SSVD: Image Quality Assessment

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OUTLINE

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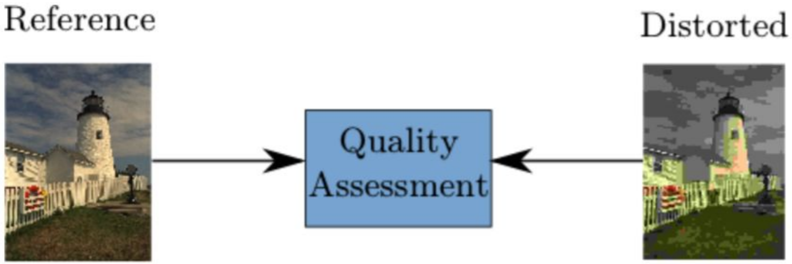
01 PROBLEM STATEMENT

Background

Image quality assessment (IQA) is a very important factor in different image processing applications. A visual signal can be affected by a wide range of modifications/distortions during signal acquisition, transmission, compression. The obvious way of measuring quality is to solicit the opinion of human observers. [1]



Ref: R. Soundararajan, Image Quality Assessment

Problem

Designing an IQA metric which predicts human judgments is a challenging issue.

[1] Kumar, S. & Prajapati, P.. (2015). A Review Paper on Image Quality Assessment Metrics. International Journal of Advance Research in Computer Science and Management. 2. 129-132.

Comparing IQA Metrics

- **Structural-based:**
  - **FSIM (Feature Similarity Index Measure)[1]**

Phase congruency and image gradient magnitude feature are considered. The former measure a significance of a local structure and the latter can expressed by convolution masking. Both of them reflect different aspect of HVS in assessing the local quality of the input images.

[1] L. Zhang, L. Zhang, X. Mou, D. Zhang, FSIM: a feature similarity index for image quality assessment, IEEE Trans. Image Process., 20 (2011), pp. 2378-2386

Comparing IQA Metrics (cont')

- **Structural-based:**
  - **Multi-scale structural similarity for image quality assessment (MS-SSIM)[1]**

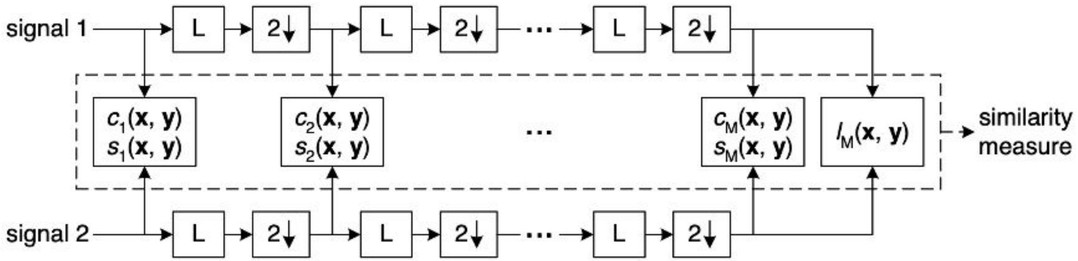


Fig. 1. Multi-scale structural similarity measurement system. L: low-pass filtering; 2 ↓: downsampling by 2.

Multi-scale method is top-down approach and a convenient way to incorporate image details at different resolutions, comparing to single scale method.

$$\mathrm{SSIM}(\mathbf{x},\mathbf{y}) = [l_M(\mathbf{x},\mathbf{y})]^{\alpha_M} \cdot \prod_{j=1}^{M} [c_j(\mathbf{x},\mathbf{y})]^{\beta_j} [s_j(\mathbf{x},\mathbf{y})]^{\gamma_j} .$$

[1] Z. Wang; E.P. Simoncelli; A.C. Bovik, "Multiscale structural similarity for image quality assessment", *2003*, DOI: 10.1109/ACSSC.2003.1292216

Comparing IQA Metrics (cont')

- **HVS-based:**
  - **PSNR (Peak Signal-to-Noise Ratio)[1]**

The **simplest and widely used** full reference image quality measurements via mean square error. However, it is well-known not reliable enough since they do not consider the image structure.

