LEARNING DIVERSIFIED FEATURE REPRESENTATIONS FOR FACIAL EXPRESSION RECOGNITION IN THE WILD

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ABSTRACT

Diversity of the features extracted by deep neural networks is important for enhancing the model generalization ability in different learning tasks. Facial expression recognition in the wild has attracted interest recently due to the challenges existing for extracting discriminative features from occluded images in real-world scenarios. In this paper, we propose a mechanism to diversify the features extracted by CNN layers of facial expression recognition models for enhancing the model capacity in learning discriminative features. To evaluate the effectiveness of the proposed approach, we incorporate this mechanism in two state-of-the-art models to (i) diversify local/global features in an attention-based model and (ii) diversify features extracted by different learners in an ensemble-based model. Experimental results on three well-known facial expression recognition in-the-wild datasets, AffectNet, FER+ and RAF-DB, show the effectiveness of our method, achieving state-of-the-art performance of 89.99% on RAF-DB, 89.34% on FER+ and the competitive accuracy of 60.02% on AffectNet.

Index Terms— ensemble learning, facial expression recognition, attention mechanism, deep learning, feature diversity

1. INTRODUCTION

Facial expression as a fundamental natural signal for human social communication plays an important role in different applications of artificial intelligence, such as Human Computer Interaction (HCI), healthcare, and driver fatigue monitoring. Deep Convolutional Neural Networks (CNNs) have led to considerable progress in automatic Facial Expression Recognition (FER) on large-scale datasets in real-world scenarios. FER methods aim to solve a visual perception problem by learning feature representations from facial images/videos to be classified as an emotional category, i.e., happiness, sadness, fear, anger, surprise, disgust, neutral, and contempt. In laboratory-controlled datasets, such as CK+ [1] and JAFFE [2], where the facial images are in fixed frontal pose without any occlusion, FER methods have achieved excellent performance. However, these methods confront challenges for in-the-wild datasets, such as AffectNet [3], FER+ [4], and RAF-DB [5], where facial images come with illumination, occlusion and pose variations causing considerable change in facial appearance. To address that, many recent methods rely on transfer learning to exploit the feature representations learned for other visual perception tasks, such as object recognition, with well-designed networks, like ResNet-18 [6], trained on large datasets, like VGG-Face [7] and MS-Celeb-1M [8], to be transferred for facial expression recognition in challenging in-the-wild datasets. However, considering that many face datasets are small and imbalanced, these deep neural networks are mostly over-parameterized and tend to overfit on the training data, which can degrade their generalization ability on unseen data.

Increasing the diversity of features learned by different network layers/neurons has been recognized as an effective way to improve model generalization [9]. It is theoretically shown in [10,11] that the within-layer activation diversity improves the generalization performance of neural networks and lowers the effect of overfitting. In this paper, we propose a mechanism for learning diversified facial feature representations by encouraging the learner to extract diverse spatial and channel-wise features. This mechanism can be used in different CNN architectures to increase the features diversity between layers or branches, spatial regions, and/or channels of feature maps. We incorporate our proposed optimization mechanism into two state-of-the-art models, i.e., the MA-Net [12] and the ESR [13], and conduct experiments on three well-known in-the-wild datasets, i.e., AffectNet, FER+ and RAF-DB. Experimental results demonstrate the effectiveness of learning diversified features in improving the accuracy and generalization of the pretrained state-of-the-art models on new samples. The contributions of the paper can be summarized as follows:

• We propose a mechanism for learning diversified features in spatial and channel dimensions of CNNs to improve the model's accuracy in discriminating facial expressions.

• We evaluate our feature extraction mechanism by incorporating it into two state-of-the-art models which have different properties, i.e., one benefits from a region-based attention mechanism and transfer learning, and the other one is an efficient ensemble-based architecture. In both cases, our diversified feature learning mechanisms boost the performance.

• Conducted experiments on three benchmark in-the-wild datasets, including the large-scale dataset AffectNet, indicate the effectiveness and adaptability of our method, which can be used in different types of models. Our code will be publicly available.

