architecture search (NAS) \cite{12, 13}. By setting a predefined search space, search strategy and evaluation metric, we can automatically optimize the model architecture with little human intervention.

In addition to model design, another challenge in SER is how to represent audios \cite{14, 15}. Recently, wav2vec \cite{16} has demonstrated its effectiveness in speech representation learning. It is a self-supervised framework that can learn robust acoustic representations with the help of large amounts of unlabeled data. Despite its success, wav2vec may lose some critical information for emotion recognition \cite{17, 18}. In contrast, spectrograms can preserve more information because they can reconstruct original audios via vocoders \cite{19, 20}. Therefore, we take full advantage of these two complementary features.

In this paper, we propose a novel framework for SER, called “EmotionNAS”. Figure 1 shows the overall structure of our method. Specifically, we take wav2vec and spectrogram features as the inputs, followed with NAS to optimize model architectures automatically. Emotion probabilities are obtained by fusing the prediction scores of these features. To verify the effectiveness of our method, we evaluate EmotionNAS on IEMOCAP, a popular benchmark dataset for SER. Experimental results demonstrate that our method succeeds over currently advanced approaches, setting the new state-of-the-art records.

The remainder of this paper is organized as follows: In Section 2 we describe our proposed method in detail. In Section 3 we present the experimental data and setup. In Section 4 we illustrate experimental results and verify the effectiveness our method. Finally, we conclude the whole paper in Section 5.

2. Methodology

EmotionNAS is a multi-stream framework that combines two acoustic representations for SER: spectrogram and wav2vec. To optimize the model architecture automatically, we explore the use of NAS in model design.

2.1. Architecture Search for Spectrogram

Spectrograms contain rich time-frequency information. To make full use of this time-frequency information, various convolutional neural networks (CNNs) have been designed during previous years \cite{6, 17}. Despite their success, these manually designed networks heavily rely on expert knowledge, which are time-consuming but cannot exhaust all possible structures. To address this problem, we automatically optimize the model structure through the efficient architecture search algorithm DARTS \cite{21}. It divides the entire network structure into several cells. Each cell selects and optimizes the internal operations, and finally filters them according to their importance.

The architecture search process is shown in Figure 2. Suppose each cell consists of an ordered sequence of $N$ nodes, $x^{(i)}$ represents the latent features of the $i^{th}$ node. Let $\mathcal{O}$ be a set of candidate operations, and $|\mathcal{O}|$ be the number of operations. To make the search space continuous, DARTS fuses all possible operations through the weights calculated by the softmax function. We take the operations from $x^{(i)}$ to $x^{(j)}$ for example:

\[
\alpha^{(i,j)}_o = \text{softmax} \left( \theta^{(i,j)}_o \right), \tag{1}
\]
Figure 1: The overall structure of EmotionNAS. It is a two-stream architecture that takes spectrogram and wav2vec as the inputs, followed with NAS to optimize the model architecture automatically. To integrate complementary information in these features, we further fuse the prediction results of two branches.

Figure 2: DARTS architecture search in a cell. Different colored arrows represent distinct operations: (a) the initial state of a cell with 4 nodes and 3 operations, i.e., \( N = 4, |O| = 3 \); (b) during training, the weight of some operations is weakened, and the corresponding line color becomes lighter; (c) only the operations with the highest weight are retained at the end.

\[
x^{(j)} = \sum_{o \in O} \alpha^{(i,j)} o(x^{(i)}),
\]

where \( \theta^{(i,j)}_o \) and \( \alpha^{(i,j)}_o \) represent the original weight and the normalized weight of the operation \( o \in O \) from \( x^{(i)} \) to \( x^{(j)} \). The task of architecture search reduces to learning a set of continuous variables \( \alpha = \{ \alpha^{(i,j)}_o \} \). At the end of the search, only the operations with the highest weight are retained.

DARTS divides the entire network into several cells. Suppose the model consists of \( L \) cells. For cell \( k \), it takes the outputs of cell \( (k - 1) \) and cell \( (k - 2) \) as the inputs. There are two types of cells in DARTS: normal and reduction cells. These cells have different strides. We set the stride to 1 for all operations adjacent to the normal cell and 2 for the reduction cell.

To improve the generalization performance, DARTS leverages a bi-level optimization approach. The weight \( \omega \) is trained on the training set, and its loss is denoted as \( L_{\text{train}} \). The encoding vector \( \alpha \) is trained on the validation set, and its loss is denoted as \( L_{\text{val}} \). The goal of the search process is to find \( \alpha^* \) that minimizes the validation loss \( L_{\text{val}}(\omega^*, \alpha^*) \), where \( \omega^* \) is obtained by minimizing the training loss \( L_{\text{train}}(\omega, \alpha) \):

\[
\begin{align*}
& \min_{\alpha} \quad L_{\text{val}}(\omega^*, \alpha) \\
& \text{s.t.} \quad \omega^*(\alpha) = \text{argmin}_\omega L_{\text{train}}(\omega, \alpha)
\end{align*}
\]

2.2. Architecture Search for Wav2vec

Recently, wav2vec has demonstrated its effectiveness in various downstream tasks (such as emotion recognition and speaker classification) \[22, 23\]. Since wav2vec contains rich temporal information, researchers attempt to capture temporal-sensitive dependencies through various methods. Among these methods, the RNN and its variants are widely utilized due to their promising results in emotion recognition \[24, 25\]. In this paper, we also search for recurrent neural architectures via NAS.

