Blind Image Quality Assessment Based on Machine Learning

高新波

ISN国家重点实验室

西安电子科技大学

Nov. 1~3, 2013

Outline

- Image Quality Assessment (IQA)
- Machine Learning and IQA
- Related Work of My Group
- Opening Issues

Outline

- Image Quality Assessment (IQA)
- Machine Learning and IQA
- Related Work of My Group
- Opening Issues

A Picture Is Worth a Thousand Words

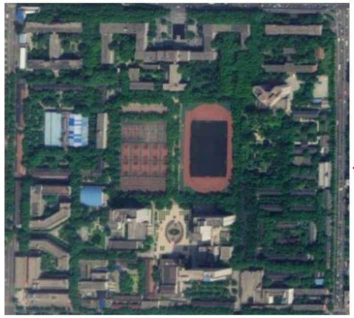
Image Quality Assessment (IQA)

Fidelity

The ***distortion level*** between the test and reference images in the process of observation of the human eye.

Intelligibility

The ***ability*** of the test image on ***providing information*** for human / machine consumers with respect to the reference image.



IQA and Its Applications

Monitor image quality in quality control systems

Benchmark image-processing systems and algorithms

Optimize the systems and parameter settings

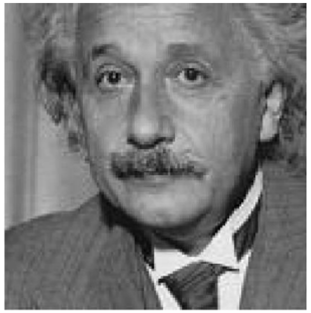
Subjective IQA

R	User satisfaction	MOS
100	Very Satisfied	4.3
90	Satisfied	4.0
80	Some Users Dissatisfied	3.6
70	Many Users Dissatisfied	3.1
60	Nearly All Users Dissatisfied	2.6
50		
0	Not Recommended	1.0

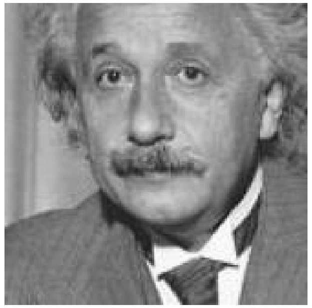
[ITU, BT. 500-13]

- Mean Opinion Score (MOS)
- The most reliable way
- Expensive and inefficient

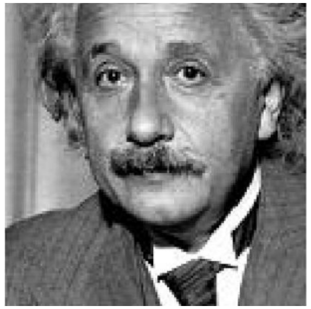
Objective IQA



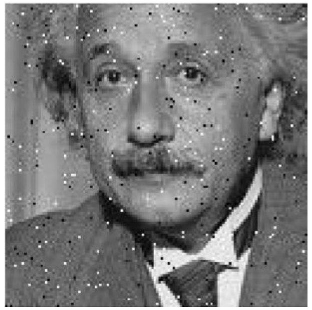
Original Image



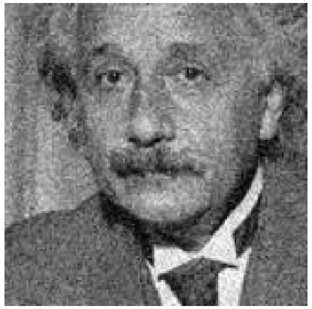
Luminance Shift (MSE=309)



Contrast Stretch (MSE=306)



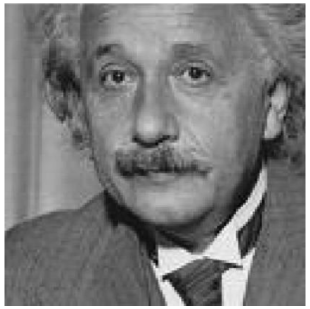
Impulsive Noise (MSE=313)



Gaussian Noise (MSE=309)

Blurring (MSE=308)

JPEG Compression (MSE=309)



Spatial Shift (MSE=590)

- Calculate pixel-wise distances.
- Lack of consideration of human visual property.

[Wang & Bovik, *IEEE SPM*, 2009]

Image Quality Assessment (IQA)

IQA

Image Fidelity Metrics

Accumulate physical errors of the image

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

HVS Model Metrics

Simulate various aspects of the HVS perception property

- Daly visible differences predictor (VDP)
- Perceptual Distortion Metric (PDM)

Signal Structure Metrics

Describe image degradation with perceived change in Structural information

- Structure Similarity (SSIM)
- Feature-Similarity (FSIM)

Machine Learning Metrics

Utilize machine learning in different aspects of image quality assessment

- Blind Image Quality Index (BIQI)
- Blind/Referenceless Image Spatial QUality Evaluator (BRISQUE)

Outline

- Image Quality Assessment (IQA)
- Machine Learning and IQA
- Related Work of My Group
- Opening Issues

Machine Learning

Machine Learning seeks to develop theories and computer systems for

- *representing*;
- *classifying*, clustering and recognizing;
- *reasoning* under uncertainty;
- *predicting*;
- and *reacting* to
- …

complex, real world data, based on the system's own experience with data, and (hopefully) under a unified model or mathematical framework, that

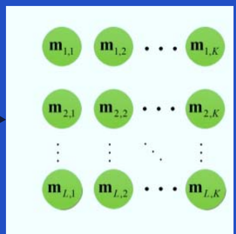
- can be *formally* characterized and analyzed
- can take into account human *prior knowledge*
- can *generalize* and adapt across data and domains
- can operate *automatically* and *autonomously*
- and can be *interpreted* and perceived by human.

Machine Learning and IQA

Machine Learning: subjective IQA → objective IQA

Utilize the machine learning to model the different modules of the subjective IQA

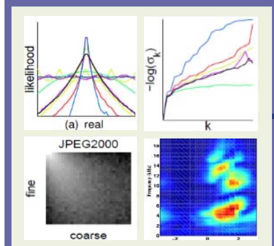
Machine Learning for *Feature Representation*



Image

Features

Machine Learning for *Distortion Identification*

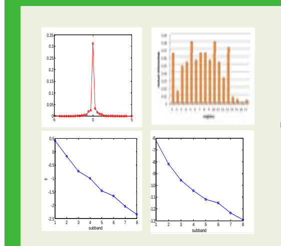


Features

- JPEG
- JPEG2k
- White Noise
- Gaussian Blur
- Fast Fading
- ……

Distortions

Machine Learning for *Quality Prediction*



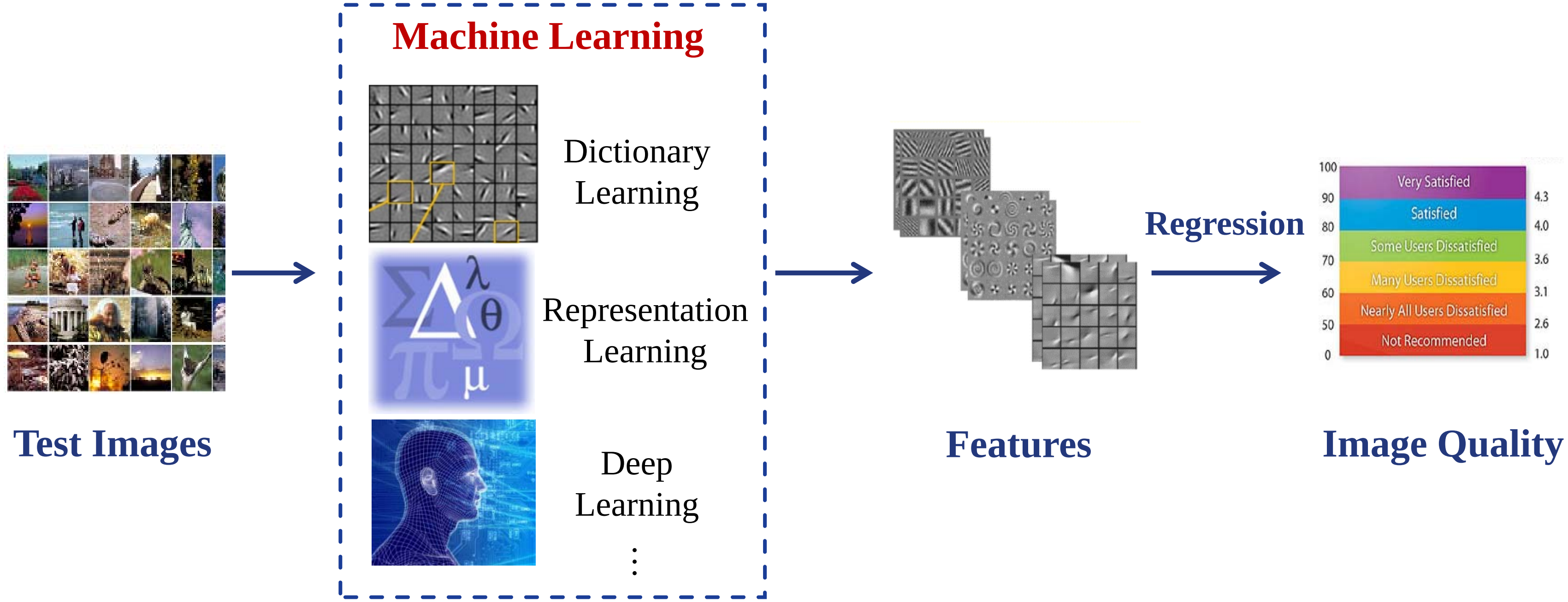
Features

Quality

Machine Learning and IQA

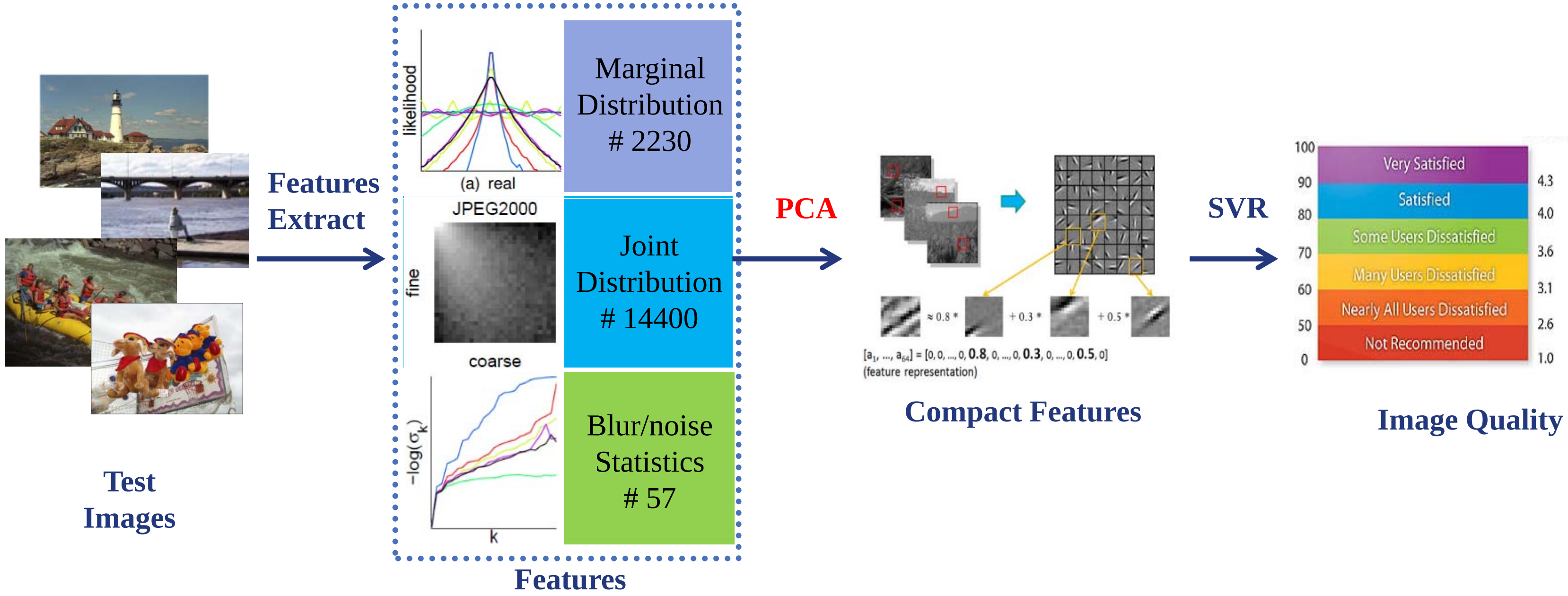
Machine Learning for ***Feature Representation***

- Represent image features *sparsely* and recombine image features optimally
- Obtain effective feature *representations* for image quality perception
- Enhance the *reliability* of image quality assessment algorithm



Machine Learning and IQA

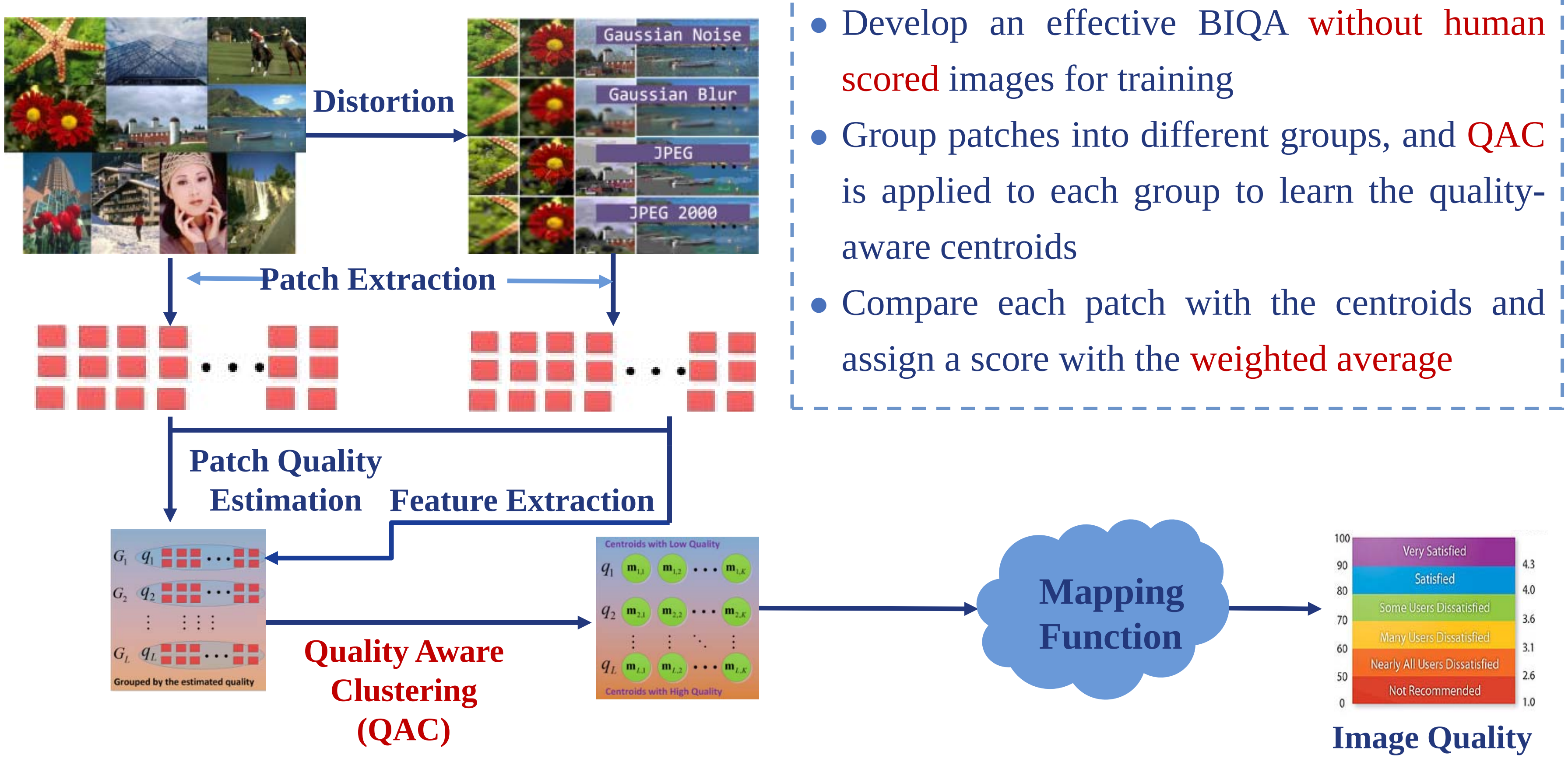
Learning a Blind Measure of Perceptual Image Quality



