

Image Quality Assessment and Perceptual Optimization: **A Non-local Modeling Approach**

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Outline

1. Background
2. Related Works
3. Local and Non-local Analyses of Natural Images
4. Proposed Non-local Modeling Method
5. Conclusions

Part 1: Background

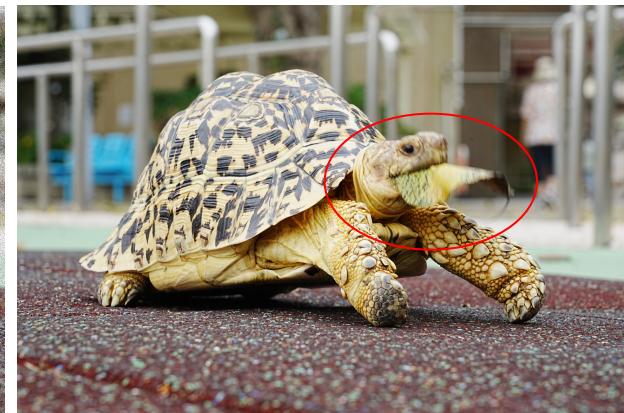
Image Quality Assessment and Distortions



Reference/Pristine Image



Distorted Image
by Gaussian Noise



Motion Blur
by Low Shutter Speed

Visual Quality Assessment: Synthetic and Authentic Distortions

Part 1: Background

IQA Category and Problem Definition

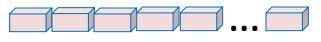
Full Reference

IQA



Reference Image

Reduced Reference IQA



Features of Reference Image

No Reference
(Blind) IQA



Distorted Image

IQA Model

Oh! This image looks
**excellent/good/fair/
poor/bad!**

→
Image Quality

"If you can't measure it, you can't improve it."

— William Thomson

Image Quality Assessment

Automatically measure the input image's **visual quality**

Synthetic Distortion

Synthetically generated distortions
(mainly global uniform distortions)

Authentic Distortion

Images **captured in the wild**
include **various content** and **diverse types of distortions**
(**global uniform distortions & local non-uniform distortions**)

Part 1: Background Image Quality Assessment Roles

IQA Roles



Professional Generated Content (PGC)



User Generated Content (UGC)



AI Generated Content (AIGC)



NR
IQA
Model

→ ○
Image Quality



Deblur System



De-blurred Image

Evaluation
or
Optimization



PSNR
SSIM
LPIPS



Reference Image

Blurred Image

Part 2: Related Works – Full-reference IQA

1. Signal Fidelity Approaches

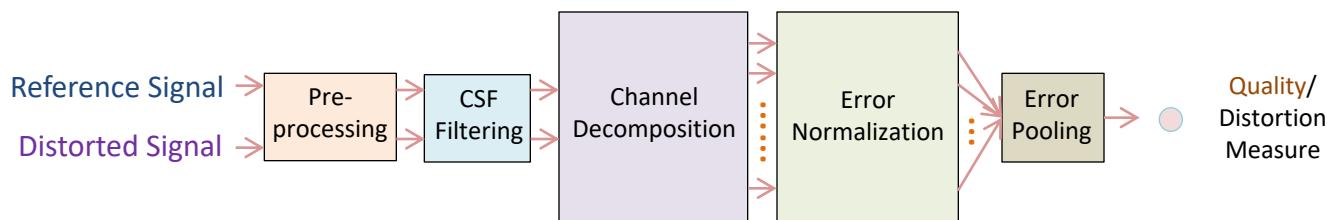
Mean Squared Error (MSE) and Peak Signal-to-Noise Ratio (PSNR)

I_p : the number of pixels in the image; x_i and y_i are the i^{th} pixels of the ref. and dis. images.

$$\text{MSE} = \frac{1}{I_p} \sum_{i=1}^{I_p} (x_i - y_i)^2, \quad \text{PSNR} = 10 \times \log_{10} \left(\frac{255^2}{\text{MSE}} \right).$$

2. Bottom-Up Approaches

Separately **model each basic module** of the Human Visual System (HVS)



A prototypical quality assessment system based on error sensitivity.

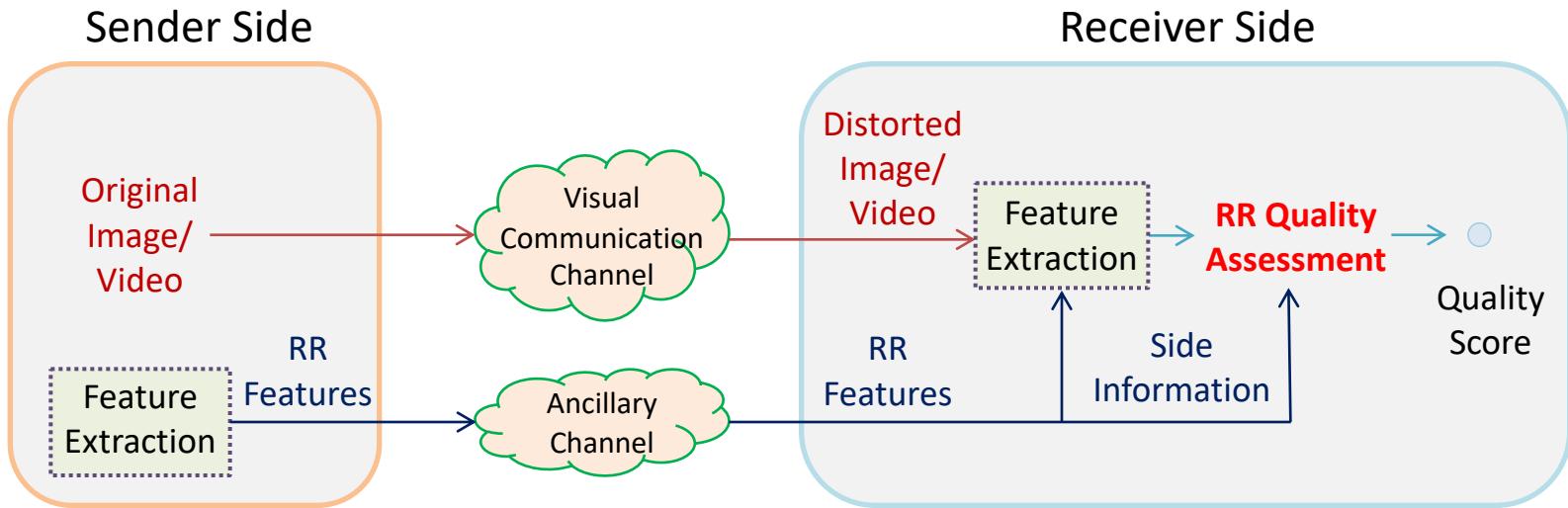
Image by courtesy of Wang *et al.*

3. Top-Down Approaches

Directly imitate the function of HVS as a **single model**

Part 2: Related Works

General Framework – Reduced-reference IQA



A general framework of an RR image or image QA system.

