Peak-Piloted Deep Network for Facial Expression Recognition

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ECCV'16 EUROPEAN CONFERENCE ON COMPUTER VISION

1. Introduction

In this work, we present a novel peak-piloted deep network (PPDN) that uses a sample with peak expression (easy sample) to supervise the intermediate feature responses for a sample of non-peak expression (hard sample) of the same type and from the same subject. The expression evolving process from non-peak expression to peak expression can thus be implicitly embedded in the network to achieve the invariance to expression intensities.

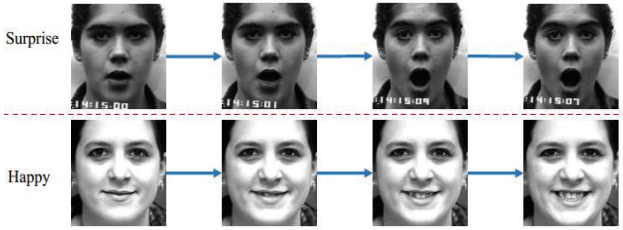


Fig1. Expression evolving process from non-peak expression to peak expression

2. Motivation

It is usually difficult to capture critical and subtle expression details from non-peak expression images, which can be hard to distinguish across expressions. In principle, an mapping from non-peak to peak expression could improve recognition.

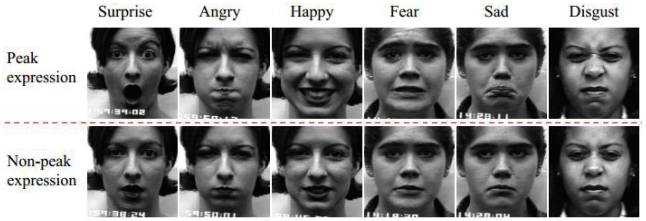
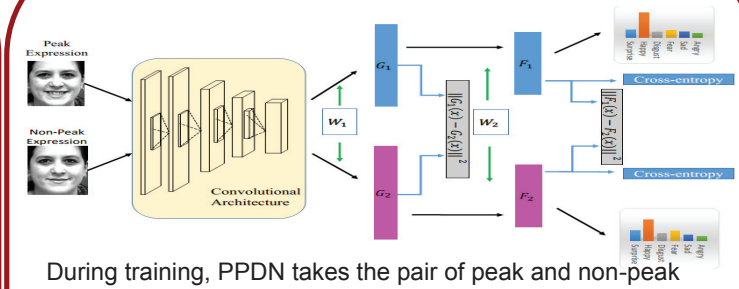


Fig2. Examples of six facial expression samples, including surprise, angry, happy, fear, sad and disgust. For each subject, the peak and non-peak expressions are shown

3.1 Network Structure



During training, PPDN takes the pair of peak and non-peak expression images as input. After passing the pair through several convolutional and fully-connected layers, the intermediate feature maps can be obtained for peak and nonpeak expression images, respectively. The L2-norm loss between these feature maps is optimized for driving the features of the non-peak expression image towards those of the peak expression image. The network parameters can thus be updated by jointly optimizing the L2-norm losses and the losses of recognizing two expression images. During the back-propagation process, the Peak Gradient Suppression (PGS) is utilized.

3.2 Network Optimization

We denote the training set as$S = \{x_i^p, x_i^n, y_i^p, y_i^n, i = 1 \ldots . N\}$, where x_i^n denotes a face with non-peak expression, x_i^p a face with corresponding peak expression, and y_i^n and y_i^p are corresponding expression labels. Let J1, J2 and J3 indicate the L2-norm of the feature differences and the two cross-entropy losses for recognition, respectively. The proposed peak gradient suppression (PGS) learning algorithm uses instead the updates

$$W^+ = W - \frac{\gamma}{N}\frac{\partial J_1(W; x_i^n, x_i^p)}{\partial f_j(W; x_i^n)} \times \frac{\partial f_j(W; x_i^n)}{\partial W} - \frac{1}{N}\gamma \nabla_W J_2(W; x_i^p, y_i^p) - \frac{1}{N}\gamma \nabla_W J_3(W; x_i^n, y_i^n) - 2\gamma W.$$

Where γ is learning rate. The feature responses of the peak expression image are suppressed in PGS.

4. Experiments

To evaluate the PPDN, we conduct extensive experiments on two popular FER datasets: CK+ [1] and Oulu-CASIA [2]. To further demonstrate that the PPDN generalizes to other recognition tasks, we also evaluate its performance on face recognition over the public Multi-PIE dataset [3] .

Table1. Performance comparisons on six facial expressions with four state-of-the-art methods and the baseline on CK+ database.

Method	Average Accuracy
CSPL [10]	89.9%
AdaGabor [34]	93.3%
LBPSVM [11]	95.1%
BDBN [4]	96.7%
GoogLeNet(baseline)	95.0%
PPDN	**97.3%**

Table2. Performance comparisons on six facial expressions with UDCS method and the baseline on Oulu-CASIA.

Method	Average Accuracy
UDCS [35]	49.5%
GoogLeNet(baseline)	66.6%
PPDN	**72.4%**

Table3. Performance comparison on CK+ when evaluating on three different test sets, including "weak expression", "peak expression" and "combined", respectively.

Method	weak expression	peak expression	combined
PPDN(standard SGD)	81.34%	99.12%	94.18%
GoogLeNet (baseline)	78.10%	98.96%	92.19%
PPDN	**83.36%**	**99.30%**	**95.33%**

Trable4. Performance comparison on Oulu-CASIA database when evaluating on three different test sets, including "weak expression", "peak expression" and "combined", respectively.

Method	weak expression	peak expression	combined
PPDN(standard SGD)	67.05%	82.91%	73.54%
GoogLeNet (baseline)	64.64%	79.21%	71.32%
PPDN	**67.95%**	**84.59%**	**74.99%**

Table 5. Face recognition rates for various poses on Multi-PIE with some state of the arts.

Method	−45°	−30°	−15°	+15°	+30°	+45°	Average
Li et al. [38]	56.62%	77.22%	89.12%	88.81%	79.12%	58.14%	74.84%
Zhu et al. [27]	67.10%	74.60%	86.10%	83.30%	75.30%	61.80%	74.70%
CPI [28]	66.60%	78.00%	87.30%	85.50%	75.80%	62.30%	75.90%
CPF [28]	73.00%	81.70%	89.40%	89.50%	80.50%	70.30%	80.70%
GoogLeNet (baseline)	56.62%	77.22%	89.12%	88.81%	79.12%	58.14%	74.84%
PPDN	**72.06%**	**85.41%**	**92.44%**	**91.38%**	**87.07%**	**70.97%**	**83.22%**

[1] Lucey, P., Cohn, J.F., Kanade, T., Saragih, J., Ambadar, Z., Matthews, I.: The extended cohnkanade dataset (ck+): A complete dataset for action unit and emotion-specified expression. In: Computer Vision and Pattern Recognition Workshops (CVPRW), 2010 IEEE Computer Society Conference on, IEEE (2010) 94–101
[2] Zhao, G., Huang, X., Taini, M., Li, S.Z., Pietikainen, M.: Facial expression recognition from near-infrared videos. Image and Vision Computing 29(9) (2011) 607–619
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