- Extract features that measure aspects of image structure and statistics
- Redundancy of features are reduced via **PCA**
- Compact features are projected to quality scores through SVR
- The method addresses the limitation which assumes that only one distortion type dominates in the image and it can handle additional distortion types

[H. Tnag, N. Joshi, & A. Kapor, *CVPR*, 2011]

Learning without Human Scores for Blind IQA



- Develop an effective BIQA without human scored images for training
- Group patches into different groups, and QAC is applied to each group to learn the quality-aware centroids
- Compare each patch with the centroids and assign a score with the weighted average

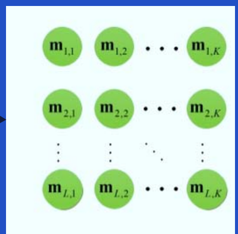
[Xue & Zhang, *CVPR*, 2013]

Machine Learning and IQA

Machine Learning: subjective IQA → objective IQA

Utilize the machine learning to model the different modules of the subjective IQA

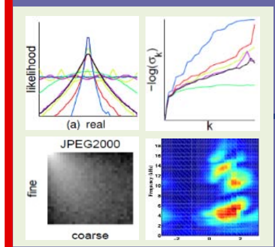
Machine Learning for *Feature Representation*



Image

Features

Machine Learning for *Distortion Identification*

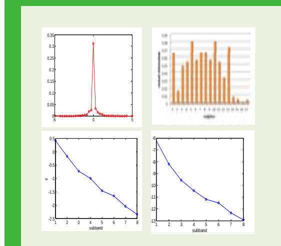


Features

JPEG
JPEG2k
White Noise
Gaussian Blur
Fast Fading
……

Distortions

Machine Learning for *Quality Prediction*



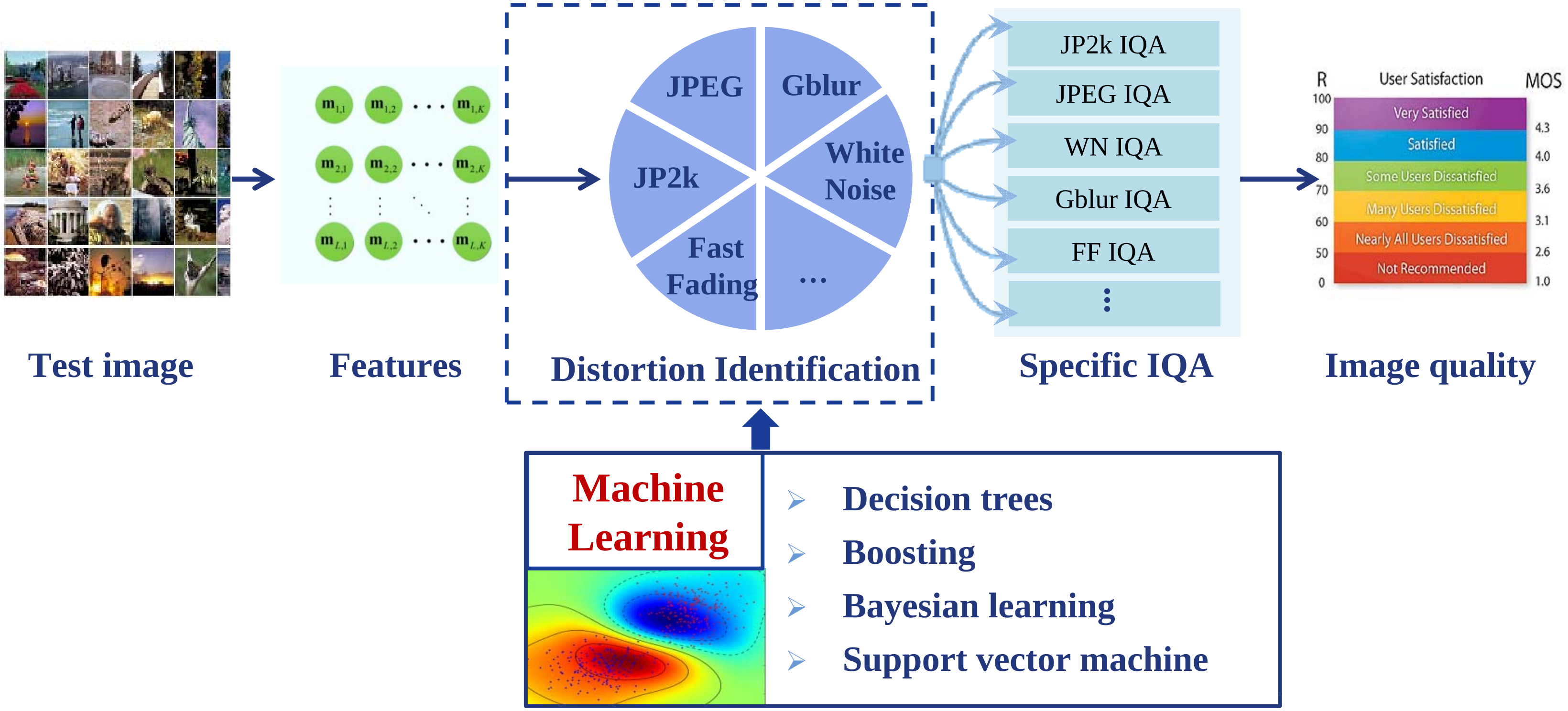
Features

Quality

Machine Learning and IQA

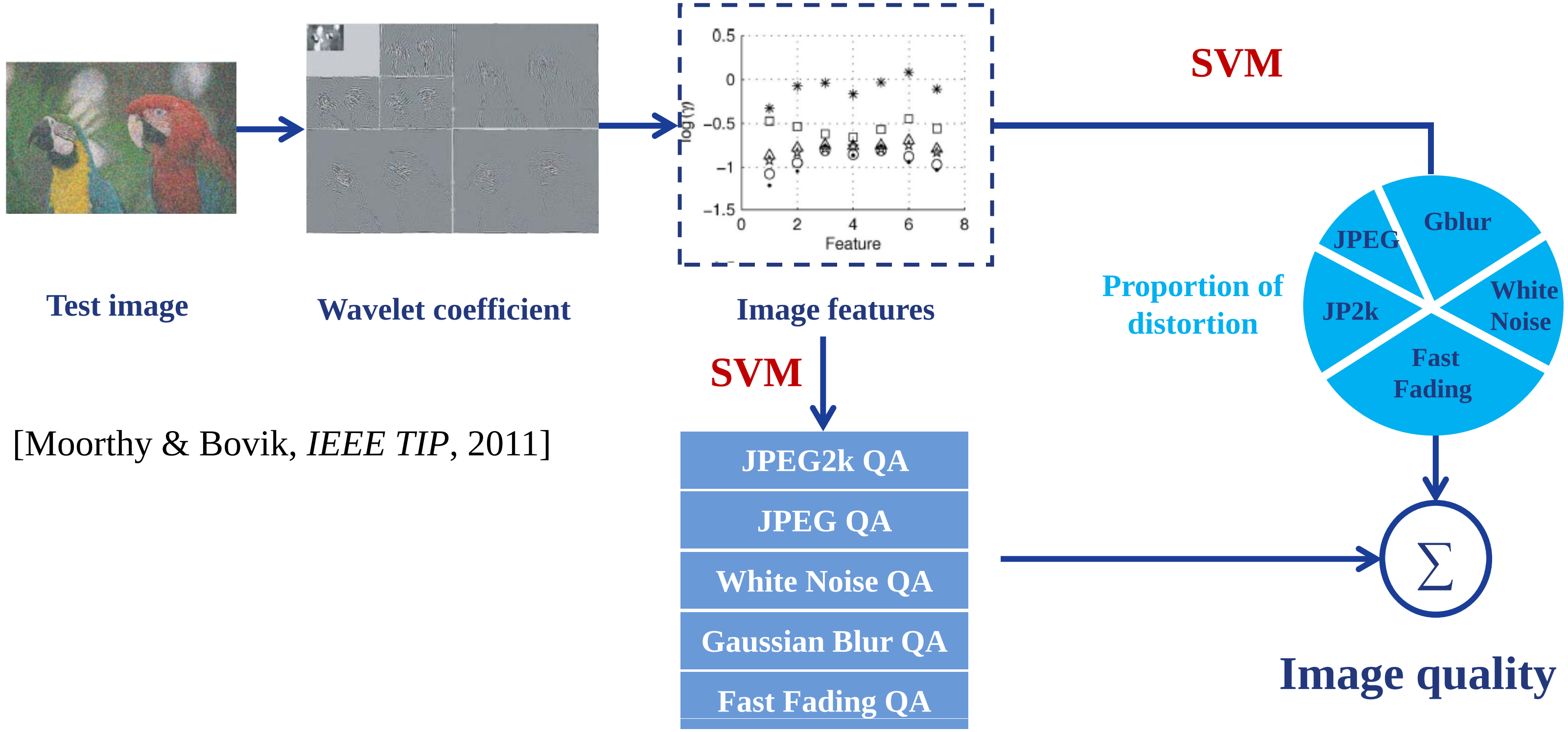
Machine Learning for ***Distortion Identification***

- Divide image by the distortion types with learning method
- Construct evaluation model of the corresponding distortion type
- Improve the *generalization* of image quality evaluation algorithm



Machine Learning and IQA

Blind IQA: From Natural Scene Statistics to Perceptual Quality

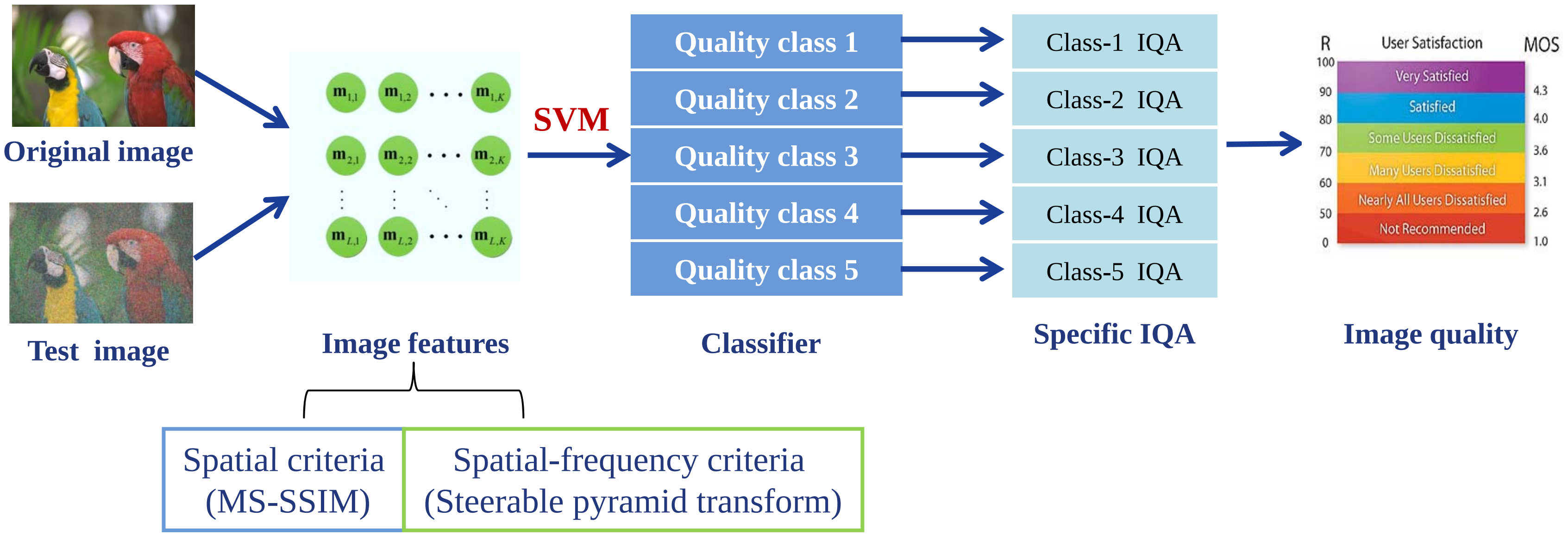


[Moorthy & Bovik, *IEEE TIP*, 2011]

- The presence of distortions in natural images alters the natural statistical properties of images
- The statistics features are used to first classify the distorted image into one of distortions, and then the same set of statistics are used to evaluate the distortion-specific quality of the image
- A combination of the two stages leads to a quality score for the image

Machine Learning and IQA

Machine Learning to Design Full-reference IQA Algorithm



- This quality measure is based on a *learned classification process* in order to respect human observers
- Compute feature vector of image, perform *SVM multi-class classification process* to provide the final quality class, apply SVR process to score the quality
- The proposed method yields a *sensitivity* adaptation to image quality

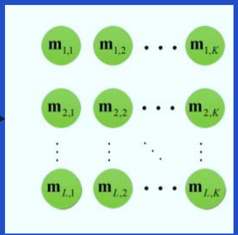
[Charrier& Gilles Lebrun, *SP*, 2012]

Machine Learning and IQA

Machine Learning: subjective IQA → objective IQA

Utilize the machine learning to model the different modules of the subjective IQA

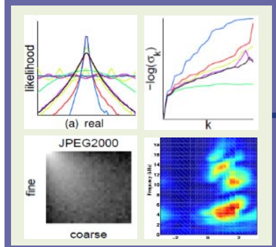
Machine Learning for *Feature Representation*



Image

Features

Machine Learning for *Distortion Identification*

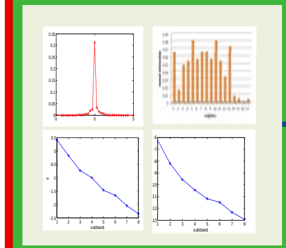


- JPEG
- JPEG2k
- White Noise
- Gaussian Blur
- Fast Fading
- ……

Features

Distortions

Machine Learning for *Quality Prediction*



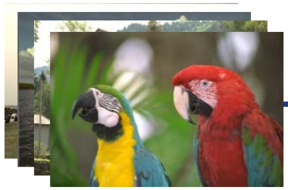
Features

Quality

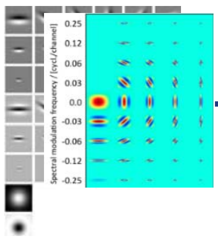
Machine Learning and IQA

Machine Learning for ***Quality Prediction***

- Optimize and refine the *mapping* between the image features and image quality
- Reflect the *variation* of image quality precisely
- Raise the *stability* of image quality assessment algorithm