Image by courtesy of Wang *et al.*

Feature Extraction in the **Spatial Domain** and **Transform Domain**

Part 2: Related Works – No-reference (Blind) IQA

- **Distortion-Specific Modeling**

Aware of image distortion types → build distortion-specific models

- **General NR-IQA Modeling**

Natural Scene Statistics (NSS) Modeling

Feature Extraction in the **Spatial Domain** and **Transform Domain**

Human Visual System (HVS) Modeling

CNNs Modeling Methods

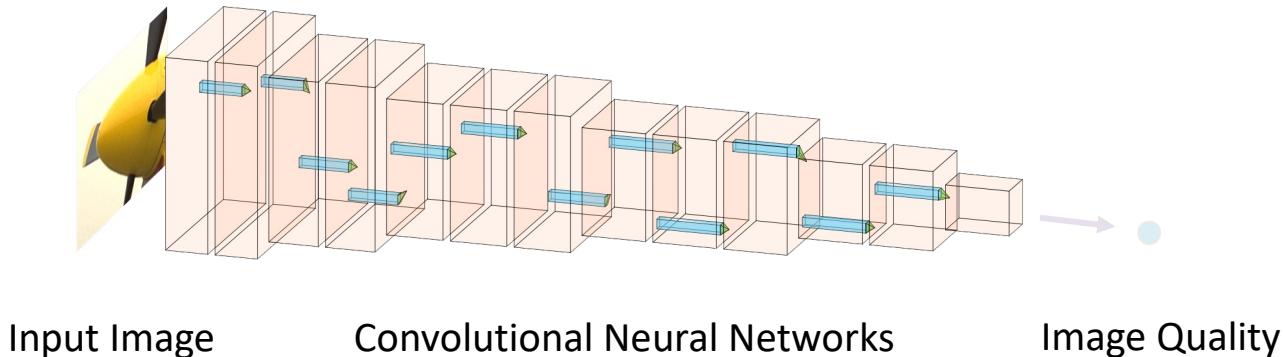
Assisted with visual importance information, reference image information during training, ranking-based methods, graph representation learning, etc.

Codebook-based Modeling

Constructing a **Codebook**

Part 3: Local Modeling Analyses of Natural Images

Taking **Convolutional Neural Networks (CNNs)** as an example



- **Advantages**

- ✓ Pooling → **Translation invariance**
- ✓ Convolution → **Translation equivalence**
- ✓ Weight sharing → **Sharable and fewer parameters**

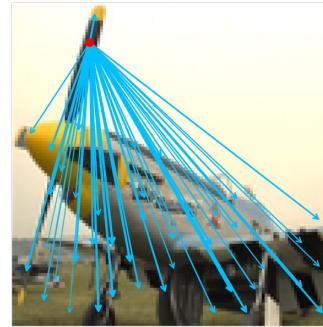
- **Limitations**

- ✓ Small-sized receptive field → **Extracted features are too local**
- ✓ Parameters fixed across the whole image → **Image content is equally treated**
- ✓ Lack of geometric and relational modeling → **Missing complex relations and dependencies**

Part 3: Non-local Modeling Analyses of Natural Images



Local Feature Extraction

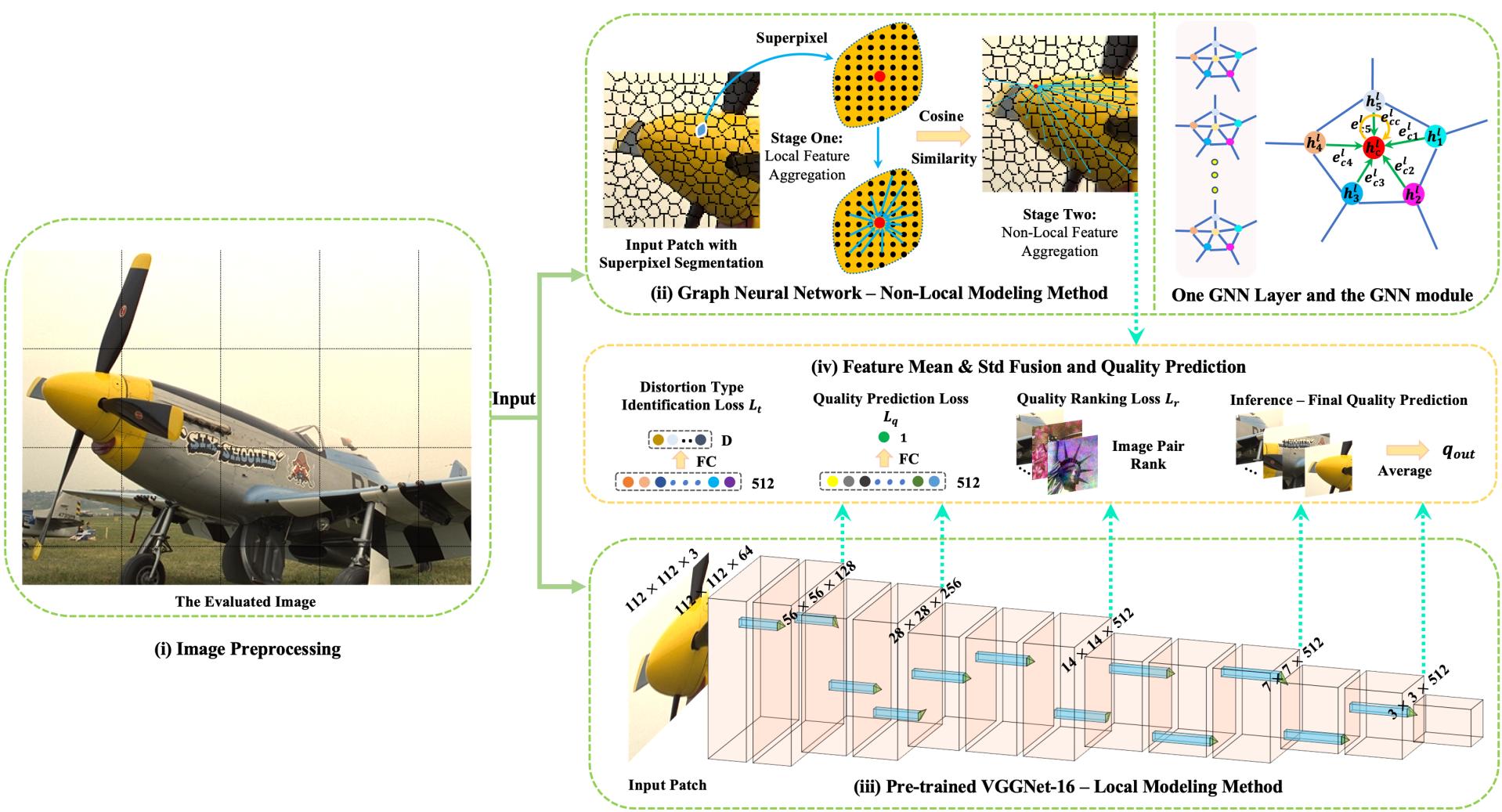


Non-local Dependency

- **Advantages**
 - ✓ Non-local statistics (natural scene statistics) → **Perceptually relevant to HVS**
 - ✓ Non-local dependency and relational modeling → **Semantics and content understanding**
 - ✓ Effective image-specific prior → **Reflect the statistical property of the world**
- **Motivations**
 - ✓ HVS → **Adaptive to the local content**
 - ✓ HVS perceives image quality → **Long-range dependency constructed among different regions**

