Affective Expression Analysis in-the-wild using Multi-Task Temporal Statistical Deep Learning Model

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Abstract—Affective behavior analysis plays an important role in human-computer interaction, customer marketing, health monitoring. ABAW Challenge and Aff-Wild2 dataset raise the new challenge for classifying basic emotions and regression valence-arousal value under in-the-wild environments. In this paper, we present an affective expression analysis model that deals with the above challenges. Our approach includes STAT and Temporal Module for fine-tuning again face feature model. We experimented on Aff-Wild2 dataset, a large-scale dataset for ABAW Challenge with the annotations for both the categorical and valence-arousal emotion. We achieved the expression score 0.543 and valence-arousal score 0.534 on the validation set.

I. INTRODUCTION

Understanding affective behavior analysis is an active research due to its fundamental role in wide applications such as human-computer interaction, customer marketing, health monitoring, etc. Through the many years, it is a challenging task due to complex and dynamic properties in expression as well as diverse environments in-the-wild.

The important target of the affective behavior analysis focuses on helping the machine to be able to understand the human emotions or emotion (expression) recognition. The most popular emotion representation is to describe by seven basic emotions such as Neutral, Angry, Disgust, Fear, Happy, Sad, Surprise by Paul Ekman’s work [4]. The differences from the emotions are based on the properties of distinctive physiology, universal signals, thoughts, memories, images, etc. The other representation of human emotion is described in continuous space using the 2D Valence-Arousal Emotion Wheel. The valence axis measures the level of pleasure. Besides, the arousal axis indicates the level of affective activation [12].

Recently, to promote the development of the Affective Behavior Analysis problems and the requirements of the huge real-world data for deep learning approach, Kollias et al. provide the large-scale dataset Aff-Wild2 [9], [13], propose many baseline methods [6], [8], [10], [11], and organize the Affective Behavior Analysis in-the-wild (ABAW) [7].

The Aff-Wild2 [9] is the extension version of Aff-Wild [13] to the large-scale dataset. It is collected the huge in-the-wild videos from YouTube with the wide-range subjects about age, ethnicity, profession, head pose, illumination conditions, etc. Moreover, it contains the annotations with valence and arousal, discrete emotions and action units.

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In this paper, we describe the proposed method for joining track 1 about valence-arousal regression and track 2 about categorical emotion recognition in the ABAW challenge. We analyze data and recognize it contains some difficulties.

Next, the task predicts the emotion by frame-by-frame with small displacements in the faces as Fig.1. It is different from the AFEW dataset [3] and EmotiW Challenge [2] with the ground-truth for the video emotion. So, it is difficult to recognize the emotion between two consecutive frames in the same video. In Fig.1 we see the bottom-right image is nearly the value of valence-arousal emotion with the bottom-right image. But it is different from the category emotion with surprise emotion (for the bottom-right image) against neutral emotion (for the bottom-left image). Moreover, the top-left and bottom-left images are the same categorical emotion but big different from valence-arousal emotion.

Finally, the problem needs to deal with the imbalance dataset on neutral emotion (very high) and angry, disgust emotion (very small).

To overcome the in-the-wild environment, we use the pre-trained weight on the VGG-Face2 Resnet50 model for training on AffectNet and RAF-DB dataset. We transfer learning the model learned from the well-known and good datasets to the Aff-Wild2 dataset.
Fig. 2. Overview of the proposed system for predicting the categorical emotion and arousal-valence regression. The STAT module will merge the prediction probability scores from the previous continuous frames by mean, max, and min operator. LSTM module consists one or two LSTM cell to exploit the temporal relation of the probability scores from the frame blocks. After that, all features from STAT, LSTM module and probability score, face features of current frames will be merged. The classification and regression blocks will receive the fusion features to output results.

To deal with the unbalanced-data problem, we use the balance emotion sampling and online data augmentation technique on every batch during the training process.

To enhance under the noises in the ground-truth among consecutive frames, we use the statistical encoding to merge the features of the previous consecutive frames by the min, max, average. After that, we concatenate all the features from the current frame, the temporal features from the previous consecutive frames, and the statistical encoding features for multi-task learning. Multi-task learning contains categorical emotion classification and valence-arousal emotion regression. It has the role of the regularizing effect based on shared features among classification and regression tasks.

