Beyond Pixel

Why Image Quality Is More Than a Number?

Research Seminar

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A Visual Experiment!!!

210

SAME MSE

The pixel-error trap

Every image below has the same mean squared error from the original.



CONTRAST SHIFT



JPEG COMPRESSION



GAUSSIAN BLUR



SALT & PEPPER

Equal pixel error ≠ equal perceived quality

A photograph is not a screenshot

Visual structure changes what quality loss actually means.

NATURAL-SCENE CONTENT



Reference



Distorted

texture · edges · fine detail

SCREEN CONTENT



Reference



Distorted

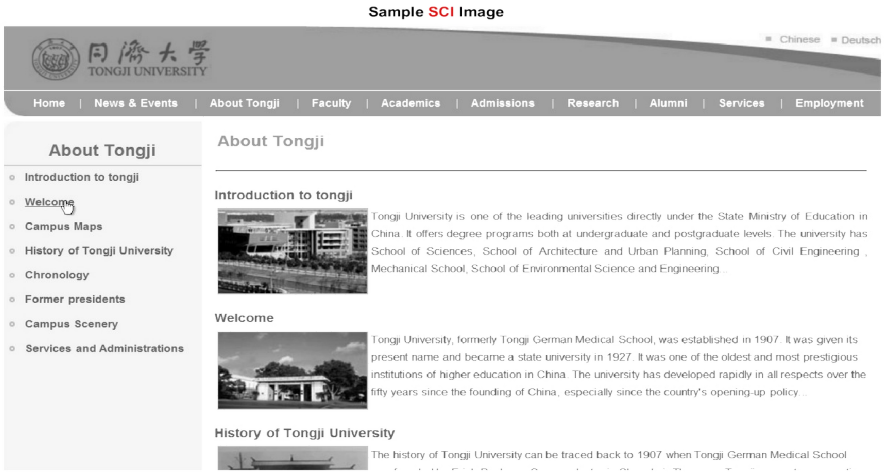
text · graphics · sharp boundaries

Can one quality model remain reliable across both?

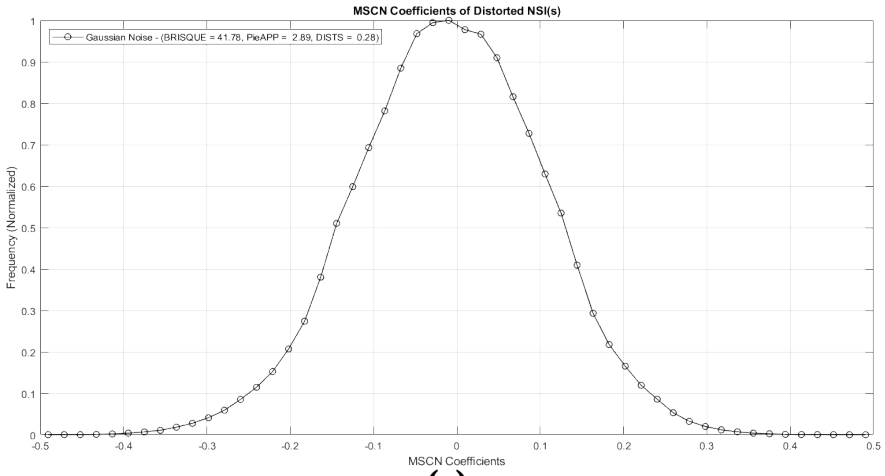
Natural-Scene vs Screen-Content Images



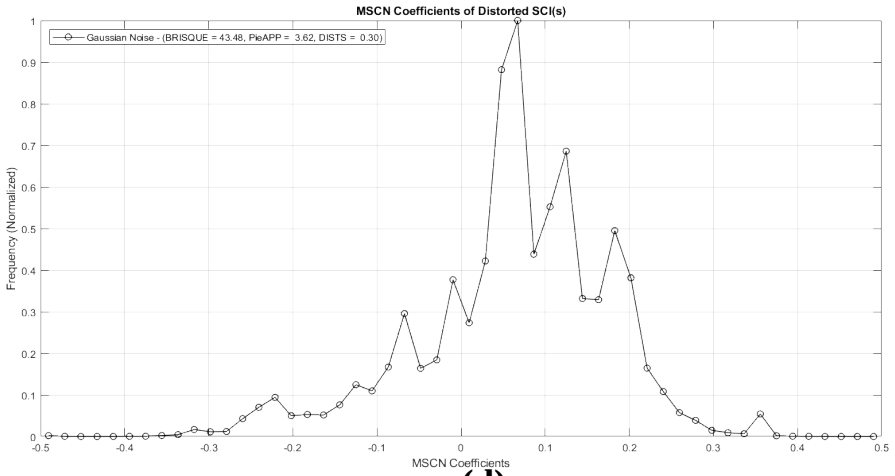
(a)



