Image quality assessment

E. Decencière

Mines Paris
PSL Research University
Center for Mathematical Morphology

Contents

Why do we want to measure image quality?

Why do we want to measure image quality?

- To improve image acquisition

Why do we want to measure image quality?

- To improve image acquisition
- To compare different acquisition systems

Why do we want to measure image quality?

- To improve image acquisition
- To compare different acquisition systems
- To evaluate the result of an image transformation

Why do we want to measure image quality?

- To improve image acquisition
- To compare different acquisition systems
- To evaluate the result of an image transformation
- To optimize an image transformation

Why do we want to measure image quality?

- To improve image acquisition
- To compare different acquisition systems
- To evaluate the result of an image transformation
- To optimize an image transformation

Why do we want to measure image quality?

- To improve image acquisition
- To compare different acquisition systems
- To evaluate the result of an image transformation
- To optimize an image transformation

We will only consider here the second and third use cases.

Notations

- X, x : ground-truth image set, original image

Notations

- X, x : ground-truth image set, original image
- Y, y : degraded image set, degraded image

Notations

- X, x : ground-truth image set, original image
- Y, y : degraded image set, degraded image
- $\hat{X}, \hat{x}$: restored image set, restored image

Notations

- X, x : ground-truth image set, original image
- Y, y : degraded image set, degraded image
- $\hat{X}, \hat{x}$: restored image set, restored image
- $f_{\boldsymbol{\theta}}$: image transformation parameterized by vector $\boldsymbol{\theta}$

Contents

Pixel-wise comparisons

- Mean squared error, PSNR
- Mean absolute error

Taking structure into account: SSIM

Idea

The measure is based on this quantity:

$$\left[1 - \frac{(\mu_x - \mu_y)^2}{\mu_x^2 + \mu_y^2}\right] \times \left[1 - \frac{(\sigma_x - \sigma_y)^2}{\sigma_x^2 + \sigma_y^2}\right] \times \frac{\sigma_{xy}}{\sigma_x \sigma_y}$$

Taking structure into account: SSIM

Idea

The measure is based on this quantity:

$$\left[1 - \frac{(\mu_x - \mu_y)^2}{\mu_x^2 + \mu_y^2}\right] \times \left[1 - \frac{(\sigma_x - \sigma_y)^2}{\sigma_x^2 + \sigma_y^2}\right] \times \frac{\sigma_{xy}}{\sigma_x \sigma_y}$$

Structure similarity index measure

$$SSIM(x, y) = \frac{2\mu_x\mu_y + c_1}{\mu_x^2 + \mu_y^2 + c_1} \times \frac{2\sigma_{xy} + c_2}{\sigma_x^2 + \sigma_y^2 + c_2}$$

where c_1 and c_2 are conveniently chosen strictly positive constants to avoid numerical problems.

Taking structure into account: SSIM

Idea

The measure is based on this quantity:

$$\left[1 - \frac{(\mu_x - \mu_y)^2}{\mu_x^2 + \mu_y^2}\right] \times \left[1 - \frac{(\sigma_x - \sigma_y)^2}{\sigma_x^2 + \sigma_y^2}\right] \times \frac{\sigma_{xy}}{\sigma_x \sigma_y}$$

Structure similarity index measure

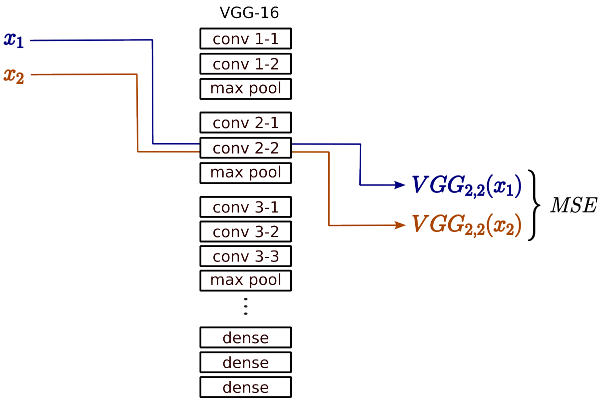
$$SSIM(x, y) = \frac{2\mu_x\mu_y + c_1}{\mu_x^2 + \mu_y^2 + c_1} \times \frac{2\sigma_{xy} + c_2}{\sigma_x^2 + \sigma_y^2 + c_2}$$

where c_1 and c_2 are conveniently chosen strictly positive constants to avoid numerical problems.

Remarks

- Typically applied within a sliding window.
- Several variants exist, like the multi-scale SSIM.

Using artificial neural networks



Contents

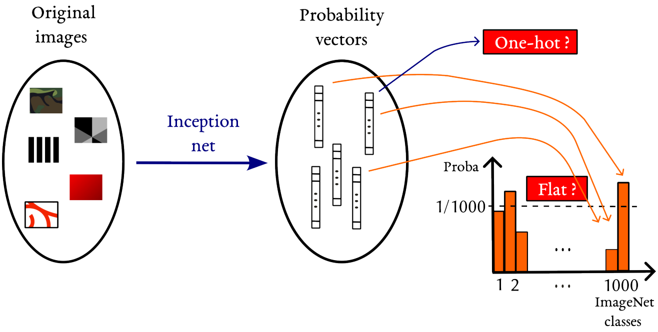
Classical methods

- Many methods: CBIQ, LBIQ, BLIINDS-II, DIVINE, BRISQUE, TMIO, NIQE [Mittal et al., 2013]

Classical methods

- Many methods: CBIQ, LBIQ, BLIINDS-II, DIVINE, BRISQUE, TMIO, NIQE [Mittal et al., 2013]
- Generally based on natural image statistics