[2] $$MSE = \frac{1}{m\,n}\sum_{i=0}^{m-1}\sum_{j=0}^{n-1}[I(i,j) - K(i,j)]^2$$

$$\begin{aligned} PSNR &= 10 \cdot \log_{10}\left(\frac{MAX_I^2}{MSE}\right) \\ &= 20 \cdot \log_{10}\left(\frac{MAX_I}{\sqrt{MSE}}\right) \\ &= 20 \cdot \log_{10}(MAX_I) - 10 \cdot \log_{10}(MSE) \end{aligned}$$

[1] *Al-Najjar, Y. & Chen, S. D. (2012). "Comparison of image quality assessment: PSNR, HVS, SSIM, UIQI", International Journal of Scientific & Engineering Research. 3. pp. 1-5.*

[2] *"Peak signal-to-noise ratio", Retrieved December 15, 2020, from https://en.wikipedia.org/wiki/Peak_signal-to-noise_ratio*

Comparing IQA Metrics (cont')

- **HVS-based:**
  - **HaarPSI (Haar wavelet-based Perceptual Similarity Index) [1]**

It **assesses the perceptual similarity of two images in the interval** which two identical images will be exactly one and two completely different images will be close to zero. When original image consisted of Gaussian blur, the performance is consistently lower than other similarity metrics.

$$\mathrm{HaarPSI}: \ell^2(\mathbb{Z}^2) \times \ell^2(\mathbb{Z}^2) \to [0,1],$$

[1] *Reisenhofer R., Bosse S., Kutyniok G., Wiegand T (2018)., "A Haar wavelet-based perceptual similarity index for image quality assessment", Signal Processing:Image Communication, 61, pp. 33-43.*

Comparing IQA Metrics (cont')

- **Statistical-based:**

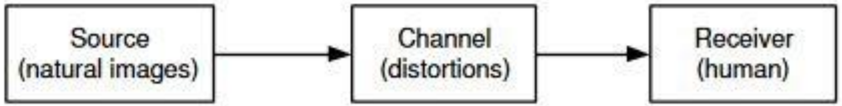
  These methods depend mainly on *Natural Scenes Statistics* (NSS).

  In other words, Natural images are treated as signals with certain statistical features.

Let's discuss briefly

Comparing IQA Metrics (cont')

- **Statistical-based:**
    - **IFC (Information Fidelity Criterion)**

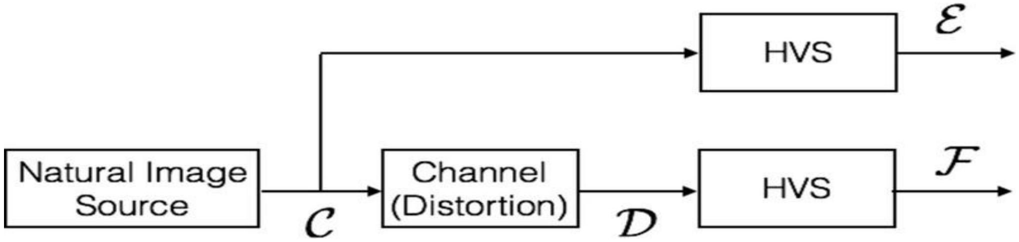


- Source Model: It's modeled using independent Gaussian Scale Mixture (GSM) coefficients..
- Distortion Model: Some signal attenuation and additive noise for each subband.
- Receiver Model: It represents the information extracted from both previous models.

https://live.ece.utexas.edu/publications/2004/hrs_ieeetip_2004_infofidel.pdf

Comparing IQA Metrics (cont')

- **Statistical-based:**
  - **VIF (Visual Information Fidelity)**



It's an extension of the previously-mentioned IFC. However, it's more numerically stable, as it limits the output, instead of [0, ∞), to [0, 1] for normal images.

P.S. It can exceed 1 for contrasted images.

https://upload.wikimedia.org/wikipedia/commons/d/dd/Vif_wiki.pdf

Comparing IQA Metrics (cont')

- **Statistical-based:**
  - **Advantages:**
    1. These methods are parameterless. So, there's no need for any stabilizing constants or configuration parameters.
    2. Signal attenuations aren't ignored, and they're treated differently from the additive noise.
  - **Disadvantages:**
    1. It lacks color statistics.
    2. It uses either GSM or generalized Gaussian density to predict the non-Gaussian marginal distribution of wavelets.
    3. Inter-subband correlations aren't utilized efficiently.

