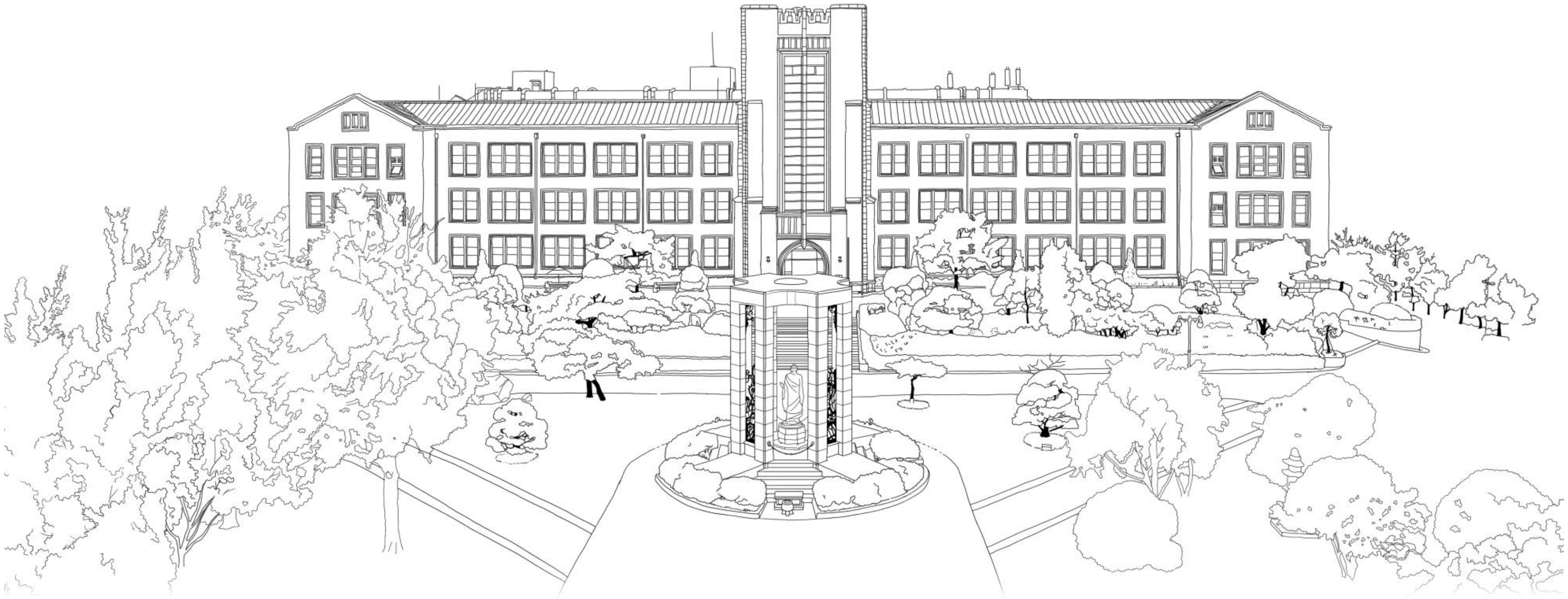

A New Image Quality Metric for Image Auto-Denoising

K. Xiangfei, L.Kuan and Y.Qingxion, " A New Image Quality Metric for Image Auto-Denoising" ICCV, 2013, pp. 2888-2895.

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Contents

❖ Image Denoising

- Image Degradation & Restore Model

$$noise(x,y)$$

$$f(x,y) \rightarrow \boxed{h(x,y)} \rightarrow \oplus \rightarrow g(x,y) \quad \boxed{Filter} \rightarrow f^{\wedge}(x,y) \rightarrow e(f^{\wedge}(x,y))$$

Original image — Degradation function — Result image — Restoration function — Restored image — Evaluate restored image

Denoising & evaluating part

- Image Denoising
  - ➢ Purpose: recovering the original image signal as much as possible from noise-corrupted version
  - ➢ $g(x,y)$: noise-corrupted image, Filter : denoising algorithm
    $f^{\wedge}(x,y)$: denoised image, $e(\,)$: Image Quality Assessment (IQA) metrics
  - ➢ In this paper, focus on IQA metrics

❖ Motivation

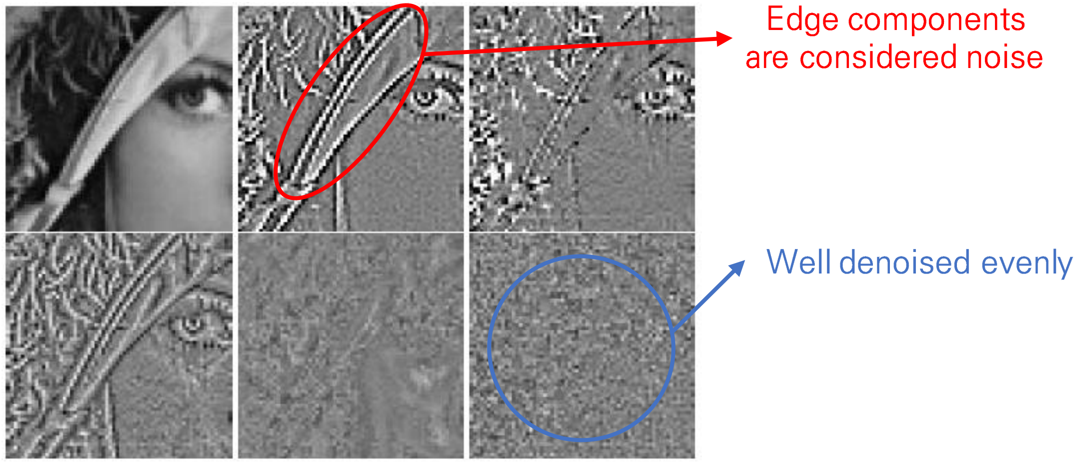
- Typical image quality assessment (IQA) metrics cannot be used
  - ➢ Mean squared error (MSE)
  - ➢ Peak signal to noise ratio (PSNR)