(b)



(c)



(d)

Figure (a) Natural-Scene Image, **(b)** Screen-Content Image, **(c)** MSCN co-efficients of (a), and **(d)** MSCN co-efficients of (b).

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Measure what matters. Then use it.

QUESTION ONE

Can we assess quality across different content?

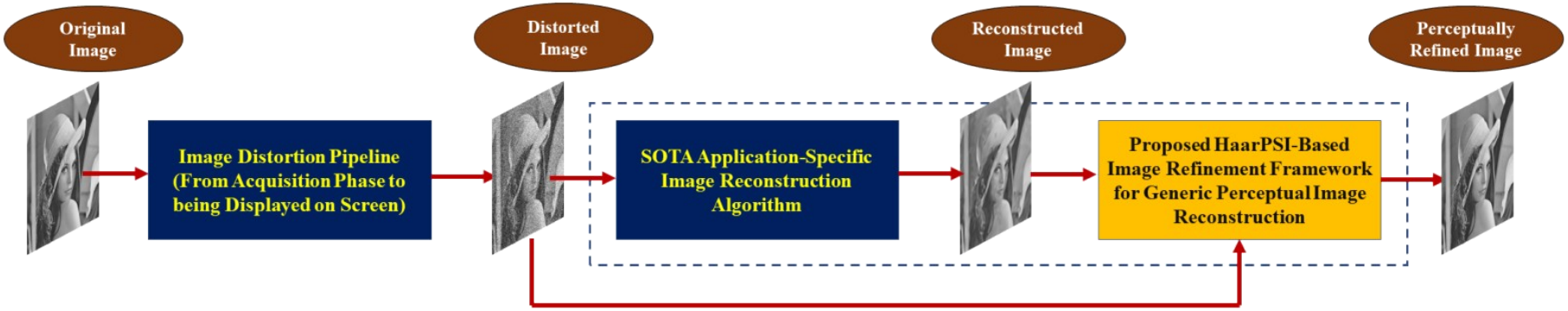
PEFRF · IW-PEFRF · DFeaSim

QUESTION TWO

Can quality assessment improve restoration?

Stage 1: reconstruct → Stage 2: perceptually refine

HaarPSI-Based Image Refinement Framework for Generic Perceptual Image Reconstruction



Proposed HaarPSI-based refinement framework for perceptual image reconstruction.

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Estimation of the Variance of MAP using a HaarPSI-Based Non-linear Filter:

Weights Estimation using a Non-linear Filter:

$$w_{ik} = \exp\left(-\frac{\|B_i - A_{ik}\|^2}{2\sigma_1^2}\right)\exp\left(-\frac{\|D - D_k\|^2}{2\sigma_2^2}\right)$$

Weights Estimation using a Modified HaarPSI-Based Non-linear Filter:

$$w_{ik}^{HaarPSI} = \exp\left(-\frac{HaarPSI(B_i, A_{ik})}{2\sigma_1^2}\right)\exp\left(-\frac{\|D - D_k\|^2}{2\sigma_2^2}\right)$$