2. RELATED WORKS

Recent studies are focused on addressing the challenges of in-the-wild facial expression recognition by training models with multi-pose examples [14], and extracting key facial features based on facial landmarks and region-based attention mechanisms [15–17]. Learning facial features from global and local perspectives simulates the human brain’s perception mechanism and helps achieving better performance in visual perception problems. MA-Net [12] is a global
multi-scale and local attention network which extracts features with different receptive fields, to increase the diversity and robustness of global features. This state-of-the-art method comprises of a backbone based on ResNet-18 for extracting preliminary features which are fed into a two-branch network with global multi-scale and local attention modules for high-level feature extraction. The first branch receives the preliminary feature maps as input and applies several multi-scale convolutions to extract both deeper semantic and shallower geometry features. The second branch of the network also receives the preliminary feature maps extracted by the backbone network as input, divides the feature maps into several local spatial regions without overlap, and then applies several parallel local attention networks to highlight the most important facial features in each region. At the end, a decision-level fusion strategy is employed to classify the extracted multi-scale and local attention features into different facial expression categories. However, this large network with 50.54 M parameters needs to be trained on a large dataset, and consistent with other state-of-the-art methods [16,18], this network is first trained on MS-Celeb-1M dataset, and then finetuned on in-the-wild facial datasets AffectNet and RAF-DB.

ESR [13] has solved this issue by proposing an efficient ensemble-based method which reduces the residual generalization error on the AffectNet and FER+ datasets, and achieves state-of-the-art performance while training from scratch on these datasets. ESR model consists of two building blocks: 1) the base network which is composed of a stack of convolutional layers and is responsible for extracting low/middle-level features, 2) the ensemble network composed of several network branches which are supposed to learn distinctive features. All branches in this ensemble module receive the same feature maps extracted by the base network as input, and they compete for a common resource which is the base network. The training algorithm of ESR starts with training the base network and one ensemble branch. Thereafter, more convolutional branches are added one by one while training, so that the base network leads and speeds up learning by providing all ensemble branches with shared preliminary feature maps which are suitable for all the branches. Therefore, this method reduces redundancy in low-level feature learning and focuses on learning high-level discriminative features to be classified. Finally, the input facial image is classified to an emotion category by fusing the predictions of all the ensemble branches and applying majority voting.

In this paper we propose to complement discriminative feature extraction by increasing the features diversity between attention-regions, channel dimensions, and ensemble branches. In the next section, the diversified feature learning mechanism is introduced, and accordingly the modified learning mechanism for MA-Net and ESR methods is described.

3. PROPOSED METHOD

Diversity of feature representations is important in deep learning for enhancing the model generalization, and improving model’s accuracy in perceptual tasks by extracting non-redundant and discriminative features. Inspired by [10], we propose to increase spatial and channel-wise feature diversity in CNN architectures and ensemble-based models for facial expression recognition.

Let us assume that $\Phi_l, l \in \{1, 2, ..., L\}$ is a feature map of size $C \times H \times W$ extracted by a CNN learner. The diversity between different feature maps obtained by different learners or different layers of a CNN model can be obtained in channel and spatial dimensions as illustrated in Fig. 1 by first applying pooling on spatial and channel dimensions and then computing the average similarity between every two pooled feature maps $l, k$ using radial basis function as follows:

$$S_{lk} = \frac{1}{N} \sum_{i=1}^{N} \exp(-\gamma \| \phi_l(x_i) - \phi_k(x_i) \|^2), \tag{1}$$

where $x_i$ is the sample (image/frame) $i$ fed to the learner, $N$ denotes the number of samples from which feature maps are extracted, $\gamma$ is a hyperparameter, $\phi_l(\cdot)$ and $\phi_k(\cdot)$ denote the pooled feature maps of the $l^{th}$ and $k^{th}$ learners, respectively. The feature maps are of size $1 \times H \times W$ and $C \times 1 \times 1$ when similarity is measured on spatial (Fig. 1 top row) and channel (Fig. 1 bottom row) dimensions, respectively. Similar feature maps indicate low diversity of the learner. Accordingly, using the pairwise similarities between feature maps, the model diversity is obtained by computing the determinant of the matrix $S$ indicating pairwise similarities of learners as $S_{lk}$, i.e.,:

