Exploiting High-Level Semantics for No-Reference Image Quality Assessment of Realistic Blur Images

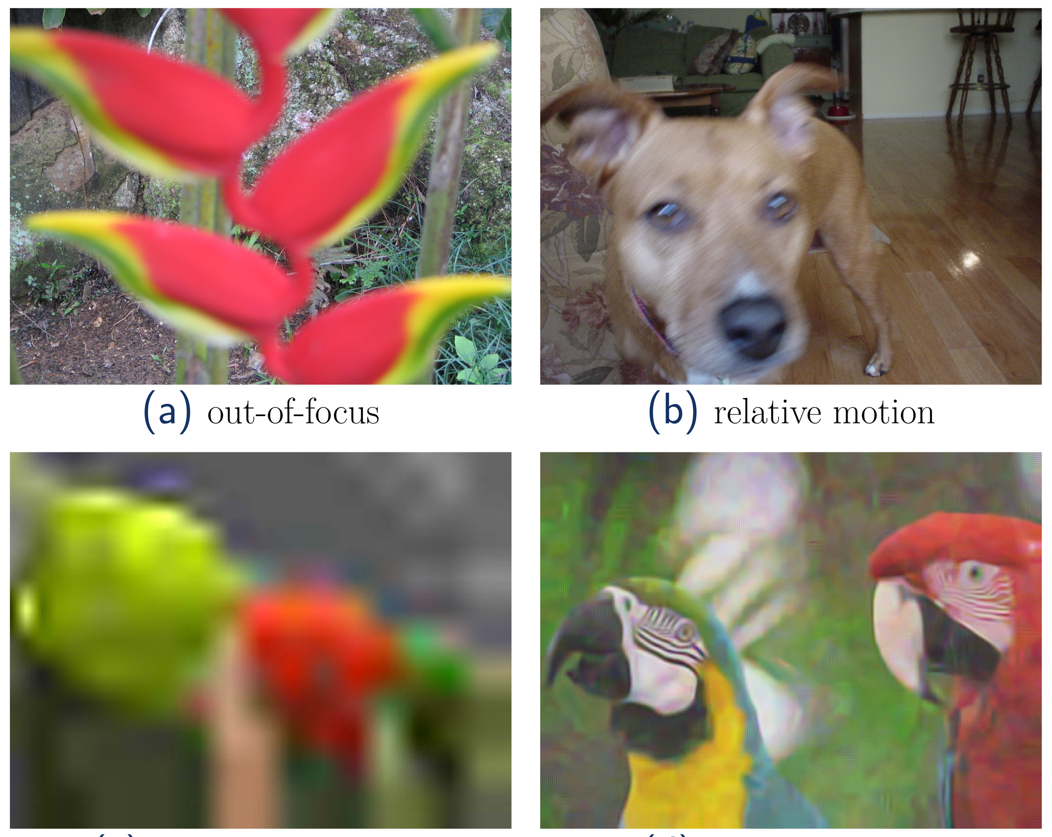
ACMmultimedia25
Mountain View, CA USA
October 23-27 2017

Dingquan Li, Tingting Jiang and Ming Jiang
{dingquanli,ttjiang,ming-jiang}@pku.edu.cn
北京大學
PEKING UNIVERSITY

Background

If you can't measure it, you can't improve it. - Peter Drucker

- **Image quality assessment (IQA)** is a critical precondition for providing a satisfying end-user experience.
- **Subjective IQA** is reliable, but it is often cumbersome, expensive and hard to carry out in reality.
- **Objective IQA**: FR-IQA, RR-IQA and NR-IQA.
- **NR-IQA** is preferable but also more challenging in most practical applications.
- **Image blur** is one of the most common distortions in practice, which relates to image quality.



(a) out-of-focus (b) relative motion (c) image compression (d) image denoising

Figure 1: Typical causes of image blur in practice.

Motivation

Traditional blur-specific NR-IQA methods are mainly based on the assumptions that blur leads to

- the spread of edges [1]
- the smoothing effect [2]
- the reduction of high-frequency energy [3]
- the loss of local phase coherence [4].

Which has better visual quality?

Figure 2: The clear blue sky or a blurry mouse?

- The above low-level features based methods may contravene **human perception** on predicting the relative quality of image pairs with various **image content**.
- To tackle this issue, we resort to the high-level **semantics**.