Part 4: Proposed Non-local Modeling Method

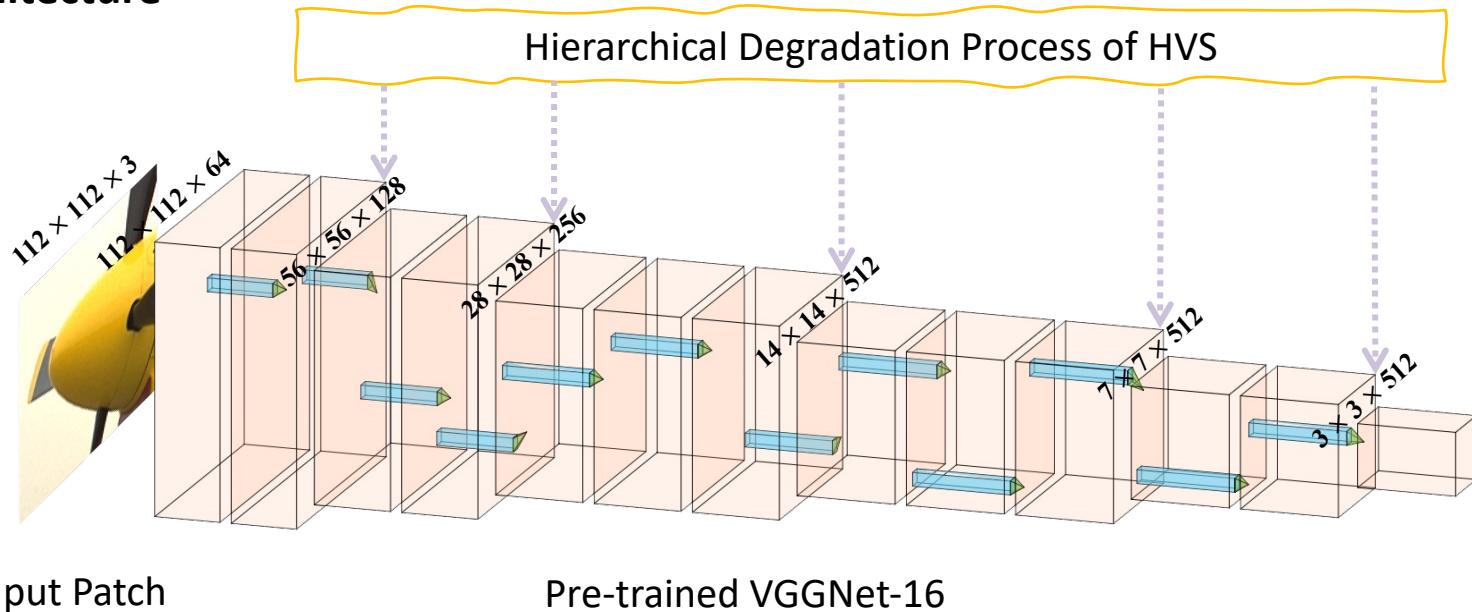
NLNet Architecture



Part 4: Proposed Method

Local Modeling

1. Architecture



Pre-trained VGGNet features: “unreasonable” effectiveness in measuring **perceptual quality** [1]

2. Model Input

Randomly cropped image patches with the size of $112 \times 112 \times 3$

3. Feature Extraction

Quality-aware features: hierarchical feature means and standard deviations [2]

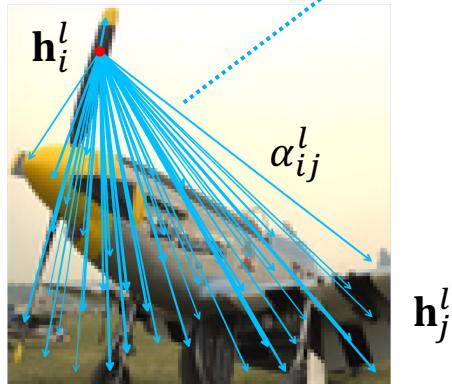
Experimental Results: 0.936 PLCC and 0.951 SRCC on the CSIQ Database

Part 4: Proposed Method

Non-local Modeling



**Convolution
Pixel-to-Pixel
Modeling**



Local region feature extraction and non-local dependency feature extraction.

**Non-Local
Object-to-Pixel
Modeling**

Spatial Integration of Information

$$\mathbf{h}_i^l = \text{ELU} \left(\sum_{j \in \mathcal{N}(i)} \alpha_{ij}^l \mathbf{W}^l \mathbf{h}_j^l \right),$$

Spatial Weighting Functions

$$\alpha_{ij}^l = \frac{\exp(a_{ij}^l)}{\sum_{k \in \mathcal{N}(i)} a_{ik}^l},$$

$$a_{ij}^l = \text{LeakyReLU} \left(\text{FC}([\mathbf{W}^l \mathbf{h}_i^l \parallel \mathbf{W}^l \mathbf{h}_j^l]) \right).$$

Local Modeling

Encodes **Spatially Proximate Local Neighborhoods**

Non-local Modeling

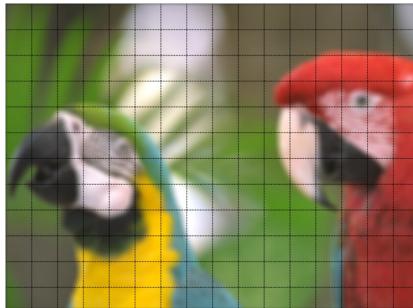
Establishes **Spatial Integration of Information** by Long- and Short-Range Communications with different **Spatial Weighting Functions**

Part 4: Proposed Method

Superpixel Segmentation



(a)



(b)



(c)



(d)

The superpixel vs. square patch representation

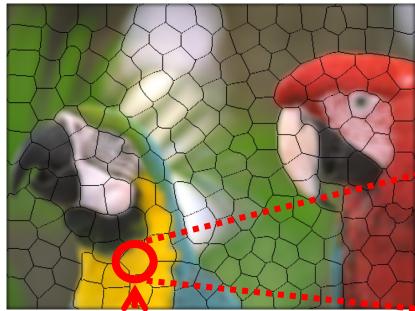
(**a/b**: Gaussian Blur, **c/d**: Gaussian Noise)

Superpixel vs. Square Patch

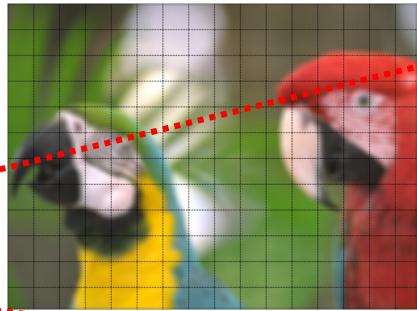
- ✓ Adherence to Boundaries
- ✓ Visually Meaningful
- ✓ Accurate Feature Extraction

Part 4: Proposed Method

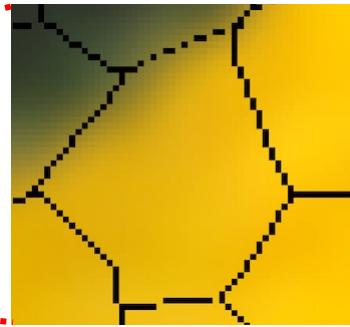
Superpixel Segmentation



Flat



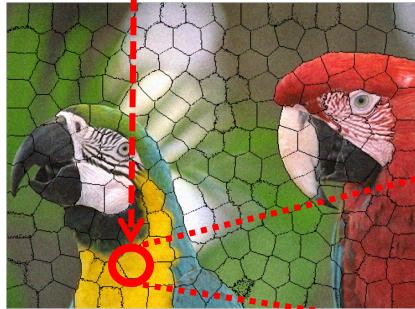
(b)



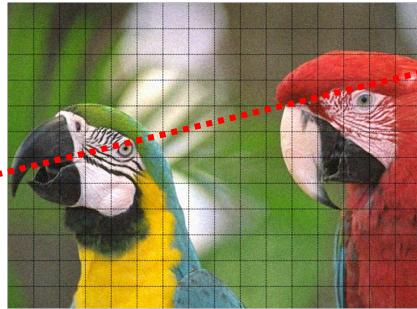
Gaussian Blur



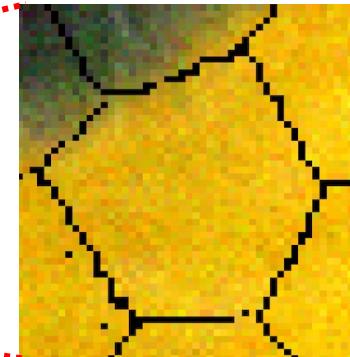
Reference



(c)



(d)



Gaussian Noise

The superpixel vs. square patch representation

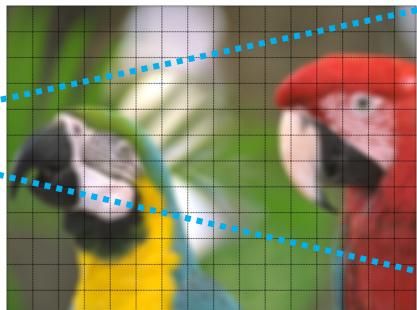
(a/b: Gaussian Blur, c/d: Gaussian Noise)