$$D = \text{det}(S). \tag{2}$$

The model can be optimized in an end-to-end manner by minimizing the combined loss function comprising of classification loss and diversity. That is, the overall loss value to be minimized is:

$$\text{Loss} = \mathcal{L} - (D_{ch} + D_{sp}), \tag{3}$$

where $\mathcal{L}$ denotes the cross-entropy classification loss, and $D_{ch}, D_{sp}$ denote the feature diversity computed through channel and spatial dimensions, respectively using Eq. (1) and Eq. (2).

This mechanism can be used in CNN-based models to increase diversity between the feature maps at different levels. Considering the fact that diversity of learners is important in ensemble learning, encouraging each branch of ESR to learn complementary features of data can lead to better ensemble classification. To reach this goal, we modified the architecture of ESR by adding the CBAM attention mechanism [19] into each layer of the network and maximizing the diversity of both channel and spatial attention maps between different branches. The combined loss function of the modified ESR model is defined as a summation of the diversity loss between branches and the cross-entropy loss of each branch as follows:

$$\mathcal{L}_{esr} = \sum_{b} \mathcal{L}(f_b(X)) - (D_{ch} + D_{sp}), \tag{4}$$

where $\mathcal{L}$ denotes the cross-entropy classification loss function for each of the ensemble learners $f_b$ which is combined with a negative
In MA-Net, the focus is on exploiting both local and global features in two model branches. CBAM attention mechanism is originally employed in this method to highlight the key global and local facial regions for recognizing the expression. As illustrated in Fig. 3, the first branch of the network employs the feature map tensor in its initial shape to extract the global features, but the second branch divides the feature map into four patches to learn and highlight the local feature in each of the patches separately. We modified MA-Net structure to encourage the local branch to learn diversified regional features. In this regard, channel and spatial pooling operations are applied on divided patches and the diversity between them are computed to be added to the model classification loss function. Besides, in order to make the two branches of the network as effective as ensemble learner, the global and the local features extracted by these two branches can be diversified as well. In this regard, the local feature patches are concatenated and introduced to the global average pooling layer, along with the global feature map, and the pooled features are diversified by the branch diversity block and then classified by the fully connected layer. Therefore, our only modification to MA-Net is computing the branch/patch diversity loss in its optimization problem without adding any new trainable parameter to the model. The whole model is optimized by minimizing a combined loss function comprising of local and global classification loss summation of spatial and channel diversity of the whole ensemble model. In other words, by optimizing $L_{\text{esr}}$, the features of ensemble branches (learner) are diversified, while each branch is encouraged to classify features with minimum loss. Fig. 2 illustrates the new structure of ESR with added attention modules in each layer and our augmented module which computes the ensemble diversity to be optimized with cross entropy loss.

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$$Loss = \lambda L_{\text{local}} + (1 - \lambda)L_{\text{global}} - (D_b + D_{sp} + D_{ch}),$$

(5)

where $L_{\text{local}}$, $L_{\text{global}}$ denote the cross-entropy classification loss in the local and global branches, respectively. $0 \leq \lambda \leq 1$ is a hyperparameter balancing the two parts and the best performance of MA-Net is obtained for $\lambda = 0.6$. $D_b$ is the diversity between the two branches and $D_{sp}$, $D_{ch}$ indicate spatial and channel diversity between the local feature patches.

4. EXPERIMENTS

We conducted experiments on three widely used in-the-wild datasets, AffectNet [3], FER+ [4], RAF-DB [5].

AffectNet is the largest in-the-wild dataset containing more than one million images collected from the Internet by querying emotion keywords in different languages. Following the same experimental setting as in RAN [16], ESR [13], and SCN [18], we used 450,000 images of this dataset which are manually annotated with 8 discrete expressions containing 6 basic ones (happiness, surprise, sadness, anger, disgust, fear) plus neutral and contempt. 287,568 images are used as training data and 4,000 images are used as test data.