Dataset

TID 2013 [1] contained the same fixed size 512×384 pixel images, and 3000 distorted images (25 test images with 24 types and 5 levels of distortions)

Application

Visual processing applications such as **image/video coding**, **information hiding** and **visual enhancement**

Measure Performance

- Spearman rank order correlation coefficient **(SROCC)**
- Kendall rank order correlation coefficient **(KROCC)**

[1] *Ponomarenko N., Jin L., Ieremeiev O., Lukin V., Egiazarian K., Astola J., et al., Image database TID2013: Peculiarities, results and perspectives, Signal Process., Image Commun., 30(2015), pp. 57-77*
[2] *A. Mansouri, A. Mahmoudi-Aznaveh, "SSVD: structural SVD-based image quality assessment", Signal Processing: Image Communication, vol. 16, no. 2, pp. 49–53, 2019. DOI: 10.1016/j.image.2019.01.007.*

02 METHODOLOGY

Recall SVD

$$A_{m\times n} = \sum_{i=1}^{k} S_i U_i V_i^T, \quad k = \min(m,n)$$

$$S_i = \|AV_i\|$$

$$U_i = \begin{cases} 0, & if\ S_i = 0 \\ AV_i/S_i, & otherwise \end{cases}$$

"SVD" estimation of distorted image[1]

$$\hat{S}_i = \|\hat{A}V_i\|$$

$$\hat{U}_i = \begin{cases} 0, & if\ \hat{S}_i = 0 \\ \hat{A}V_i/\hat{S}_i, & otherwise \end{cases}$$

A - reference image

$\hat{A}$ - distorted image

[1] *A. Mahmoudi-Aznaveh, A. Mansouri, F. Torkamani-Azar, M. Eslami, Image quality measurement besides distortion type classifying, Opt. Rev. 16 (2009) 30–34.*

SSVD method

Image distortion

Luminance factor

Structural factor

$$A_{m\times n} = \sum_{i=1}^{k} \boxed{S_i}\,\boxed{U_i V_i^T}$$

[1] *A. Mahmoudi-Aznaveh, A. Mansouri, F. Torkamani-Azar, M. Eslami, Image quality measurement besides distortion type classifying, Opt. Rev. 16 (2009) 30–34.*

SSVD method

Luminance factor

1. $U, S, V = \mathbf{svd}(A)$ — SVD of the reference image

2. $\hat{S}_{Vi} = \|\hat{A}V_i\|$ — Estimate of the singular values by left singular vectors

3. $F^{LV} = \sqrt{\sum_{i=1}^{CPF} \left|(S_i - \hat{S}_{Vi})\right| w_i}$ — Calculate how much they differ from singular values of reference image

   where $w_i = S_i \Big/ \sum_{i=1}^{blk-size} S_i$

4. Same for Su

5. $F^L = \dfrac{F^{LU} + F^{LV}}{2}$ — Average with right eigenvalues

Structural factor

1. $U, S, V = \mathbf{svd}(A)$ — SVD of the reference image

2. $\hat{S}_i = \|\hat{A}V_i\|$

   $\hat{U}_i = \begin{cases} 0, & if\ \hat{S}_i = 0 \\ \hat{A}V_i/\hat{S}_i, & otherwise \end{cases}$ — Estimate of the left singular vectors of distorted image

3. $S_V = \mathbf{svdvals}(U\hat{U}^T)$ — Calculate how much they differ from singular vectors of reference image

4. $F^{SV} = \sqrt{\sum_{i=1}^{CPF} [(S_{V_i} - 1)w_i]^2}$

   where $w_i = S_i \Big/ \sum_{i=1}^{blk-size} S_i$

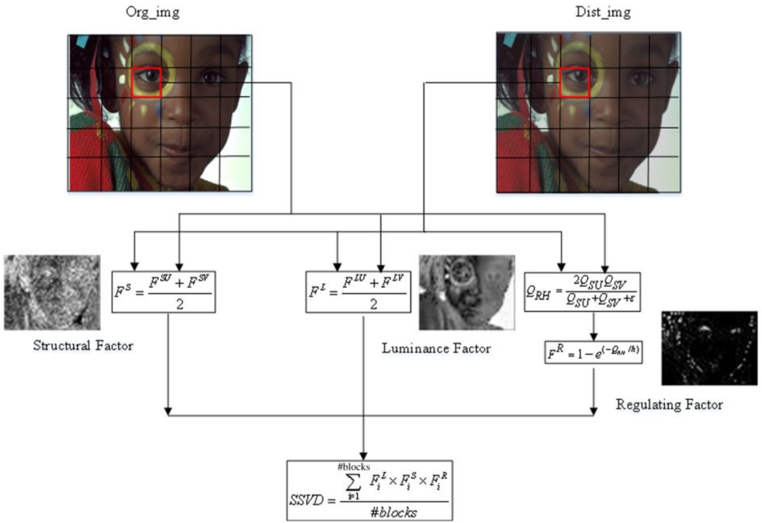
5. Same for Su

6. $F^L = \dfrac{F^{LU} + F^{LV}}{2}$ — Average with right eigenvalues

[1] *A. Mahmoudi-Aznaveh, A. Mansouri, F. Torkamani-Azar, M. Eslami, Image quality measurement besides distortion type classifying, Opt. Rev. 16 (2009) 30–34.*