Part 4: Proposed Method

Superpixel Segmentation



(a)



(b)



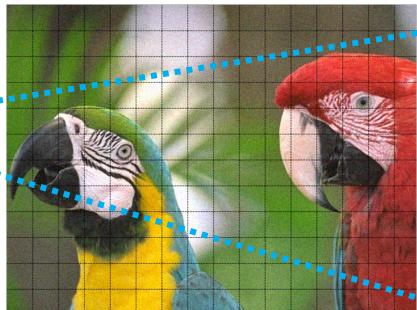
Gaussian Blur



Reference



(c)



(d)



Gaussian Noise

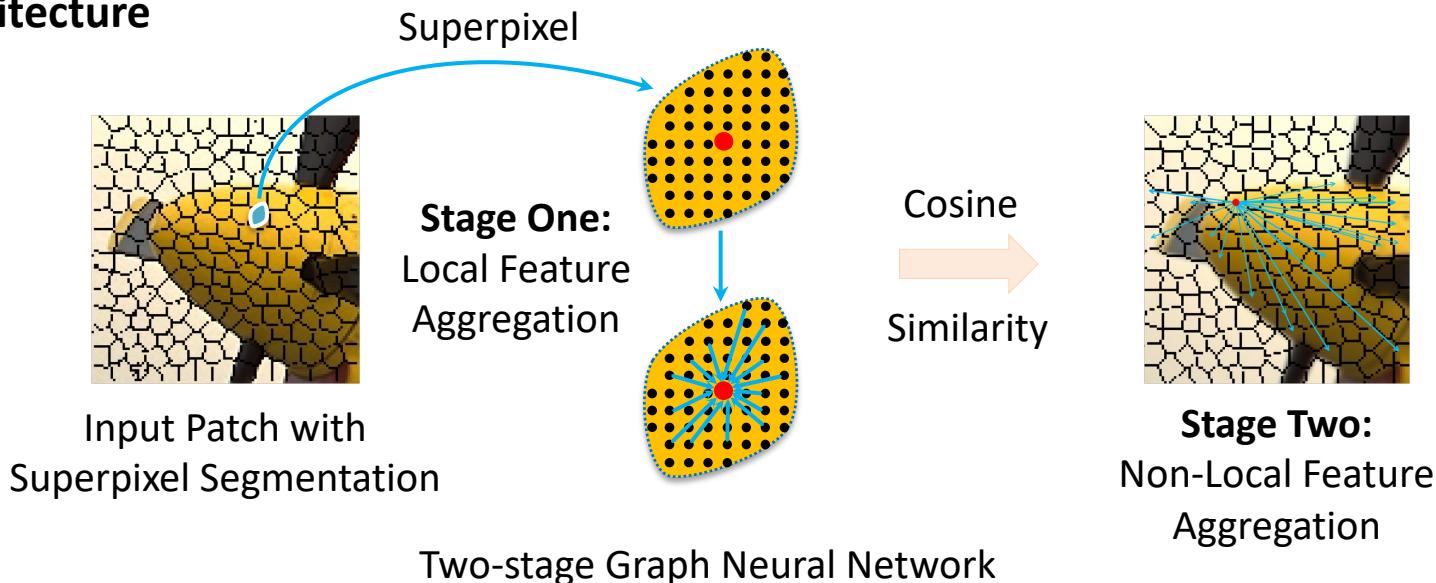
The superpixel vs. square patch representation

(a/b: Gaussian Blur, c/d: Gaussian Noise)

Part 4: Proposed Method

Non-local Modeling

1. Architecture



Graph Nodes Construction → Non-local Feature Aggregation

2. Model Input

Superpixel-segmented cropped patches with the size of $112 \times 112 \times 3$ (superpixel size $\approx 8 \times 8$)

3. Feature Extraction

Local feature aggregation: **complete graph**

Non-local feature aggregation: **dense graph** measured by Cosine similarity

Experimental Results: 0.625 PLCC and 0.577 SRCC on the CSIQ Database

Part 4: Proposed Method

Non-local Behavior Visualization

Object-to-Pixel Modeling
Region Feature Extraction



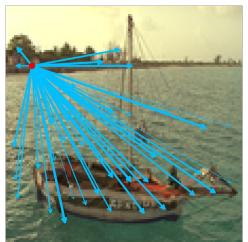
Non-local
Dependency & Relational
Modeling



Semantics and Content
Understanding



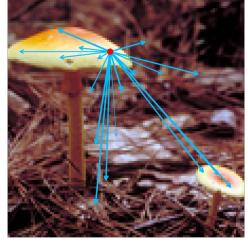
(a)



(b)



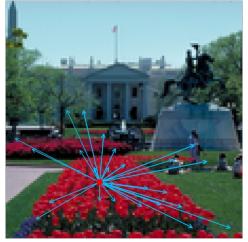
(c)



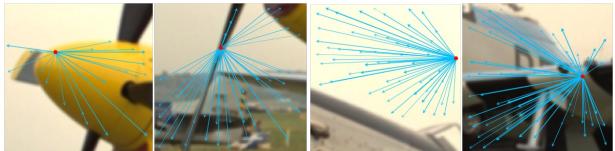
(d)



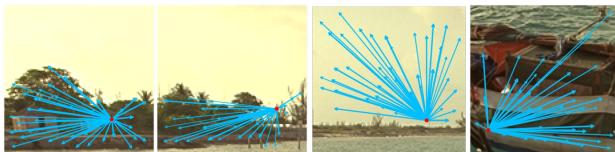
(e)



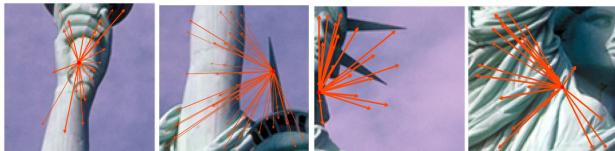
(f)



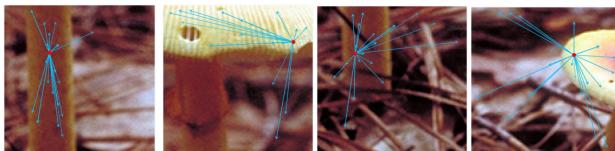
The cropped images form (a)



The cropped images form (b)



The cropped images form (c)



The cropped images form (d)

The non-local behavior of the long-range dependency and relational modeling.
(a) The plane image with a query on wings. **(b)** The boat image with a query on the nearby river bank. **(c)** The Statue of Liberty image with a query on the lady. **(d)** The shrooms image with a query on one shroom. **(e)** The butterfly image with a query on the wing. **(f)** The Lafayette Square, Washington, D.C. image with a query on flowers.

