Multi-task Cross Attention Network in Facial Behavior Analysis

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Abstract. Facial behavior analysis is a broad topic with various categories such as facial emotion recognition, age and gender recognition, . . . . Many studies focus on individual tasks while the multi-task learning approach is still open and requires more research. In this paper, we present our solution and experiment result for the Multi-Task Learning challenge of the Affective Behavior Analysis in-the-wild competition. The challenge is a combination of three tasks: action unit detection, facial expression recognition and valence-arousal estimation. To address this challenge, we introduce a cross-attentive module to improve multi-task learning performance. Additionally, a facial graph is applied to capture the association among action units. As a result, we achieve the evaluation measure of 1.24 on the validation data provided by the organizers, which is better than the baseline result of 0.30.

Keywords: multi-task learning, facial behavior analysis, cross attention, action unit detection, facial expression recognition, valence and arousal estimation

1 Introduction

In affective computing, emotion recognition is a fundamental research topic and our face is an obvious indicator to analyze the human affect [13]. With the development of computer vision and deep learning, there are numerous studies and modern applications related to facial behavior analysis [7], [12], [10], [20], [8], [6]. The ABAW 4th Workshop, with the vision of solving the problem of affective behavior analysis in-the-wild, has organised a competition with two challenges which are multi-task learning (MTL) challenge and learning from synthetic data (LSD) challenge. The purpose LSD challenge is creating a model that is trained on synthetic images and able to operate effectively on real data. The LSD challenge is beyond the scope of this work.

The MTL challenge aims to design a model performing following three tasks with facial image data as input:

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1. Action unit detection (AU detection): a multi-label classification task, which involves the detection the presence of 12 types of movements on the subject’s face.

2. Facial Expression recognition (FER): a multi-class classification task, which involves identifying the emotion of the subjects among 8 categories: anger, disgust, fear, happiness, sadness, surprise, neutral and other state.

3. Valance Arousal estimation (VA estimation): a regression task that estimate the valence (how positive or negative the subject is) and arousal (how active or passive the subject is). The output is two continuous values in range $[-1, 1]$.

This paper proposes utilizing attention mechanism for MTL problem. By attending to the output of one specific task, the model can learn to boost the result of other related task. In addition, we leverage the graph-based neural network to learn the relation among action units (AUs) in AU detection task.

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**Fig. 1.** Block diagram of the proposed method

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2 Related Work

Savchenko [16] introduced a multi-head model with CNN backbone to resolve the facial expression and attributes recognition. The model was sequentially trained with typical face corpora [18], [2], [15] for various of facial analysis tasks. In ABAW 3rd competition, Savchenko [17] also developed a lightweight model using EfficientNet [19] to effectively learn the facial features, and achieved top 3 best performance in MTL challenge.

Kollias [9] showed an association between emotions and AUs distribution. Each emotion has its prototypical AUs, which are always active along with it; and observational AUs, which are frequently present with the emotion at certain rate. From this assumption, the authors proposed co-annotation and distribution matching to couple the emotions and AUs. Luo [14] introduced a graph-based method with multi-dimensional edge features to learn the association among
AUs. The AU detection block in our model is inspired by the node feature learning in [14].

3 Proposed Method

Our method is based on two observations: (1) there are informative connections among AU activations [14] and (2) the presence of the AUs is related to the facial expression [9]. Following these statements, we proposed a model with a graph convolution network (GCN) to exploit the AUs’ connections and a cross attention module to learn the influence of AUs presence to the facial emotion expression.

The model’s architecture is described in Fig 1. We used a pre-trained Efficientnet [16] to extract the facial feature vector from the input image. The image feature is then fed to three blocks corresponding to three tasks. Regarding the AU detection task, we utilized the AU relation graph to create the AU-specific features. For expression recognition and valance-arousal estimation, we used two full connected layers to generate the predictions. In addition, we devised an attention-based module to learn the effect of facial AUs on the prediction of emotion recognition task.