- No-reference IQA metrics are emerging
  - ➢ Existing metrics are computationally expensive
  - ➢ Require different mean opinion scores collected from humans

❖ proposed metric

- The authors propose to use method noise image (MNI)[1]
  - ➢ Only contains a noise
  - ➢ Can make MNI by calculating the difference between noisy image and denoised image.
  - ➢ Can get useful information

Denoised image



Method noise image(MNI)

[1] A. Buades, B. Coll, and J. Morel. A non-local algorithm for image denoising. In *CVPR*, pages 60–65, 2005.

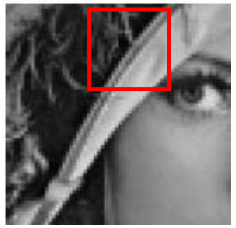
Introduction

❖ Goal of proposed metric

- Maximize the structure similarity between noisy image & MNI
  - ➢ Maximize the noise reduction
  - ➢ Homogeneous region

Homogeneous region

- Maximize the structure similarity between noisy image & denoised image
  - ➢ Maximize the structure preservation
  - ➢ Highly-structured region



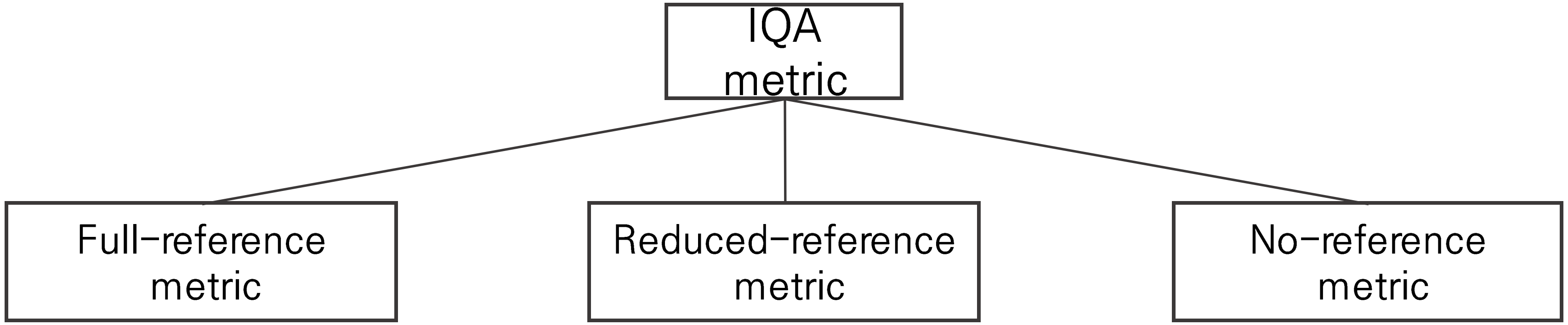
Highly-structured region

- A value that can consider two measurements is used as the IQR method.

Related Works

❖ IQA metrics (cont’d)

- Category of IQA metrics



Full-reference metric:

- MSE (RMSE)
- PSNR
- SSIM

No-reference metric:

- Q-metric
- Proposed metric

➢ The IQA metrics are categorized based on the existence of reference image

➢ Proposed metric is based on SSIM

➢ The performance of proposed metric is compared with the performance of Q-metric

Related Works

❖ Full-reference IQA metrics

- Compare the processed image with the original(reference) image

- Mean Squared Error (MSE)
  - $e = \frac{1}{n}\sum(y - y')^2$
  - y : noise-free image, y : denoised image

- Peak Signal Noise Ratio (PSNR)
  - $e = 10\log_{10}\frac{MAX_I^2}{MSE}$
  - MAX_I : maximum value of pixel

- Not correlated well with the visual perception of human vision system (HVS)
  - Do not consider structural or spatial information
  - Visual evaluation may differ from the result of equation

Related Works

❖ Full-reference IQA metrics (cont'd)

- Structure Similarity Index Measure (SSIM)
  - ➢ Separate the task of similarity measurement into luminance, contrast, structure
  - ➢ Assume that HVS is highly adapted for structures and less sensitive to the variance of the luminance and contrast
  - ➢ The proposed metric also exploits image structure term in SSIM for image quality assessment

- Components of Structure Similarity Index Measure (SSIM)

