A PAIRWISE DISCRIMINATIVE TASK FOR SPEECH EMOTION RECOGNITION

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ABSTRACT

Speech emotion recognition is an important task in human-machine interaction. However, it faces many challenges such as the ambiguity of emotion expression and the lack of training samples. To solve these problems, we propose a novel “Pairwise discriminative task”, which attempts to learn the similarity and distinction between two audios rather than specific labels. In the task, pairwise audios are fed into audio encode networks to extract audio vectors, followed with discrimination networks behind to judge whether audios belong to the same emotion category or not. The system is optimized in an end-to-end manner to minimize the loss function, which cooperates cosine similarity loss and cross entropy loss together. To verify the performance of audio representation vectors extracted from the system, we test them on IEMOCAP - a common evaluation corpus. We gain 56.33% unweighted accuracy on the test dataset, which surpasses above 5% compared with traditional end-to-end speech emotion recognition networks.

Index Terms— discrete emotion recognition, end-to-end methods, pairwise discriminative task, SVM

1. INTRODUCTION

With the development of artificial intelligence, more and more human-interact machines are being produced giving us the entertainment and convenience. Emotion recognition as an essential aspect in human-machine interaction has been attaching increasingly attention recently.

Speech emotion recognition as an important aspect in emotion recognition has changed deeply under the influence of deep learning (DL). Traditional method is a multi-step process. Original signals are segmented into overlapped frames and extracted frame-level features first. Then statistic functions are utilized to gain utterance-level features for the whole audio, followed with classifiers in the end [8, 9, 10]. However, targets of multi-step are not consistent. Besides, there is no agreement on appropriate handcrafted features for emotion recognition.

To solve these problems, DL replaces traditional step-by-step methods by end-to-end approach. End-to-end approach changes the mainstream methods of emotion recognition [5, 6, 7], which has already contributed to generate state-of-art performances in many tasks, such as machine translation [1], scene classification [2], image caption generation [3] and speech synthesis [4]. DL trends to process the speech signal or the log-spectrogram directly. Features are extracted using the convolutional neural networks (CNN) or recurrent neutral networks (RNN). Outputs are fed into a softmax layer to gain probabilities for each emotion. The whole system is optimized in an end-to-end manner to minimize the loss function [10, 11, 12].

Pairwise learning methods, which utilize pairwise samples as the inputs, have been widely discussed in transfer learning and unsupervised learning. [13] utilizes RGB images and paired depth images, transferring knowledge of well-trained RGB networks to process depth images through a teacher-student approach. [14] transfers knowledges of object recognition and scene recognition from images to audio networks through audio-image pairs. [15] proposes an audio-visual correspondence task to gain high representation of auditory and visual information through training with audio-image pairs. [16] learns the joined embedding space for food images and pairwise cooking recipes to search corresponded recipes for images.

Combining end-to-end methods and pairwise methods, we propose a novel “Pairwise discriminative task” (PDT) to deal with the ambiguity of emotion expression and the lack of training samples. Compared with the classification task, advantages of the PDT lie in three aspects. Firstly, judgment the similarity between pairwise audios is more direct for ambiguous problems where gaining a specific label is not easy. Secondly, pairwise methods can largely increase training samples through different combination. Finally, representative vectors will be extracted through the harder PDT, which should not only figure out emotions, but also judge the similarity of pairwise inputs. Therefore, the PDT is easier to label and harder to solve compared with classification methods.

The paper is organized as follows. In Section 2, we describe the proposed system and the PDT in detail. Experimental setup and results are illustrated in Section 3 and Section 4 separately. In Section 5, we conclude the whole paper and discuss the future work to optimize and extend proposed methods.
2. SYSTEM DESCRIPTION

In this study, we propose the PDT to extract more powerful representation vectors from input signals than the traditional end-to-end speech emotion classification task. We attempt to figure out similarity of pairwise audios, instead of learning the category of a single audio, through the PDT.

The whole system only has a single network whose inputs are pairwise audios and outputs are 2-way possibilities, which judge the similarity of pairwise inputs. The flowchart of proposed system can be found in Fig. 1. Two audio vectors are gained from pairwise audios through audio encoder networks. Then we concatenate them together and feed into discrimination networks producing classification outputs. In the training process, we utilize the combination of cosine similarity loss and cross entropy loss together as the loss function with end-to-end optimization methods. In test process, the performance of audio vectors is verified under support vector machine (SVM).