The Proposed Semantic Feature Aggregation (SFA) based Method

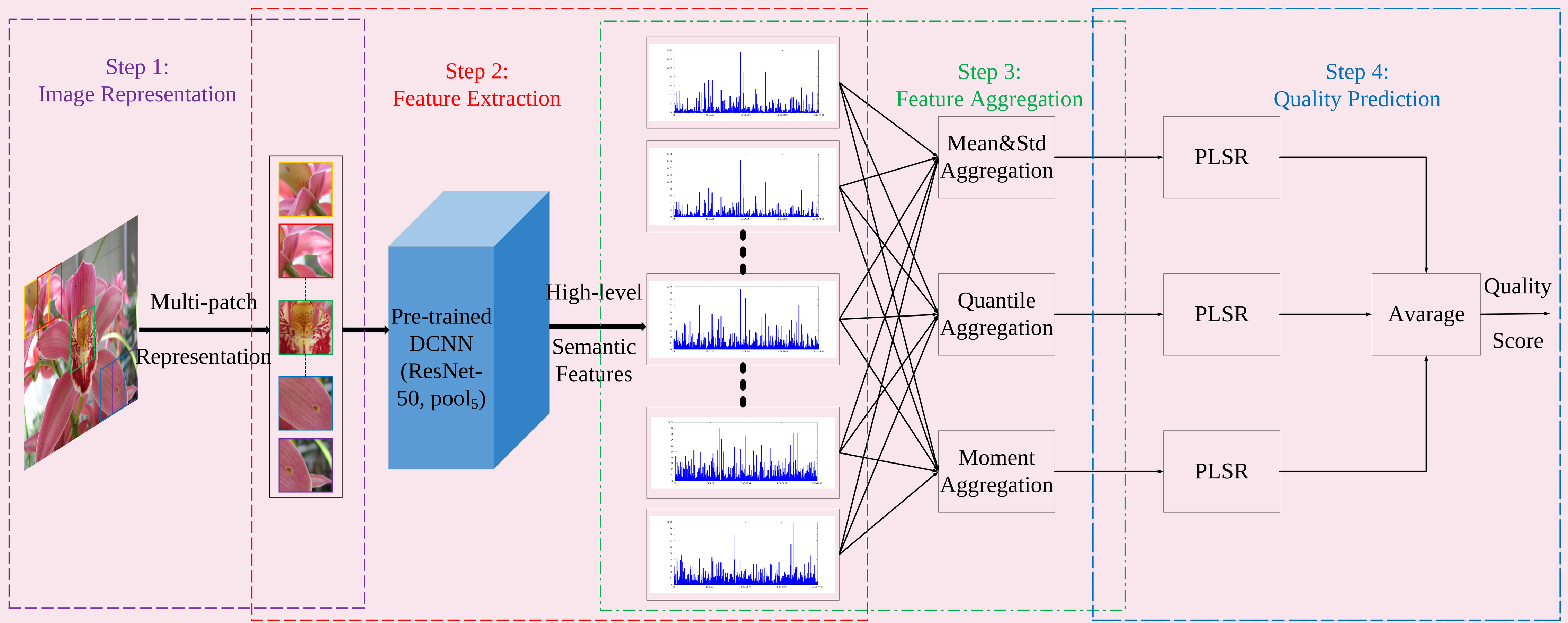


Figure 3: The overall framework of the proposed method, mainly includes four steps: image representation, feature extraction, feature aggregation, and quality prediction. The choices in all steps are determined by the performance on validation data of BID.