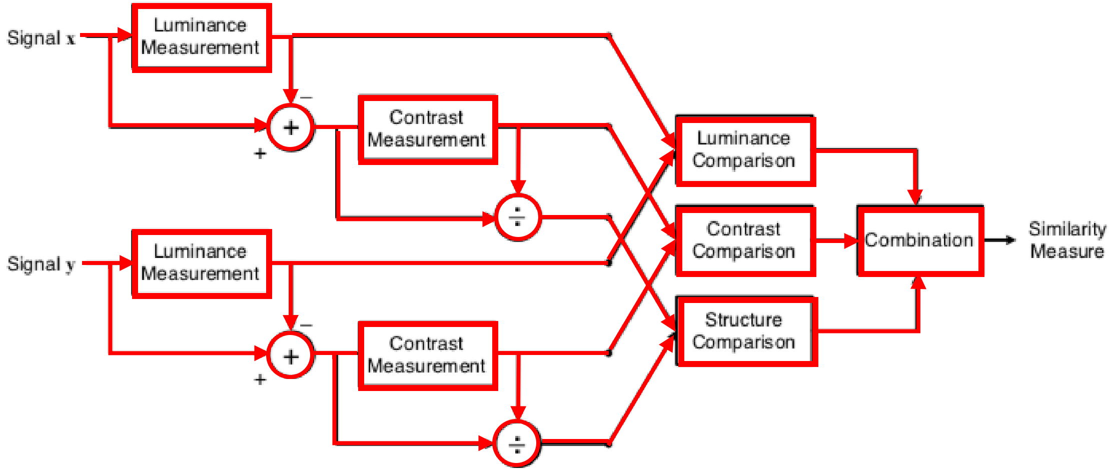


Fig. 3. Diagram of the structural similarity (SSIM) measurement system. [2]

- ○ Step 1 : calculate luminance of input image x, y
- ○ Step 2 : calculate contrast of input image x, y
- ○ Step 3 : define luminance & contrast comparison
- ○ Step 4 : define structure comparison
- ○ Step 5 : combination three terms

[2]
Z. Wang, A. C. Bovik, H. R. Sheikh, and E. P. Simoncelli. Image quality assessment: From error visibility to structural smilarity. TIP, 13(4):600–612, 2004.. .

Related Works

❖ Full-reference IQA metrics (cont'd)

- Definition of Structure Similarity Index Measure (SSIM)
  - ➢ Step 1 : calculate luminance
    - ✓ The luminance is estimated as the mean intensity
    - ✓ $\mu_x = \frac{1}{N}\sum_{i=1}^{N} x_i$
  - ➢ Step 2 : calculate contrast
    - ✓ The contrast is estimated as the standard deviation
    - ✓ $\sigma_x = (\frac{1}{N-1}\sum_{i=1}^{N}(x_i - \mu_x)^2)^{\frac{1}{2}}$
  - ➢ step 3 : define luminance & contrast comparison
    - ✓ $l(x,y) = \frac{2\mu_x\mu_y + C_1}{\mu_x^2 + \mu_y^2 + C_1}$
    - ✓ $c(x,y) = \frac{2\sigma_x\sigma_y + C_2}{\sigma_x^2 + \sigma_y^2 + C_2}$ (C_1, C_2 are the constant for stability)
    - ✓ $l(x,y) = 1$ or $c(x,y) = 1$, when the comparison of luminance or contrast of image x, y are same

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Related Works

❖ Full-reference IQA metrics (cont'd)

- Definition of Structure Similarity Index Measure (SSIM)

  - Step 4 : define structure comparison
    - ✓ The structure is normalized by its own standard deviation → $(x - \mu_x)/\sigma_x$, $(y - \mu_y)/\sigma_y$
    - ✓ Correlation coefficient between x and y is equivalent to the correlation between $(x - \mu_x)/\sigma_x$, $(y - \mu_y)/\sigma_y$
    - ✓ $\mathrm{s}(x, y) = \frac{\sigma_{xy} + C_3}{\sigma_x \sigma_y + C_3}$

  - Step 5 : Combine three terms
    - ✓ $SSIM(x, y) = l(x, y) \times c(x, y) \times s(x, y)$

$$= \frac{(2\mu_x\mu_y + C_1)\times(\sigma_{xy} + C_2)}{(\mu_x^2 + \mu_y^2 + C_1)(\sigma_x^2 + \sigma_y^2 + C_2)} \qquad (C_3 = C_2/2)$$

    - ✓ Now we can evaluate image using luminance, contrast, structure

Related Works

❖ Reduced-reference IQA metrics

- Utilize only partial information of the reference image
  - ➢ Features are extracted using certain models
  - ➢ compared to extracted features from some representations of noisy images

❖ No-reference IQA metrics

- Q-metric[3]
  - ➢ Compared with proposed metric
  - ➢ Step 1: Select sparse patches that have strong structure from the noisy image
  - ➢ Step 2 : compute the score at extracted patches
  - ➢ Step 3 : the average of extracted patches' is the IQR value

Selected patches

[3] X. Zhu and P. Milanfar. Automatic parameter selection for denoising algorithms using a no-reference measure of image content. *TIP*, 19(12):3116–3132, 2010.

Proposed Metric

❖ Introduction

- **Parameter setting**
  - ➢ Good parameter setting is important to make proper balance between preserving structure and reduction of the noise
    - ✓ preserve too many structural details → denoising effect is insufficient
    - ✓ Remove too much noise → structural details loss

- **Measurements for evaluating**
  - ➢ Noise reduction Map N & Structure preservation Map P
  - ➢ computed by using the similarity comparison from the SSIM
  - ➢ Unlike SSIM, proposed metric don't use reference image

Proposed Metric

❖ Overview

- proposed algorithm

Algorithm 1 A Non-reference Metric for Image Denoising

Input: the noisy image I and the denoised image $\hat{I}_h$.
Output: the image quality score e.

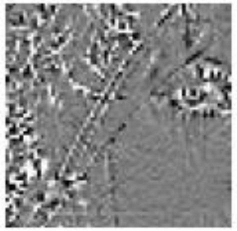
1. Compute the MNI which is the difference of the input noisy image I and the denoised image $\hat{I}_h$: $M_h = I - \hat{I}_h$;
2. Compute structure similarity map N between the input noisy image I and the MNI M_h via SSIM metric (Eq. 3);
3. Compute structure similarity map P between the input noisy image I and the denoised image $\hat{I}_h$ via SSIM metric (Eq. 4);
4. Compute image quality score e as the linear correlation coefficient of the two structure similarity maps N and P.

