Abstract

The audio-video based emotion recognition aims to classify a given video into basic emotions. In this paper, we describe our approaches in EmotiW 2019, which mainly explores emotion features and feature fusion strategies for audio and visual modality. For emotion features, we explore audio feature with both speech-spectrogram and Log Mel-spectrogram and evaluate several facial features with different CNN models and different emotion pretrained strategies. For fusion strategies, we explore intra-modal and cross-modal fusion methods, such as designing attention mechanisms to highlight important emotion feature, exploring feature concatenation and factorized bilinear pooling (FBP) for cross-modal feature fusion. With careful evaluation, we obtain 65.5% on the AFEW validation set and 62.48% on the test set and rank second in the challenge.

CCS Concepts

- Computer systems organization → Embedded systems; Redundancy; Robotics; • Networks → Network reliability.

Keywords

Emotion Recognition; Attention Mechanism; Deep learning; Affective Computing; Convolutional Neural Networks

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1 INTRODUCTION

Emotion recognition (ER) has attracted increasing attention in academia and industry due to its wide range of applications such as human-computer interaction [7], clinical diagnosis [19], and cognitive science [14]. Although great progress in the face and video analysis has been made [4, 23, 26–29], audio-video emotion recognition in the wild remains a challenging problem due to the expression suffers from the large pose, illumination variance, occlusion, motion blur, etc.

Audio-Video emotion recognition can be summarized as a simple pipeline shown in Fig 1, which includes four parts, namely Video preprocessing, Feature Extraction, Feature Fusion, and Classifier. Specifically, video preprocessing refers to extract the spectrogram of the audio, the faces or landmarks of video. Feature extraction and feature fusion respectively extracts emotion features from the audio or visual signal and fuses emotion features into compact feature vectors, which are subsequently fed into a classifier for prediction.

Reviewing the methods of Audio-Video emotion recognition, we find that some methods emphasize feature extraction and other methods emphasize feature fusion. Yao et al [31] construct Holonet as discriminative feature extraction, which combines residual structure [12] and CReLU [22] to increase network depth and maintain efficiency. The EmotiW 2017 winner team [13] gets robust feature extraction with Supervised Scoring Ensemble (SSE) which adds supervision to intermediate layers and shallow layers. Since SSE only uses high-level representations, Fan et al [8] further improve SSE by utilizing middle feature maps to provide more discriminative features. These methods mainly use average pooling to obtain video-level representation from frame-level.

Many feature fusion strategies have been used in previous EmotiW challenges. [9, 18, 25] extract CNN-based frame features and use LSTM [10] or BLSTM [11] to fuse them. [1, 15, 17] use Statistical encoding module to aggregate frame features which compute the mean, variance, minimum, and
maximum of the frame feature vectors. However, these methods ignore the importance of frames. Besides, all previous methods mainly apply score averaging or feature concatenation for audio-video fusion, which ignores the correlation between the features from different modalities.

In this paper, we exploit three types of intra-modal fusion methods, namely self-attention, relation-attention, and transformer[24]. They are used to learn weights for frame features to highlight important frames. For cross-modal fusion, we explore feature concatenation and factorized bilinear pooling (FBP) [32]. Besides, we evaluate different emotion features, including convolutional neural networks (CNN) for audio information with both speech-spectrogram and Log Mel-spectrogram and several facial features with different CNN models and different emotion pretrained strategies. Finally, we obtain 62.48% and rank second in the challenge.

Our contributions and findings can be summarized as follows.

- We experimentally show that better face recognition CNN models and choosing suitable emotion datasets to further pretrain the face CNN models is important.
- We design three kinds of attention mechanisms for visual and audio feature fusion.
- We apply a Factorized Bilinear Pooling (FBP) for cross-modal feature fusion.

2 THE PROPOSED METHOD

We develop our ER system based on the pipeline of Video preprocessing-Feature Extraction-Feature Fusion-Classifier.

Video preprocessing

Face detection and alignment. We apply face detection and alignment by Dlib toolbox\(^1\). We extend the face bounding box with a ratio of 30% and then resize the cropped faces to scale of \(224 \times 224\). We do not apply face detection and alignment for AffectNet dataset, due to the face bounding box had been provided. For AFEW dataset, If no face is detected in the picture, the entire frame is passed to the network.

Audio processing and Spectrogram calculation. For each audio, the speech spectrogram and log Mel-spectrogram extraction process is consistent with [32] and [3] respectively. For speech spectrogram, we use the Hamming window with 40 msec window size and 10 msec shift. Finally, the 200-dimensional low-frequency part of the spectrogram is used as the input to the audio modality. As for log Mel-spectrogram, we calculate its deltas and delta-deltas.