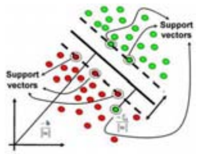


Image

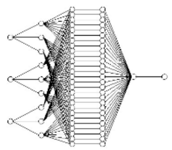


Features

Machine Learning



Support Vector Machine



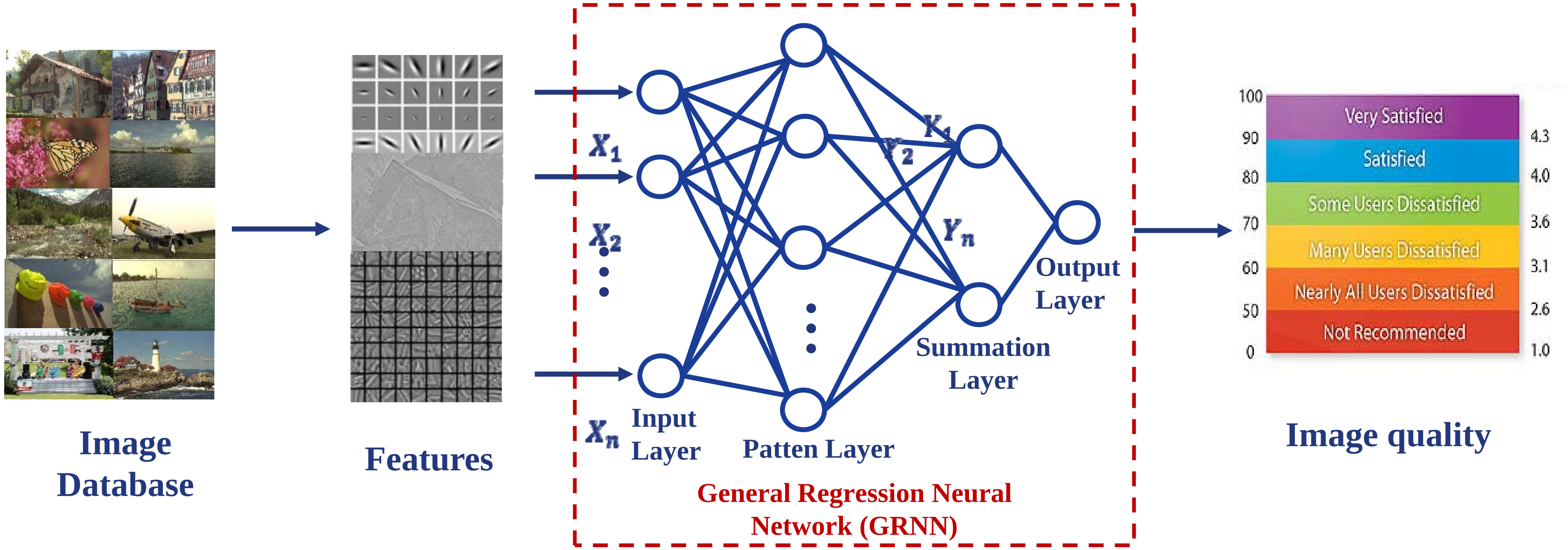
Neutral Network

Deep Learning

⋮

Image quality

Blind IQA Using a General Regression Neural Network

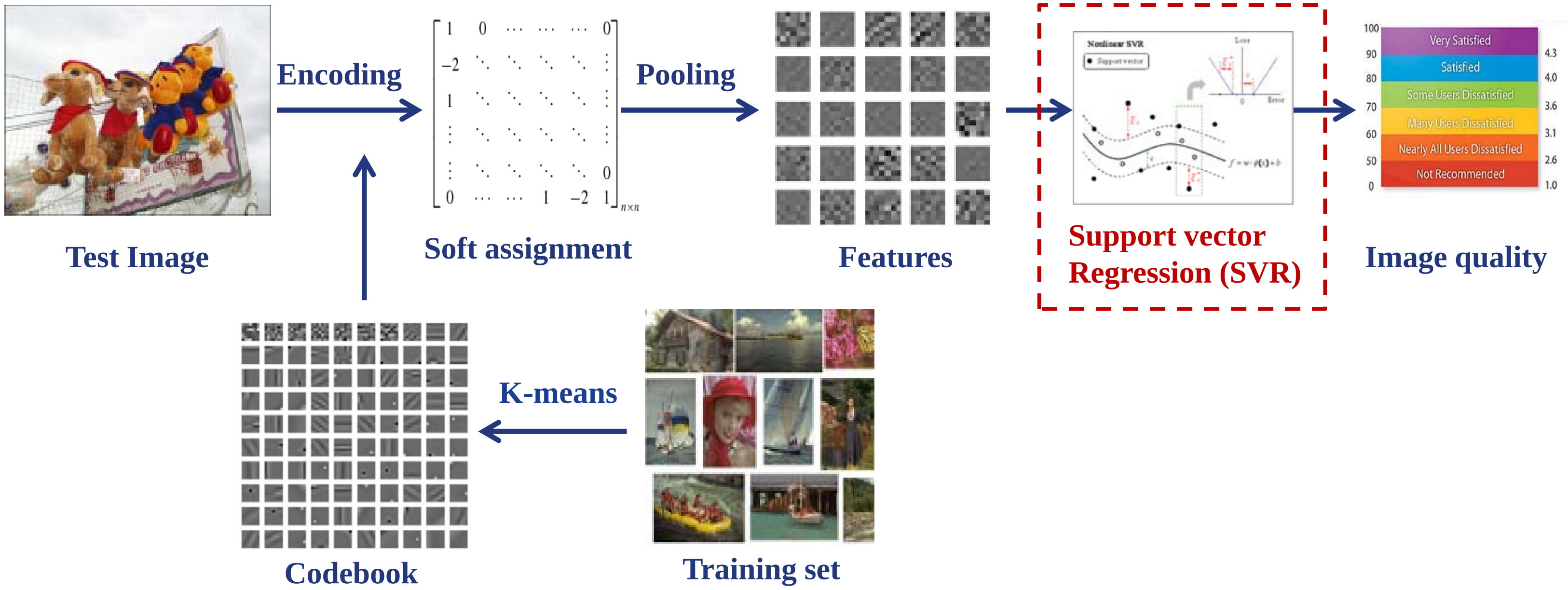


- This quality measure based on several complementary and perceptually relevant image features fed to a GRNN network
- Approximating the functional relationship between these features and subjective mean opinion scores
- Experimental results show the method be closely with human subjective judgment

[Li & Bovik, *IEEE TNN*, 2011]

Machine Learning and IQA

Unsupervised Feature Learning for No-reference IQA



- Raw-image-patches are used to learn a codebook via *K-means clustering*
- Soft-assignment coding with max pooling to obtain effective feature representations
- Image features are projected to quality scores through *support vector regression*.
- It is a general-purpose no-reference IQA method and can be adapted to different domains.

[P. Ye, D. Doermann, *et al.*, *CVPR*, 2012]

Outline

- Image Quality Assessment (IQA)
- Machine Learning and IQA
- Related Work of My Group
- Opening Issues

Related Work of My Group

I. NR-IQA in Contourlet Domain

II. NR-IQA with Hidden Markov Tree

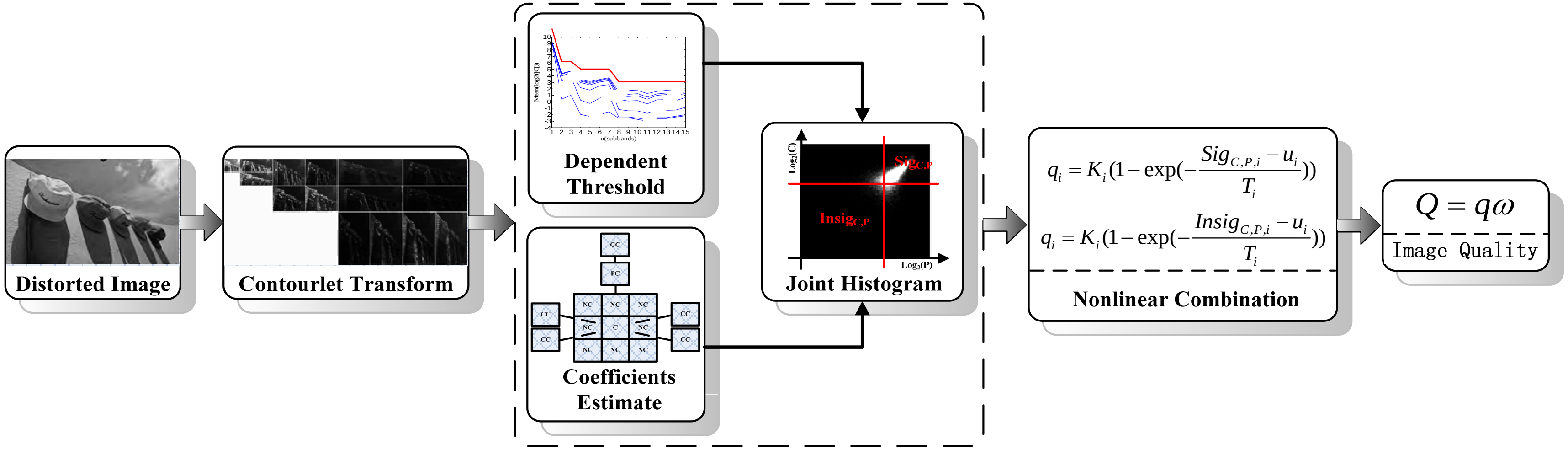
III. NR-IQA with Multiple Kernel Learning

IV. NR-IQA with Sparse Representation

V. NR-IQA with Semi-supervised LLE

NR-IQA in Contourlet Domain

- Framework



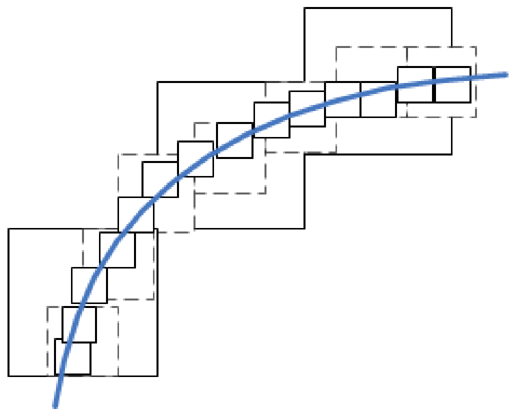
- Contourlet is utilized to achieve an *optimal approximation* rate of piecewise smooth function
- The relationship of contourlet coefficients is represented by the *joint statistics distribution*
- The statistics of contourlet coefficients are applicable to indicate variation of *image quality*
- Image quality can be obtained by combine the extracted *features* in each subband *nonlinearly*

[W. Lu, K. Zeng, D. Tao, Y. Yuan, X.-B. Gao, *Neurocomputing*, 2010]

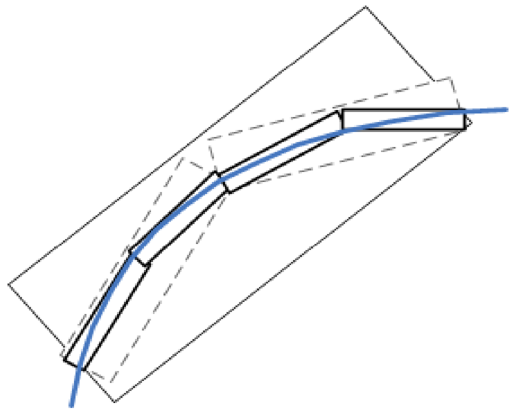
NR-IQA in Contourlet Domain

Ideal Image model

- Mulit-resolution—Image can gradually approximate from rough to precise
- Localization—Image representation can focus on time and frequency domain
- Critically sampled—Image representation is a basic and low redundant structure
- Directionality—Image representation contains basic function in all directions
- Anisotropy—Image contains various shapes of basic function



(a) Approximation using Wavelet



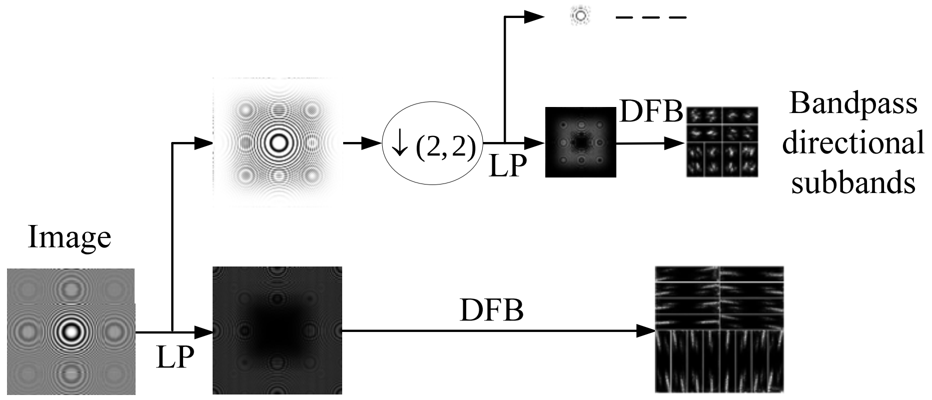
(b) Approximation of expectation (Contourlet)

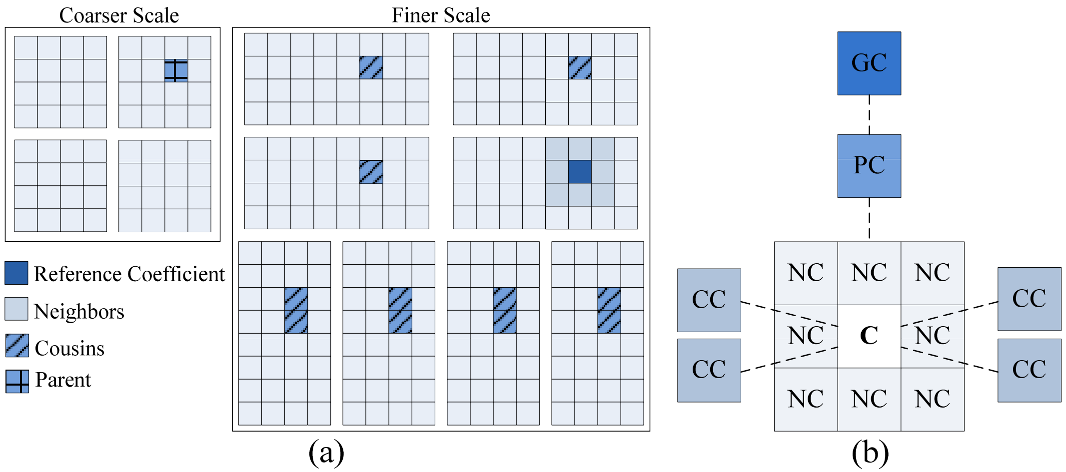
[W. Lu, K. Zeng, D. Tao, Y. Yuan, X.-B. Gao, *Neurocomputing*, 2010]

NR-IQA in Contourlet Domain

- Relationship of Contourlet Coefficients

The scatter plot of Contourlet decomposition





$$C = MP + N$$

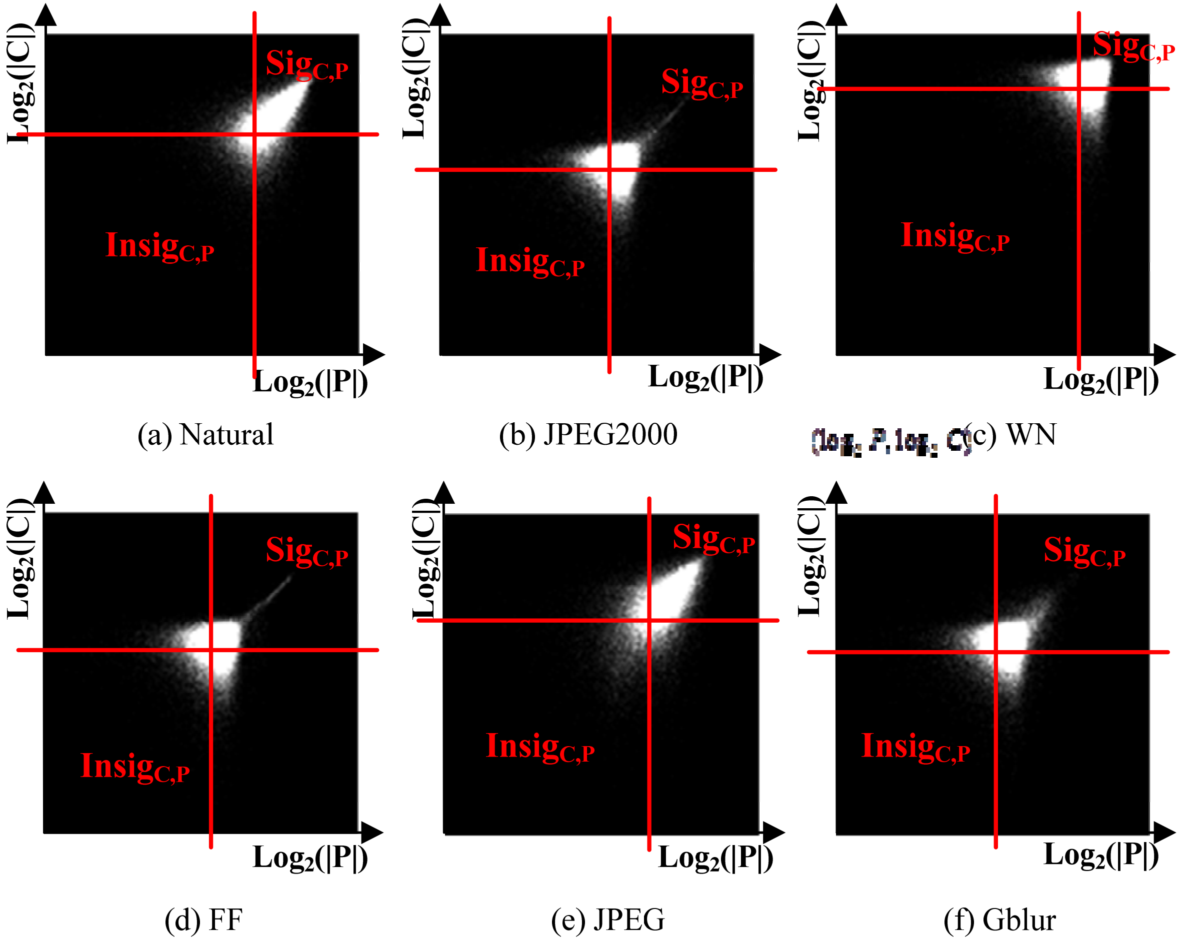
$$P = \sum_{i=1}^{n} l_i C_i$$

Relationships of Contourlet coefficients

[W. Lu, K. Zeng, D. Tao, Y. Yuan, X.-B. Gao, *Neurocomputing*, 2010]

NR-IQA in Contourlet Domain

- Joint Histograms of Contourlet Coefficients and Its Prediction



$$Sig_{C,P} = \frac{n_{C>T,P>T}}{n_{C,P}}$$

$$Insig_{C,P} = \frac{n_{C<T,P<T}}{n_{C,P}}$$

$n_{C>T,P>T}$ and $n_{C<T,P<T}$ is the number of significant and inignificant *C* and *P* in subband,

$n_{C,P}$ is the total number of contourlet coefficient in subband,

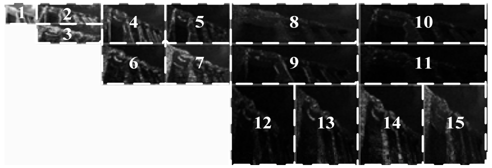
T is image dependent threshold.