Part 4: Proposed Method

Training Objective Functions and Inference

- Training

1. Quality Prediction Loss

Huber Loss

$$L_q = \frac{1}{B} \sum_k \text{HuberLoss}(\hat{q}_k - q_k).$$

2. Distortion Type Classification Loss

Cross-entropy Loss

$$L_t = -\frac{1}{B} \sum_{i=1}^B \sum_{d=1}^D p_{i,d} \ln \hat{p}_{i,d}.$$

3. Quality Ranking Loss

Huber Loss

$$L_r = \frac{1}{B(B-1)/2} \sum_{j < k} \text{HuberLoss}((\hat{q}_j - \hat{q}_k) - (q_j - q_k)).$$

- Inference

The average quality score of all the **non-overlapping patches**

Notations	
B	Batch Size
\hat{q}_k	The predicted quality score
q_k	Mean Opinion Score (MOS)
D	The number of distortion types
$p_{i,d}$	The label probability of the d^{th} distortion type
$\hat{p}_{i,d}$	The predicted probability of the d^{th} distortion type

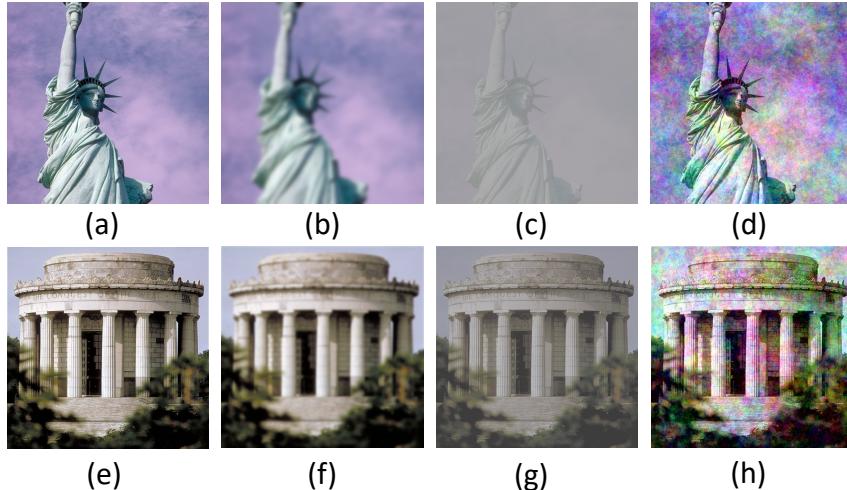


q_{out}
average

Part 4: Proposed Method

Definition of Global and Local Distortions

Non-Local Recurrence



Global Distortion

(**a/e**: reference image, **b/f**: Gaussian Blur, **c/g**: global contrast decrements, **d/h**: additive pink Gaussian noise)

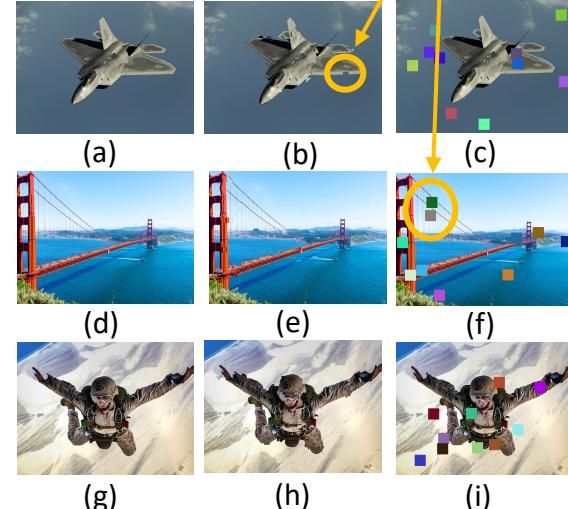
Global Distortion

Globally and Uniformly Distributed distortions with
Non-Local Recurrences over the image

Local Distortion

Local Nonuniform-Distributed distortions in a Local Region

Local Distortion



Local Distortion

(**a/d/g**: reference image, **b/e/h**: non eccentricity patch, **c/f/i**: color block)

Part 4: Proposed Method

Experimental Setup

- **Databases**
LIVE, CSIQ, TID2013, and KADID-10k
- **Experimental Settings**
Intra-Database Experiments:
→ 60% training
20% validation
20% testing
With “random” seeds from 1 to 10
→ **Median** PLCC and SRCC are reported.

Cross-Database Evaluations:

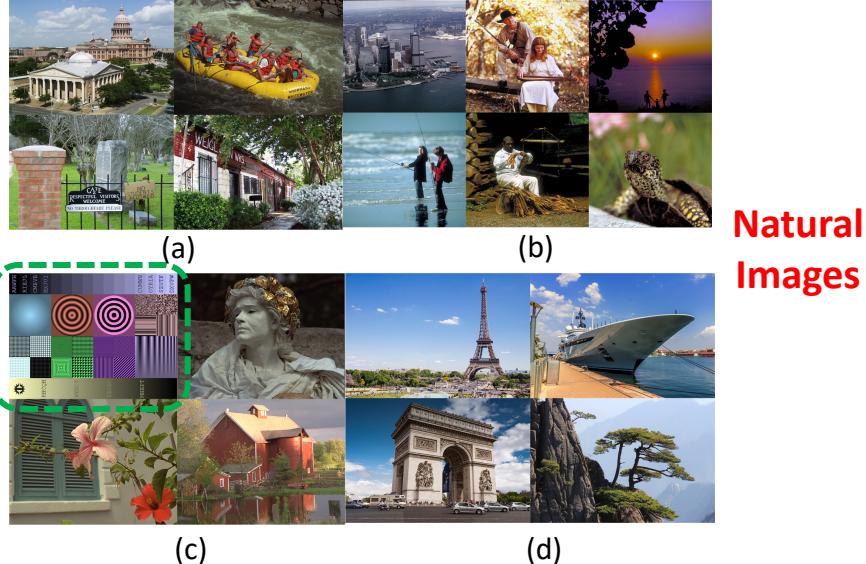
- One database as the training set
The other databases as the testing set
- Report the last epoch’s performance

Evaluation Metrics

PLCC (Prediction **Accuracy**)

SRCC (Prediction **Monotonicity**)

Screen Content Image



(a) LIVE Database **(b)** CSIQ Database
(c) TID2013 Database **(d)** KADID-10k Database

A brief summary of the LIVE, CSIQ, TID2013, and KADID-10k databases.

Database	LIVE [13]	CSIQ [14]	TID2013 [15]	KADID-10k [16]
Num. of Reference Images	29	30	25	81
Num. of Distorted Images	779	866	3,000	10,125
Num. of Distortion Types	5	6	24	25
Num. of Distortion Levels	5 ~ 8	3 ~ 5	5	5
Annotation	DMOS	DMOS	MOS	MOS
Range	[0, 100]	[0, 1]	[0, 9]	[1, 5]

Part 4: Proposed Method

Intra-Database Experiments

Performance comparisons on the LIVE, CSIQ, and TID2013 databases. The top two results are highlighted in bold.

SOTA
Transformer

Method	LIVE		CSIQ		TID2013	
	SRCC	PLCC	SRCC	PLCC	SRCC	PLCC
BRISQUE (2012) [10]	0.939	0.935	0.746	0.829	0.604	0.694
CORNIA (2012) [104]	0.947	0.950	0.678	0.776	0.678	0.768
M3 (2015) [105]	0.951	0.950	0.795	0.839	0.689	0.771
HOSA (2016) [103]	0.946	0.947	0.741	0.823	0.735	0.815
FRIQUEE (2017) [90]	0.940	0.944	0.835	0.874	0.68	0.753
DIQaM-NR (2018) [35]	0.960	0.972	-	-	0.835	0.855
DB-CNN (2020) [64]	0.968	0.971	0.946	0.959	0.816	0.865
HyperIQA (2020) [65]	0.962	0.966	0.923	0.942	0.729	0.775
GraphIQA (2022) [86]	0.968	0.970	0.920	0.938	-	-
TReS (2022) [87]	0.969	0.968	0.922	0.942	0.863	0.883
NLNet	0.962	0.963	0.941	0.958	0.856	0.880

Fewer Training Data

↓ 20% Total Data

↑ Highly Competitive Performance

Performance comparisons on the KADID-10k database.

The top two results are highlighted in bold.

Method	BRISQUE [10]	CORNIA [104]	HOSA [103]	InceptionResNetV2 [16]	DB-CNN [64]	HyperIQA [65]	TReS [87]	NLNet
SRCC	0.519	0.519	0.609	0.731	0.851	0.852	0.859	0.846
PLCC	0.554	0.554	0.653	0.734	0.856	0.845	0.858	0.850

Part 4: Proposed Method

Cross-Database Evaluations

Cross-database performance comparisons.