Feature Extraction

Visual Features. We apply three CNN backbones to extract facial emotion features, namely VGGFace, ResNet18, and IR50 [4]. The dimensions are 4096, 512, and 512, respectively.

Audio Feature. We extract the feature maps of the audio from the last Pooling layer of AlexNet. The size of a 3-dimensional feature map is \(H \times W \times C\), where the \(H(W)\) is the height(width) of the feature map, and \(C\) is the number of the channel of the feature map. The feature maps are then split into \(n\) vectors(\(n = H \times W\)). Each vector is \(C\)-dimensional.

Intra-modal Feature Fusion

We apply the attention-based strategies for intra-modal feature fusion. It converts a variable number of emotion features(from audio or visual modality) into a fixed-dimension feature. We explore three attention methods, namely Self-attention, Relation-attention, and Transformer-attention. Formally, we denote a number of emotion features as \(\{f_1, \cdots, f_n\}\).

Self-attention. We apply 1-dimensional Fully-Connected(FC) layer \(W^0_{d \times 1}\) and a sigmoid function \(\sigma\) for each emotion feature, the weight of the \(i\)-th feature \(f_i\) is defined by:

\[w_i = \sigma(W^0_{d \times 1}f_i)\]
\[
\alpha_i = \sigma(f_i^T \cdot W_{\theta}^{f_i})
\]  
(1)

With these self-attention weights, we aggregate all the emotion features into a global representation \(f_s\) as follows:

\[
f_s = \frac{\sum_{i=1}^{n} \alpha_i f_i}{\sum_{j=1}^{n} \alpha_j}.
\]  
(2)

**Relation-attention.** This attention module was designed to learn weights from the relationship between features. After the self-attention, features are aggregated into a single vector \(f_s\). Since \(f_s\) inherently contains global representation of these features, we use the sample concatenation of individual features and global representation \([f_i : f_s]\) to model the global-local relation. Similar to the Self-attention module, with individual emotion features, we apply 1-dimensional FC layer \(W_{d \times 1}\) and a sigmoid function \(\sigma\). The relation-attention weight of the \(i\)-th feature \([f_i : f_s]\) is formulated as follows:

\[
\beta_i = \sigma([f_i : f_s]^T \cdot W_{d \times 1}^T).
\]  
(3)

With Self-attention and Relation-attention weights, all the emotion features was convert into a new feature as follows:

\[
f_r = \frac{\sum_{i=1}^{n} \alpha_i \beta_i [f_i : f_s]}{\sum_{j=0}^{n} \alpha_j \beta_j}.
\]  
(4)

**Transformer-attention.** Inspired by the works in [32] and [30], we formulate the attention weight as follows:

\[
f'_i = W_{m \times d}^2 \cdot f_i + b
\]  
(5)

\[
y_i = \exp(u_i^T \cdot \tanh(f'_i))
\]  
(6)

To reduce the dimension of the feature \(f_i\), we use a \(w \times d\)-dimensional FC layer \(W_{m \times d}^2\) in Eq.(5). Then the weight of the \(i\)-th feature \(f_i\) is processed by a 1-dimensional FC layer \(u_i^T\) \(\exp()\) and \(\tanh()\) function in Eq.(6).

With these transformer-attention weights, we aggregate all the emotion features into a single feature \(f_i\) as follows:

\[
f_t = \frac{\sum_{i=1}^{n} y_i f_i}{\sum_{j=1}^{n} y_j}.
\]  
(7)

**Cross-modal Feature Fusion**

We apply **Factorized Bilinear Pooling (FBP)** for cross-modal feature fusion. Given two features in different modalities, i.e. the audio feature vector \(a \in \mathbb{R}^m\) for a spectrogram and visual feature \(\sigma \in \mathbb{R}^n\) for frame sequence, the simplest cross-modal bilinear model is defined as follows:

\[
z_t = a^T W_{\sigma} \sigma
\]  
(8)

where \(W \in \mathbb{R}^{m \times n}\) is a projection matrix, \(z_t \in \mathbb{R}\) is the output of the bilinear model. We use the Eq.(9) to obtain the output feature \(z = [z_1, \cdots, z_n]\). The formula derivation from formula Eq.(8) to Eq.(9) was discribed in the paper[32].

\[
z = [z_1, \cdots, z_n] = \text{SumPooling}(\tilde{U}^T a \circ \tilde{V}^T \sigma, k)
\]  
(9)
We use the well-trained IR50 model to extract features and only train softmax classifier using these features. The IR50 models pre-trained on FER+, RAF-DB, and AffectNet achieve 50.13%, 51.436%, and 53.78%, respectively. Therefore, we choose the IR50 model pretrain on AffectNet as our visual features in the following fusion experiments.