Joint histograms of $(\log_2 P, \log_2 C)$ for one subband of different distorted images

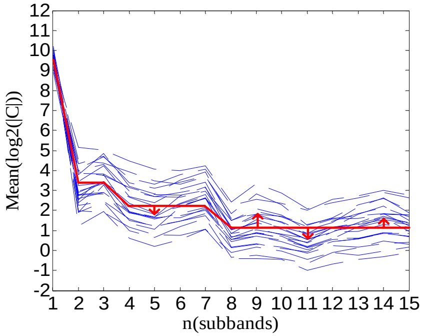
[W. Lu, K. Zeng, D. Tao, Y. Yuan, X.-B. Gao, *Neurocomputing*, 2010]

NR-IQA in Contourlet Domain

- Image Dependent Threshold



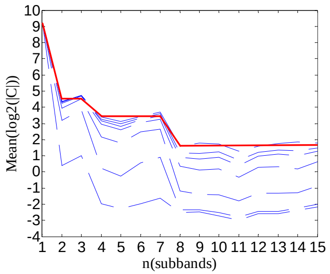
(a)



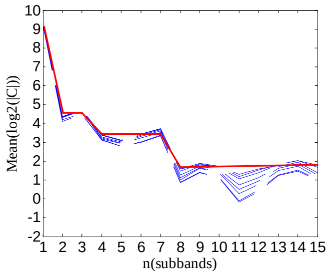
(b)

$$T_{scale,i} = C_l + diff_{i,l}$$

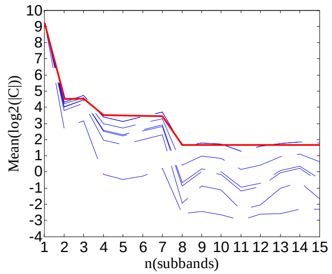
$$T_{subband,j} = T_{scale,i} + T_{offset,i,j}$$



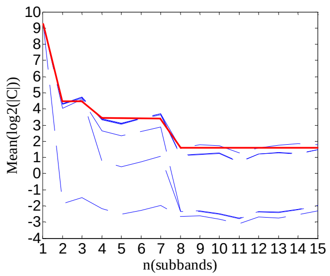
JPEG2000



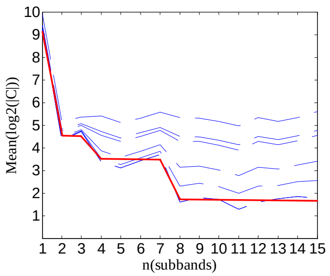
JPEG



Gaussian Blur



Fast Fading



White Noise

- Calculation of Image Quality

$$q_i = K_i\left(1-\exp\left(-\frac{(Sig_{C,P,i} \mid Insig_{C,P,i}) - u_i}{T_i}\right)\right)$$

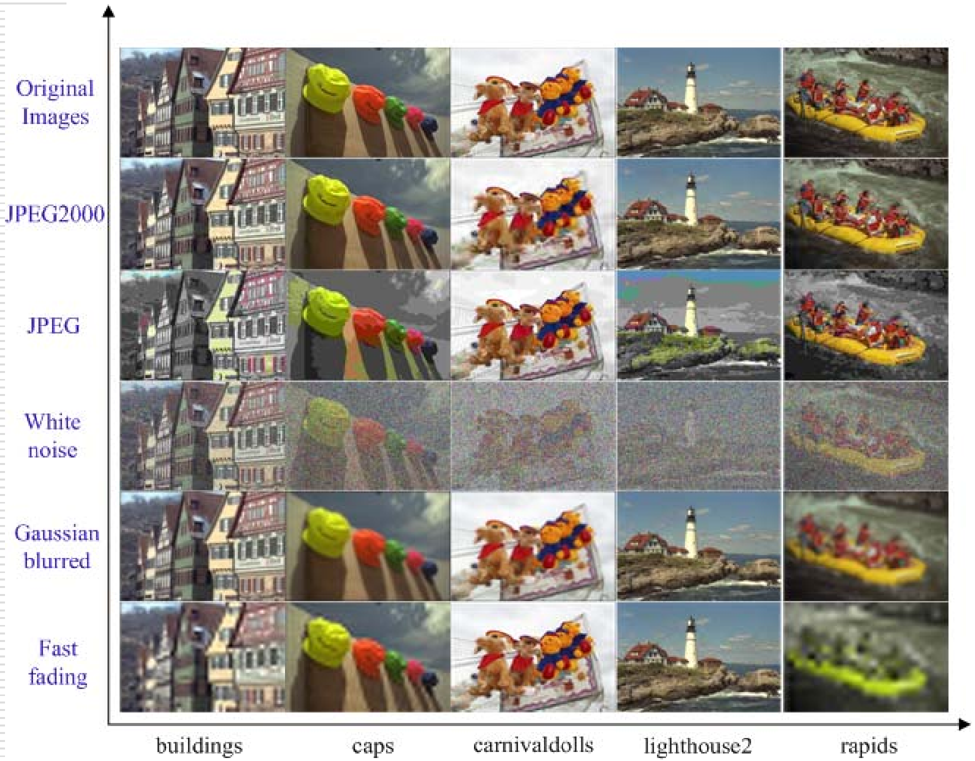
$$q = [q_1, q_2, q_3, \ldots, q_n]$$

$$Q = q\omega$$

[W. Lu, K. Zeng, D. Tao, Y. Yuan, X.-B. Gao, *Neurocomputing*, 2010]

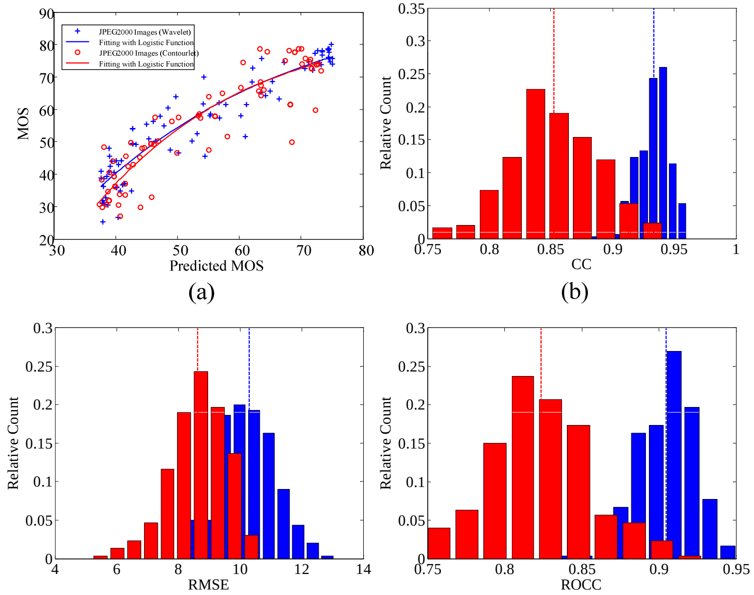
NR-IQA in Contourlet Domain

- Experimental Results



[W. Lu, K. Zeng, D. Tao, Y. Yuan, X.-B. Gao, *Neurocomputing*, 2010]

		CC	RMSE	ROCC
Wavelet	**Mean**	0.8527	8.6205	0.8238
	Std	0.0351	0.9209	0.0324
Proposed	**Mean**	0.9332	10.2955	0.9047
	Std	0.0127	0.8633	0.0185



(a) (b) (c) (d)

[W. Lu, K. Zeng, D. Tao, Y. Yuan, X.-B. Gao, *Neurocomputing*, 2010]

Related Work of My Group

I. NR-IQA in Contourlet Domain

II. NR-IQA with Hidden Markov Tree

III. NR-IQA with Multiple Kernel Learning

IV. NR-IQA with Sparse Representation

V. NR-IQA with Semi-supervised LLE

NR-IQA with Hidden Markov Tree

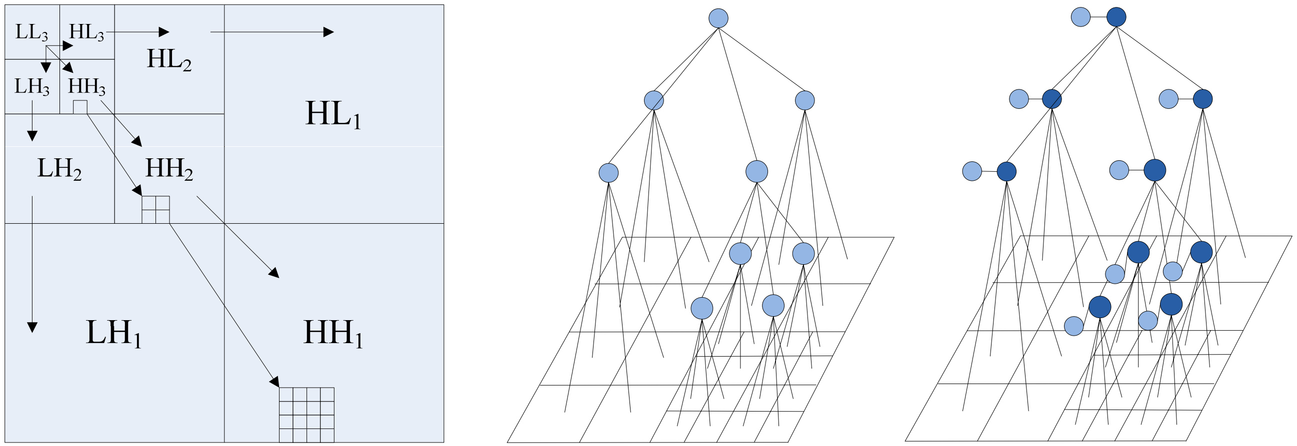
- **Non-Gaussianity:**
  - Gaussian mixture model (GMM): to model the distribution of coefficients in each subband

$$f(x) = \omega_L * g(m_L, \sigma_L) + \omega_S * g(m_S, \sigma_S)$$

Gaussian Distribution

where $m_S = m_L = 0, \sigma_L \geq \sigma_S$, L and S denote whether the (hidden) state is large or small.

- **Persistency and local dependency:**
  - The Markov dependencies implies that the possibility of a wavelet coefficient being “large” or “small” is only related with its parent coefficient.



(a) (b) (c)

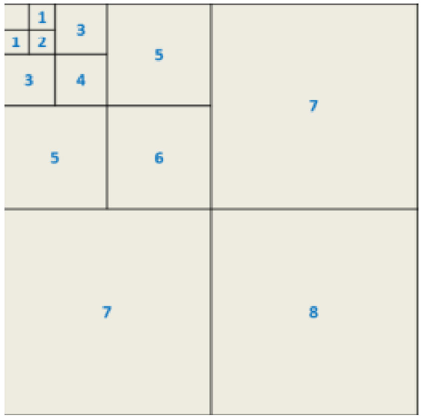
(a) Two-dimensional wavelet decomposition, (b) quad-tree of the wavelet coefficients (c) two-dimensional HMT model. Here, light color joints indicate the wavelet coefficients, while dark joints the hidden states which are used to dictate whether one coefficient is large or small.

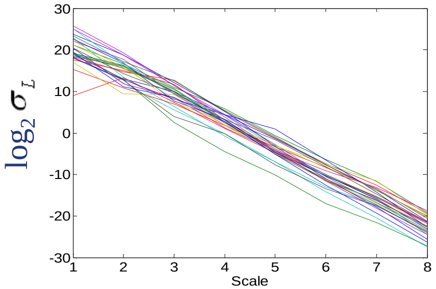
[F. Gao, X.-B. Gao, W. Lu, D. Tao, X. Li, *VCIP2010*, 2010]

NR-IQA with Hidden Markov Tree

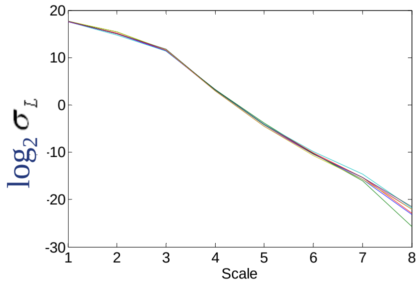
Correlation with Image Quality

- For the reference images: the distribution of σ_L (or σ_S) is broadly linear in the logarithmic domain, and the scopes are almost the same for different images.
- For the distorted images: σ_L(or σ_S) changes dramatically in some scales, but changes little in other scales.

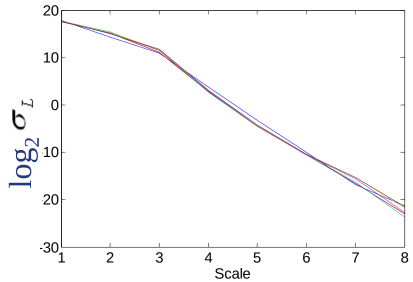




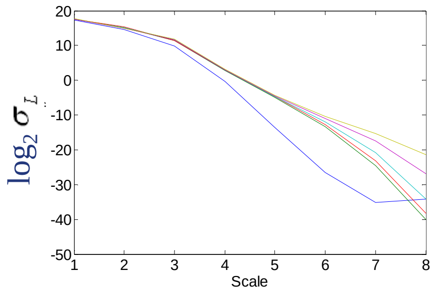
(a) Reference



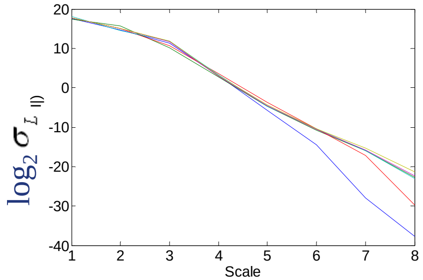
(b) JPEG2000



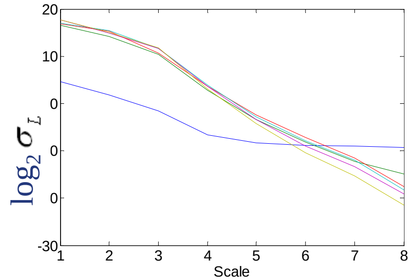
(c) JPEG



(d) Gaussian Blurred



(e) Fast Fading



(f) White Noise

[F. Gao, X.-B. Gao, W. Lu, D. Tao, X. Li, *VCIP2010*, 2010]

NR-IQA with Hidden Markov Tree

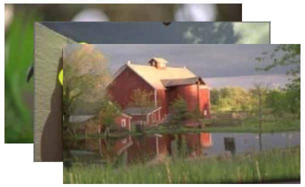
Framework

- Estimate the features of the corresponding reference image from the features of the test image.