The search space includes all regular operations in RNNs, including linear mapping, blending, activation function and element-wise operation \[26\]. The optimized cell structure is shared across different time steps. For step \( t \), the initial nodes include the input vector \( x_t \) and two hidden states \( h_{t-1}^1 \) and \( h_{t-1}^2 \). Our goal is to optimize the cell architecture and generate new hidden states for the next step \( h_t^1 \) and \( h_t^2 \).

At the end of the search, we take wav2vec features as the input, followed with the optimized recurrent neural architecture to generate frame-level hidden representations. Since different frames have distinct contributions to emotion recognition, we exploit the attention mechanism to prioritize important frames and fuse these features via attention weights \[27\]. The fused representations are fed into fully-connected layers, followed with a softmax function to predict emotional states.

2.3. Decision-level Fusion

Different acoustic features describe audios from distinct aspects. To integrate complementary information in these features, we leverage decision-level fusion, a widely utilized fusion strategy in SER \[28, 29, 30\]. Specifically, we take the output probabilities of different features as the inputs, followed with a multi-layer perception to generate final results.

3. Experimental Databases and Setup

3.1. Database

IEMOCAP \[31\] is a benchmark dataset for SER. It consists of five sessions and each session has two speakers. For fair comparison, we adopt five-fold cross-validation using the leave-one-session-out strategy \[31, 37\]. Eight speakers from four sessions are used as the training set. One speaker from the remaining session is used as the validation set and the other one is used
as the test set. We select the model with the best performance on the validation set and report its results on the test set. We evaluate on four emotions of the improvised data (i.e., Neutral, Angry, Happy and Sad), in line with previous works [6,17].

3.2. Feature Extraction

Our two-stream framework takes full advantage of spectrogram and wav2vec for emotion recognition. The feature extraction process is described as follow:

**Spectrogram:** We use the Librosa toolkit [32] to extract spectrograms from audios. DARTS generally takes fixed-size features as the inputs [24]. To extract fixed-size spectrograms, we unify the duration of audios into 8 seconds. Longer ones are truncated, and shorter ones are padded with zeros. Then, audios are segmented into frames by 25ms Hamming windows with 14ms overlap. Each frame is passed into Fast Fourier Transform to extract 140-dimensional features. Finally, we perform non-overlapping average pooling in the frame dimension, down-sampling the feature matrix to the shape of \((140 \times 140)\).

**Wav2vec:** We use the pre-trained wav2vec-large [16] as the acoustic feature extractor. Audios have various lengths, resulting in variable-length wav2vec features. To extract fixed-length features, we unify wav2vec features to the maximum length by zero-padding, followed with non-overlapping average pooling to down-sample the feature matrix to the shape of \((727 \times 512)\).

3.3. Implementation Details

Our proposed method consists of three key components: 1) NAS for spectrogram; 2) NAS for wav2vec; 3) decision-level fusion. Based on the emotion recognition performance, we set the implementation details as follows:

**NAS for spectrogram:** In each cell, the number of nodes \(N\) and the number of operations \([0]\) are set to 4 and 8, respectively. The search space contains regular operations in CNNs, including \(3 \times 3\) max pooling, \(3 \times 3\) average pooling, skip connection, \(3 \times 3\) separable convolution, \(5 \times 5\) separable convolution, \(3 \times 3\) dilated convolution, \(5 \times 5\) dilated convolution, and no connection. Meanwhile, the number of cells is set to 3, and the number of channels is set to 6. To optimize the parameters \(\omega\) in Eq. [3] we use the SGD optimizer with a learning rate of 0.025, a momentum of 0.9, and a weight decay of 3e-4. To optimize the parameters \(\alpha\) in Eq. [5] we use the Adam optimizer [33] with a learning rate of 3e-4. We train the model for 50 epochs.

**NAS for wav2vec:** The search space contains regular operations in RNNs, including linear function, blending, element-wise product, element-wise sum, tanh function, sigmoid function, and LeakyReLU function. Previous works [26] provided various RNN-based cell structures searched on the Penn Tree Bank dataset [34]. We choose the cell structure with the lowest validation loss in IEMOCAP. To optimize the trainable parameters, we use the Adam optimizer with a learning rate of 1e-3. We train the model for 50 epochs.