The paper is organized as follows. In Section 2, we provide the details of our proposed method for track 1 and 2 of the challenge. Then we show experimental results and discussion. Finally, we conclude our research and discuss further works.

II. PROPOSED METHOD

A. Problem Overview

Given an input face frame \( F_{i,k} \in R^{h \times w \times 3} \) at time \( k \) of a video sequence \( v_i \), our objective is to predict the face frame to the valence-arousal emotion value \( c_{i,k} \in [-1, 1] \) and categorical emotion \( e_{i,k} \in [0, 6] \) corresponding to \{Neutral, Angry, Disgust, Fear, Happy, Sad, Surprise\}. This problem needs not only to detect continuous and discrete emotion in the current frame with the spatial dimension but also to exploit the similarities among consecutive frames in the same video.

To tackle this problem, we first train the VGGFace2 network on AffectNet and RAF-DB datasets for transfer learning. This model has the role as the feature extraction with two outputs: face emotion feature representation and emotion probability scores.

Besides, we assume the emotion at the current frame only affected by previous frames. The reason is that during the ground-truth process, the labelers make a decision at the current frame only affected by the view of the previous frames in the same video. This assumption also helps the model to reduce the input space and improve performance.

Therefore, the input of the proposed model as Fig.2 is the current frame \( F_{i,k} \) and the previous consecutive frames \( F_{i,k}, F_{i,k-1}, ..., F_{i,k-s+1} \) where \( s \) is the number of selection frames. We use probability scores from the face feature model for exploiting the temporal and statistical relation by two module LSTM and STAT. The features from two modules are merged with the features of the current frame for predicting the result.

Finally, we use the multi-task loss for the regularizing effect between the categorical emotion values and the valance arousal continuous emotion values.

B. Face Feature Model

In our proposed method, we utilize ResNet50 network [5] pre-trained on VGGFace2 [1] as a feature extraction network. The ResNet50 network is a conventional convolutional neural network that trained on the million face images from the Internet of the large-scale VGGFace2 dataset. It has 50 layers deep using 4 stages of the convolutional and identity blocks to classify the face image into 8631 classes for person recognition.

We modify the pre-trained VGGFace2 network by eliminating the last layer and inserting the new classification layer with 7 classes for basic categorical emotion. From there, we fine-tune again on AffectNet and RAF-DB datasets. As a result, the network can learn rich feature representations from the large-scale face emotion datasets.
C. Proposed Model

Our proposed model as Fig. 2 consists of the face feature model, LSTM and STAT Module, feature fusion section and classification & regression section.

For the face feature model, we use the pre-trained VGGFace2 ResNet50 network described in the previous section. We freeze all weight values exception the last stage convolution and identity block as well as the classification layer. The current frame and the block of previous consecutive frames are inputted to the model for outputting the feature and probability scores.

The LSTM Module will receive the probability scores of the previous frames to exploit the temporal relationship among the frames. It consists of one or two bidirectional LSTM cells with 1024 length, and return the temporal features.

Similarly, the STAT module will take the probability scores and face features and calculate the mean, max, average from input values. From there, the module gives the statically attributes of the previous frames. It will help our model to prevent the noise and learn the statistical features from the group of frames.

All temporal and statistical features from the group of frames will be fused with the probability scores and face features of the current frame. Fusion features will input to one classification branch and three regression branches. The classification branch has two dense layers and one soft-max layer for outputting seven classes of basic emotion. The three regression branches have two dense layers and the last dense layer using tanh activation. The regression outputs include arousal, valence, one average value, and two different values for mean square error (MSE) loss.

D. Multi-task Loss

For the basic emotion classification, we use the categorical cross-entropy loss as follows:

$$L_{class} = -\sum_{i=1}^{C} y_i \log \hat{y}_i$$

(1)

where $y_i$ is the one-hot vector of the ground-truth of the basic emotion, $\hat{y}_i$ is the predicted probability vector, and $C$ is the seven emotion.

For the arousal and valence regression, we use the Concordance Correlation Coefficient (CCC) loss, one vector with length 5 corresponding to arousal, valence, one average value, and two different values for mean square error (MSE) loss.