**Table 1: Exploration of CNN models and pretrained emotion datasets.**

| Model     | FER+    | RAF-DB | AffectNet |
|-----------|---------|--------|-----------|
| VGGFace   | 88.84%  | 86.93% | 51.425%   |
| ResNet18  | 88.65%  | 86.96% | 52.075%   |
| IR50      | 89.257% | 89.075%| 53.925%   |

**Deployment of Fusion Strategies**

We explore three intra-modal attention strategies with the FBP cross-modal fusion. We use speech spectrogram for audio CNN, which obtains 38% on AFEW validation set individually. In the Table 2, we find the FBP improves performance for all the intra-modal fusion methods. Transformer attention for intra-modal fusion is the best for FBP.

**Table 2: Evaluation of intra-modal fusion methods.**

| Audio | Visual | Self | Relation | Transformer |
|-------|--------|------|----------|-------------|
| Self  |        | 54.6%| 56.9%    | 60.3%       |
| Relation |      | 54.0%| 57.2%    | 60%         |
| Transformer |  | 54.8%| 58%      | 61.1%       |

We also use log Mel-spectrogram for audio CNN, which obtains a little better performance, but the final results are very similar after intra- and cross-modal fusion. Besides, the concatenation of audio and visual vectors gets 58% accuracy in AFEW validation set with transformer attention. This is 3% lower than FBP which shows the effectiveness of FBP.

**Feature Enhancement**

In the Table 3, the Basic Features means that we only extract one feature vector for each frame. Besides, we apply 5 kinds of feature enhancement strategies as presented in Table 3. Specifically, for feature F-Mean, we first obtain 18 transformation frames by using three rotations, three scales, and flipping for a frame. After that, we compute the features of these 18 transformation frames and average these 18 features as the feature F-Mean. For the feature F-MeanStd, we compute the average feature and feature standard deviation of these 18 features. We then concatenate the average feature and the standard deviation as F-MeanStd. For the feature F-normFFT, we first compute the Fast Fourier transform(FFT) of the Basic Feature, and then normalize the feature and concatenate the real and imaginary parts as F-normFFT. For the feature F-AR-Mean, A means that the features are extracted by the models pre-trained on Affectnet, and R by the models pre-trained on RAF-DB, we concatenate these two mean features of two different pretrained models as F-AR-Mean.

**Table 3: Exploration of five feature enhancement strategies. The default setting is Rotation ∈ [−2°, 0°, 2°], scale ∈ [1, 1.03, 1.07]**

| Feature Enhancement | Augmentation details | AFEW Val acc |
|---------------------|----------------------|--------------|
| Basic Feature       | ---                  | 61.1%        |
| Basic Feature_RAFF-DB | default setting      | 58.5%        |
| F-Mean              | default setting      | 62.14%       |
| F-MeanStd           | default setting      | 63.7%        |
| F-MeanStd-2         | Rotation ∈ [−15°, 0°, 15°], scale ∈ [0.75, 1, 1.25] | 62.4% |
| F-NormFFT           | Normalized FFT       | 61.35%       |
| F-AR-Mean           | default setting      | 62.92%       |
| FG-Net              | ---                  | 59%          |

Table 3 shows that the five feature enhancement methods further improve the performance of FBP where the feature F-MeanStd achieves the best result on the validation set.

**Table 4: Submission results of different model combinations.**

| Sub | Val | Test | Fusion detail |
|-----|-----|------|---------------|
| (1) | --- | 62.481% | 4 FG-Net-1   |
| (2) | --- | 59.112% | 2 F-MeanStd-2 + 2 F-AR-Mean |
| (3) | --- | 54.518% | 4 FG-Net-2   |
| (4) | 64.5% | 61.41%  | 4 F-MeanStd   |
| (5) | 65.5% | 62.328% | F-Mean + F-MeanStd + F-NormFFT + F-MeanStd-2 + F-AR-Mean |

**Results On EmotiW2019**

In the Table 4. The first three submitted models are trained on the training and validation set of AFEW, and the last two models are trained on the training set of AFEW. We find that it is difficult to choose models and fuse models if combining the validation set with the training set. We adopt class weight in all submissions, which means that we reweight the predicted scores by the square root of the sample numbers([0.15, 0.097, 0.129, 0.185, 0.138, 0.082, 0.215]).

**4 CONCLUSIONS**

In this paper, we exploit three types of intra-modal fusion methods, namely self-attention, relation-attention, and transformer. They are mainly used to highlight important emotion.
feature. For the fusion of audio and visual information, we explore feature concatenation and factorized bilinear pooling (FBP). Besides, we evaluate different emotion features, including an audio feature with both speech-spectrogram and Log Mel-spectrogram and several facial features with different CNN models and different emotion pretrained strategies. With careful evaluation, we obtain 62.48% and rank second in the EmotiW 2019 Challenge.

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