- ○ I : input noisy image
- ○ $\hat{I_h}$: denoised image obtained from a denoising algorithm
- ○ h : parameter configuration
- ○ M_h: MNI obtained with parameter configuration h (estimated image noise)
- ○ map N : local structure similarity between I and M_h
- ○ map P : local structure similarity between I and I_h

Proposed Metric

❖ Overview (cont'd)

- proposed algorithm
  - ➢ Step 1 : compute the MNI
    - ✓ We can get "Method Noise Image" through equation $M_h = I - \hat{I_h}$



MNI

=

Noisy image

−

denoised image

  - ➢ Step 2 ~ 3 : compute structure similarity map N and P
    - ✓ Using SSIM metric
    - ✓ $N_p = S(I^p, M_h^p)$, $P_p = S(I^p, \hat{I}_h^p)$
  - ➢ Step 4 : compute image quality score e
    - ✓ use linear correlation coefficient of maps N and P as image quality score e

Algorithm 1 A Non-reference Metric for Image Denoising

Input: the noisy image I and the denoised image $\hat{I}_h$.
Output: the image quality score e.

1. Compute the MNI which is the difference of the input noisy image I and the denoised image $\hat{I}_h$: $M_h = I - \hat{I}_h$;
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- ○ I : input noisy image
- ○ $\hat{I_h}$: denoised image
- ○ h : parameter configuration
- ○ M_h: MNI obtained with parameter configuration h
- ○ map N : local structure similarity between I and M_h
- ○ map P : local structure similarity between I and I_h

Proposed Metric

❖ Structure Comparison

- Assumption
  - ➢ Denoising algorithm does not change the luminance nor the contrast of a noisy image
    - ✓ Luminance & contrast are same in noisy & denoised image
    - ✓ In $SSIM$, $l(A,B) = c(A,B) = 1$
    - ✓ $SSIM(A,B) = l(A,B) \times c(A,B) \times s(A,B) = s(A,B)$
  - ➢ estimate the visual quality of a denoised image only with the structure comparison term

- Structure Comparison Function
  - ➢ Same process with $SSIM$
    - ✓ Luminance : $\mu_A = \frac{1}{N}\sum_{i=1}^{N} A_i,\ \ \mu_B = \frac{1}{N}\sum_{i=1}^{N} B_i$
    - ✓ Contrast : $\sigma_A = (\frac{1}{N-1}\sum_{i=1}^{N}(A_i - \mu_A)^2)^{\frac{1}{2}},\ \ \sigma_B = (\frac{1}{N-1}\sum_{i=1}^{N}(B_i - \mu_B)^2)^{\frac{1}{2}}$
    - ✓ Normalization : $(A - \mu_A)/\sigma_A,\ \ (B - \mu_B)/\sigma_B$
    - ✓ $s(A,B) = \frac{\sigma_{AB} + C}{\sigma_A \sigma_B + C}$

Proposed Metric

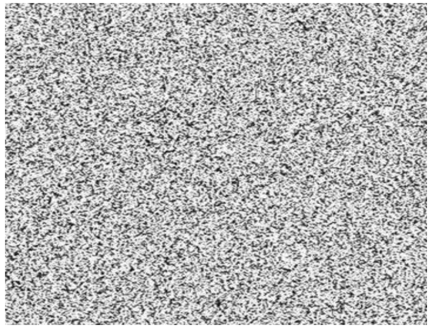
❖ Noise and Structure Measurement

- Define structure similarity map N
  - ➢ I^p, M_h^p : local image patch of image I & M_h at pixel p
  - ➢ N_p: The noise reduction measurement at p
    - ✓ Structure similarity with I^p, M_h^p
    - ✓ $N_p = S(I^p, M_h^p)$
  - ➢ N is a map composed of N_p

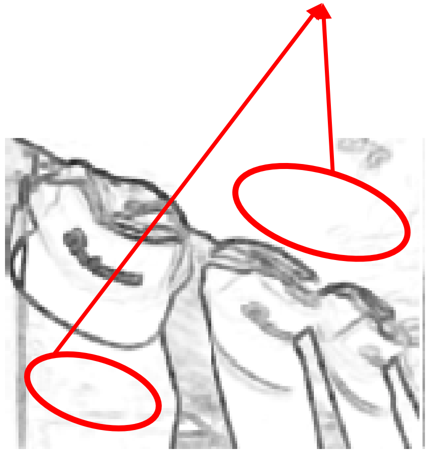
Homogeneous region

① Most of the noise has been removed
② Removed noise should present in the MNI at the same location
③ The structure of the noisy image I and the MNI M_h should be locally similar
④ Correlation coefficient relatively high (white)

Noisy image
(I)



MNI
(M_h)



Maps for noise reduction (N)

Proposed Metric

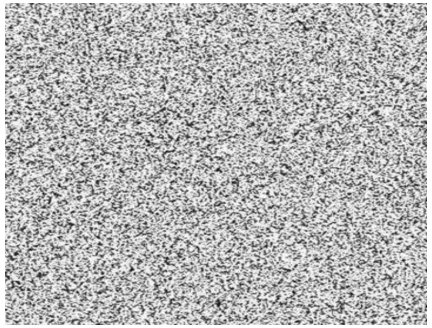
❖ Noise and Structure Measurement

- Define structure similarity map N
  - ➢ I^p, M_h^p : local image patch of image I & M_h at pixel p
  - ➢ N_p: The noise reduction measurement at p
    - ✓ Structure similarity with I^p, M_h^p
    - ✓ $N_p = S(I^p, M_h^p)$
  - ➢ N is a map composed of N_p