3.1 AU relation graph

To learn the representation of AUs, we adopted the Action unit Node feature learning (ANFL) module proposed by Luo [14]. The ANFL module consists of \( N \) fully connected layers corresponding to \( N \) AUs. These layers generate the AU-specific feature vectors \( \{v_i\}_{i=1}^N \) using the extracted image feature \( X \). Mathematically, the AU-specific feature vectors are given by:

\[
v_i = \sigma (W_i X + b_i)
\]  

Subsequently, we constructed a fully connected graph with \( N \) nodes corresponding to \( N \) AU-specific feature vectors. The edge weight of two nodes is the inner dot product of the two corresponding vectors. The graph is simplified by removing edges with low weights. We chose k-nearest neighbors to keep valuable connections between nodes. We used the simplified topology to create the adjacency matrix of a GCN. The GCN is used to enrich the connection information among AU-specific feature vectors. Generally, the AU-specific feature vectors learned by the GCN network are denoted by:

\[
V^{FGG} = f_{FGG} (V)
\]  

Finally, we calculate the similarity between the \( v_i^{FGG} \) and \( s_i \) to get the probability of each AU activation using the node features from the GCN. The similarity function is defined by:

\[
\hat{y}_{AU,i} = \frac{ReLU (v_i^{FGG})^T ReLU (s_i)}{\| ReLU (v_i^{FGG}) \|_2 \| ReLU (s_i) \|_2}
\]
where \( s_i \) is trainable vector having same dimension as \( v_i^{FGG} \). The operation of ANFL is illustrated in Fig 2. More detail about ANFL is in [14].

![Diagram of AUs Relationship-aware Node Feature Learning](image)

**Fig. 2.** The AUs Relationship-aware Node Feature Learning proposed in [14]

### 3.2 FER and VA estimation heads

To estimate FER and VA, we simply put the image feature \( X \) into two fully connected layers in parallel. We used Batch Normalization and Tanh activation function to produce the valance-arousal value \( \hat{y}_{VA} \). Meanwhile, FER head generates unweighted logit prediction \( \tilde{y}_{EX} \) without any activation function.

\[
\hat{y}_{VA} = \tanh (W_{VA}X + b_{VA}) \\
\tilde{y}_{EX} = W_{EX}X + b_{EX}
\]

### 3.3 Attention Module

Inspired by the additive attention of Bahdanau [1], we devised a multi-task cross attention module to discover the relationship between AU prediction and facial expression. Given an AU prediction \( \hat{y}_{AU} \) (query) and FER unweighted prediction \( \tilde{y}_{EX} \) (key), the module generates the attention weight.

\[
a(y_{AU}, \tilde{y}_{EX}) = \tanh (W_q\hat{y}_{AU} + W_k\tilde{y}_{EX})
\]

The attentive output is the element-wise product of attention weight \( a \) and the FER unweighted prediction \( \tilde{y}_{EX} \) (value).

\[
\hat{y}_{EX} = a \ast \tilde{y}_{EX}
\]

### 3.4 Loss function

We used the weighted asymmetric loss proposed by Luo [14] for AU detection task training process.
\[ \mathcal{L}_{AU} = -\frac{1}{N} \sum_{i=1}^{N} w_i \left[ y_{AU,i} \log (\hat{y}_{AU,i}) + (1 - y_{AU,i}) \hat{y}_{AU,i} \log (1 - \hat{y}_{AU,i}) \right] \]  

(8)

The weighted factor \( w_i \) is computed from occurrence rate \( r_i \) of AU \( i_{th} \) in the training set.

\[ w_i = N \frac{1}{\sum_{j=1}^{N} \frac{1}{r_j}} \]  

(9)

The loss we use for FER task is weighted cross entropy function, which is given by:

\[ \mathcal{L}_{EX} = -\sum_{i}^{C} P_i y_{EX,i} \log (\rho_i (\hat{y}_{EX})) \]  

(10)

where \( \rho_i (\hat{y}_{EX}) \) represents the softmax function, \( P_i \) is the refactor weight calculated from training set distribution and \( C \) is the number of facial expressions.