Training Testing	LIVE		CSIQ		TID2013	
	CSIQ	TID2013	LIVE	TID2013	LIVE	CSIQ
BRISQUE (2012) [10]	0.562	0.358	0.847	0.454	0.790	0.590
CORNIA (2012) [104]	0.649	0.360	0.853	0.312	0.846	0.672
M3 (2015) [105]	0.621	0.344	0.797	0.328	0.873	0.605
HOSA (2016) [103]	0.594	0.361	0.773	0.329	0.846	0.612
FRIQUEE (2017) [90]	0.722	0.461	0.879	0.463	0.755	0.635
DIQaM-NR (2018) [35]	0.681	0.392	-	-	-	0.717
DB-CNN (2020) [64]	0.758	0.524	0.877	0.540	0.891	0.807
HyperIQA (2020) [65]	0.697	0.538	0.905	0.554	0.839	0.543
NLNet	0.771	0.497	0.923	0.516	0.895	0.730

Similar
Distortions

TID2013:
More Distortion Types & Levels

Part 4: Proposed Method

Single Distortion Type Evaluation on the LIVE Database

The **average SRCC** and **PLCC** results of the individual distortion type on the LIVE database. The top two results are highlighted in bold.

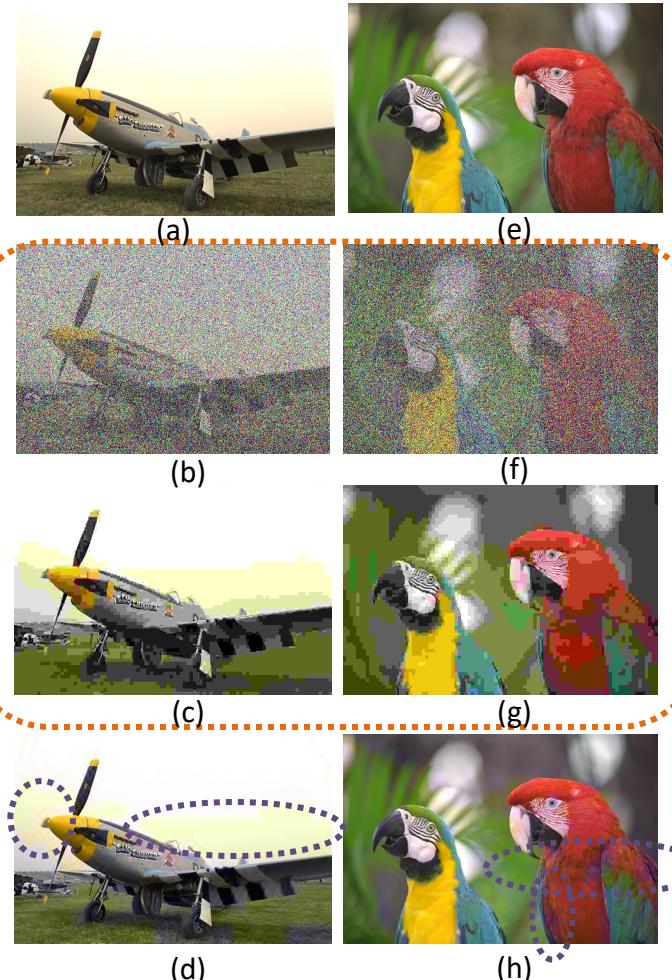
SRCC	Global Distortion				Local Distortion
	JPEG	JP2K	WN	GB	
BRISQUE (2012) [10]	0.965	0.929	0.982	0.964	0.828
CORNIA (2012) [104]	0.947	0.924	0.958	0.951	0.921
M3 (2014) [105]	0.966	0.930	0.986	0.935	0.902
HOSA (2016) [103]	0.954	0.935	0.975	0.954	0.954
FRIQUEE (2017) [90]	0.947	0.919	0.983	0.937	0.884
dipIQ (2017) [82]	0.969	0.956	0.975	0.940	-
WaDIDQaM (2018) [35]	0.953	0.942	0.982	0.938	0.923
DB-CNN (2020) [64]	0.972	0.955	0.980	0.935	0.930
HyperIQA (2020) [65]	0.961	0.949	0.982	0.926	0.934
NLNet	0.979	0.958	0.990	0.964	0.941
PLCC	Global Distortion				Local Distortion
	JPEG	JP2K	WN	GB	FF
BRISQUE (2012) [10]	0.971	0.940	0.989	0.965	0.894
CORNIA (2012) [104]	0.962	0.944	0.974	0.961	0.943
M3 (2014) [105]	0.977	0.945	0.992	0.947	0.920
HOSA (2016) [103]	0.967	0.949	0.983	0.967	0.967
FRIQUEE (2017) [90]	0.955	0.935	0.991	0.949	0.936
dipIQ (2017) [82]	0.980	0.964	0.983	0.948	-
DB-CNN (2020) [64]	0.986	0.967	0.988	0.956	0.961
NLNet	0.986	0.961	0.993	0.964	0.951

Noisy &
Compressed
Images

Global
Distortion

Non-local
Recurrence

Local
Distortion



Demonstrations of the global distortions (a/e: reference image, b/f: white noise and c/g: JPEG) and local distortions (d/h: fast fading Rayleigh)

Part 4: Proposed Method

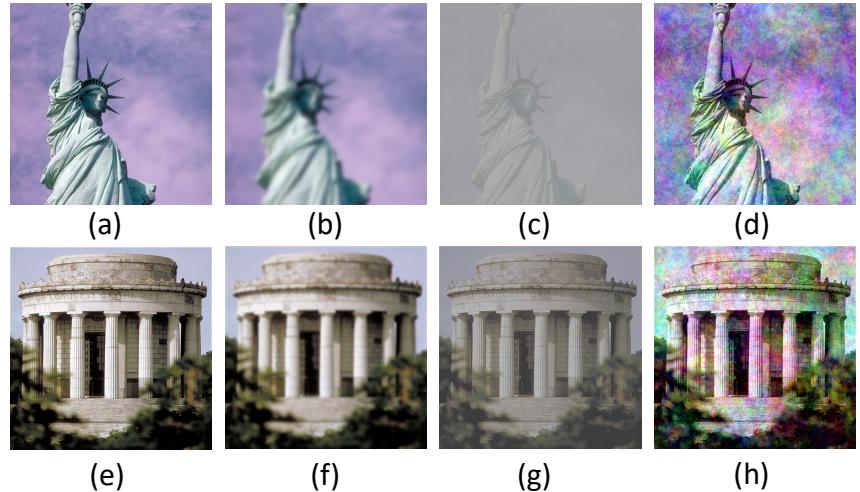
Single Distortion Type Evaluation on the CSIQ Database

The **average SRCC** and **PLCC** results of the individual distortion type on the CSIQ database.

The top two results are highlighted in bold.