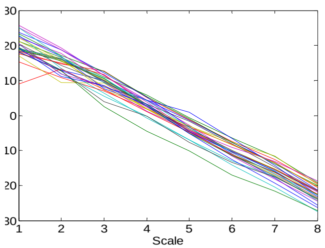
$$\sigma_{L,i,ref} = k_L \sigma_{L,u} + o_{L,i}$$

$$\sigma_{S,i,ref} = k_S \sigma_{S,u} + o_{S,i}$$

$k_{L(S)}$ is the estimated scope of σ_L (or σ_S) of the reference image.
$\sigma_{L(S),u}$ is σ_L (or σ_S) in the scale whose parameters change little with the quality.
$o_{L,i}$ is the offsets in the i^{th} scale
$\sigma_{L,i,ref}$ is the estimated σ_L (or σ_S) of the corresponding reference image in the i^{th} scale



Training images

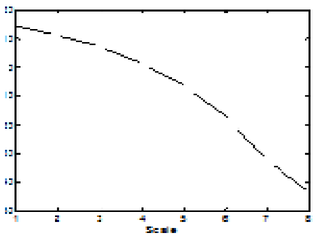


$k_{L(S)}$, $o_{L(S)}$

$$\sigma_{L,i,ref} = k_L \sigma_{L,u} + o_{L,i}$$

$$\sigma_{S,i,ref} = k_S \sigma_{S,u} + o_{S,i}$$

Test image



$$d_L = \sum_i \left|\sigma_{L,i} - \sigma_{L,i,ref}\right|$$

$$d_S = \sum_i \left|\sigma_{S,i} - \sigma_{S,i,ref}\right|$$

$$d = d_L + d_S$$

Quality Score

$$Q = \alpha / \left(1 + e^{-\beta(d-\gamma)}\right)$$

[F. Gao, X.-B. Gao, W. Lu, D. Tao, X. Li, *VCIP2010*, 2010]

NR-IQA with Hidden Markov Tree

- **Results of the proposed IQA method**

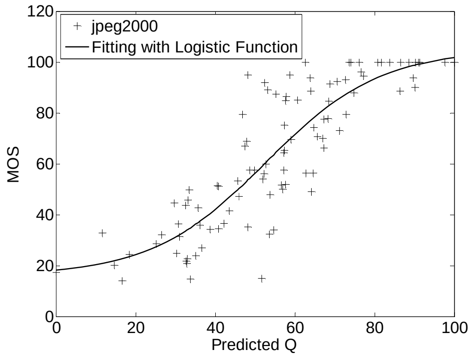
		CC		RMSE		ROCC	
		Mean	St. D.	Mean	St. D.	Mean	St. D.
JP2k	NSS[1]	0.9332	0.0127	10.296	0.8633	0.9047	0.0185
	Proposed	0.7367	0.0531	18.719	1.6486	0.7380	0.0494
JPEG	NSS[1]	0.3837	0.0872	30.117	1.5913	0.2732	0.1055
	Proposed	0.9179	0.0132	13.574	1.0005	0.8946	0.0137
Gblur	NSS[1]	0.7611	0.0545	12.985	1.4523	0.7033	0.0689
	Proposed	0.8832	0.0214	11.1826	0.9574	0.8882	0.0228
FF	NSS[1]	0.7212	0.0745	19.299	1.9953	0.7126	0.0567
	Proposed	0.7906	0.0409	19.028	1.5538	0.7434	0.0414
WN	NSS[1]	0.9498	0.0094	10.060	0.6615	0.9151	0.0145
	Proposed	0.9442	0.0090	10.855	0.8204	0.9269	0.0123

[1] Sheikh, R. H., Bovik, C. A., and Cormack, L., IEEE TIP, 14(11), 1918-1927 (2005).

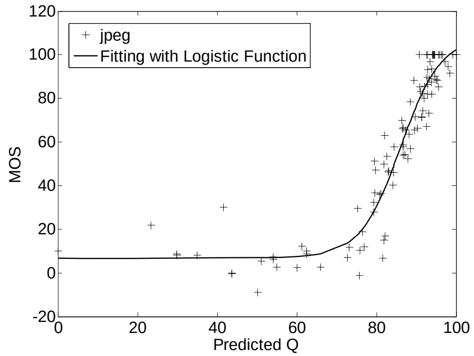
[F. Gao, X.-B. Gao, W. Lu, D. Tao, X. Li, *VCIP2010*, 2010]

NR-IQA with Hidden Markov Tree

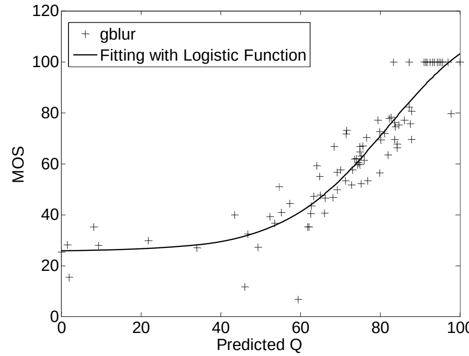
■ Results of the proposed IQA method



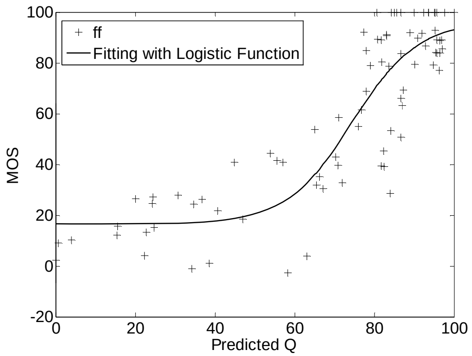
(a) JPEG2000



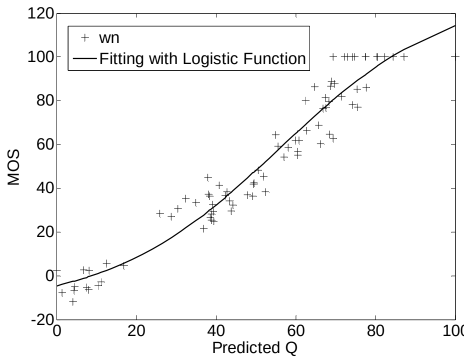
(b) JPEG



(c) Gaussian Blur



(d) Fast Fading



(e) White Noise

The results of the proposed IQA method on JPEG2000, JPEG, Gblur, FF, and WN images for one of the runs against the MOS.

[F. Gao, X.-B. Gao, W. Lu, D. Tao, X. Li, *VCIP2010*, 2010]

Related Work of My Group

I. NR-IQA in Contourlet Domain

II. NR-IQA with Hidden Markov Tree

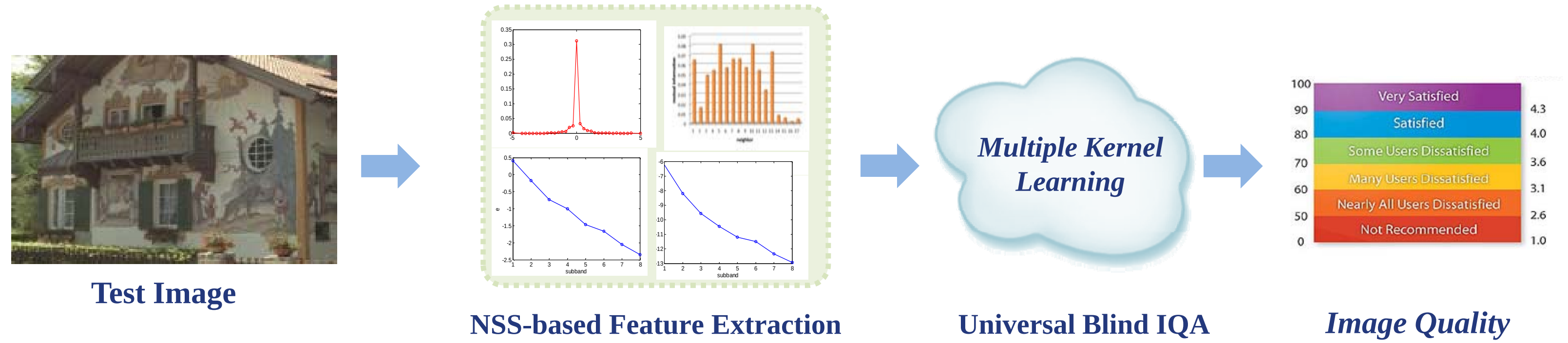
III. NR-IQA with Multiple Kernel Learning

IV. NR-IQA with Sparse Representation

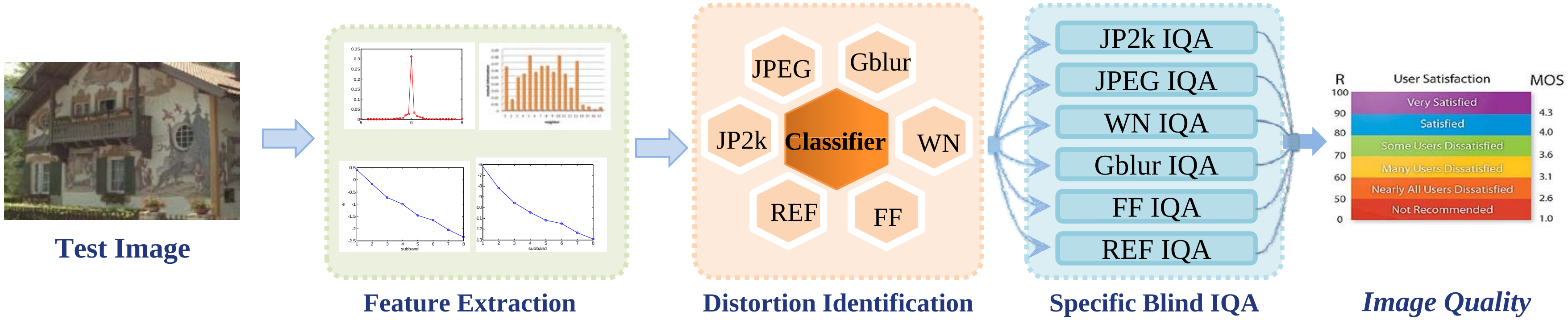
V. NR-IQA with Semi-supervised LLE

NR-IQA with Multiple Kernel Learning

■ Diagram of NSS Global Scheme (NSS-GS)



■ Diagram of NSS Two-step Scheme (NSS-TS)



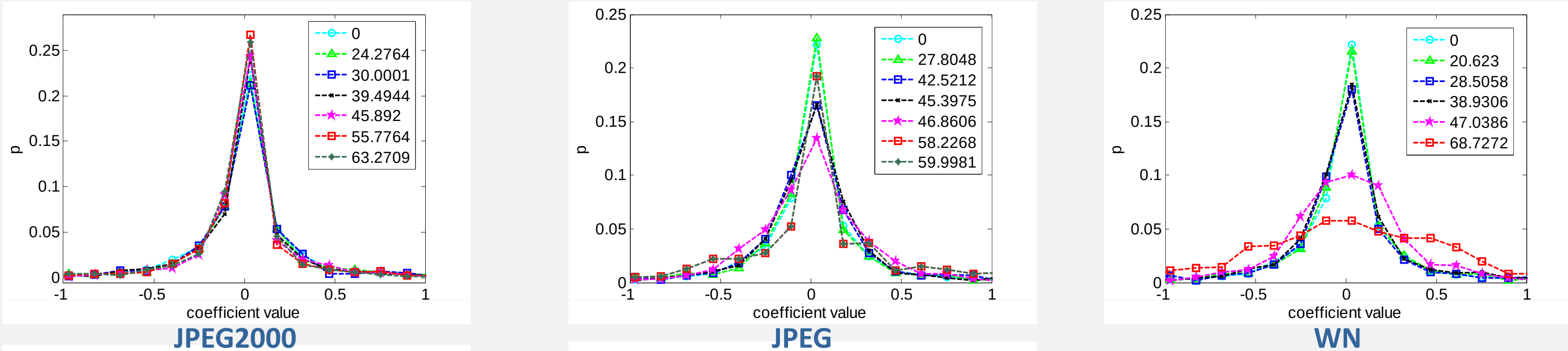
[X.-B. Gao, F. Gao, D. Tao, X. Li, *IEEE TNNLS*, 2013]

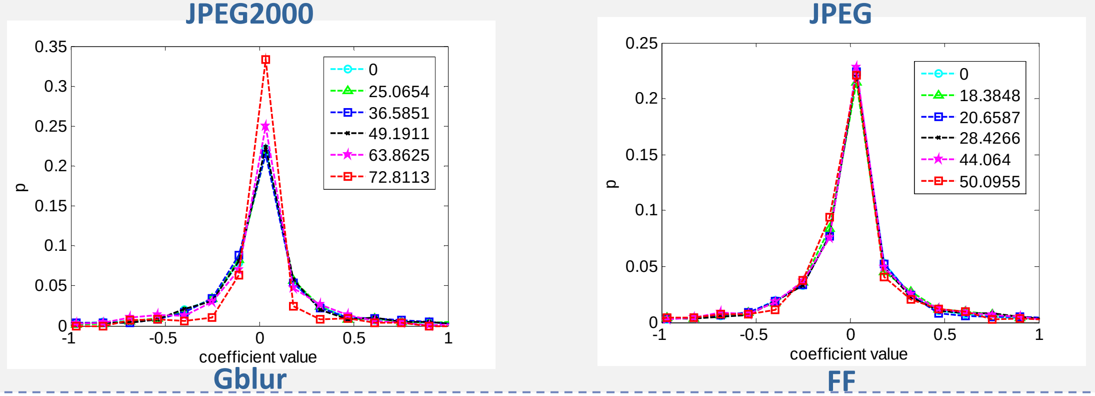
NR-IQA with Multiple Kernel Learning

NSS-based features extraction

- **Non-Gaussianity (NG)**: the NG of natural images is exploited by using the original marginal distribution of wavelet coefficients. [Srivastava *et al*. JMIV’03]

$$\boldsymbol{p}_k = histogram\left(\boldsymbol{C}_k\right) \qquad \boldsymbol{f}_{NG} = \left[\boldsymbol{p}_1, \boldsymbol{p}_2, \ldots, \boldsymbol{p}_{3L}\right]$$





*** Numbers in the legend are the difference mean opinion score (DMOS) of each image. DMOS is the difference between the quality of an image and the perfect quality. Thus a greater DMOS value indicates poorer quality.**

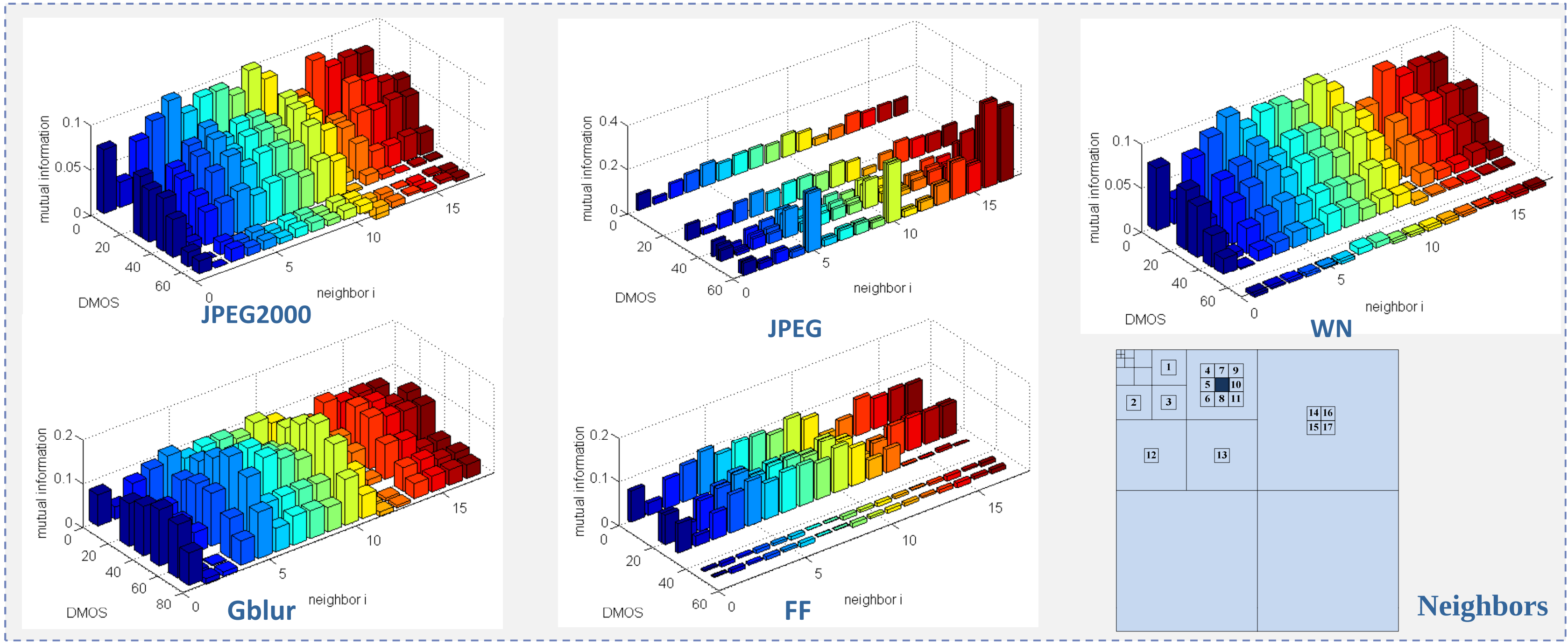
[X.-B. Gao, F. Gao, D. Tao, X. Li, *IEEE TNNLS*, 2013]

NR-IQA with Multiple Kernel Learning

NSS-based features extraction

- **Local Dependency (LD)**: measure correlations between wavelet coefficients by using mutual information defined in information theory. [Petrov and Zhaoping, JOSA'87]

$$I\left(C^k \middle\| C_i^k\right)=\sum_{y\in\mathcal{C}^k}\sum_{x\in\mathcal{C}_i^k} p(x,y)\log\left(\frac{p(x,y)}{p(x)p(y)}\right)$$