**Decision-level fusion:** To integrate complementary information in spectrogram and wav2vec, we fuse the output emotion probabilities of these features through a three-layer perceptron. The input and output of each layer are set to \((8, 8)\), \((8, 4)\) and \((4, 4)\). To optimize the trainable parameters, we use the Adam optimizer with a learning rate of 1e-3. We train the model for 100 epochs.

### Results and Discussion

In this paper, we propose a NAS-based architecture for SER. To verify the effectiveness of our method, we first conduct comparative experiments with previous manually designed models. Then, we prove the importance of each branch in our two-stream framework. Finally, we reveal the impact of different hyper-parameters and visualize the search results.

4.1. Comparison with Existing Works

To verify the effectiveness of EmotionNAS, we conduct comparative studies against various manually designed models. We present the performance of different methods in Table [1]. Experimental results demonstrate that EmotionNAS succeeds over currently advanced approaches by 6.5%. These methods [6,7,8,17,35] heavily rely on expert knowledge, but they cannot exhaust all possible situations. In contrast, our NAS-based framework can optimize the model architecture automatically, which is more efficient than previous methods. These results verify the effectiveness of our method.

### Table 1: Performance of different methods on IEMOCAP. We report scores using unweighted accuracy. The best performance is highlighted in bold.

| Method              | UA(%) |
|---------------------|-------|
| CNN-LSTM [17]       | 62.0  |
| RNN-ELM [35]        | 63.9  |
| CNN-GRU [6]         | 64.2  |
| CTC-RNN [7]         | 66.2  |
| PCNSE-SADRN-CTC [8] | 66.3  |
| EmotionNAS (Ours)   | 72.8  |

### Table 2: Importance of each branch in EmotionNAS. We compare the number of parameters and unweighted accuracy.

| Method               | Parameters | UA (%) |
|---------------------|------------|--------|
| Spectrogram branch  | 0.13M      | 63.5   |
| Wav2vec branch      | 2.23M      | 70.3   |
| EmotionNAS          | 2.36M      | 72.8   |
4.2. Importance of Each Branch

EmotionNAS is a two-stream framework that takes spectrogram and wav2vec as the input. In this section, we reveal the importance of each branch. Experimental results are listed in Table 2. Benefiting from NAS, spectrogram and wav2vec achieve 63.5% and 70.3% on UA. Meanwhile, we further fuse the outputs of these features through a multi-layer perception and improve the performance to 72.8%. These results verify that spectrogram and wav2vec contain complementary information. Our method can take full advantage of this complementary information, resulting in performance improvements on SER.

4.3. Parameter Tuning

To evaluate the impact of different hyper-parameters, we visualize parameter tuning on IEMOCAP. For spectrogram and wav2vec, we utilize different structure search methods and therefore need to adjust different hyper-parameters.

**NAS for spectrogram** mainly contains two user-specified parameters: the number of cells $L$ and the number of channels $C$. Experimental results in Table 3 demonstrate that we can achieve the best performance when $L = 3$ and $C = 6$. As the model complexity increases, the classification performance improves first and then degrades. The reason lies in that a shallow model cannot capture all critical information in spectrograms, while a complex model increases the risk of over-fitting. Therefore, we should carefully choose hyper-parameters.

**NAS for wav2vec** mainly contains two user-specified parameters: the number of cells $L$ and the number of hidden state $h$. Experimental results in Table 4 demonstrate that we can achieve the best performance when $L = 2$ and $h = 256$. As the model complexity increases, the number of parameters increases exponentially, but the performance improvement is limited. Therefore, we set $L = 2$ and $h = 256$ in our experiment.

4.4. Search Result Visualization

In this section, we further visualize the search results on IEMOCAP. Details can be found in Figure 3-4.

Figure 3 shows the search results for spectrograms. There are two kinds of cells in our model: the normal cell and the reduction cell. For cell $k$, the input nodes are defined as the inputs, followed with the optimized cell structure to generate new hidden states for the next step $t$. Therefore, we should carefully choose hyper-parameters.

**NAS for wav2vec** mainly contains two user-specified parameters: the number of cells $L$ and the number of hidden state $h$. Experimental results in Table 4 demonstrate that we can achieve the best performance when $L = 2$ and $h = 256$. As the model complexity increases, the number of parameters increases exponentially, but the performance improvement is limited. Therefore, we set $L = 2$ and $h = 256$ in our experiment.

4.5. Conclusions

In this paper, we propose a NAS-based framework for SER, called “EmotionNAS”. This framework takes spectrogram and wav2vec as the inputs, followed with NAS to optimize the network structure automatically. We further leverage decision-level fusion to integrate complementary information in these features. Experimental results on IEMOCAP demonstrate the effectiveness of EmotionNAS. Our proposed method outperforms existing manually designed models, setting the new state-of-the-art records. Meanwhile, we also verify the necessity of each branch and the effectiveness of our fusion strategy.

In the future, we will extend the applications of our method to other audio understanding tasks. Furthermore, besides the acoustic modality, we will extend our NAS-based framework to other modalities, such as lexical and visual modalities.

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