SRCC	JPEG	JP2K	WN	GB	PN	CC
BRISQUE (2012) [10]	0.806	0.840	0.723	0.820	0.378	0.804
CORNIA (2012) [104]	0.513	0.831	0.664	0.836	0.493	0.462
M3 (2014) [105]	0.740	0.911	0.741	0.868	0.663	0.770
HOSA (2016) [103]	0.733	0.818	0.604	0.841	0.500	0.716
FRIQUEE (2017) [90]	0.869	0.846	0.748	0.870	0.753	0.838
dipIQ (2017) [82]	0.936	0.944	0.904	0.932	-	-
MEON (2018) [71]	0.948	0.898	0.951	0.918	-	-
WaDIQaM (2018) [35]	0.853	0.947	0.974	0.979	0.882	0.923
DB-CNN (2020) [64]	0.940	0.953	0.948	0.947	0.940	0.870
HyperIQA (2020) [65]	0.934	0.960	0.927	0.915	0.221	0.874
NLNet	0.972	0.963	0.965	0.955	0.969	0.968
PLCC	JPEG	JP2K	WN	GB	PN	CC
BRISQUE (2012) [10]	0.828	0.887	0.742	0.891	0.496	0.835
CORNIA (2012) [104]	0.563	0.883	0.687	0.904	0.632	0.543
M3 (2014) [105]	0.768	0.928	0.728	0.917	0.717	0.787
HOSA (2016) [103]	0.759	0.899	0.656	0.912	0.601	0.744
FRIQUEE (2017) [90]	0.885	0.883	0.778	0.905	0.769	0.864
dipIQ (2017) [82]	0.975	0.959	0.927	0.958	-	-
MEON (2018) [71]	0.979	0.925	0.958	0.946	-	-
DB-CNN (2020) [64]	0.982	0.971	0.950	0.969	0.250	0.895
NLNet	0.991	0.976	0.967	0.9746	0.966	0.969

Global
Distortions



Demonstrations of the global distortions

(a/e: reference image, b/f: Gaussian Blur, c/g: global contrast decrements, d/h: additive pink Gaussian noise)

Part 4: Proposed Method

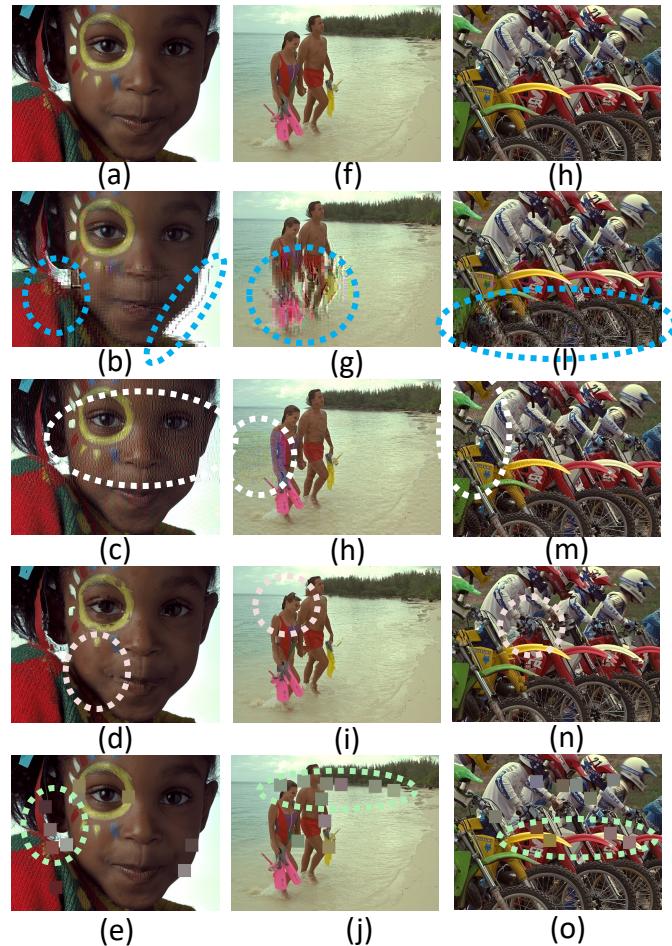
Single Distortion Type Evaluation on the TID2013 Database

The **average SRCC** results of the individual distortion type on the TID2013 database.

The top two results are highlighted in bold.

SRCC	Distortion Type	BRISQUE [10]	FRIQUEE [90]	HOSA [103]	MEON [71]	M3 [105]	DB-CNN [64]	CORNIA [104]	NLNet
Global Distortion	Additive Gaussian noise	0.711	0.730	0.833 ↑ 8.4%	0.613	0.766	0.790	0.692	0.917
	Lossy compression of noisy images	0.609	0.641	0.838	0.772	0.692	0.860 ↑ 7.5%	0.712	0.935
	Additive noise in color components	0.432	0.573	0.551	0.722 ↑ 12.8%	0.682	0.700	0.137	0.850
	Comfort noise	0.196	0.318	0.622	0.406	0.353	0.752 ↑ 11.8%	0.617	0.870
	Contrast change	-0.001	0.585	0.362	0.252	0.155	0.548	0.254	0.793
	Change of color saturation	0.003	0.589	0.045	0.684	-0.199	0.631	0.169	0.827
	Spatially correlated noise	0.746	0.866	0.842	0.926 ↑ 3.2%	0.882	0.826	0.741	0.958
	High frequency noise	0.842	0.847	0.897	0.911 ↑ 1.0%	0.800	0.879	0.815	0.921
	Impulse noise	0.765	0.730	0.809	0.901 ↑ 1.2%	0.738	0.708	0.616	0.913
	Quantization noise	0.662	0.764	0.815	0.888 ↑ 4.1%	0.842	0.825	0.661	0.929
	Gaussian blur	0.871	0.881	0.883	0.887	0.896	0.859	0.850	0.912
	Image denoising	0.612	0.839	0.854	0.797	0.709	0.865 ↑ 1.7%	0.764	0.882
	JPEG compression	0.764	0.813	0.891	0.850	0.844	0.894 ↑ 1.1%	0.797	0.905
	JPEG 2000 compression	0.745	0.831	0.919 ↑ 1.1%	0.891	0.885	0.916	0.846	0.930
	Multiplicative Gaussian noise	0.717	0.704	0.768	0.849 ↑ 5.5%	0.888	0.711	0.593	0.904
	Image color quantization with dither	0.831	0.768	0.896	0.857	0.908	0.833	0.683	0.911
	Sparse sampling and reconstruction	0.807	0.891	0.909	0.855	0.893	0.902	0.865	0.940
	Chromatic aberrations	0.615	0.737	0.753	0.779	0.570	0.732	0.696	0.773
	Masked noise	0.252	0.345	0.468	0.728	0.577	0.646	0.451	0.700
	Mean shift (intensity shift)	0.219	0.254	0.211	0.177	0.119	-0.009	0.232	0.358
Local Distortion	JPEG transmission errors	0.301	0.498	0.730	0.746	0.375	0.772 ↑ 3.3%	0.694	0.805
	JPEG 2000 transmission errors	0.748	0.660	0.710	0.716	0.718	0.773 ↑ 10.2%	0.686	0.875
	Non eccentricity pattern noise	0.269	0.076	0.242	0.116	0.173	0.270 ↑ 34.6%	0.200	0.616
	Local block-wise distortions with different intensity	0.207	0.032	0.268	0.500	0.379	0.444	0.027	0.493

Noise and Compression-related Distortions



Demonstrations of the local distortions

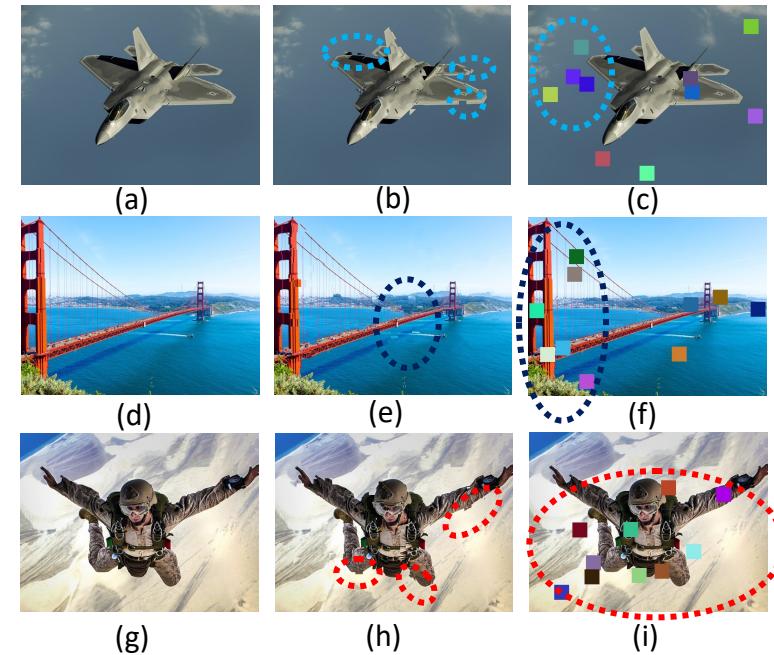
(a/f/h: reference image, b/g/l: JPEG transmission errors, c/h/m: JPEG2000 transmission errors, d/i/n: non eccentricity pattern noise, e/j/o: local block-wise distortions of different intensity)