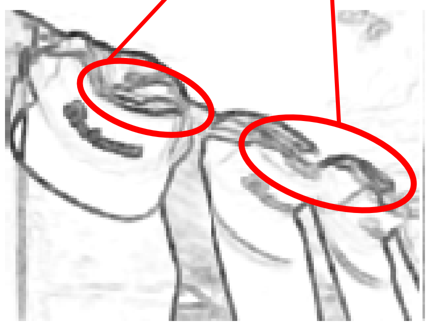
Highly textured region

① Most of the structure preserved
② No value in the MNI at the same location
③ The structure of the noisy image I and the MNI M_h should be locally dissimilar
④ Correlation coefficient relatively low (black)

Noisy image
(I)



MNI
(M_h)



Maps for noise reduction (N)

Proposed Metric

❖ Noise and Structure Measurement (cont'd)

- Define structure similarity map P
  - ➢ $I^p, I_h^{\wedge p}$: local image patch of image I & $I_h^{\wedge}$ at pixel p
  - ➢ p_p: The structure preservation measurement at p
    - ✓ Structure similarity with $I^p, I_h^{\wedge p}$
    - ✓ $p_p = S(I^p, \ \ I_h^{\wedge p})$
  - ➢ P is a map composed of p_p

Highly textured region

① Structure is well preserved
② The structure of the edge component of image I and the denoised image $I_h^{\wedge}$ should be locally similar
③ Correlation coefficient relatively high (white)

Noisy image
(I)

denoised image
($I_h^{\wedge}$)

Maps for structure
Preservation (P)

Proposed Metric

❖ Noise and Structure Measurement (cont'd)

- Define structure similarity map P
  - ➢ $I^p, I_h^{\wedge p}$: local image patch of image I & $I_h^{\wedge}$ at pixel p
  - ➢ p_p: The structure preservation measurement at p
    - ✓ Structure similarity with I^p, $I_h^{\wedge p}$
    - ✓ $p_p = S(I^p, \ I_h^{\wedge p})$
  - ➢ P is a map composed of p_p

Homogeneous region

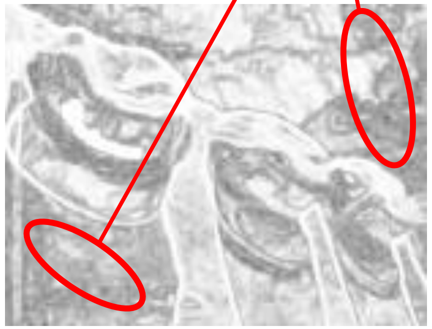
① Most of the noise has been removed
② The structure of the image I and the denoised image $I_h^{\wedge}$ should be locally dissimilar
③ Correlation coefficient relatively low (black)

Noisy image
(I)

✖

denoised image
($I_h^{\wedge}$)

➡

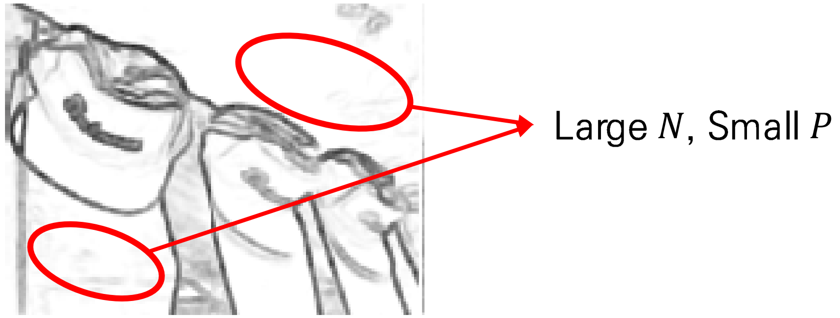


Maps for structure
Preservation (P)

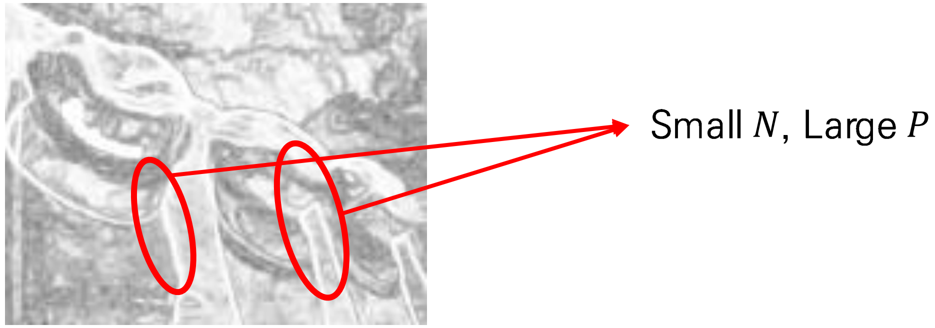
Proposed Metric

❖ Integration of Measurements

- Balance between $\boldsymbol{N}$ & $\boldsymbol{P}$
  - ➢ Good denoising algorithm should maintain a good balance and maximize both map N & P
    - ✓ In region with large N values (homogenous region) → P value should be small
    - ✓ In region with large P values (highly-textured region) → N value should be small



Maps for noise reduction (N)



Maps for structure preservation (P)

  - ➢ By using correlation coefficient, we can compute the dependency relation between N & P
    - ✓ Consider N & P as random variables
    - ✓ They have linear correlation

Proposed Metric

❖ Integration of Measurements (cont'd)