SSVD method

Illustration for the SSVD method [1]



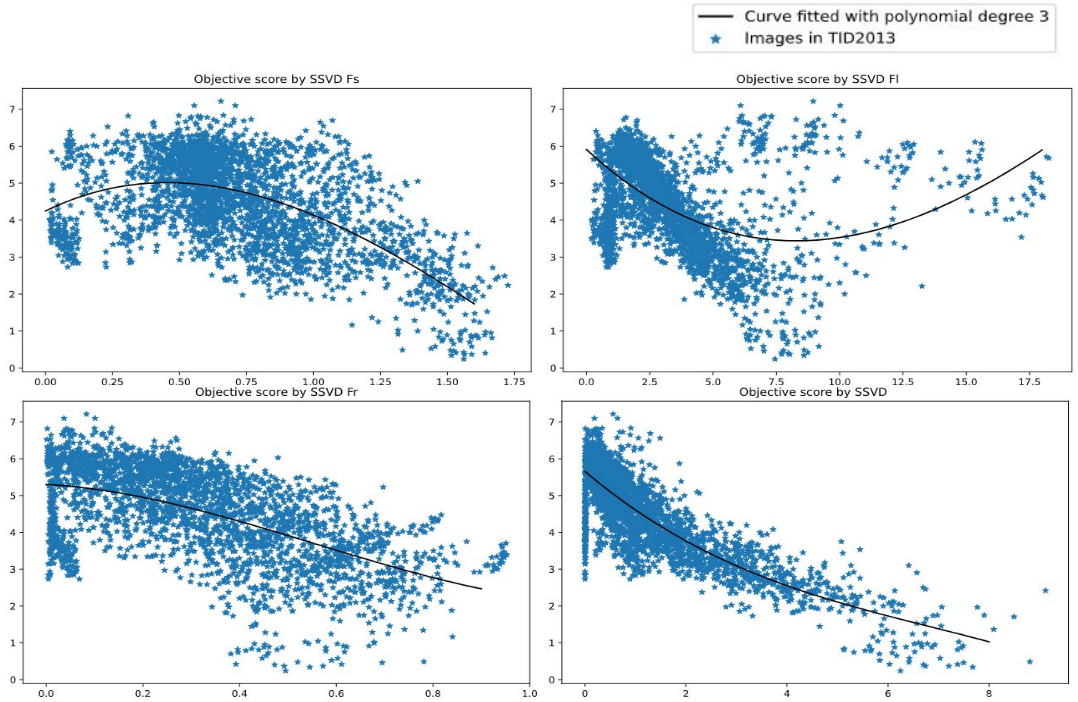
Dataset: TID 2013 [2]

[1] A. Mansouri & A. Mahmoudi-Aznaveh, *"SSVD: Structural SVD-based image quality assessment. Signal Processing: Image Communication", 2019*

