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

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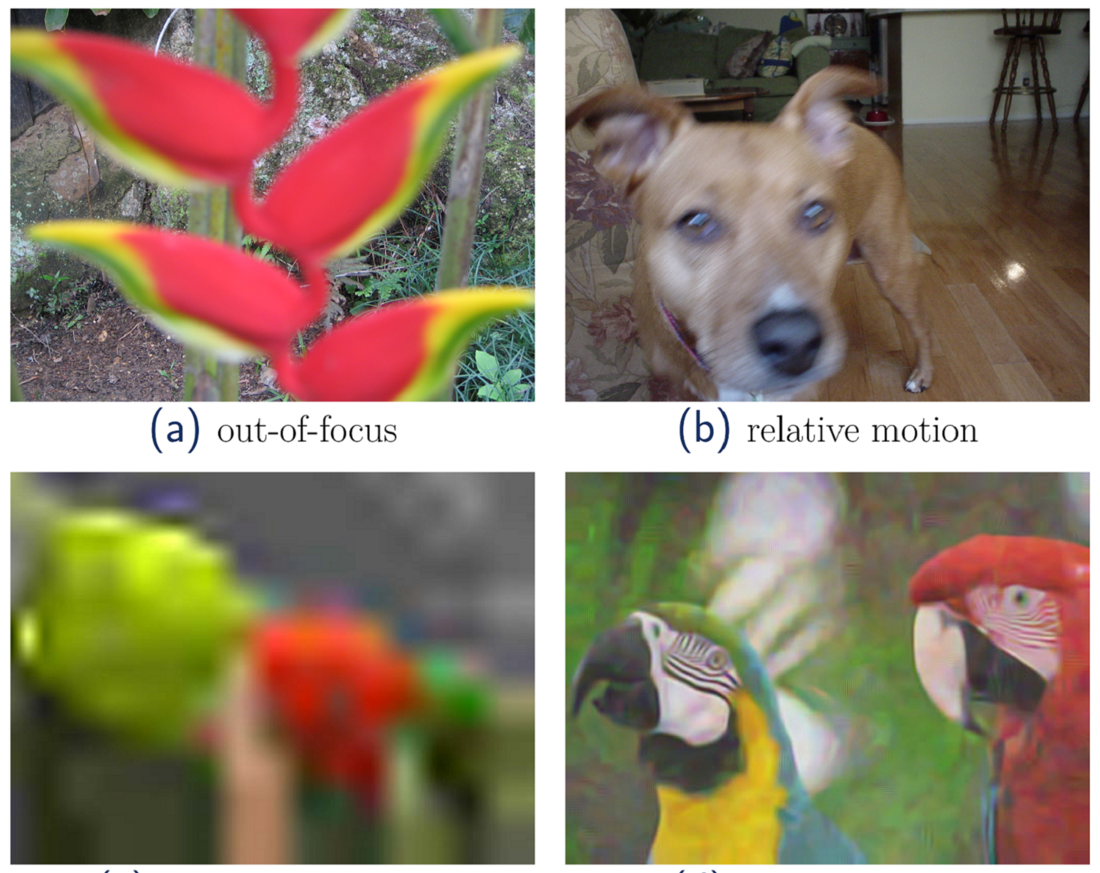
Background

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: full-reference IQA (FR-IQA), reduced-reference IQA (RR-IQA) and no-reference IQA (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 (*e.g.*, MDWE [1]), the smoothing effect (*e.g.*, ARISM [2]), the reduction of high-frequency energy (*e.g.*, FISH [3]) or the loss of local phase coherence (*e.g.*, LPC [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**, which is derived from a *pre-trained deep convolutional neural network model*.