- Pearson correlation coefficient
  - $\rho(X,Y) = \frac{COV(X,Y)}{\sigma_X \sigma_Y}$
  - Pearson correlation coefficient between N & P are image quality score e
- Spearman correlation coefficient
  - Rank order correlation
  - The order of the elements are changed, therefore the spatial distribution of the measurements is changed
- Therefore, the proposed method utilize the Pearson correlation coefficient

Proposed Metric

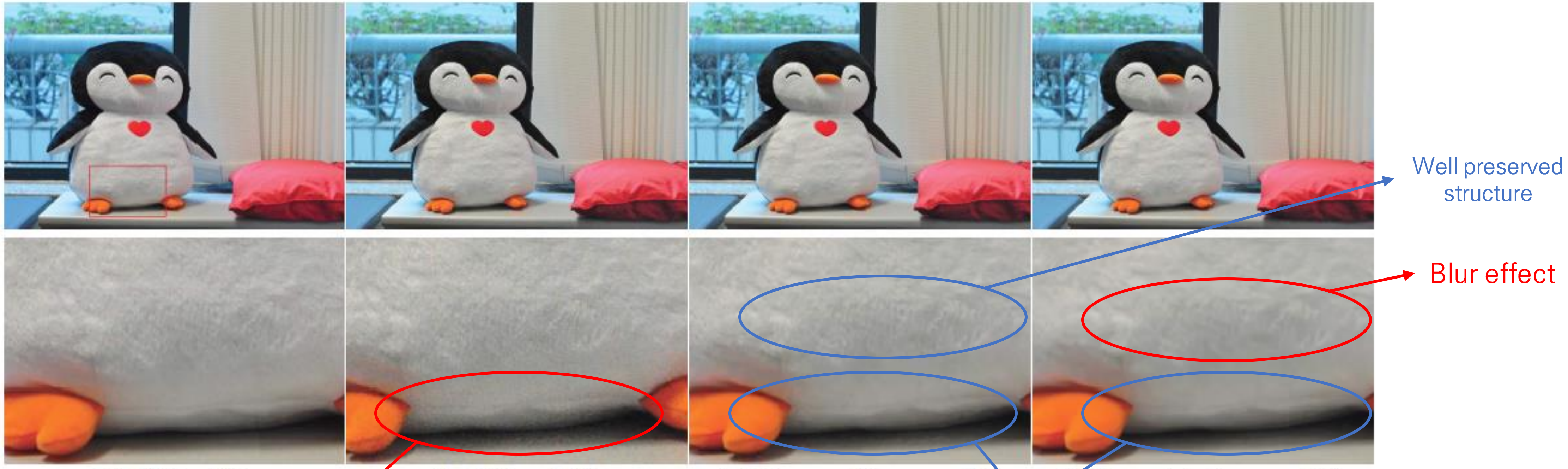
❖ Auto denoising formulation

- Proposed IQA metric can be employed by a parametric denoising algorithm

- Auto–denoising is formulated as a parameter selection problem
  - ➢ Select the optimal parameter configuration h
  - ➢ $h_i \in (h_1, h_2, \ldots, h_K)$, $K-$ possible parameter configurations for denoising algorithm
  - ➢ $I_h^{\wedge} = \overset{I^{\wedge h_i}}{argmax}\ e(I^{\wedge h_i}, I)$
  - ➢ $e(\ )$: Pearson correlation coefficient between map N & P

❖ Denoising with Real Noisy Images

- Images are captured with digital camera
  - Low ISO (a) – little noise ≈ noise free image
  - High ISO (b) – much noise ≈ noisy image
  - Use BM3D[4] denoising algorithm
  - Optimize parameter σ



(a) ISO = 200 (b) ISO = 6400 (c) Proposed ($\sigma_{est} = 11$) (d) Q-metric ($\sigma_{est} = 28$)

[4] K. Dabo, A. Foi, V. Katkovnik, and K. Egiazarian. Image denoising by sparse 3-d transform-domain collaborative filtering. TIP, 16(8):2080–2095, 2007..

Experimental Results

❖ Denoising with Synthetic Noisy Images

- **The quantitative evaluation is conducted**
  - ➢ Two image benchmark datasets $TID\ 2008$[5] (25 images), $LIVE2$[6] (29 images)
  - ➢ Use BM3D (parameter σ) & SKR[7] denoising algorithm (parameter i)
  - ➢ White Gaussian Noise(WGN) is added to the test image
    - ✓ Deviation σ from 5 to 20

- **Measurement method**
  - ➢ Use PSNR metric, because we have reference(original) image
  - ➢ Set optimized parameter using PSNR & compute optimal PSNR value by using original image
  - ➢ Compare PSNR error

PSNR error = Optimal PSNR value − PSNR value

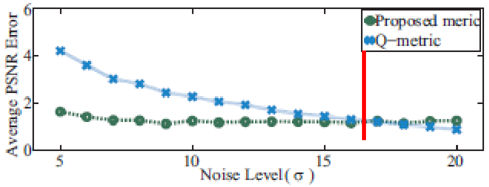
Between Denoised & noisy image

[5] N. Ponomarenko, V. Lukin, A. Zelensky, K. Egiazarian, and F. B. M. Carli. TID2008 – a database for evaluation of fullreference visual quality assessment metrics. Adv. Modern Radioelectron., 10:30–45, 2009..
[6] H. Sheikh, Z. Wang, L. Cormack, and A. Bovik. LIVE image quality assessment database release 2..
[7] H. Takeda, S. Farsiu, and P. Milanfar. Kernel regression for image processing and reconstruction. TIP, 16(2):349–399, 2007..