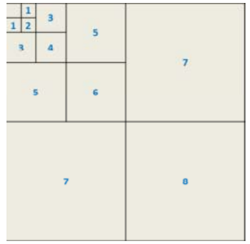


[X.-B. Gao, F. Gao, D. Tao, X. Li, *IEEE TNNLS*, 2013]

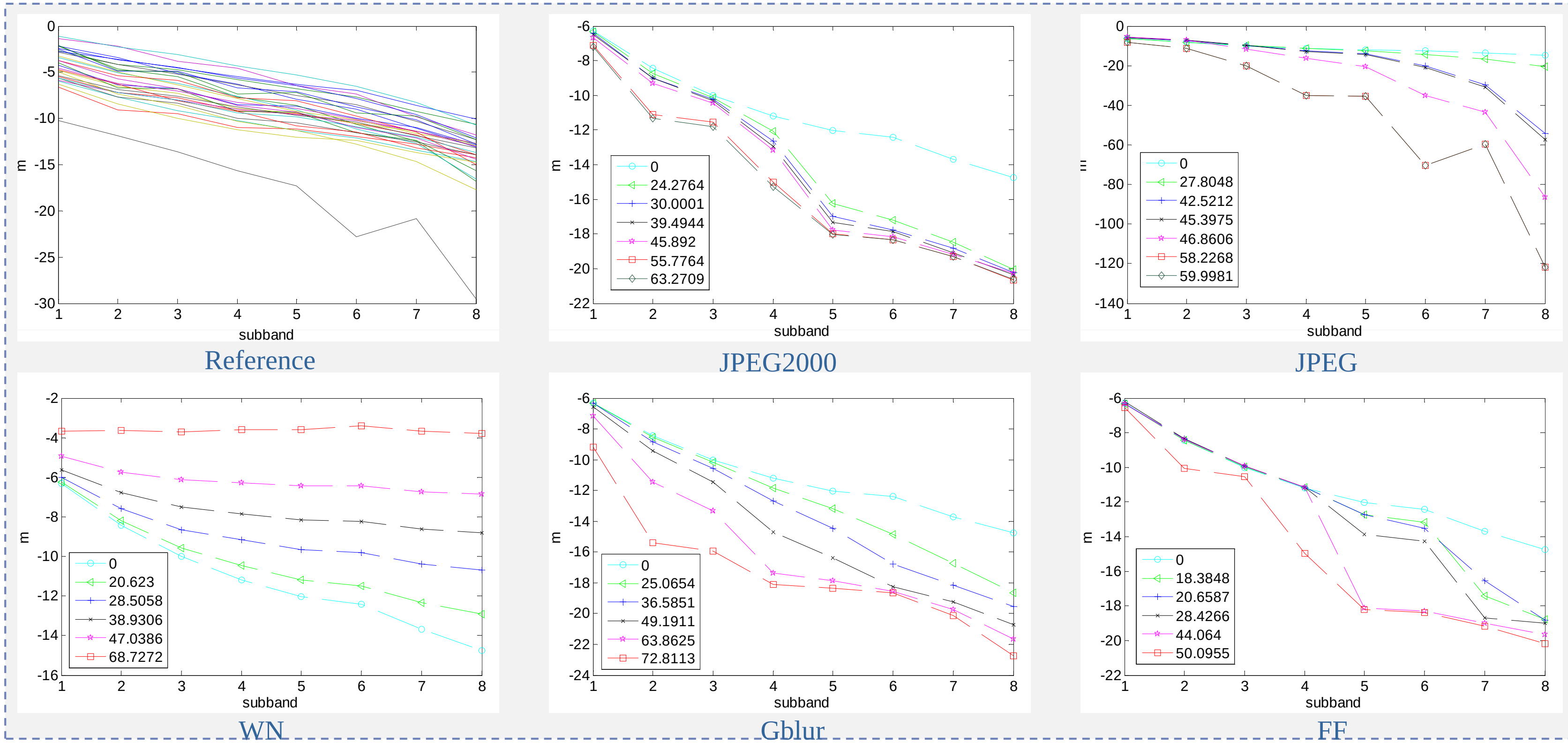
NR-IQA with Multiple Kernel Learning

NSS-based features extraction

- **Exponential Decay Characteristic (EDC)** [Dufour and Miller, SP’98; Field, JOSA’87]



$$m_k = \frac{1}{N_k \cdot M_k} \sum_{j=1}^{N_k} \sum_{i=1}^{M_k} \log_2 \left\| C^k(i,j) \right\|_2^2 \qquad \boldsymbol{m}_{EDC} = [m_1, m_2, \cdots, m_{2L}]$$

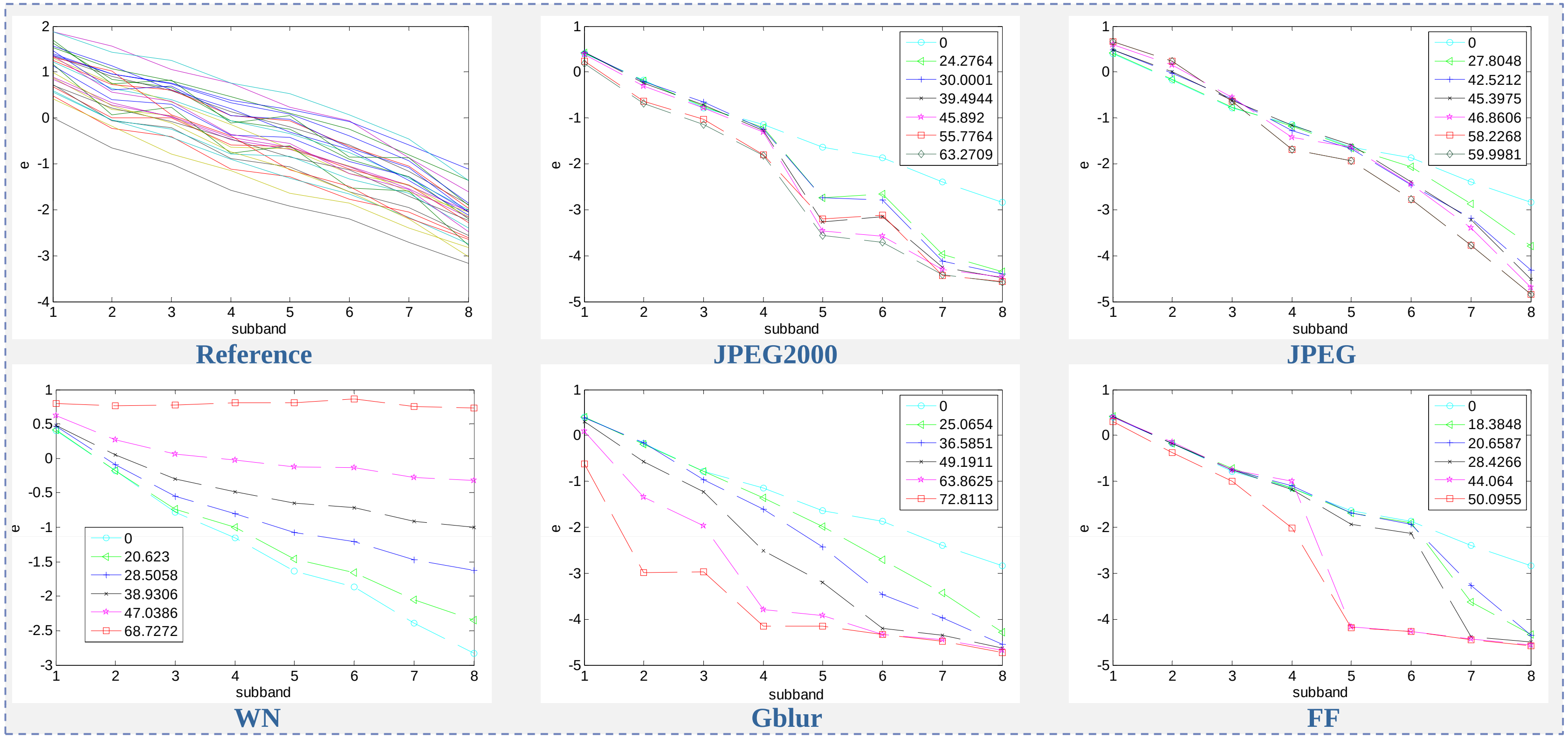


[X.-B. Gao, F. Gao, D. Tao, X. Li, *IEEE TNNLS*, 2013]

NR-IQA with Multiple Kernel Learning

- **NSS-based features extraction**
  - **Exponential Decay Characteristic (EDC)**

$$e_k = \log_2\left(-\sum_{i=1}^{N_b} p_i \ln p_i\right) \qquad \boldsymbol{e}_{EDC} = [e_1, e_2, \cdots e_{2L}] \qquad \boldsymbol{f}_{EDC} = [\boldsymbol{m}_{EDC}, \boldsymbol{e}_{EDC}]$$

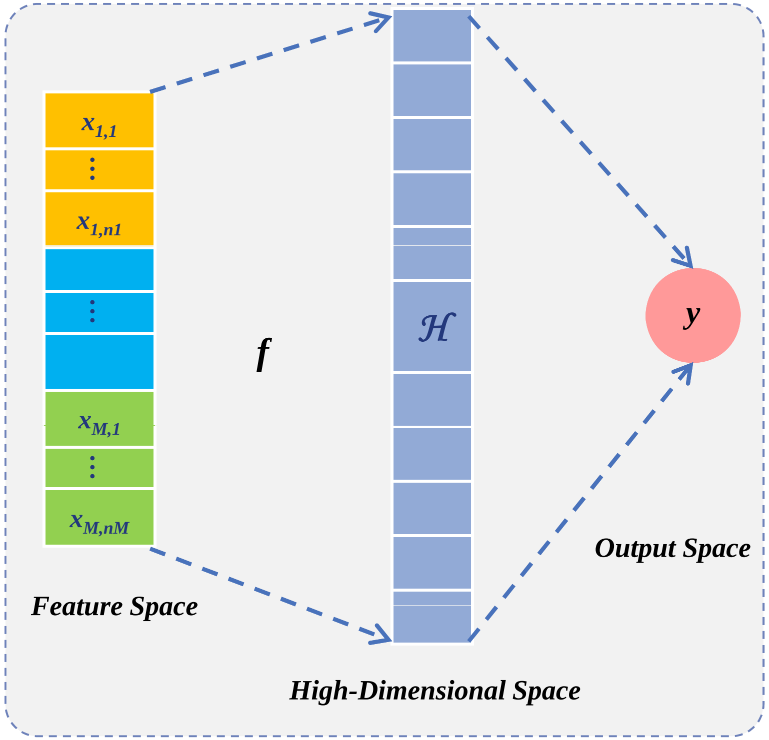


[X.-B. Gao, F. Gao, D. Tao, X. Li, *IEEE TNNLS*, 2013]

NR-IQA with Multiple Kernel Learning

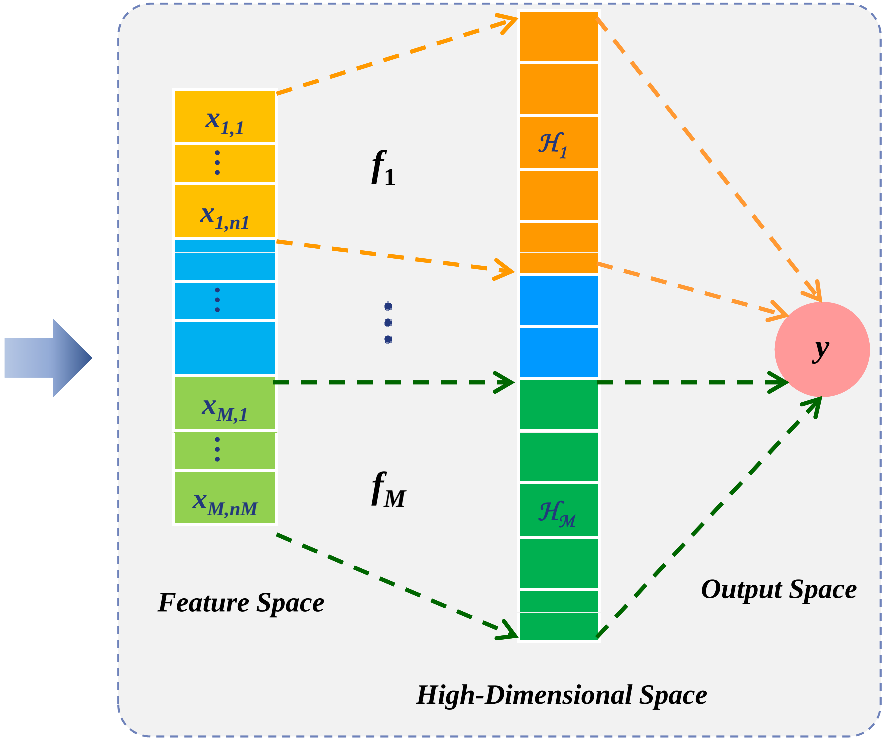
Multiple Kernel Learning (MKL)

- Different features have different properties, and MKL can measure the similarity of different features by using different kernels.



Support Vector Machine (SVM)

$$K = \langle f, f \rangle$$



Multiple Kernel Learning (MKL)

$$K_m = \langle f_m, f_m \rangle, K = \sum_{m=1}^{M} K_m$$

[X.-B. Gao, F. Gao, D. Tao, X. Li, *IEEE TNNLS*, 2013]

NR-IQA with Multiple Kernel Learning

Multiple kernel learning (MKL)

- Primal problem of MKL [Lanckriet et al., Bioinformatics'04]

$$\min_{\{f_m\},b,\xi,d} \frac{1}{2}\sum_{m=1}^{M} \frac{1}{d_m}\| f_m \|_{\mathcal{H}_m}^2 + C\sum_i \xi_i$$

$$s.t. \quad y_i \sum_{m=1}^{M} f_m(x_i) + y_i b \geq 1 - \xi_i, \xi_i > 0, \forall i$$

$$\sum_{m=1}^{M} d_m = 1$$

- Kernels adopted in MKL-GS and MKL-TS
  - SKLD kernel

$$K_{SKLD}(x_i, x_j) = \frac{1}{\sqrt{2\pi\sigma^2}} \exp\left(-\frac{D_{SKL}(x_i \| x_j)}{2\sigma^2}\right)$$

$D_{SKL}(\cdot)$ is the symmetric Kullback-Leibler divergence (SKLD).

  - Gaussian kernel

$$K_{Gauss}(x_i, x_j) = \frac{1}{\sqrt{2\pi\sigma^2}} \exp\left(-\frac{(x_i - x_j)^2}{2\sigma^2}\right)$$

- The **SimpleMKL** toolbox [A. Rakotomamonjy, *et al.* JMLR'08] has been employed to solve the MKL problem.