The Proposed Semantic Feature Aggregation (SFA) based Method

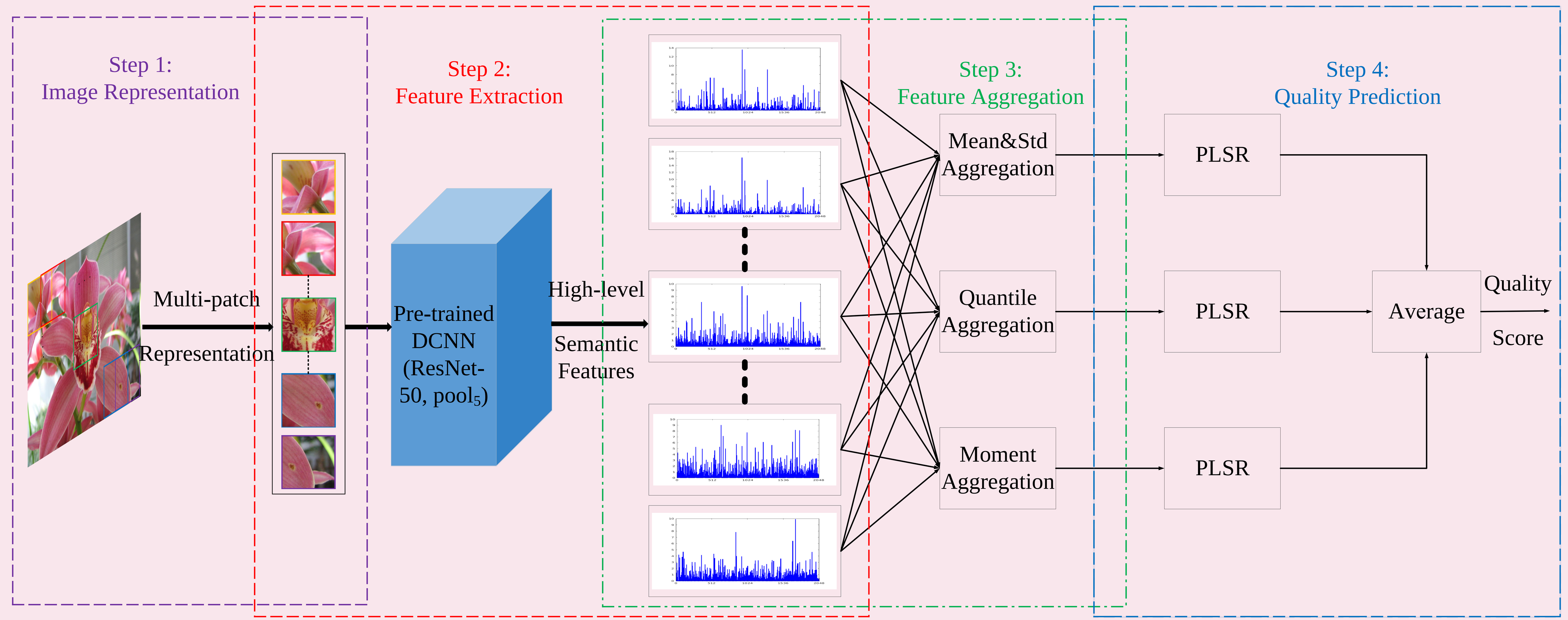


Figure 3: The overall framework of the proposed method, mainly includes four steps: image representation, feature extraction, feature aggregation, and quality prediction. The choices in all steps are determined by the performance on validation data of BID.

How to represent an image?

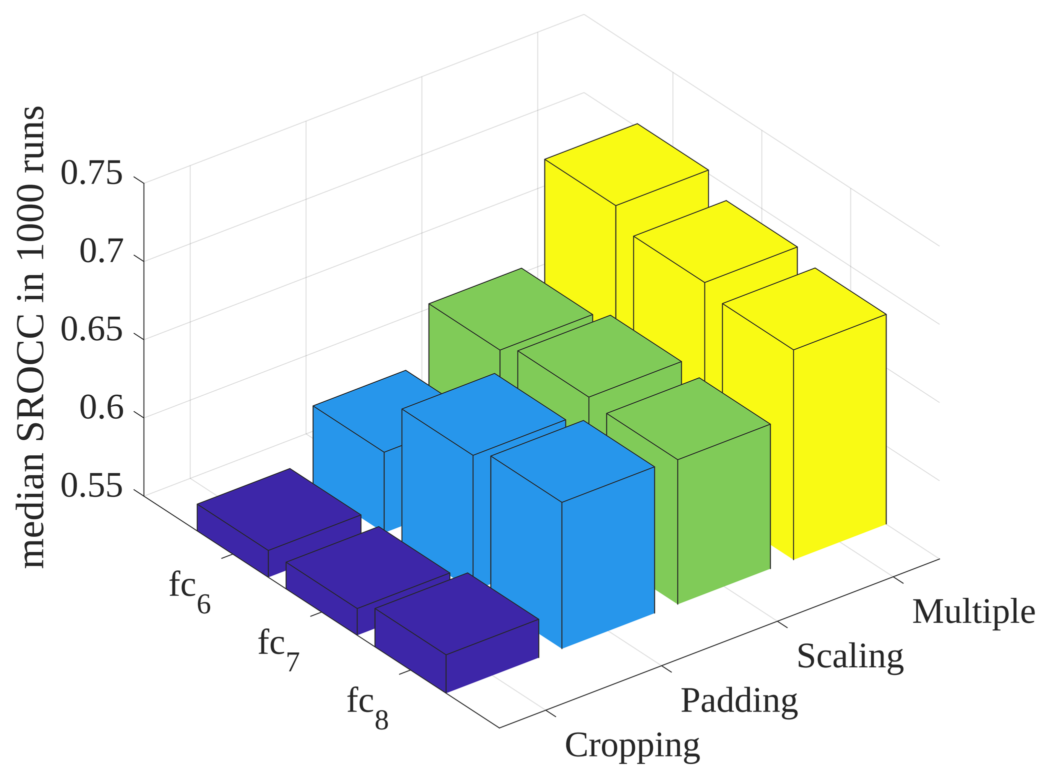


Figure 4: Comparison among different image representations.

