A Multi-modal and Multi-task Learning Method for Action Unit and Expression Recognition

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Abstract

Analyzing human affect is vital for human-computer interaction systems. Most methods are developed in restricted scenarios which are not practical for in-the-wild settings. The Affective Behavior Analysis in-the-wild (ABAW) 2021 Contest provides a benchmark for this in-the-wild problem. In this paper, we introduce a multi-modal and multi-task learning method by using both visual and audio information. We use both AU and expression annotations to train the model and apply a sequence model to further extract associations between video frames.

We achieve an AU score of 0.712 and an expression score of 0.477 on the validation set. These results demonstrate the effectiveness of our approach in improving model performance.

1. Introduction

Nowadays, analyzing human affect is becoming more and more important for Artificial Intelligence (AI) systems, especially for human-computer interaction. The ability for machines to recognize the human face is mature, but the ability to understand human emotions still has a long way to go.

The Affective Behavior Analysis in-the-wild (ABAW) 2021 Competition [6][10][12][8][7][13][9][21] is held by Kollias et al. in conjunction with ICCV 2021. It provides a benchmark for three main tasks of Valence- Arousal Estimation, seven Basic Expression Classification and twelve Action Unit Detection[3]. The Facial Action Coding System (FACS) is a comprehensive system for describing facial movement. Action Units (AU) are individual components of muscle movements[3].

All three tasks are based on a large-scale in-the-wild database, Aff-Wild2[12][11]. It consists of 548 videos with 2,813,201 frames and provides annotations for all of these tasks. All videos are collected from Youtube which provides a real-world setting. So it is much more difficult to analyze affect than for other datasets. Data imbalance issues make this competition quite challenging. See figure[1].

To tackle these problems, we propose a multi-task method to learn Action Unit (AU) and facial expressions jointly using both visual and audio information. First, we train a visual model. Second, we freeze the parameters of the visual model and train the audio model. Third, we concatenate both visual and audio features and train the sequence model.

2. Related Work

In the first ABAW2 competition, lots of teams presented great methods for this challenging problem. Deng et al.[2] proposed a multi-task learning method to learn from missing labels. They used a data balancing technique to the dataset. First, they used the ground truth labels of all three tasks to train a teacher model. Secondly, they used the output of the teacher model as the soft labels. They used the soft labels and the ground truth labels to train their student models.

Kuhnke and Rumberg[14] proposed a two-stream aural-visual model. Audio and image streams are first proposed separately and fed into a CNN network. Then they use temporal convolutions to the image stream. They use additional features extracted during facial alignment and correlations between different emotion representations to boost...
3. Method

We use a multi-modal multi-task learning method for facial action units and expression recognition. See Figure 2.

First, we train the visual model separately by using both AU and expression annotations. Secondly, we freeze the parameters of the visual stream and add an audio stream to extract the audio feature. Finally, the visual feature and the audio feature are concatenated and fed into a transformer encoder to further extract temporal features.

3.1. Multi-Task Visual model

A multi-task framework is used to train the visual model, see Figure 3.

First, we train the visual backbone with Cosface loss[20]. The dataset we use is Glint360K[11]. It is the largest and cleanest face recognition dataset, which contains 17,091,657 images of 360,232 individuals. Using the pre-trained visual backbone boosts the performance because it provides sufficient human face information.

Both AU and expression heads share weights of the same backbone. AU and expression heads are fully connected layers that map features to the number of output classes. The annotations of AU and expression is incomplete, that is, some frames have both AU and expression annotation, but other frames only have one of these two annotations. To tackle this problem, we design two ways to do backpropagation when training.

1) Epoch by epoch: The parameters of the AU head and expression head are updated in rotation epoch by epoch. For example, we have a set of images, annotations of AU, and annotations of expression. At epoch 1, we use images with expression annotations, do backpropagation, and only update the parameters of backbone and expression head. At epoch 2, we use images with AU annotations, do backpropagation, and only update the parameters of the backbone and AU head. Then we repeat the above steps.

2) Batch by batch: The parameters of the AU head and expression head are updated in rotation batch by batch. For example, for the first batch, we use images with expression annotations, do backpropagation, and only update the parameters of the backbone and expression head. For the next batch, we use images with AU annotations, do backpropagation, and only update the parameters of the backbone and AU head. Then we repeat the above steps.