[X.-B. Gao, F. Gao, D. Tao, X. Li, *IEEE TNNLS*, 2013]

NR-IQA with Multiple Kernel Learning

Experimental Results

PLCC in the LIVE database

Metric	Type	JPEG2000	JPEG	WN	Gblur	FF	Overall
PSNR	FR	0.896	0.860	0.986	0.783	0.890	0.824
SSIM	FR	0.937	0.928	0.970	0.874	0.943	0.863
VIF	FR	0.962	0.943	0.984	0.974	0.962	0.950
FSIM	FR	0.962	0.952	0.929	0.952	0.921	0.731
BIQI	Blind	0.750	0.630	0.968	0.800	0.722	0.740
BLIINDS	Blind	0.807	0.597	0.914	0.870	0.743	0.680
DIIVINE	Blind	0.922	0.921	0.988	0.923	0.888	0.917
BLIINDS-II	Blind	0.963	0.979	0.985	0.948	0.944	0.923
NSS-GS^{SVM}	Blind	0.937	0.919	0.960	0.941	0.912	0.911
NSS-TS^{SVM}	Blind	0.944	0.928	0.972	0.953	0.912	0.909
NSS-GS	Blind	0.933	0.904	0.931	0.928	0.920	0.918
NSS-TS	Blind	**0.947**	**0.933**	**0.963**	**0.950**	**0.942**	**0.926**

- **NSS-GS^{SVM} denotes the algorithm using SVM with a radial basis function (RBF) kernel and the global scheme, and NSS-TS^{SVM} the algorithm using SVM and the two-step scheme.**
- **The best universal blind metric is highlighted in boldface for each distortion.**

[X.-B. Gao, F. Gao, D. Tao, X. Li, *IEEE TNNLS*, 2013]

Related Work of My Group

I. NR-IQA in Contourlet Domain

II. NR-IQA with Hidden Markov Tree

III. NR-IQA with Multiple Kernel Learning

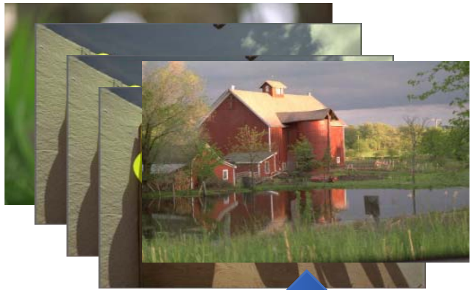
IV. NR-IQA with Sparse Representation

V. NR-IQA with Semi-supervised LLE

NR-IQA with Sparse Representation

- **Motivation**

Images



Robust Mapping (SVM, NN)

Quality

A large number of samples

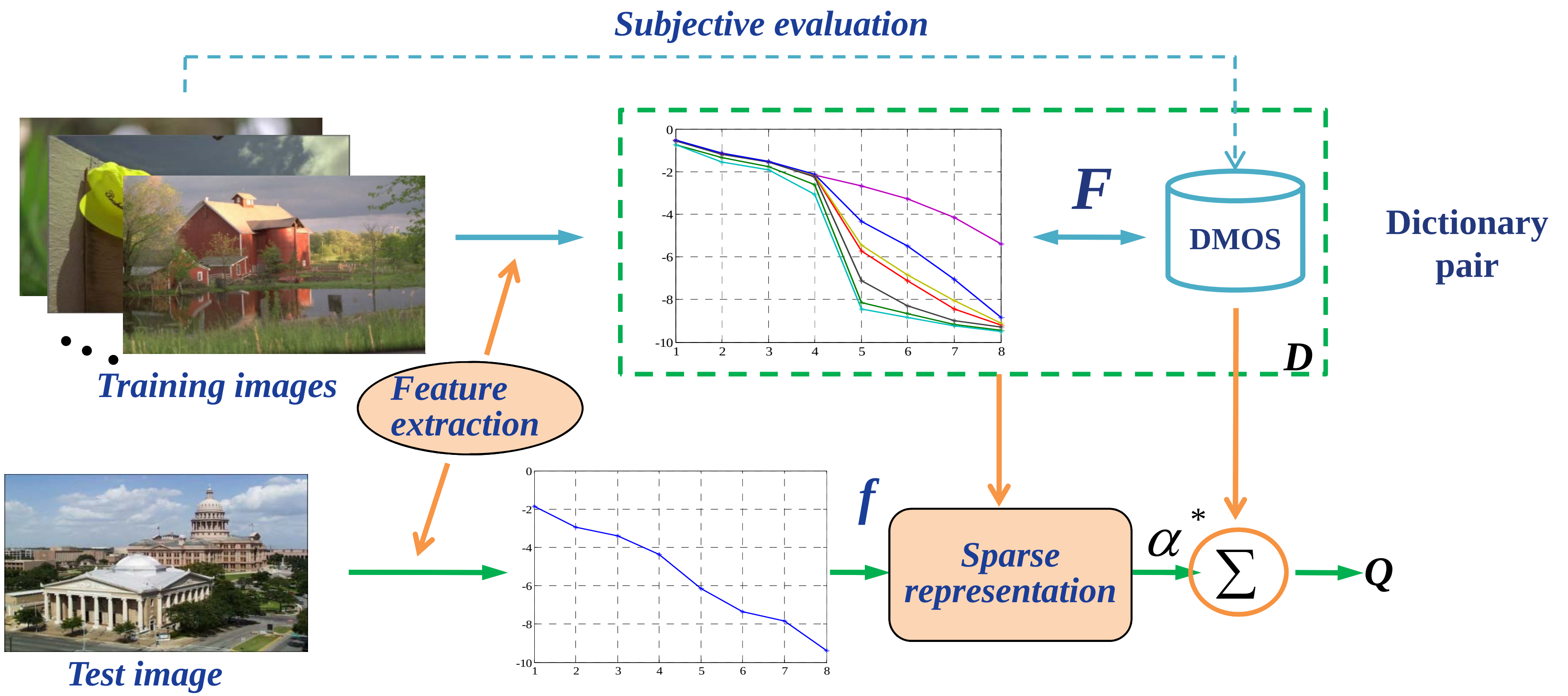
Sensitive to different database

Re-trained when new training samples are available

[L. He, D. Tao, X. Li, X.-B. Gao, *CVPR2012*, 2012]

NR-IQA with Sparse Representation

- **Framework**



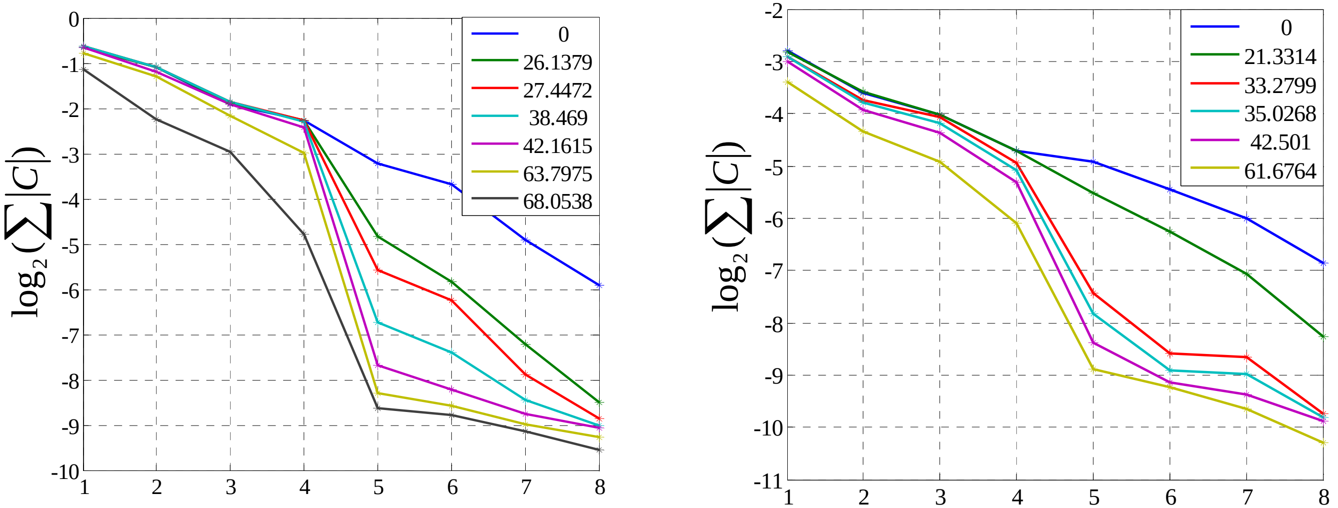
DMOS: *differential mean opinion score*

$$f = [m_1, m_2, ..., m_8, v_1, v_2, ..., v_8, e_1, e_2, ..., e_8]^T$$

[L. He, D. Tao, X. Li, X.-B. Gao, *CVPR2012*, 2012]

NR-IQA with Sparse Representation

- **Feature Extraction: Exponential Decay Across Scale**



Exponential decay curves of a group of some distorted images.

Hypothesis: **If two images have the identical quality values, they have the similar distribution.**

[L. He, D. Tao, X. Li, X.-B. Gao, *CVPR2012*, 2012]

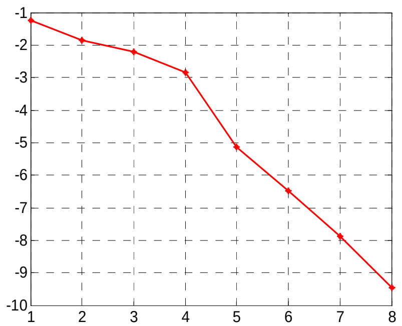
NR-IQA with Sparse Representation

- **Formula**

$$\min \|x\|_1 \qquad s.t. \quad \|Ax - y\|_2 \le \varepsilon$$

$$y = \sum_{i=1}^{N} x_i a_i$$

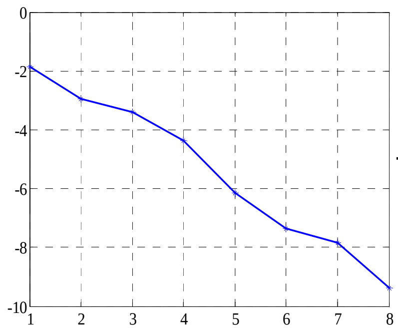
y



Q ?

$$= \cdots + x_{i-1} \times$$

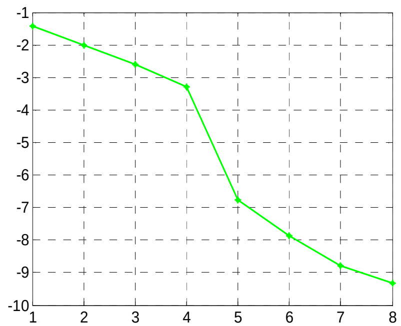
a$_{i-1}$



DMOS$_{i-1}$

$$+ x_i \times$$

a$_i$



DMOS$_i$

$$+ \cdots$$

Quality: $Q = \sum_{i=1}^{N} x_i \cdot \mathrm{DMOS}_i$

[L. He, D. Tao, X. Li, X.-B. Gao, *CVPR2012*, 2012]

NR-IQA with Sparse Representation

Databases

Database	Original images	Distorted images	Types of distortion
LIVE II	29	982	5
TID2008	25	1700	17
MICT	14	168	2
IVC	10	195	4
CSIQ	30	750	5

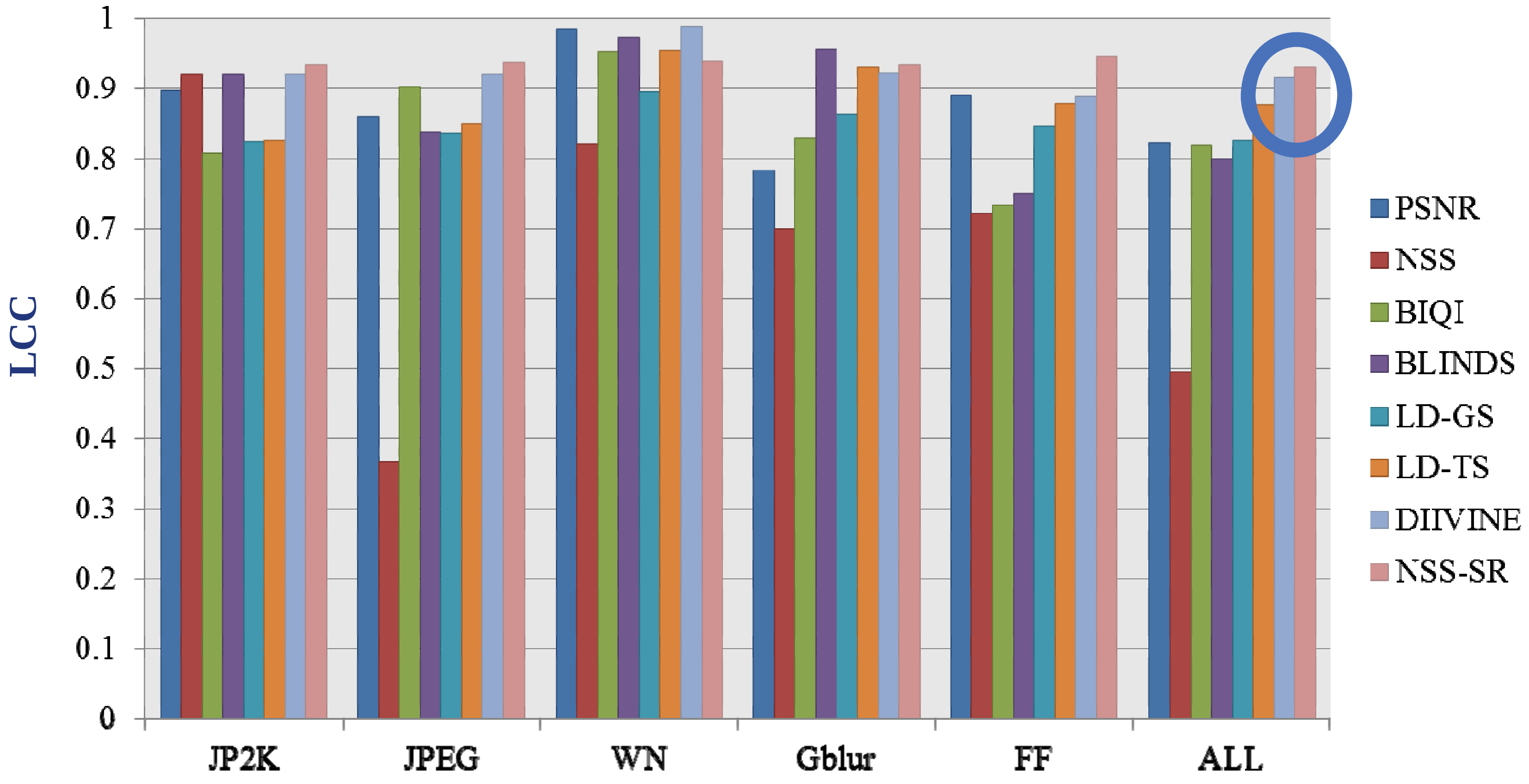
Evaluation criteria metrics

- **LCC**: Pearson linear correlation coefficient, provides the prediction accuracy.
- **SROCC**: Spearman rank-order correlation coefficient, measures the prediction monotonicity.
- **RMSE**: Root mean square error.
- **MAE**: Mean absolute error.

[L. He, D. Tao, X. Li, X.-B. Gao, *CVPR2012*, 2012]

NR-IQA with Sparse Representation

- **Experimental Results**



[L. He, D. Tao, X. Li, X.-B. Gao, *CVPR2012*, 2012]

Related Work of My Group

I. NR-IQA in Contourlet Domain

II. NR-IQA with Hidden Markov Tree

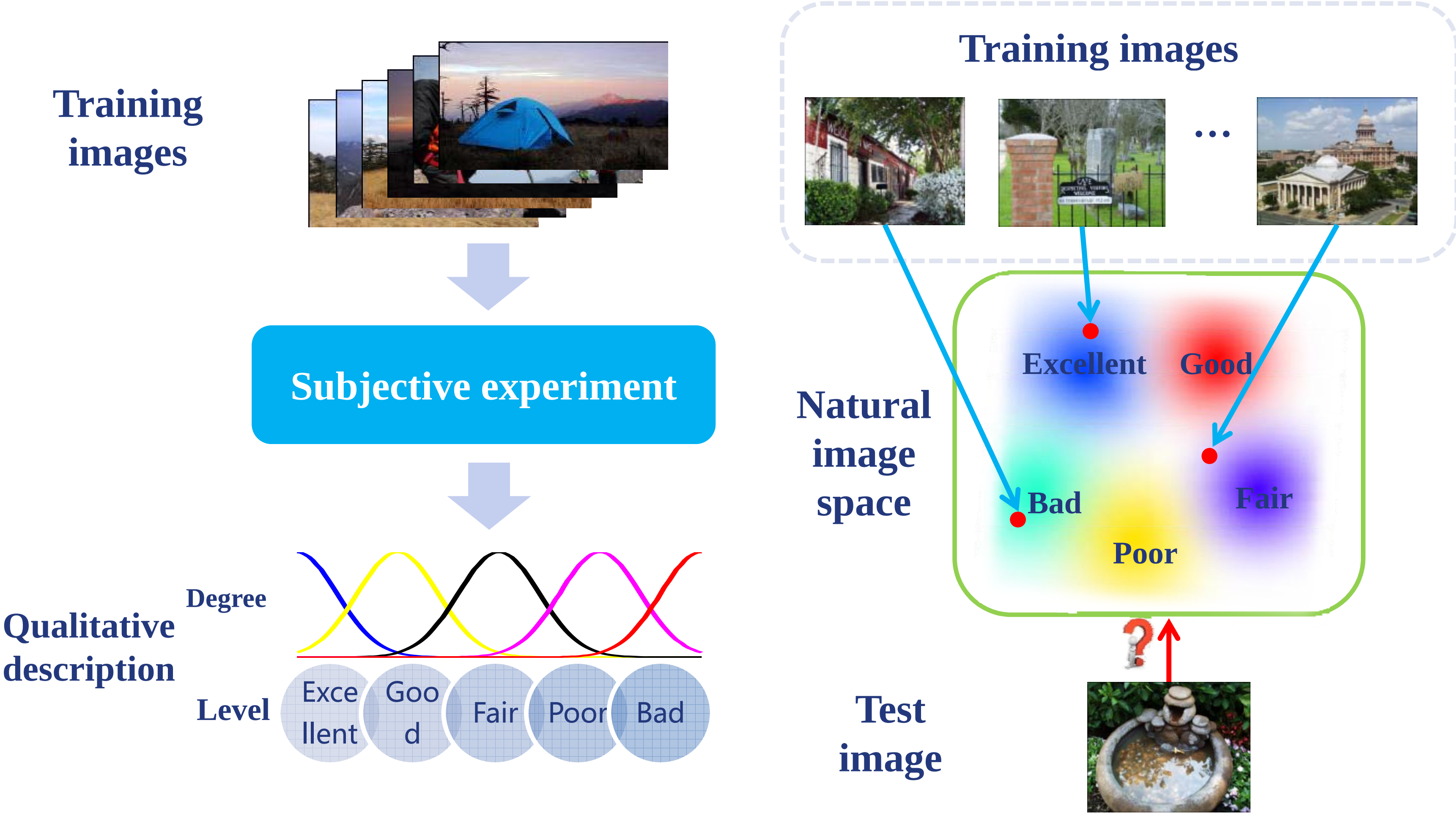
III. NR-IQA with Multiple Kernel Learning