Application-Specific Reconstruction Methods

Processes and Application-Specific Image Reconstructions		
S.No.	Cause of Distortion	Application-Specific Image Reconstruction Algorithms
1.	Deblurring	**FABF** (Gavaskar and Chaudhury (2018)), **BM3D** (Mäkinen et al. (2019)), **AMF** (Hwang and Haddad (1995)), and **IFSADA** (Cai et al. (2010))
2.	Gaussian Noise	**SAIF** (Talebi et al. (2013)), **NLEM** (Chaudhury and Singer (2012)), **NLM** (Buades et al. (2005)), **BM3D** (Mäkinen et al. (2019)), **KRF** (Takeda et al. (2007)), **SBF** (Chaudhury and Rithwik (2015)), **RBF** (Chaudhury et al. (2011)), **WBF** (Chaudhury (2012)), and **NPR** (Chaudhury and Singer (2013))
3.	Interpolation	**Bi-cubic** (Keys (1981)), **CGI** (Wei and Ma (2013)), **Directional Bi-cubic** (Zhou et al. (2012)), **SSL** (Jaiswal et al. (2011)), **KRF** (Takeda et al. (2007)), **SAI** (Zhang and Wu (2008)), **SME** (Mallat and Yu (2010)), and **SRI** (Dong et al. (2013))
4.	JPEG - Compression Ratio	**FABF** (Gavaskar and Chaudhury (2018)) and **KRF** (Takeda et al. (2007))
5.	JPEG - Quality Factor	**FABF** (Gavaskar and Chaudhury (2018)) and **KRF** (Takeda et al. (2007))
6.	Randomly Missing Pixels	**KRF** (Takeda et al. (2007)), **DPR** (Chan et al. (2005)), **IFASDA** (Li et al. (2011)), **IFSADA** (Cai et al. (2010)), **AMF** (Hwang and Haddad (1995)), **FABF** (Gavaskar and Chaudhury (2018)), and **BM3D** (Mäkinen et al. (2019))

Table. 1. Processes with corresponding SOTA and conventional image reconstruction algorithms.

What happens when we refine for perception?



ORIGINAL

REFERENCE

Ground-truth image



GAUSSIAN NOISE

17.16 dB

SSIM 0.1386

HaarPSI 0.4107



BM3D

29.79 dB

SSIM 0.4311

HaarPSI 0.7142



BPT + PA

34.23 dB

SSIM 0.8183

HaarPSI 0.7387

PSNR measures fidelity; SSIM and HaarPSI provide complementary perceptual measures. Single test case.

PSNR Improvement

Comparison of % Gain in Reconstruction Accuracy

S.No.	Processes	Distortion Level	MAPE	MAP-BF	MAP-HPSI (P1)	MAP-HPSI (P2)
1.	Deblurring	Low	09.6177%	09.4740%	10.1217%	**11.9769%**
		High	12.8175%	12.9393%	13.3749%	**18.8732%**
2.	JPEG - Compression	Low	08.2390%	07.6473%	08.3654%	**08.3949%**
		High	13.1164%	13.0082%	13.3188%	**13.5167%**
3.	Gaussian Noise	Low	13.9021%	09.0273%	13.1748%	**14.9167%**
		High	**20.5035%**	15.7383%	17.7559%	20.1718%
4.	JPEG - Quality Factor	Low	08.3879%	07.5935%	08.5266%	**08.6413%**
		High	09.9908%	09.7722%	10.4174%	**10.7253%**
5.	Randomly Missing Pixels	Low	29.6855%	04.1676%	08.3409%	**67.3915%**
		High	42.1345%	-54.5276%	08.4505%	**84.6029%**
6.	Interpolation	Low	00.1502%	00.0141%	02.6147%	**16.6750%**
		High	00.2551%	00.0170%	03.0968%	**20.5278%**

Table. 2. The table compares the restoration/reconstruction/refinement accuracy of the proposed with other MAP-based approaches in terms of percentage gain (dB). **Note:** the best performing approach is highlighted with Red colour and boldface.

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What does “good quality” mean in the real world?

Different applications care about different kinds of information.

01

UNDERWATER

Seeing through poor visibility

Water scatters and absorbs light. Images can lose contrast, colour and detail.

Can an enhancement help underwater observation without creating misleading colours or artefacts?

Xu et al. · Image and Vision Computing · 2025

02

MEDICAL IMAGING

Preserving clinically important details

Noise and limited resolution can hide subtle structures.

Can an image look clearer without inventing an anatomical feature that was never there?

Kim et al. · MICCAI · 2025

03

SATELLITE IMAGERY

Recovering information from space

Fine structures can be lost through low resolution and atmospheric effects.

Are roads, boundaries and textures preserved accurately enough for analysis?

ISPRS J. Photogrammetry & Remote Sensing · 2026

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Generative AI changes the question.

A picture may appear more realistic while drifting away from the original information.

A BETTER LOOKING IMAGE

is not automatically

a more faithful image.

What researchers are now doing

- Evaluating realistic detail AND semantic correctness
- Feeding quality assessment back into image restoration

The open question

Quality for whom — and for what?

Yin et al., CVPR Findings 2026 | Chen et al., CVPR 2026

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Thank you