Facial Action Unit Recognition Based on Transfer Learning

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Abstract

Facial action unit recognition is an important task for facial analysis. Owing to the complex collection environment, facial action unit recognition in the wild is still challenging. The 3rd competition on affective behavior analysis in-the-wild (ABAW) has provided large amount of facial images with facial action unit annotations. In this paper, we introduce a facial action unit recognition method based on transfer learning. We first use available facial images with expression labels to train the feature extraction network. Then we fine-tune the network for facial action unit recognition.

1. Introduction

Facial action units (AU) are defined by facial action coding system (FACS). We can describe facial expressions by the combination of AUs. Facial AU recognition has received a lot of attention due to its potential recently.

According to the collection environment, the databases with AU annotations can be divided into two categories, laboratory-controlled databases and in-the-wild databases. For example, BP4D [14] and DISFA [12] are two laboratory-controlled databases for AU recognition. Compared to laboratory-controlled databases, the collection environment of in-the-wild databases is more complex. The head pose, occlusion, and low resolution problems are common on the in-the-wild databases. Therefore, facial AU recognition on the in-the-wild condition is challenging.

The 3rd competition on affective behavior analysis in-the-wild (ABAW) [4–11, 13] has labeled lots of facial images with AU annotations. 547 videos of around 2.7M frames are included with 12 facial action units. According to previous works [3], the database also has data imbalance problem.

In order to improve facial AU recognition on the challenging database, we propose a method based on transfer learning. We first train the feature encoder on a balanced facial expression database. Then we fine-tune the model for facial AU recognition after adding AU classifiers. We also try to adjust the threshold of AUs to further enhance the performance.

2. Method

Figure 1 shows the overall framework, which includes two stages. In the first stage, we train the feature extractor by a facial expression recognition task. In the second stage, we fine-tune the pre-trained feature extractor for AU recognition task. Through the two stage training, patterns learned from facial expression recognition can be transferred to facial AU recognition task.

2.1. Facial expression recognition task

Facial expression recognition task tries to predict facial expressions. The overall network includes a backbone network to extract features from the input images and an expression classifier to predict expressions from the feature representations. The backbone is based on ResNet_50 network [2]. The expression classifier is one linear layer. The training loss is cross-entropy loss. The loss is defined as follow:

$$L_{exp} = l_e(\hat{y}_e, y_e)$$ (1)

where $l_e$ denotes cross-entropy loss, $\hat{y}_e$ and $y_e$ are the predicted and ground-truth facial expression labels, respectively.

2.2. Facial AU recognition task

After the training of stage one, we have a pre-trained backbone network. In order to transfer the learned patterns to facial AU recognition task, we train an AU classifier based on the pre-trained network. The AU classifier is a Multilayer Perceptron (MLP), containing two hidden layers. The loss for AU recognition is defined as follow:

$$L_{au} = l_e(\hat{y}_a, y_a)$$ (2)

where $l_e$ denotes cross-entropy loss, $\hat{y}_a$ and $y_a$ are the predicted and ground-truth AU labels, respectively. Through the two stage training, the patterns learned from...
facial expression task can be transferred to facial AU recognition.

3. Experiments

3.1. Databases

Two databases are involved for the method, including Multi-PIE [1] and Aff-Wild2 [9]. The Multi-PIE database is used to train the facial expression recognition network. And the Aff-wild2 is used to train AU recognition network. For the training on stage one, we adopt five-fold subject-independent cross-validation. For stage two, we train the network on the training set.

3.2. Evaluation Metric

For stage one, we adopt accuracy as the evaluation metric for facial expression recognition. For stage two, we evaluate the performance by F1 score for facial AU recognition.

3.3. Results

For facial expression recognition in stage one, the average accuracy is 0.94. Multi-PIE database includes multi-view images. Through training the backbone network on the multi-view images, the backbone can learn pose-robust feature representations.

For facial AU recognition in stage two, the experimental result on the validation set is 0.460 F1 score. After choosing different thresholds for AU predicting, the best result for AU recognition is 0.47.

4. Conclusion

We propose a facial action unit recognition method based on transfer learning. The overall framework includes two stages. In the first stage, the backbone network is trained by a facial expression recognition task. In the second stage, we train AU classifier based on the pre-trained backbone network. The patterns learned from the well-trained backbone network on facial expression recognition task can benefit AU recognition.

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