1. How to represent an image?

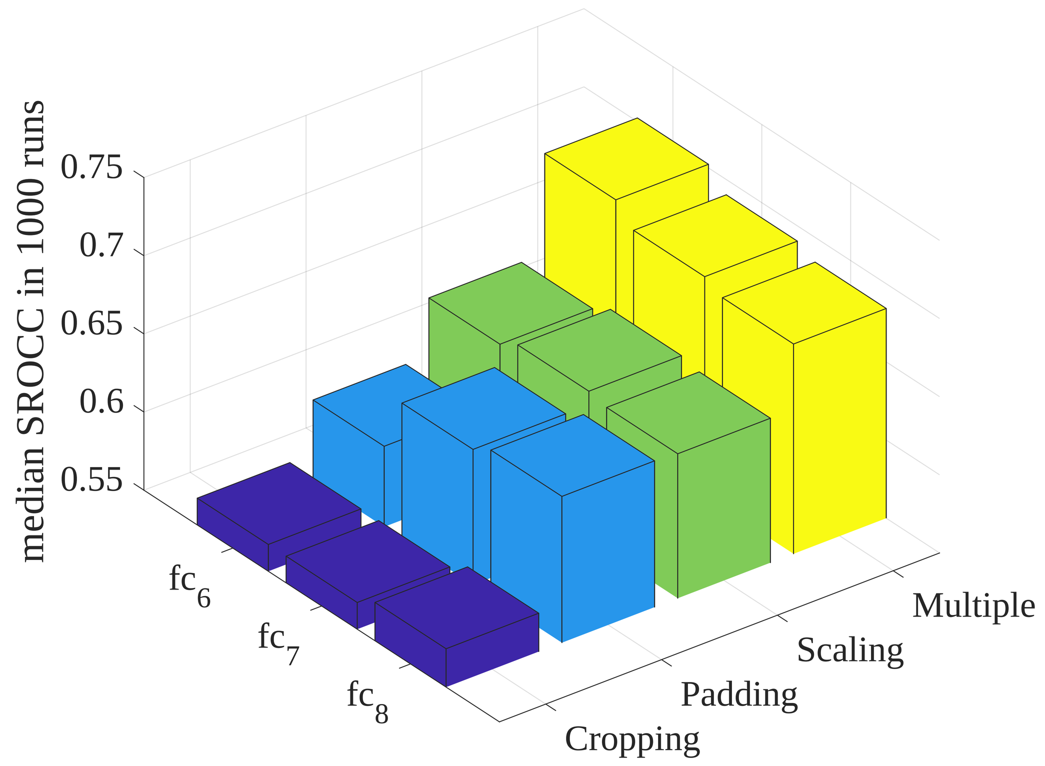


Figure 4: Comparison among different image representations.

2.1. Which layer to extract features?

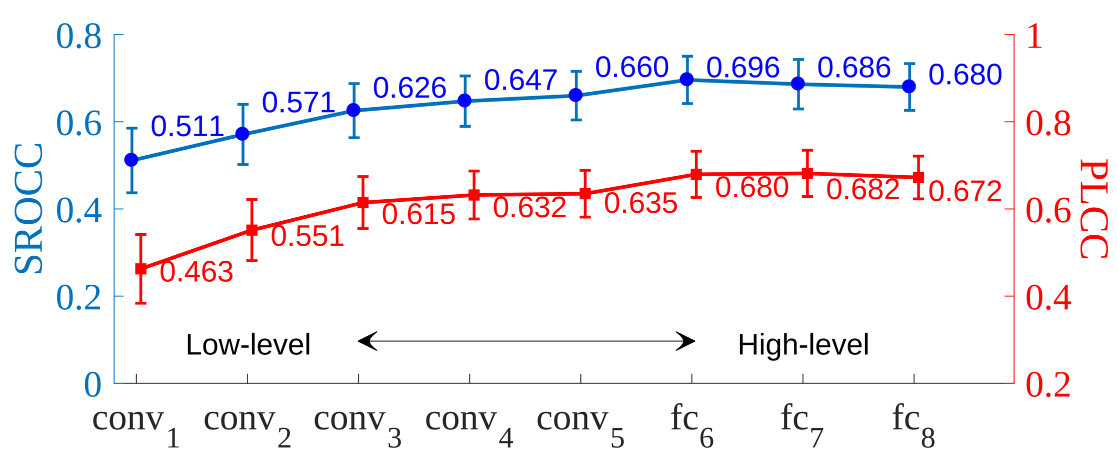


Figure 5: Comparison among different layers in AlexNet.