FER+ is an extension of FER2013 [20] dataset, which is a large-scale dataset containing 35,887 facial images collected by Google search engine with 7 expressions. FER+ annotators re-labeled the FER2013 by crowd-sourcing and added contempt expression to the dataset. All the face images in this dataset are aligned and annotated with 8 expressions.

RAF-DB dataset comprises of 30,000 facial images annotated with basic or compound expressions. Similar to the experimental
Fig. 3. Illustration of the modified MA-Net structure by adding patch diversity and branch diversity blocks to diversify local region-based features in each feature map and also increase diversity of the extracted global and local features before passing them to the classification layers.

Table 1. Comparisons of the classification accuracy of two state-of-the-art methods, ESR and MA-Net, and their modified versions with and without (channel and spatial) diversity computing on AffectNet, FER+, and RAF-DB datasets. * indicates our proposed version of the method.

| Method | Attention | Spatial | Channel | Dataset | AffectNet | FER+ | RAF-DB |
|--------|-----------|---------|---------|---------|-----------|------|--------|
| ESR-9 [13] | × | × | × | AffectNet | 59.3 | 87.17 | - |
| ESR-9* | × | × | × | AffectNet | 58.7 | 88.40 | 77.96 |
| MA-Net [12] | ✓ | ✓ | ✓ | MS-Celeb-1M | 60.29 | 88.4 | - |

Table 2. Comparisons of the classification accuracy of the state-of-the-arts with our proposed version of ESR and MA-Net methods on AffectNet dataset with 8 classes. * indicates our proposed version of the method.

| Methods | Pretrained | Acc.(%) |
|---------|------------|---------|
| MobileNet [22] | - | 56.00 |
| VGGNet [22] | - | 58.00 |
| AlexNet-WL [3] | - | 59.50 |
| RAN [16] | MS-Celeb-1M | 60.23 |
| SCN [18] | MS-Celeb-1M | 60.29 |

To reproduce the ESR results with 9 ensemble branches, referred as ESR-9, the model is trained from scratch on AffectNet dataset and then finetuned on FER+. This led to 58.8% accuracy on AffectNet which is 0.5% less than the reported result in [13], however our reproduced result for FER+ is around 0.85% higher than their originally reported accuracy. Although the performance of this method is not reported in [13] for RAF-DB dataset, we finetuned the pre-trained ESR-9 model on RAF-DB as well. To evaluate the effect of attention layers added to the ESR structure, we did an ablation study to compare the performance of ESR-9 with and without CBAM attention layers, and spatial/channel-wise diversities. According to the results reported in Table 1, the best ensemble classification accuracy is obtained by adding CBAM attention layers, as well as maximizing the diversity of both spatial and channel-wise attention between ensemble branches. It is mentioned in [13] that adding more than 9 branches to ESR does not improve the performance. However, we assume that increasing the feature diversity between branches increases the model capacity for learning features with more ensemble branches. In this regard, we increased the number of branches both...
results in Table 3, ESR-15 on small devices like embedded GPUs or CPUs. According to the results with early exits at inference time and increase inference speed performance is achieved in earlier branches so that we can get the number of branches is chosen empirically. In some cases, the best datasets compared to ESR-9. It should be noted that the maximum and indicate the improved performance of ESR-15 for all the three FER+ and RAF-DB. The results in Table 1 confirm our assumption, in the original ESR architecture and in our proposed version of ESR and MA-Net methods on FER+ dataset with 8 classes, * indicates our proposed version of the method.

| Methods       | Pretrained | Acc. (%) |
|---------------|------------|----------|
| TFE-JL [23]   |            | 84.30    |
| PLD [4]       |            | 85.10    |
| SHCNN [24]    |            | 86.54    |
| SeNet50 [25]  | VGG-Face2 [26] | 88.80 |
| RAN [16]      | MS-Celeb-1M | 88.55    |
| SCN [18]      | MS-Celeb-1M | 88.16    |
| ESR-9 [13]    | AffectNet  | 87.17    |
| ESR-9*        | AffectNet  | 89.15    |
| ESR-15*       | AffectNet  | 89.34    |
| MAN-Net [12]  | MS-Celeb-1M |         |
| MAN-Net*      | MS-Celeb-1M | 88.34    |