For VA estimation task, the loss function is obtained as the sum of individual CCC loss of valence and arousal. The formula is given by:

\[ \mathcal{L}_{VA} = 1 - CCC^V + 1 - CCC^A \]  

(11)

\( CCC^i \) is the concordance correlation coefficient (CCC) and \( i \) could be \( V \) (valence) or \( A \) (arousal). CCC is a metric measures the relation of two distributions, denoted by:

\[ CCC = \frac{2s_{xy}}{s_x^2 + s_y^2 + (\bar{x} - \bar{y})^2} \]  

(12)

where \( \bar{x} \) and \( \bar{y} \) are the mean values of ground truth and predicted values, respectively, \( s_x \) and \( s_y \) are corresponding variances and \( s_{xy} \) is the covariance value.

4 Experiment

4.1 Dataset

The experiment is conducted on the s-Aff-Wild2 dataset [5], which is a static version of Aff-Wild2 [11]. s-Aff-Wild2 is a collection of 221,928 images annotated with 12 action units, 6 basic expressions, and 2 continuous emotion labels in valence and arousal dimensions. In s-Aff-Wild2 dataset, some samples may lack annotations for one of three mentioned labels. Such missing labels may cause an imbalance in the number of valid annotations among the batches split by the data sampler. For the simplicity, instead of implementing a dedicated data sampler, we decided to train three tasks separately.

We use the cropped and aligned images provided by the competition organizer. They are resized from \( 112 \times 112 \) to \( 224 \times 224 \) pixel and normalized before the feature extraction step. For data augmentation we used random horizontal flipping.
4.2 Evaluation metrics

Following [4], the evaluation metric of the MTL challenge $P_{MTL}$ is the summation of three uni-task performance measure

$$P_{MTL} = P_{AU} + P_{EX} + P_{VA}$$ (13)

where $P_{AU}$ is the average F1 score of the 12 AUs in AU detection task, $P_{EX}$ is the average F1 score of 8 expression categories in FER task and $P_{VA}$ is average of the Concordance Correlation Coefficient of valance and arousal in VA estimation task.

4.3 Experiment setting

We implemented our solution using Pythorch framework and conducted the experiments on NVIDIA RTX 2080 Ti GPU. Stochastic Gradient Descent was applied following with Sharpness-aware Minimization Optimizer [3] to minimize the loss function of each task. The model was trained with initial learning rate of $10^{-3}$ and the batch size of 256. The weight decay was applied to prevent overfitting.

The EfficientNet in [16] is well-trained on multiple facial analysis tasks with so it can capture facial features efficiently. Therefore, we decide not to train it in our experiment. Initially, we train the ANFL module with AU detection tasks so that the model can learn the knowledge of AUs activation. Next, we continue training the model with B

4.4 Result

The performance on validation set of our proposed method is shown in Table 1. We attain the evaluation measure of 1.25 compared to 0.30 of the baseline model [4]. By utilizing the multi-task cross attention, the model improves the FER inference by taking advantage of AU detection result.

| Model                        | $P_{AU}$ | $P_{EX}$ | $P_{VA}$ | $P_{MTL}$ |
|------------------------------|----------|----------|----------|-----------|
| Baseline                     | -        | -        | -        | 0.30      |
| Proposed method (w/o cross attention) | 0.43     | 0.32     | 0.49     | 1.24      |
| Proposed method (cross attention) | 0.43     | **0.33** | 0.49     | **1.25**  |

Table 1. The comparison between our method and the baseline model
5 Conclusion

In this work, we introduced the attention-based approach in the multi-task learning problem. The idea is exploiting the output of one task to enhance the performance of another task. In particular, our model attends to AU detection task’s result to achieve better output in FER task. Our result outperforms the baseline provided in [4] and the cross attention module improves the evaluation metric on FER task. The experiment demonstrates that facial AUs have strong relationship with facial expression and this relation can be leveraged to recognize human emotion more efficiently. However, the relation between valence-arousal and other facial attributes is not exploited in this paper. In the future, we plan to study the influence between valence-arousal and other facial behavior tasks.