2.1. System architecture

Two modules compose the system: audio encode networks and discrimination networks. Audio encode networks gain audio vectors from input signals. Discrimination networks judge the similarity of pairwise inputs.

2.1.1. Audio encode networks

In audio encode networks, input signals are transformed into 257×400 log-spectrograms at first, which will be explained concretely in Section 3. Then log-spectrograms are passed through an audio encoder to obtain representative audio vectors. The audio encoder is slightly modified under the architecture in [12], which contains five convolutional networks and a full connected layer, as shown in Fig. 2. Finally, 256-dimensional (256-D) vectors are gained as the representation of input signals.

2.2. Loss function

We incorporate two loss functions on the system: cosine similarity loss and cross entropy loss, which are combined by normalized weights:

$$L = \lambda L_{cos} + (1-\lambda) L_{cros}$$

where $L_{cos}$ and $L_{cros}$ represent cosine similarity loss and cross entropy loss separately. And $\lambda$ is the weighting coefficient.

2.2.1. Cosine similarity loss

Cosine similarity is utilized to measure the similarity between pairwise audio vectors in the middle. Through optimizing the cosine similarity loss, we attempt to learn transformation to make the representative audio vectors from corresponded audio pairs “close”.

The cosine similarity loss with margin is defined as follows:
where \( \cos(x_i, x_j) \) calculates normalized cosine distance between pairwise audio vectors and \( m \) is the margin.

### 2.2.2. Cross entropy loss

We incorporate cross entropy loss, which calculates distance between prediction and ground truth of the PDT in the end. Through minimizing this loss function, we can strengthen the discriminative performance to PDT.

\[
L_{\text{cross}}(y_{\text{pred}}, y_{\text{true}}) = - \left[ y_{\text{true}} \ln y_{\text{pred}} + (1 - y_{\text{true}}) \ln(1 - y_{\text{pred}}) \right]
\]

where \( y_{\text{pred}} \) and \( y_{\text{true}} \) represent normalized true possibility of predictions and target labels separately.

### 3. EXPERIMENT SETUUP

The system is tested on The Interactive Emotional Dyadic Motion Capture (IEMOCAP) [18] database – a common evaluation corpus. It contains approximately 12 hours of audiovisual data, including video, speech, motion capture of face and text transcriptions. There are five sessions; each session has two actors perform improvisations or scripted scenarios. Sessions are manually segmented into utterance; each utterance is annotated by at least 3 human annotators. There are 10 discrete emotion labels in total including angry, happy, excited, sad, fear, neutral and so on. For this study, we utilize the same categories as in [19, 20, 21, 22]: angry, happy, sad and neutral, where happy and excited are merged into happy. To gain a speaker independent system, we utilize the same categories as in [19, 20, 21, 22]: angry, happy, excited, sad, fear, neutral and so on.

There are 10 discrete emotion labels in total including angry, happy, excited, sad, fear, neutral and so on. For this study, we utilize the same categories as in [19, 20, 21, 22]: angry, happy, excited, sad, fear, neutral and so on. For this study, we utilize the same categories as in [19, 20, 21, 22]: angry, happy, excited, sad, fear, neutral and so on.

#### Table 1: Emotion Category Distribution of IEMOCAP

| Emotion | Train | Val | Test |
|---------|-------|-----|------|
| Angry   | 606   | 327 | 170  |
| Happy   | 891   | 303 | 442  |
| Neutral | 1066  | 258 | 384  |
| Sad     | 696   | 143 | 245  |
| Total   | 3259  | 1031| 1241 |

Audios in IEMOCAP are sampled in 16 kHz with single-channel. Through statistical analysis, mean length of audios is about 4 seconds. Considering limitation of computation performance, we utilize a 4 seconds signal to represent the raw signal. The longer one is cut at 4 seconds and the shorter one is padded the last frame in the end.

To gain log-spectrogram from audios, each one second input signal is segmented into frames by 20 milliseconds hamming windows with a half-window overlap at first. Then we pass each frame into Fast Fourier Transformation to extract 512-D features. Due to symmetry of the transformation, only half part of features is selected. Through these processes, we generate 400 windows with 257 frequency bands for each four-second signal. To avoid large variance of outputs, a logarithm is also applied.