Which layer to extract features?

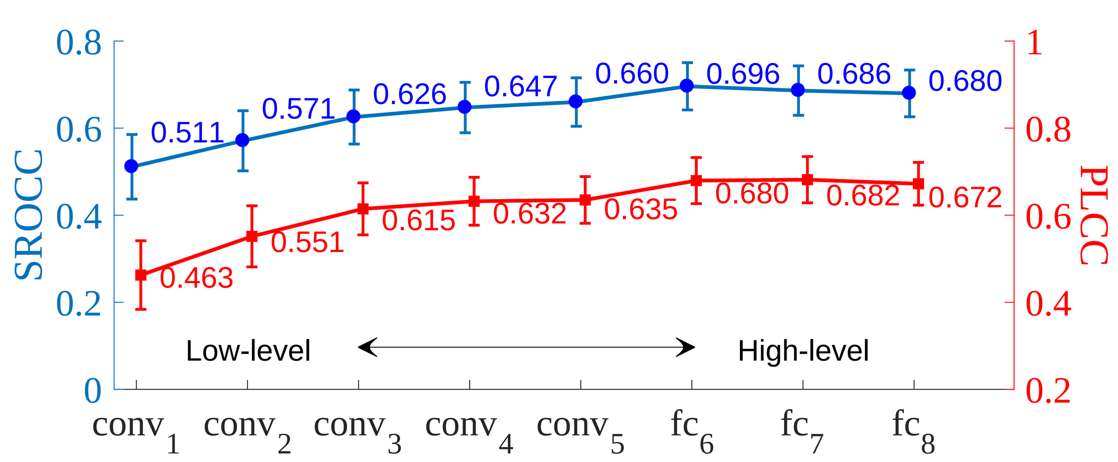


Figure 5: Comparison among different layers in AlexNet.

Which pre-trained model to extract features?

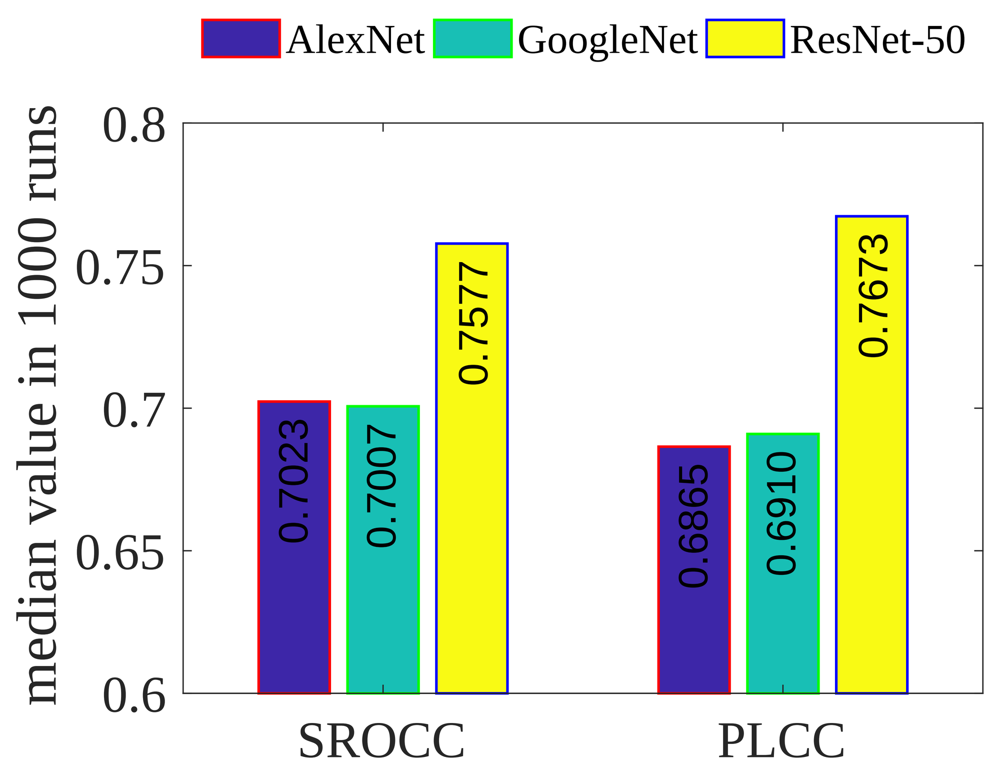


Figure 6: Comparison among different pre-trained models.

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]	<u>0.4736</u>	<u>0.4865</u>	0.8737	0.9008
ARISM [2]	0.0151	0.2427	<u>0.8851</u>	**0.9585**
LPC [4]	0.3150	0.1483	0.8805	0.9469
Proposed	**0.8269**	**0.8130**	**0.9098**	<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.

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