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References

1. Bahdanau, D., Cho, K., Bengio, Y.: Neural machine translation by jointly learning to align and translate. arXiv preprint arXiv:1409.0473 (2014)
2. Cao, Q., Shen, L., Xie, W., Parkhi, O.M., Zisserman, A.: Vggface2: A dataset for recognising faces across pose and age. In: 2018 13th IEEE international conference on automatic face & gesture recognition (FG 2018). pp. 67–74. IEEE (2018)
3. Foret, P., Kleiner, A., Mobahi, H., Neyshabur, B.: Sharpness-aware minimization for efficiently improving generalization. In: International Conference on Learning Representations (2021). https://openreview.net/forum?id=6Tm1mposlR
4. Kollias, D.: Abaw: Learning from synthetic data & multi-task learning challenges. arXiv preprint arXiv:2207.01138 (2022)
5. Kollias, D.: Abaw: Valence-arousal estimation, expression recognition, action unit detection & multi-task learning challenges. arXiv preprint arXiv:2202.10659 (2022)
6. Kollias, D., Cheng, S., Pantic, M., Zafeiriou, S.: Photorealistic facial synthesis in the dimensional affect space. In: Proceedings of the European Conference on Computer Vision (ECCV) Workshops. pp. 0–0 (2018)
7. Kollias, D., Cheng, S., Ververas, E., Kotsia, I., Zafeiriou, S.: Deep neural network augmentation: Generating faces for affect analysis. International Journal of Computer Vision 128(5), 1455–1484 (2020)
8. Kollias, D., Nikolau, M.A., Kotsia, I., Zhao, G., Zafeiriou, S.: Recognition of affect in the wild using deep neural networks. In: Computer Vision and Pattern Recognition Workshops (CVPRW), 2017 IEEE Conference on. pp. 1972–1979. IEEE (2017)
9. Kollias, D., Sharmanska, V., Zafeiriou, S.: Distribution matching for heterogeneous multi-task learning: a large-scale face study. arXiv preprint arXiv:2105.03790 (2021)
10. Kollias, D., Tzirakis, P., Nikolau, M.A., Papaioannou, A., Zhao, G., Schuller, B., Kotsia, I., Zafeiriou, S.: Deep affect prediction in-the-wild: Aff-wild database and challenge, deep architectures, and beyond. International Journal of Computer Vision pp. 1–23 (2019)
11. Kollias, D., Zafeiriou, S.: Expression, affect, action unit recognition: Aff-wild2, multi-task learning and arcface. arXiv preprint arXiv:1910.04855 (2019)
12. Kollias, D., Zafeiriou, S.: Va-stargan: Continuous affect generation. In: International Conference on Advanced Concepts for Intelligent Vision Systems. pp. 227–238. Springer (2020)
13. Kollias, D., Zafeiriou, S.: Affect analysis in-the-wild: Valence-arousal, expressions, action units and a unified framework. arXiv preprint arXiv:2103.15792 (2021)
14. Luo, C., Song, S., Xie, W., Shen, L., Gunes, H.: Learning multi-dimensional edge feature-based au relation graph for facial action unit recognition. arXiv preprint arXiv:2205.01782 (2022)
15. Mollahosseini, A., Hasani, B., Mahoor, M.H.: Affectnet: A database for facial expression, valence, and arousal computing in the wild. IEEE Transactions on Affective Computing 10(1), 18–31 (2017)
16. Savchenko, A.V.: Facial expression and attributes recognition based on multi-task learning of lightweight neural networks. In: Proceedings of the 19th International Symposium on Intelligent Systems and Informatics (Sisy). pp. 119–124. IEEE (2021). [https://arxiv.org/abs/2103.17107](https://arxiv.org/abs/2103.17107)
17. Savchenko, A.V.: Frame-level prediction of facial expressions, valence, arousal and action units for mobile devices. arXiv preprint arXiv:2203.13436 (2022)
18. Sharma, G., Ghosh, S., Dhall, A.: Automatic group level affect and cohesion prediction in videos. In: 2019 8th International Conference on Affective Computing and Intelligent Interaction Workshops and Demos (ACIIW). pp. 161–167. IEEE (2019)
19. Tan, M., Le, Q.: Efficientnet: Rethinking model scaling for convolutional neural networks. In: International conference on machine learning. pp. 6105–6114. PMLR (2019)
20. Zafeiriou, S., Kollias, D., Nicolaou, M.A., Papaioannou, A., Zhao, G., Kotsia, I.: Aff-wild: Valence and arousal ‘in-the-wild’ challenge. In: Computer Vision and Pattern Recognition Workshops (CVPRW), 2017 IEEE Conference on. pp. 1980–1987. IEEE (2017)