Due to the requirement of pairwise samples, we pick 67% negative samples, where two audios express different emotions, and 33% positive samples, where two audios sampled from the same category. Finally, we gain above four million data for training and above 50 thousand data for evaluation. The whole system is realized under Pytorch [23], a deep learning framework, and trained on one Tesla K80 GPU with 12 GB memory.

### 4. EVALUATION RESULTS

In this section, two experiments are utilized to judge the performance of audio vectors. In the first experiment, we analyze the classification performance compared with traditional end-to-end speech emotion recognition methods, marked as traditional methods. In the second experiment, we show the clustering ability through visualizing audio vectors in low dimension.

#### 4.1. Classification performance

To evaluate the classification performance of audio vectors, we use unweighted accuracy on IEMOCAP test dataset as our evaluation criteria. Proposed methods and traditional methods are compared in this section.

In training process, the proposed system is optimized in an end-to-end manner, whose hyper-parameters are listed in Table 2. The second column shows the range of parameters, followed with the best configuration beside. Adam [26] optimizer is utilized to minimize the loss function and 4 workers are opened at the same time to accelerate the input/output process. In test process, we extract audio vectors from the trained audio encoder and pass through a SVM classifier, which is realized under scikit-learn [24].

#### Table 2: Hyper-parameters of proposed system

| Hyper-parameters | Range | Best Value |
|------------------|-------|------------|
| \( m \) in Equ. (2) | 0–0.3 | 0.1 |
| \( \lambda \) in Equ. (1) | 0–1 | 0.9 |
| Learning rate | 1e-3–1e-6 | 1e-5 |
| Batch size | 32 | 32 |
| Workers number | 4 | 4 |
To show the performance of proposed methods, we train a network in traditional methods. A full connected layer and a softmax layer are combined behind the audio encoder in Fig. 2, making audio networks produce possibilities for four emotion categories directly. In the training process, cross entropy loss is chosen as loss function and the system is optimized in an end-to-end manner. We concatenate training dataset and validation dataset together and optimize through Adam optimizer whose learning rate is fixed to 1e-5.

Unweighted accuracy in test dataset is shown in Table 3.

| Exp. | Methods                  | Unweighted Accuracy (%) |
|------|--------------------------|-------------------------|
| 1    | Traditional methods, duration = 4s | 51.09                   |
| 2    | Traditional methods, duration = 5s | 54.71                   |
| 3    | Traditional methods, duration = 6s | 53.26                   |
| 4    | Traditional methods, duration = 7s | 55.36                   |
| 5    | Proposed methods, duration = 4s  | 56.33                   |

Due to the limitation of computation performance, the duration of proposed system is fixed to 4 seconds. However, the traditional method has less training data, which can deal with longer duration. Compared with Exp. 1 and 4, proposed methods can achieve better results than traditional methods with the same duration, which improve above 5%. Through Exp. 1~4, we can figure out the benefit of long duration, which contains more complete information than short ones. However, traditional methods with long duration cannot outperform the proposed method through Exp. 4 and 5.

4.2. Clustering ability

To test clustering ability of the system, we visualize outputs of audio vectors gained from training samples through t-SNE [25], which is realized under [24]. The result is shown in Fig. 3.

Through Fig. 3, we find different emotions cluster into different groups, showing the system gains the ability of clustering. However, happiness and anger have overlap. In order to find out problems, we also depict confusion matrix of proposed system in test dataset, as shown in Fig. 4. Through confusion matrix, we also find happiness is easily classified as anger. Same phenomenon is also visualized in Fig. 3 (a) in [21], showing difficulties exist when happy and angry are only determined through the single audio modality.

5. CONCLUSION

In this paper, we propose a novel “Pairwise discriminative task” to obtain high-level audio vectors. Compared with the traditional classification task, advantages of the PDT lie in three aspects. Firstly, judgment the similarity between pairwise audios is more direct for ambiguous problems where gaining a specific label is not easy. Secondly, pairwise methods can increase training samples through different combination. Finally, high-level representation vectors can be extracted through the harder PDT, which should not only figure out emotions, but also judge the similarity of pairwise inputs. Therefore, the PDT is easier to label and harder to solve. We test the system on IEMOCAP test dataset, showing better classification performance is gained than traditional methods. We also find clustering ability is learned through visualizing audio vectors in low dimension.

For future work, we will extend the system to multimodal recognition systems. The PDT can be replaced by different combination of visual modality, biological modality and audio modality further.

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