2.2. Which pre-trained model to extract features?

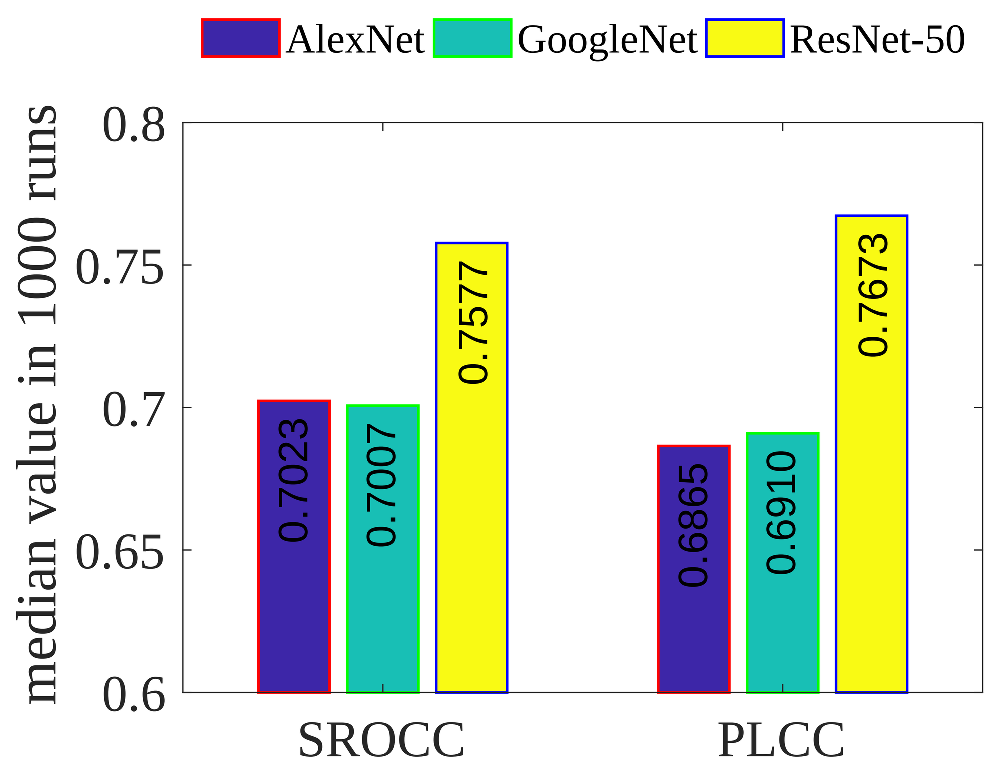


Figure 6: Comparison among different pre-trained models.

3. How to aggregate the features?

Aggregated Feature	SROCC	PLCC	RMSE
mean ($\mathbf{f}_{mean}$)	0.7577	0.7673	0.8283
mean&std ($\mathbf{f}_1$)	0.8022	0.8174	0.7333
quantile ($\mathbf{f}_2$)	0.8109	0.8254	0.7135
moment ($\mathbf{f}_3$)	0.8100	0.8254	0.7171
average-quality ($\mathbf{f}_1, \mathbf{f}_2, \mathbf{f}_3$)	**0.8154**	**0.8305**	**0.7055**

Table 1: Comparison among different aggregation structures.

Experiments

Method	BID	CLIVE	TID2008	LIVE
MDWE [1]	0.3067	0.4313	0.8556	0.9188
FISH [3]	0.4736	0.4865	0.8737	0.9008
ARISM [2]	0.0151	0.2427	0.8851	**0.9585**
LPC [4]	0.3150	0.1483	0.8805	0.9469
FRIQUEE [5]	<u>0.7359</u>	<u>0.6916</u>	**0.9261**	0.9515
Proposed	**0.8269**	**0.8130**	<u>0.9098</u>	<u>0.9523</u>

Table 2: Performance comparison (in terms of SROCC) on four databases. In each column, the best performance value is marked in boldface and the second best performance value is underlined.

Train → Test	SROCC
BID → CLIVE	0.5729
CLIVE → BID	0.6838
TID2008 → LIVE	0.9166
LIVE → TID2008	0.9243

Table 3: SROCC values of the proposed method in cross dataset evaluation.

Conclusion

- A novel NR-IQA framework is proposed based on high-level semantic feature aggregation, whose superiority and generalization capability are verified on four popular image blur databases.
- High-level semantic information is experimentally verified to be crucial in quality estimation among various image content.

References

[1] P. Marziliano, F. Dufaux, S. Winkler, and T. Ebrahimi, "Perceptual blur and ringing metrics: Application to JPEG2000," *Signal Processing: Image Communication*, vol. 19, no. 2, pp. 163–172, 2004.

[2] K. Gu, G. Zhai, W. Lin, X. Yang, and W. Zhang, "No-reference image sharpness assessment in autoregressive parameter space," *IEEE Transactions on Image Processing*, vol. 24, no. 10, pp. 3218–3231, 2015.

[3] P. V. Vu and D. M. Chandler, "A fast wavelet-based algorithm for global and local image sharpness estimation," *IEEE Signal Processing Letters*, vol. 19, no. 7, pp. 423–426, 2012.

[4] R. Hassen, Z. Wang, and M. M. A. Salama, "Image sharpness assessment based on local phase coherence," *IEEE Transactions on Image Processing*, vol. 22, no. 7, pp. 2798–2810, 2013.

[5] D. Ghadiyaram and A. C. Bovik, "Perceptual quality prediction on authentically distorted images using a bag of features approach," *Journal of Vision*, vol. 17, no. 32, 2017.