3.2. Multi-Modal Sequence Model

The Multi-modal Sequence model is composed of two sub-modal modules (Visual Model and Audio Model), a fusion layer, and an encoder layer from transformer[19].

The input of the network is a video and the output is the predicted labels of every frame in the video.

Visual model: The Visual Model is pretrained using the multi-task method in Section 3.1 to extract visual features of a single frame.

Audio model: For audio, a Mel spectrogram is computed using the TorchAudio package and TDNN[17] is used as the backbone to extract the audio features.

Sequence model: Then, the audio features and the visual features are aligned and fused to get the multi-model
features. The multi-model features are fed into the encoder network from transformer\cite{19} to extract the sequence features;

Finally, a fully connected layer is used to get the prediction result of each frame.

4. Experiments

4.1. Dataset

Aff-wild2 dataset\cite{12,11} is used for both AU and expression recognition. We discard annotations with -1.

For AU recognition, we use BP4D\cite{22} as an additional training dataset. This replenishes the number of scarce categories, like AU15, AU23, AU24.

Because some of the images in the AU and expression validation sets appear in each other’s training sets, we remove this part of the images that appear in the expression training set when validating the AU metric to ensure that there is no additional prior knowledge when validating the AU metric. The corresponding operation is also performed when verifying the expression metrics. Thus, we ensure that the validation set videos in AU and expression recognition tasks are consistent and the validation set videos of each task do not appear in the training set of the other task.

We use the cropped and aligned images provided in the Aff-wild2 dataset.

4.2. Experiment Settings

Our framework is implemented by using Pytorch\cite{16}.

**Visual model setting:** The face recognition model - IResNet100\cite{4} provided by Insightface\cite{1} is used as the pretrained model. Other visual backbones, such as SENet\cite{5} et.al. are also trained with Cosface loss\cite{20} using Glint360K\cite{1} dataset.

We use the cropped and aligned images provided by Aff-wild2 dataset. The width and height are set to 112 pixels. Data augmentations are random horizontal flip, small random crop, and small random changes to hue, saturation, and lightness. The mini-batch size is set to 64. We use SGD\cite{18} optimizer with momentum and the learning rate is set to 0.001.

**Audio model setting:** We use the following settings to compute a Mel spectrogram of the audio:

- number of mel filter banks $n_{mels} = 64$
- window size $w_{win} = 10ms$
- window stride $t_{stride} = 5ms$

*https://github.com/deepinsight/insightface
The output dimension of Time Delay Neural Network (TDNN) [17] is set to 512.

**Sequence model setting:** The input number of frames is set to 30 and the number of encoder layers from the transformer is set to 1. We use SGD [18] optimizer with momentum and the learning rate is set to 0.01.

### 4.3. Evaluation Metric

For 12 Action Unit Detection, the performance metric is:

\[
0.5 \times F_1 \text{ Score} + 0.5 \times \text{Accuracy} \quad (3)
\]

For 7 Basic Expression Classification, the performance metric is:

\[
0.67 \times F_1 \text{ Score} + 0.33 \times \text{Accuracy} \quad (4)
\]

where F1 Score is the unweighted mean and Accuracy is the total accuracy.

### 4.4. Results

We use the cropped and aligned images provided in the Aff-wild2 dataset when doing validation. Some video frames are labeled, but there are no corresponding images in the cropped and aligned folder. We discard these frames with their labels when we evaluate our results on the validation set.

We achieve an AU score of 0.712 and an expression score of 0.554 on the validation set. See Table 1 and Table 2. The results show that our method greatly exceeds the baseline method.

### 5. Conclusion and Future Work

We proposed a multi-modal and multi-task learning method by using both visual and audio information for the competition of ABAW2021 in ICCV2021. Our method obtained a score of 0.712 on AU recognition and 0.554 on expression recognition using the validation dataset. By using multi-modal information and multi-task training method, the result of our approach far exceeding the baseline result.

For future work, we will analyze our approach and do more detailed ablation studies to verify the principle that the method works.

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