MRP-Net: A Light Multiple Region Perception Neural Network for Multi-label AU Detection

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Abstract

Facial Action Units (AUs) are of great significance in communication. Automatic AU detection can improve the understanding of psychological condition and emotional status. Recently, a number of deep learning methods have been proposed to take charge with problems in automatic AU detection. Several challenges, like unbalanced labels and ignorance of local information, remain to be addressed. In this paper, we propose a fast and light neural network called MRP-Net, which is an end-to-end trainable method for facial AU detection to solve these problems. First, we design a Multiple Region Perception (MRP) module aimed at capturing different locations and sizes of features in the deeper level of the network without facial landmark points. Then, in order to balance the positive and negative samples in the large dataset, a batch balanced method adjusting the weight of every sample in one batch in our loss function is suggested. Experimental results on two popular AU datasets, BP4D and DISFA prove that MRP-Net outperforms state-of-the-art methods. Compared with the best method, not only does MRP-Net have an average F1 score improvement of 2.95% on BP4D and 5.43% on DISFA, and it also decreases the number of network parameters by 54.62% and the number of network FLOPs by 19.6%.

Facial Action Units

Facial expressions are intuitive responses to human emotions and natural ways of communication. AUs can be labeled with Facial Action Coding System(FACS). In FACS, each expression is considered to be composed of multiple AUs, which can effectively eliminate ambiguity in labeling.

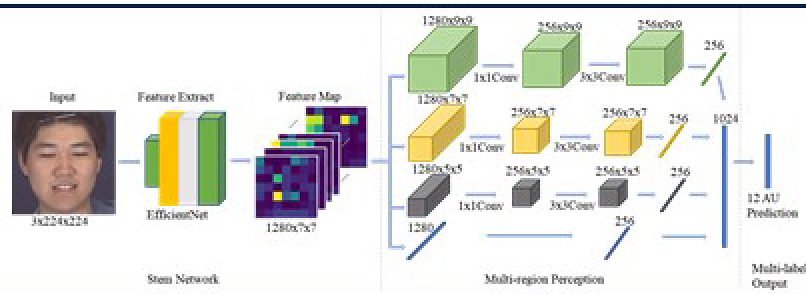
Batch Balanced Learning

During the training, we set the batch size as N. For any AU - AU_c, assume that the ideal positive-negative sample ratio is P_c. Assume that the positive-negative sample ratio for AUc in a batch is PB_c. Then, we define $A_c = PB_c / P_c$.

$$Loss(Y, \hat{Y}_{nc}) = -\frac{1}{N}\sum_{N}^{n=1}\sum_{C}^{c=1}\frac{1}{A_c}\cdot Y\cdot\log\hat{Y}_{nc}$$
$$+A_c\cdot(1-Y)\cdot\log(1-\hat{Y}_{nc}).$$

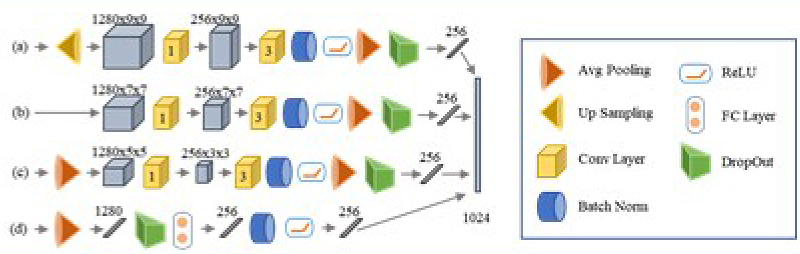
Overview of MRP

We use Efficient-Net as stem network. Only use the features which Efficient-Net outputs and delete the pooling and fully connected layers. After that, we get 1280 feature maps with a size of 7x7. Then, the features are processed by MRP module to a vector of 1024-dimension to predict AU probabilities.



Multi Region Perception

This picture gives the detailed structure of MRP module for multiple region perception. For the feature maps of stem network, we want to capture the information of different locations and sizes rather than simply reducing the dimension of features. Therefore, we divide the input feature maps into a, b, c, and d groups for processing. MRP module outputs a vector of 1024-dimension for predicting the probability of AUs.