Table 4. Comparisons of the classification accuracy of the state-of-the-arts with our proposed version of ESR and MA-Net methods on RAF-DB dataset with 7 classes, * indicates our proposed version of the method.

| Methods       | Pretrained | Acc. (%) |
|---------------|------------|----------|
| DLP-CNN [5]   |            | 84.22    |
| IPA2LT [27]   | AffectNet  | 86.77    |
| gACNN [15]    | AffectNet  | 85.07    |
| LDL-ALSG [28] | AffectNet  | 85.53    |
| RAN [16]      | MS-Celeb-1M | 86.90    |
| SCN [18]      | MS-Celeb-1M | 87.03    |
| ESR-9 [13]    | AffectNet  |          |
| ESR-9*        | AffectNet  | 82.95    |
| ESR-15*       | AffectNet  | 83.00    |
| MA-Net [12]   | MS-Celeb-1M | 88.40    |
| MA-Net*       | MS-Celeb-1M | 89.99    |

Table 3. Comparisons of the classification accuracy of the state-of-the-arts with our proposed version of ESR and MA-Net methods on FER+ dataset with 8 classes, * indicates our proposed version of the method.

in the original ESR architecture and in our proposed version of ESR and trained the ESR-15 models on AffectNet and finetuned them on FER+ and RAF-DB. The results in Table 1 confirm our assumption, and indicate the improved performance of ESR-15 for all the three datasets compared to ESR-9. It should be noted that the maximum number of branches is chosen empirically. In some cases, the best performance is achieved in earlier branches so that we can get the results with early exits at inference time and increase inference speed on small devices like embedded GPUs or CPUs. According to the results in Table 3, ESR-15*, which is our modified version of ESR-15 with diversified features, outperforms all the state-of-the-arts with no need to be pretrained on large-scale datasets like MS-Celeb-1M or VGG-Face. Figure 4 illustrates visualization results using Grad-CAM [29] for an example image featuring a “Happy” expression. In this illustration, it is evident that all branches of ESR predominantly focus on the region surrounding the eyes and nose. Conversely, various branches of ESR* exhibit attention towards distinct facial areas, including the eyes, nose, mouth, and forehead, for recognizing the facial expression. As CBAM attention layers exist in the original structure of MA-Net, we did not modify the structure of the layers in this model. MA-Net is first trained on MS-Celeb-1M dataset, and the pretrained weights are then finetuned on AffectNet and RAF-DB datasets. In our experiments, we used the pretrained weights of MA-Net on MS-Celeb-1M, and finetuned the weights on all the datasets. However the reproduced classification accuracy on AffectNet is 0.44% less than their reported accuracy of 60.29%, while for RAF-DB it is 0.28% higher than the original one. After augmenting branch and patch diversity blocks into the MA-Net structure and diversifying local and global features, we achieved the state-of-the-art performance of 89.99% on RAF-DB dataset which outperforms all the other state-of-the-arts listed in Table 4.

Overall, our results show the potential of improving performance in feature extractors by increasing their feature diversity. This idea can be applied to different feature extractors with different architectures. In this paper, we used this idea to improve the performance of the two state-of-the-art methods at the time. In a similar way, the integration of our proposed idea in other methods with deep CNN, MLP, or transformer-based feature extractors might also improve performance, which can be explored as a future work.

5. CONCLUSION

In this paper we proposed a mechanism to diversify features extracted by different CNN learners for facial expression recognition in the wild. We targeted two state-of-the-art methods based on ensemble learning and multi-scale attention networks to evaluate the effect of learning diversified features in the model performance. Experimental results show that diversifying features extracted by different ensemble learners can enhance the overall ensemble classification performance while increasing the model’s capacity to include more learners for feature extraction. Furthermore, diversifying local regional features extracted by a CNN learner improves the model performance in exploiting local features and classifying facial images.

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