Finaly, our network combines $L_{class}$, $L_{arousal,ccc}$, $L_{valence,ccc}$ and $L_{mse}$ as follows:

$$\mathcal{L}_{total} = w_1 \mathcal{L}_{class} + w_2 \mathcal{L}_{arousal,ccc} + w_3 \mathcal{L}_{valence,ccc} + w_4 \mathcal{L}_{mse}$$

(4)

In this paper, we set $w_1 = 1.0$, $w_2 = w_3 = 0.4$, and $w_4 = 0.2$.

III. EXPERIMENTS AND DISCUSSION

A. Datasets and Environments

For face feature model, we fine-tuned on Affect-Net and RAF-DB datasets. In the AffectNet dataset, the images are chosen with the only seven labels same as the Aff-Wild2 dataset. There are 283,901 images for training, and 3,500 images for validation. In the RAF-DB dataset, there are 12,271 for training and 3,068 for validation.

Aff-Wild2 is the dataset used in ABAW Challenge. There are three tracks: Valence-Arousal Regression, Basic Emotion Recognition and Emotion Action Unit Recognition. In track basic emotion recognition, we eliminated these frames without the annotations in training and validation. So, there are 917835 images and 251 videos in the training set, 318503 images, and 69 videos in the validation set as well as 997332 images and 223 videos in the testing set.

Fig. 3 shows Aff-Wild2 has the face images under in-the-wild environments with a variety of age, pose, illumination, occlusion, etc. Especially, there are many neutral images near the images in the other emotions such as the fourth image.
TABLE I

| Model No. | Name            | Input                               | Output                        |
|-----------|-----------------|-------------------------------------|-------------------------------|
| 1         | Emotion Image   | Image                               | Expression                    |
| 2         | Emotion VA Image| Image                               | Expression, Valence-Arousal   |
| 3         | Emotion Frame   | Image, previous blocks              | Expression                    |
| 4         | Emotion VA Frame| Image, previous blocks              | Expression, Valence-Arousal   |
| 5         | Emotion Frame with LSTM | Image, previous blocks      | Expression                    |
| 6         | Emotion VA Frame with LSTM | Image, previous blocks           | Expression, Valence-Arousal   |

We used the average fusion with the result for the expression score 0.543, and valence-arousal score 0.527. As Table
### Table III

Result Comparison in Expression Score, and Valence-Arousal Score on Test set with baseline in [7]

| Track | Submission | Model | Acc. | F1 | Expr. Score | Aro. | Val. | VA Score |
|-------|------------|-------|------|----|-------------|------|------|---------|
| 1     | -          | [7]   | -    | -  | -           | 0.27 | 0.11 | 0.19    |
| 1     | 1          | 2     | -    | -  | -           | 0.295 | 0.256 | 0.325   |
| 1     | 2          | 4     | -    | -  | -           | 0.342 | 0.368 | 0.355   |
| 1     | 3          | 6     | -    | -  | -           | 0.383 | 0.381 | **0.382** |
| 1     | 4          | Fusion | -   | -  | -           | 0.354 | 0.326 | 0.37    |
| 2     | -          | [7]   | -    | -  | -           | -    | -    | -       |
| 2     | 1          | 2     | 0.546 | 0.263 | 0.356 | -    | -    | -       |
| 2     | 2          | 4     | 0.48  | 0.264 | 0.335 | -    | -    | -       |
| 2     | 3          | 2     | 0.547 | 0.311 | **0.389** | -    | -    | -       |
| 2     | 4          | Fusion | 0.563 | 0.295 | 0.364 | -    | -    | -       |

In Table III, we showed our results for the submission on Track 1 (Valence-Arousal Challenge) and Track 2 (Expression Challenge). For Track 1, we only used the models 2 (Emotion VA Image), 4 (Emotion VA Frame), 6 (Emotion VA Frame with LSTM). The best result **0.382** achieved with the model 6 on the test set. For Track 2, the model 2 achieved the best result **0.389**.

### IV. CONCLUSIONS AND FUTURE WORKS

In this paper, we presented the effective method for affective behavior analysis in-the-wild on Aff-Wild2 dataset. It contains the temporal and stat module to exploit and fine-tune again the face feature extraction model. We achieved accuracy higher than the baseline model on track 1 and 2 of the ABAW Challenge.

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