

# Learning a Blind Measure of Perceptual Image Quality

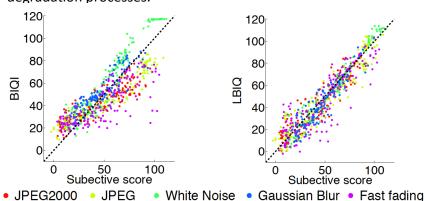
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Research

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**Designing Image Quality Features** 

#### Motivation

- Provide a measure of image quality as perceived by a human observer:
- Assessment does not require knowing the ground-truth image or degradation process.
- The score it provides is consistent across images and types of degradation processes.

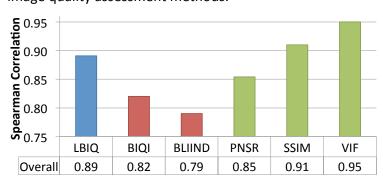


## **Challenges**

- Direct noise measures do not map well with perceptual quality.
- The reference image and distortion type are unknown and estimating them can be difficult.
- Different types of image degradation processes affect an image's structure and statistics in a variety of ways.

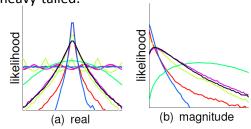
#### **Contributions**

- Several novel low-level features for measuring image quality.
- An algorithm to combine these features in order to learn a perceptually relevant image quality measure.
- Our LBIQ measure significantly outperforms state of art blind image quality assessment methods.

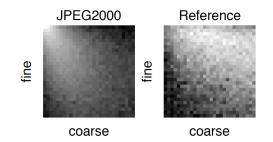


#### **Natural image statistics**

 High frequency responses of natural images are often zero-peaked and heavy-tailed.

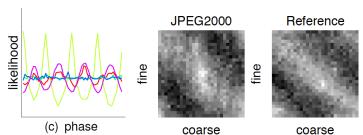


• High quality images often show selfsimilarity across scales.



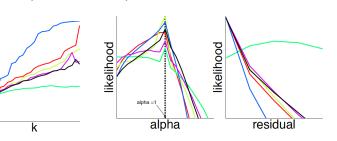
#### **Texture of degradation artifacts**

 Phase statistics are a good indicator of distortion artifacts.

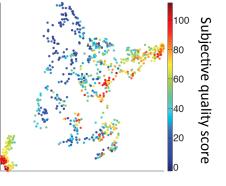


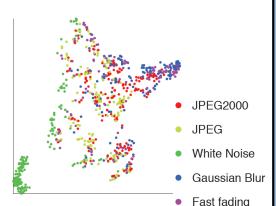
#### Blur/noise statistics

Noise and blur are two fundamental degradation processes that occur in a variety of distortion types, and they can be directly measured.



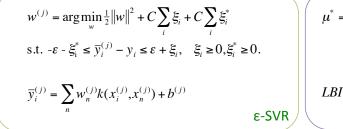
# t-SNE embedding of image features

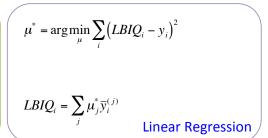




## **Learning Framework**

# Marginal wavelet statistics Joint wavelet statistics $x_i^{(2)}$ Blur/noise statistics $x_i^{(3)}$ $y_i^{(3)}$ $y_i^{(3)}$





### Performance