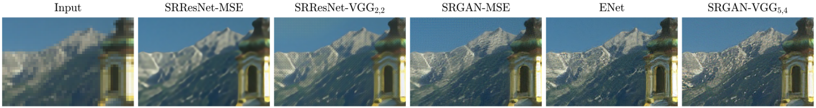
Inception score [Salimans et al., 2016]



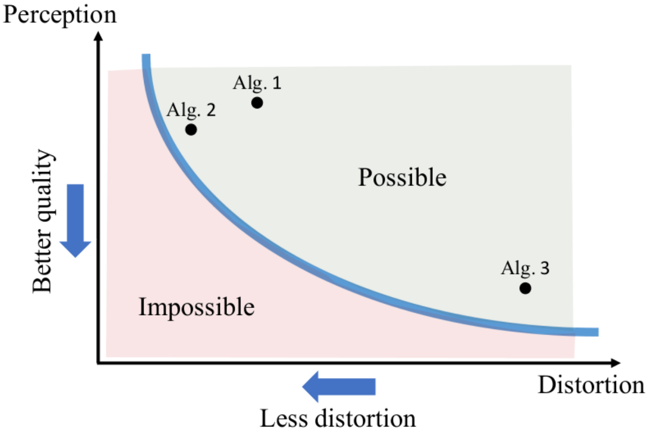
Fréchet inception distance [Heusel et al., 2017]

Contents

Observation [Blau and Michaeli, 2018]



Perception-distortion tradeoff [Blau and Michaeli, 2018]



Definitions

- Δ : distortion measure.

Definitions

- Δ : distortion measure.
- d : divergence between distributions.

Definitions

- Δ : distortion measure.
- d : divergence between distributions.

Definitions

- Δ : distortion measure.
- d : divergence between distributions.

Distortion, perception

- Distortion between X and $\hat{X}$: $E[\Delta(X, \hat{X})]$

Definitions

- Δ : distortion measure.
- d : divergence between distributions.

Distortion, perception

- Distortion between X and $\hat{X}$: $E[\Delta(X, \hat{X})]$
- Perception : $d(p_X, p_{\hat{X}})$

Theorem

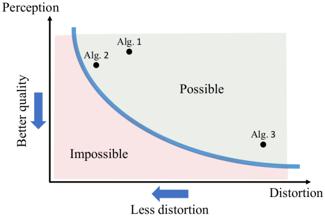
Perception-distortion function

$$P(D) = min_{p_{\hat{X}|Y}} d(p_X, p_{\hat{X}}) \quad s.t. \quad E(\Delta[X, \hat{X}]) \leq D$$

Theorem

Perception-distortion function

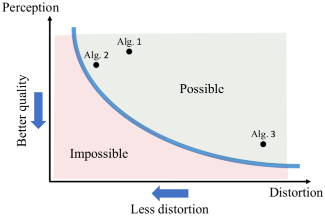
$$P(D) = min_{p_{\hat{X}|Y}} d(p_X, p_{\hat{X}}) \quad s.t. \quad E(\Delta[X, \hat{X}]) \leq D$$



Theorem

Perception-distortion function

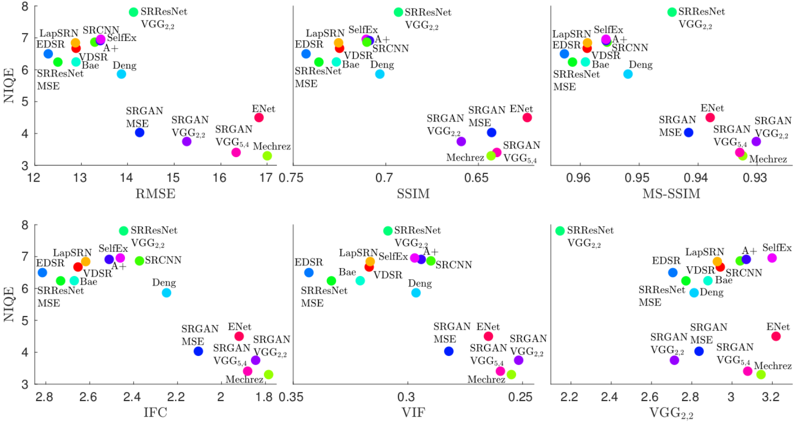
$$P(D) = min_{p_{\hat{X}|Y}} d(p_X, p_{\hat{X}}) \quad s.t. \quad E(\Delta[X, \hat{X}]) \leq D$$



Theorem

If the divergence d is convex in its second argument (which is the case for most common divergences) then $P(D)$ is monotonically non-increasing and convex.

Experiments



Contents

Conclusion

- The tradeoff depends on the application

Conclusion

- The tradeoff depends on the application
- In practice: choose an acceptable distortion, and try to optimize perceptual quality

References I

[Blau and Michaeli, 2018] Blau, Y. and Michaeli, T. (2018). The Perception-Distortion Tradeoff. In *2018 IEEE/CVF Conference on Computer Vision and Pattern Recognition*, pages 6228–6237. ISSN: 2575-7075.

[Heusel et al., 2017] Heusel, M., Ramsauer, H., Unterthiner, T., Nessler, B., and Hochreiter, S. (2017). GANs Trained by a Two Time-Scale Update Rule Converge to a Local Nash Equilibrium. In *Advances in Neural Information Processing Systems*, volume 30. Curran Associates, Inc.

[Mittal et al., 2013] Mittal, A., Soundararajan, R., and Bovik, A. C. (2013). Making a "Completely Blind" Image Quality Analyzer. *IEEE Signal Processing Letters*, 20(3):209–212. Conference Name: IEEE Signal Processing Letters.

[Salimans et al., 2016] Salimans, T., Goodfellow, I., Zaremba, W., Cheung, V., Radford, A., and Chen, X. (2016). Improved techniques for training gans. *Advances in neural information processing systems*, 29.