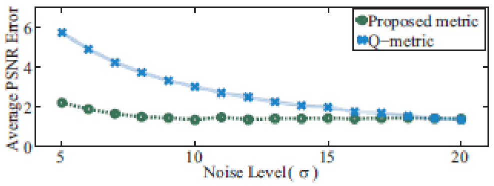
Experimental Results

❖ Denoising with Synthetic Noisy Images (cont'd)

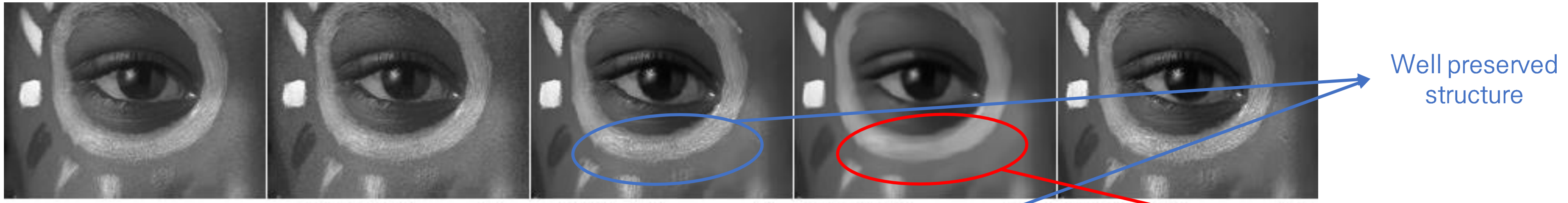
- When noise level(σ) is low ($\sigma < 10$)
  - ➢ Proposed metric has lower PSNR error than Q−metric, when using BM3D algorithm (a), (b)



(a) BM3D on TID.



(b) BM3D on LIVE.



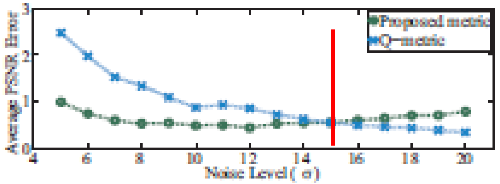
(34.15 dB, $\sigma = 5$) (38.23 dB, $\sigma_{est} = 6$) (33.10 dB, $\sigma_{est} = 20$) (38. 83 dB, $\sigma_{est} = 5$)

(a) Original. (28.13 dB, $\sigma = 10$) (b) Noisy. (32.8 dB, $\sigma_{est} = 13$) (c) Proposed. (25.91 dB, $\sigma_{est} = 20$) (d) Q-metric. (33.05 dB, $\sigma_{est} = 14$) (e) "optimal".

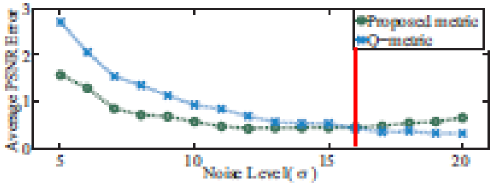
Experimental Results

❖ Denoising with Synthetic Noisy Images (cont'd)

- **When noise level(σ) is high ($\sigma > 15$)**
  - ➢ Proposed metric has higher PSNR error than Q−metric, when using SKR algorithm $(c), (d)$



(c) SKR on TID.



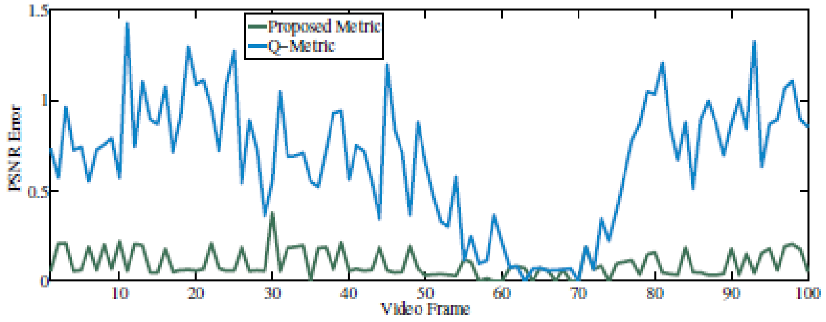
(d) SKR on LIVE.

  - ➢ Average PSNR errors in $(c), (d)$ are both lower than 1 when $\sigma > 15$
  - ➢ The performance of the proposed & Q−metric is very close to optimal PSNR metric

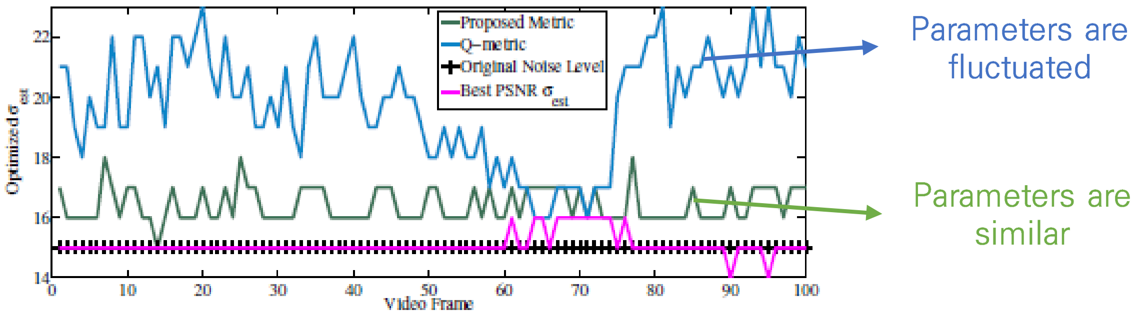
(a) Ground Truth. (22.45 dB, $\sigma = 20$) (b) Noisy. (24.63 dB, $itr = 18$) (c) Proposed. (24.79 dB, $itr = 8$) (d) Q-metric. (24.90 dB, $itr = 12$) (e) "optimal".