Results

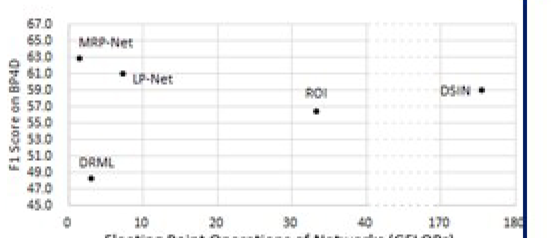
For the sake of rigorous and reasonable experimental results, we compare MRP-Net with the current image-based AU detection methods that using 3-fold cross-validation on different datasets.

Besides, comparison of network parameters, network FLOPs (Floating Point Operations) and performance between our MRP-Net and existing image-based AU auto-detection methods was given.

F1 score on DISFA Dataset

Method	AU1	AU2	AU4	AU6	AU9	AU12	AU25	AU26	Avg.
LSVM [32]	10.8	10.0	21.8	15.7	11.5	70.4	12.0	22.1	21.8
DRML [10]	17.3	17.7	37.4	29.0	10.7	37.7	38.5	20.1	26.7
APL [8]	11.4	12.0	30.1	12.4	10.1	65.9	21.4	26.9	23.8
ROI [25]	41.5	26.4	66.4	**[50.7]**	8.5	89.3	88.9	15.6	48.5
JAA-Net [33]	**43.7**	**[46.2]**	56.0	41.4	44.7	69.6	88.3	**58.4**	56.0
DSIN [34]	42.4	**39.0**	68.4	28.6	46.8	70.8	90.4	42.2	53.6
LP-Net [26]	29.9	24.7	**[72.7]**	46.8	**49.6**	**72.9**	**93.8**	**[65.0]**	**56.9**
MRP-Net	**[49.68]**	29.1	**70.9**	**50.1**	**[54.33]**	**[79.74]**	**[94.15]**	52.0	**[60.0]**

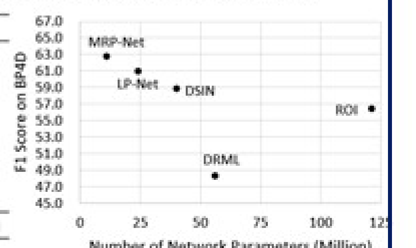
Bracketed and bold numbers indicate best performance; bold numbers indicated second best.



F1 score on BP4D Dataset

Method	AU1	AU2	AU4	AU6	AU7	AU10	AU12	AU14	AU15	AU17	AU23	AU24	Avg.
LSVM [32]	23.2	22.8	23.1	27.2	47.1	77.2	63.7	64.3	18.4	33.0	19.4	20.7	35.3
JPML [7]	32.6	25.6	37.4	42.3	50.5	72.2	74.1	65.7	38.1	40.0	30.4	42.3	45.9
DRML [10]	36.4	41.8	43.0	55.0	67.0	66.3	65.8	54.1	33.2	48.0	31.7	30.0	48.3
CPM [19]	43.4	40.7	43.3	59.2	61.3	62.1	68.5	52.5	36.7	54.3	39.5	37.8	50.0
EAC-Net [9]	39.0	35.2	48.6	76.1	72.9	81.9	86.2	58.8	37.5	59.1	35.9	35.8	55.9
ROI [25]	36.2	31.6	43.4	77.1	73.7	**85.0**	87.0	62.6	**[45.7]**	58.0	38.3	37.4	56.4
JAA-Net [33]	47.2	**44.0**	54.9	77.5	74.6	84.0	86.9	61.9	43.6	60.3	42.7	41.9	60.0
DSIN [34]	**51.7**	40.4	**56.0**	76.1	73.5	79.9	85.4	**62.7**	37.3	**[62.9]**	38.8	41.6	58.9
LP-Net [26]	43.4	38.0	54.2	**77.1**	**76.7**	83.8	**87.2**	**[63.3]**	**45.3**	60.5	**48.1**	**[54.2]**	**61.0**
MRP-Net	**[54.0]**	**[47.5]**	**[56.3]**	**[78.5]**	**[76.9]**	**[85.5]**	**[89.3]**	60.9	44.6	**61.5**	**[50.4]**	**48.7**	**[62.8]**

Bracketed and bold numbers indicate best performance; bold numbers indicated second best.



Acknowledgement

This work was funded by National Natural Science Foundation of China under Grant No.61701032, 61806184.