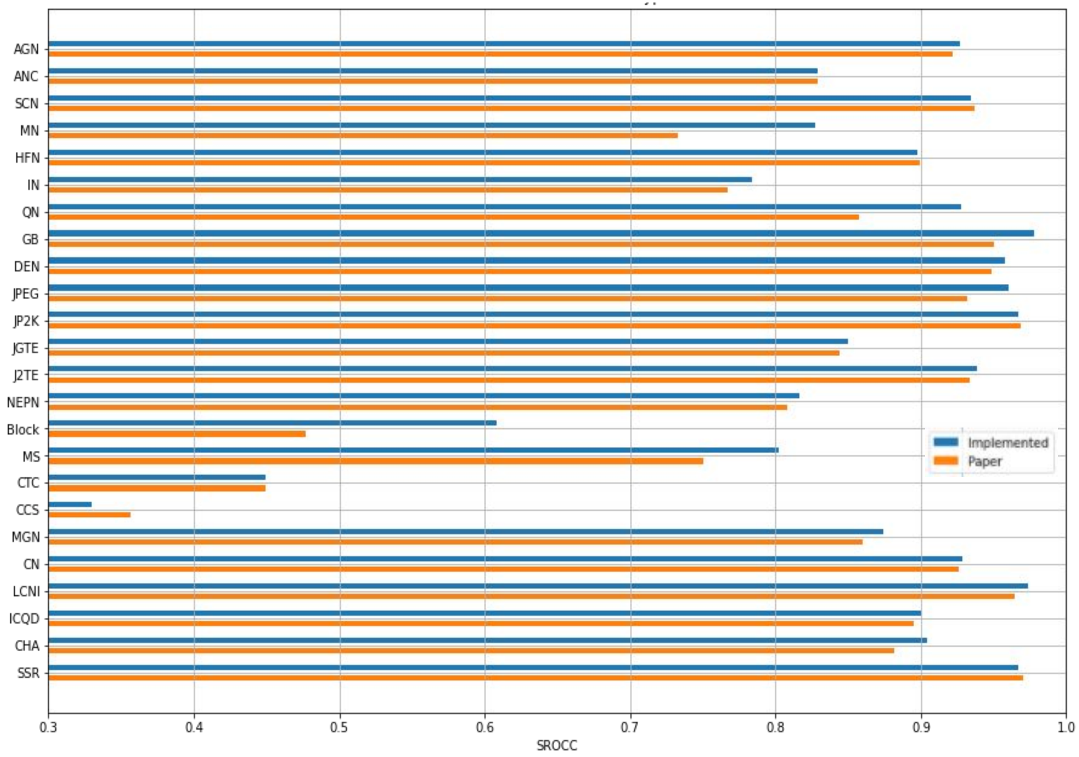
[2] *N. Ponomarenko, L. Jin, O. Ieremeiev, V. Lukin, K. Egiazarian, J. Astola, et al., Image database TID2013: Peculiarities, results and perspectives, Signal Process., Image Commun. 30 (2015) 57–77.*

03 RESULT

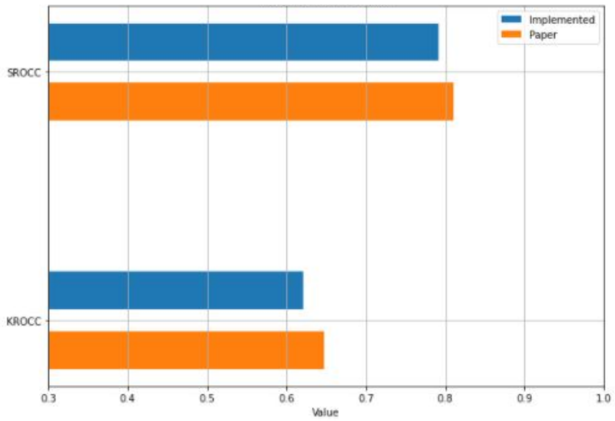
Subjective vs Objective Scores



SROCC for each distortion types



Measure Comparison



Comparison of SROCC of IQA metrics for each distortion type in TID2013

Distortion	HaarPSI	PSNR	SSVD
AGN	**0.9304**	0.9292	0.9270
ANC	0.8540	**0.8983**	0.8291
SCN	0.9199	0.9199	**0.9348**
MN	0.7851	**0.8322**	0.8277
HFN	0.9075	**0.9141**	0.8979
IN	0.8447	**0.8968**	0.7836
QN	0.8773	0.8808	**0.9276**
GB	0.9149	0.9149	**0.9782**
DEN	0.9451	0.9480	**0.9579**
JPEG	0.9432	0.9189	**0.9606**
JP2K	**0.9674**	0.8840	0.9672
JGTE	0.8490	0.7685	**0.8498**

Distortion	HaarPSI	PSNR	SSVD
J2TE	0.9215	0.8883	**0.9388**
NEPN	0.8104	0.6860	**0.8166**
Block	0.4602	0.1552	**0.6079**
MS	0.7391	0.7671	**0.8025**
CTC	**0.4622**	0.4403	0.4494
CCS	**0.4166**	0.0885	0.3296
MGN	0.8804	**0.8905**	0.8742
CN	0.9230	0.8411	**0.9288**
LCNI	0.9560	0.9145	**0.9733**
ICQD	0.8958	0.9269	**0.9004**
CHA	0.8723	0.8873	**0.9046**
SSR	0.9643	0.9042	**0.9666**

Comparison of SROCC and KROCC of IQA metrics

	HaarPSI	PSNR	SSVD
SROCC	0.8093	0.6394	0.7916
KROCC	0.6372	0.4696	0.6211

04 SUMMARY

- Structure, HVS and statistical-based IQA metrics were analysed
- SSVD, Haar and PSNR approaches were implemented
- Algorithms effectiveness were validated on TID2013 dataset

Further Analysis

- Apply SSVD approach with more datasets
- Compare algorithms effectiveness with more IQA metircs

THANK YOU!

Q&A