❖ Video Denoising

- Constant noise level
  - ➢ First 100 frames of the video are used
  - ➢ All Images are corrupted with WGN (σ=15)
  - ➢ BM3D denoising algorithm is used



PSNR error at
optimized parameter

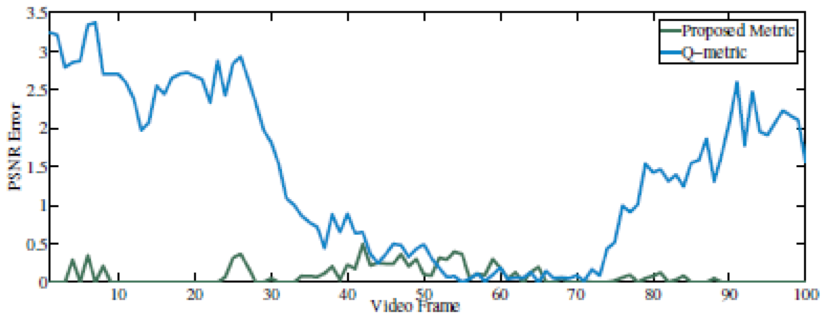


Optimized
parameter σ

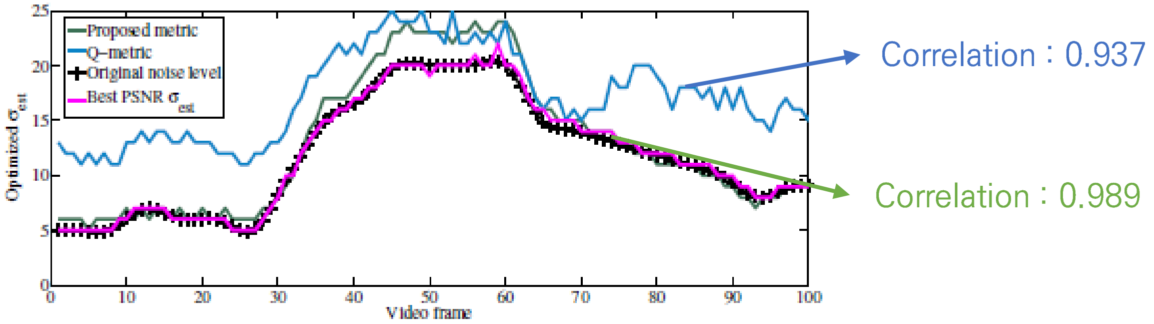
Experimental Results

❖ Video Denoising

- Dynamic noise level
  - ➢ First 100 frames of the video are used
  - ➢ The noise level is changed dynamically with respect to the time domain
  - ➢ BM3D denoising algorithm is used



PSNR error at
optimized parameter



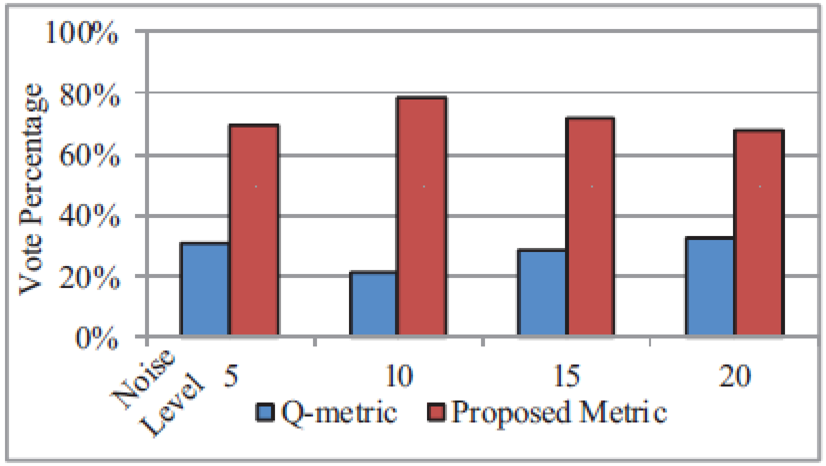
Optimized
parameter σ

Experimental Results

❖ Human Subject Study

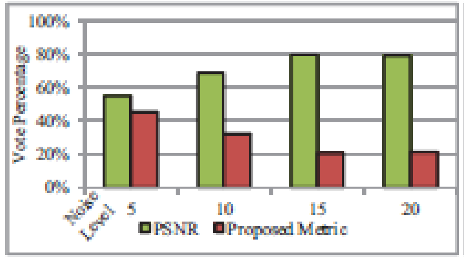
- Evaluates the perceptual performance of the metrics

- The tested images are corrupted by WGN with 4 levels in {5, 10, 15, 20}

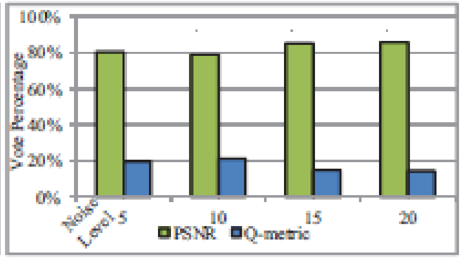


(a)

Compare Q−metric & proposed metric



(b)



(c)

Compare with PSNR

Conclusions

❖ Conclusions about this Paper

- Propose a new metric for automatizing existing image/video denoising algorithms
- Proposed metric is very simple, robust and efficient
- Experimental results demonstrate that the proposed metric outperforms the Q–metric

Thank You!