Part 4: Proposed Method

Single Distortion Type Evaluation on the KADID-10k Database

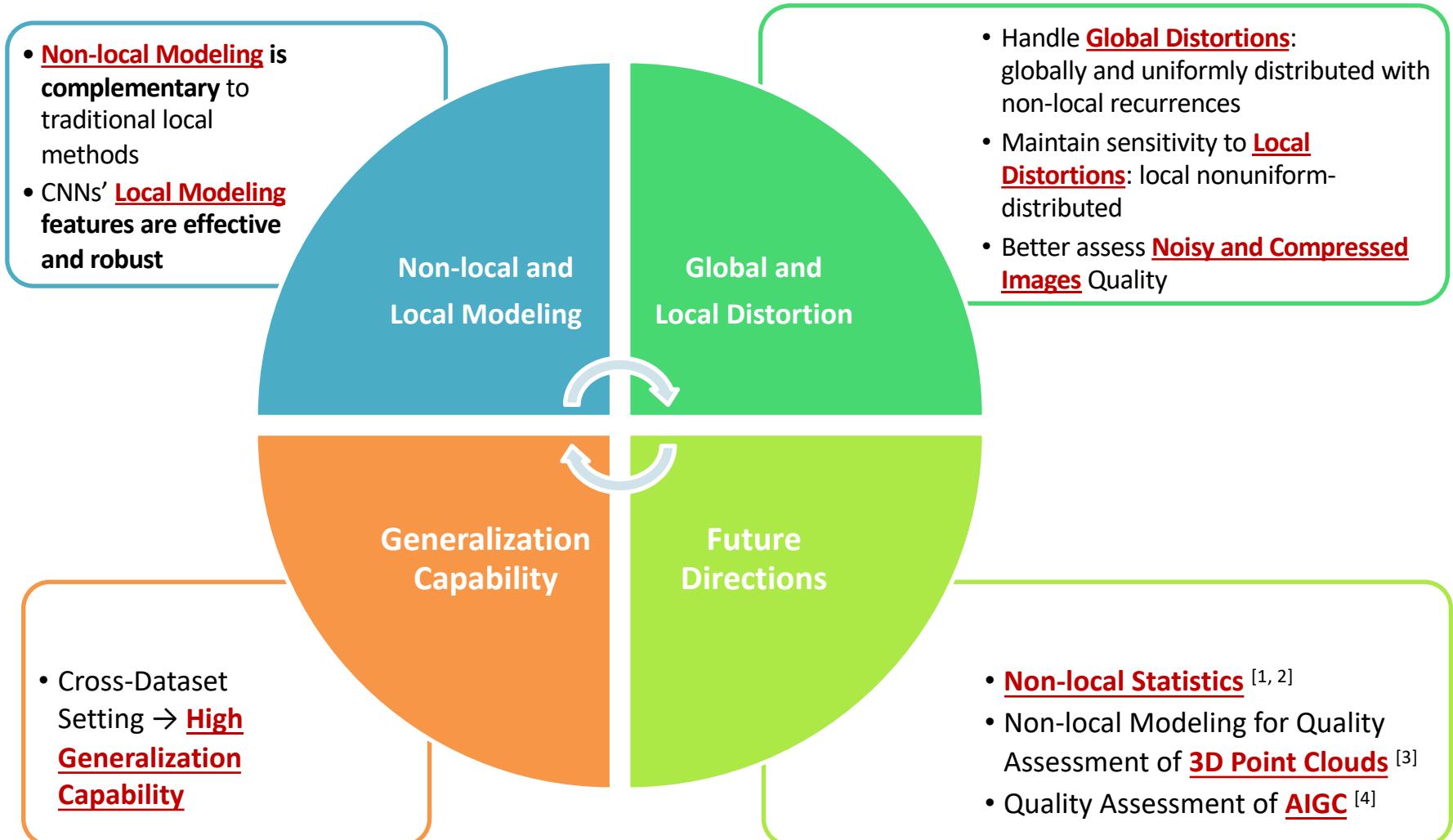
The **average SRCC** results of the individual distortion type on the KADID-10k database. The local distortions are highlighted in blue, and the top two results are highlighted in bold.

Distortion Type		BLIINDS-II [91]	BRISQUE [10]	ILNIQE [102]	CORNIA [104]	HOSA [103]	WaDIQaM [35]	NINet
Blurs	Lens blur	0.781	0.674	0.846	0.811	0.715	0.730	0.914
	Gaussian blur	0.880	0.812	0.883	0.866	0.852	0.879	0.914
	Motion blur	0.482	0.423	0.779	0.532	0.652	0.730	0.899
Color distortions	Color diffusion	0.572	0.544	0.678	0.243	0.727	0.833	0.916
	Color saturation 2	0.602	0.375	0.677	0.120	0.841	0.836	0.909
	Color quantization	0.670	0.667	0.676	0.323	0.662	0.806	0.853
	Color shift	-0.139	-0.182	0.090	-0.002	0.050	0.421	0.777
	Color saturation_1	0.091	0.071	0.027	0.019	0.216	0.148	0.604
Compression	JPEG compression	0.414	0.782	0.804 ↑ 6.2%	0.556	0.582	0.530	0.866
	JPEG 2000 compression	0.655	0.516	0.790 ↑ 6.3%	0.342	0.608	0.539	0.853
Noise	Denoise	0.457	0.221	0.856 ↑ 9.7%	0.229	0.247	0.765	0.953
	White noise in color component	0.757	0.718	0.841	0.418	0.745	↑ 1.1%	0.925
	Multiplicative noise	0.702	0.674	0.682	0.306	0.776	↑ 5.0%	0.884
	Impulse noise	0.547	-0.543	0.808	0.219	0.254	↑ 10.2%	0.814
	White Gaussian noise	0.628	0.708	0.776	0.357	0.680	↑ 1.7%	0.897
Brightness change	Brighten	0.458	0.575	0.361	0.227	0.753	0.685	0.822
	Darken	0.439	0.405	0.436	0.206	0.744	0.272	0.647
	Mean Shift	0.112	0.144	0.315	0.122	0.591	0.348	0.335
Spatial distortions	Jitter	0.629	0.672	0.441	0.719	0.391	0.778	0.899
	Pixelate	0.196	0.648	0.577	0.587	0.702	0.700	0.814
	Quantization	0.781	0.714	0.571	0.259	0.681	0.735	0.791
	Color block	-0.020	0.067	0.003	0.094	0.388	0.160	0.440
Sharpness and contrast	Non-eccentricity patch	0.083	0.191	0.218	0.121	0.461	0.348	0.433
	High sharpen	-0.015	0.361	0.681	0.114	0.230	0.558	0.932
	Contrast change	0.062	0.105	0.072	0.125	0.452	0.421	0.513



Demonstrations of the local distortions
(a/d/g: reference image, **b/e/h:** non-eccentricity patch, **c/f/i:** color block)

Part 5: Conclusions and Future Directions



Credit:

[1] Zontak *et al.*, Internal Statistics of a Single Natural Image, In CVPR 2011

[2] Buades *et al.*, A Non-local Algorithm for Image Denoising, In CVPR 2005

[3] Zhou *et al.*, Blind Quality Assessment of Dense 3D Point Clouds with Structure Guided Resampling, Under Review In IEEE TCSVT'23

[4] Zhang *et al.*, A Perceptual Quality Assessment Exploration for AIGC Images, In arXiv

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