IV. NR-IQA with Sparse Representation

V. NR-IQA with Semi-supervised LLE

NR-IQA with Semi-supervised LLE

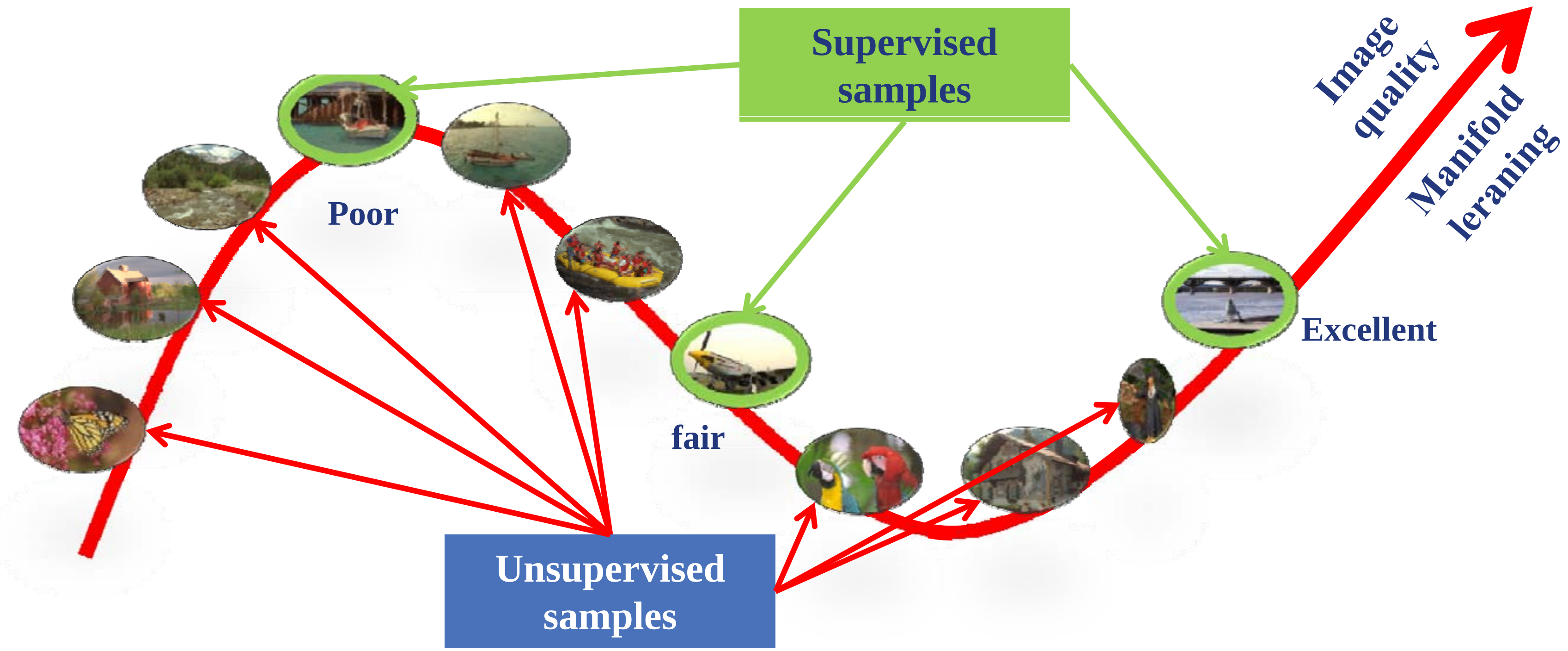
- **Motivation**



[N. Mei, F. Gao, W. Lu, X.-B. Gao, *IScIDE2013*, 2013]

NR-IQA with Semi-supervised LLE

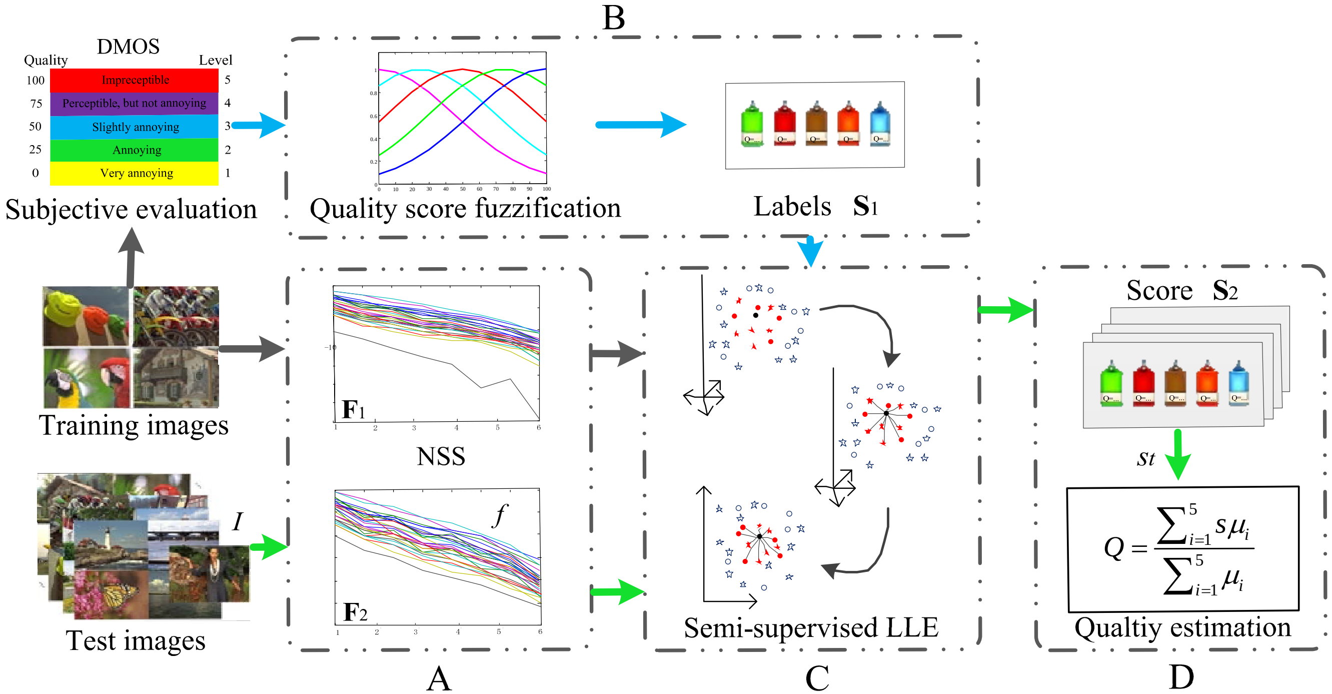
- A semi-supervised manifold learning method
  - Less Supervised samples + More unsupervised samples
  - Higher flexibility and accuracy



[N. Mei, F. Gao, W. Lu, X.-B. Gao, *IScIDE2013*, 2013]

NR-IQA with Semi-supervised LLE

Framework



- A: Extract image features based on NSS
- B: Formulate the fuzzy process of subjective quality assessment
- C: Introduce SS-LLE to learn the mapping from features to truth values
- D: Estimate the quality scores of the test images based on truth values

[N. Mei, F. Gao, W. Lu, X.-B. Gao, *IScIDE2013*, 2013]

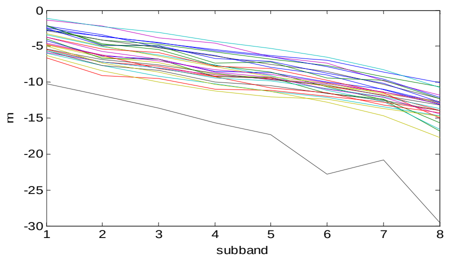
NR-IQA with Semi-supervised LLE

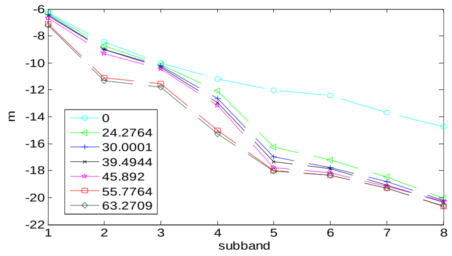
Exponential Decay Characteristic, EDC

$$f_{EDC} = [m_{EDC}, e_{EDC}]$$

$$m_k = \frac{1}{N_k \cdot M_k} \sum_{j=1}^{N_k} \sum_{i=1}^{M_k} \log_2 \left\| C^k(i,j) \right\|_2^2$$

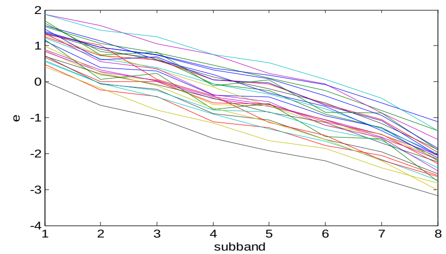
$$m_{EDC} = [m_1, m_2, \cdots, m_{2L}]$$

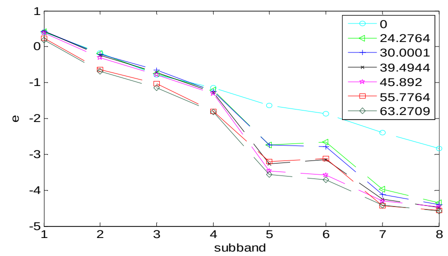




$$e_k = \log_2 \left(-\sum_{i=1}^{N_b} p_i \ln p_i \right)$$

$$e_{EDC} = [e_1, e_2, \cdots e_{2L}]$$





[N. Mei, F. Gao, W. Lu, X.-B. Gao, *IScIDE2013*, 2013]

NR-IQA with Semi-supervised LLE

- **Quality Score Fuzzification**

$$U = \{EXCELLENT, GOOD, FAIR, POOR, BAD\}$$

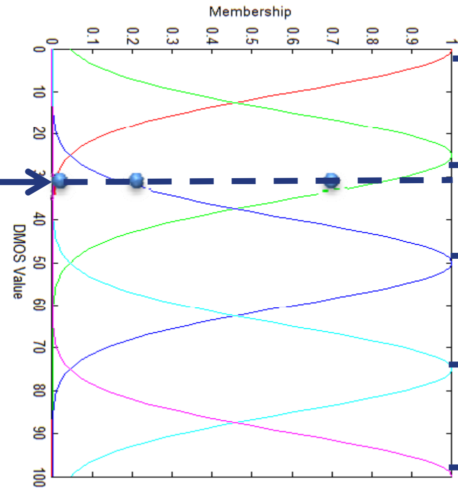
$$m_i(q) = \exp\left(-\frac{(q-\mu_i)^2}{2\sigma^2}\right),$$

Training images

DMOS

Quality		Level
100	Imperceptible	5
75	Perceptible, but not annoying	4
50	Slightly annoying	3
25	Annoying	2
0	Very annoying	1

Membership Function



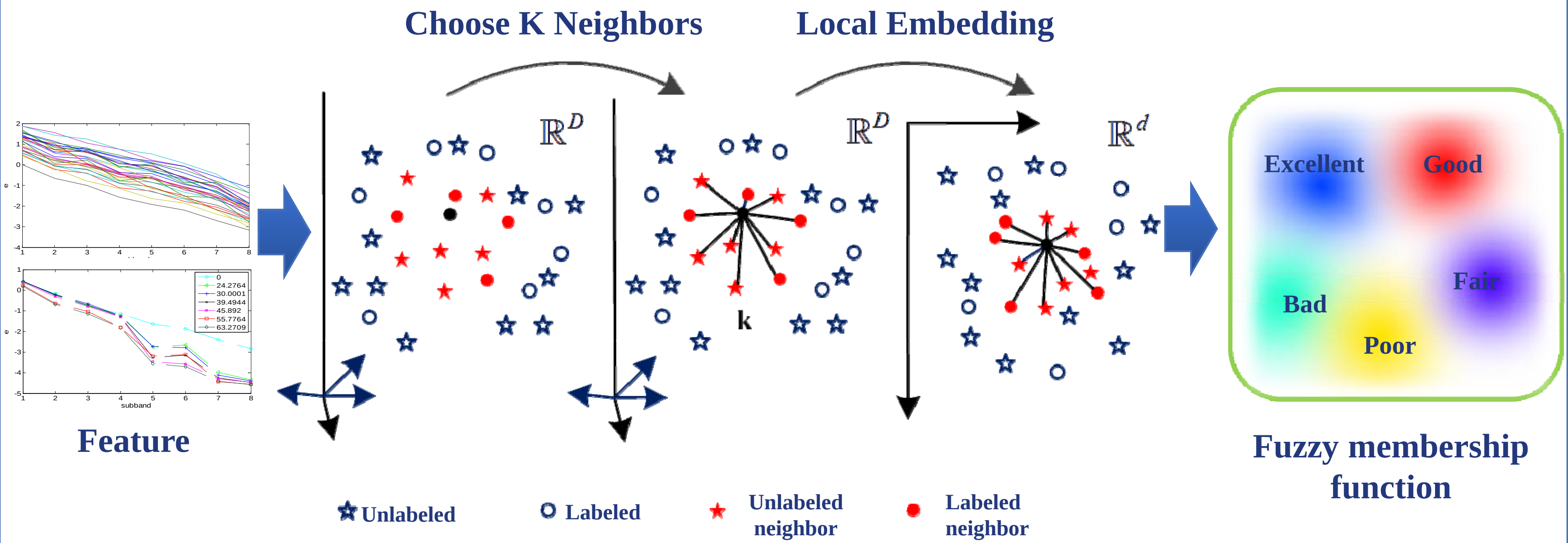
Excellent
Good
Fair
Poor
Bad

[N. Mei, F. Gao, W. Lu, X.-B. Gao, *IScIDE2013*, 2013]

NR-IQA with Semi-supervised LLE

Semi-supervised local linear embedding

Choose Neighbors	Calculate Weight	Low Dimension Embedding
$d_{ij} = \left\| \vec{X}_i - \vec{X}_j \right\|^2$	$\min_{W} \quad \varepsilon(W) = \sum_{i=1}^{n} \| \vec{X}_i - \sum_{j=1}^{K} \omega_{ij} \vec{X}_j^i \|^2$ $s.t. \quad \sum_j \omega_{ij} = 1$	$\min_{\hat{y}} \quad \varepsilon(\hat{y}) = \sum_{i=1}^{n} \| \hat{y}_i - \sum_{j=1}^{K} \omega_{ij} \hat{y}_j^i \|^2$ $s.t. \quad \hat{y}_{1,\dots,l} = y_{1,\dots,l}$

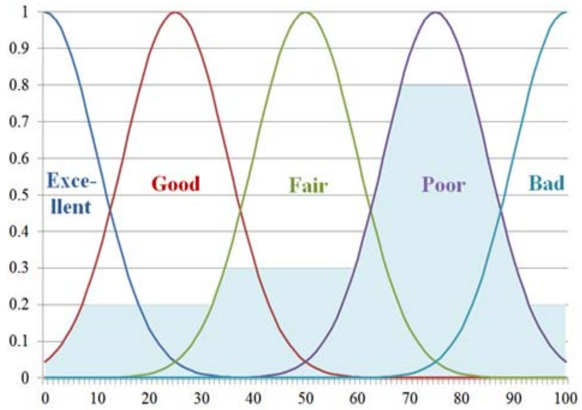


[N. Mei, F. Gao, W. Lu, X.-B. Gao, *IScIDE2013*, 2013]

NR-IQA with Semi-supervised LLE

■ Defuzzify the image quality

Fuzzy Set	Membership
Excellent	0
Good	0.2
Fair	0.3
Poor	0.8
Bad	0.2



Quality

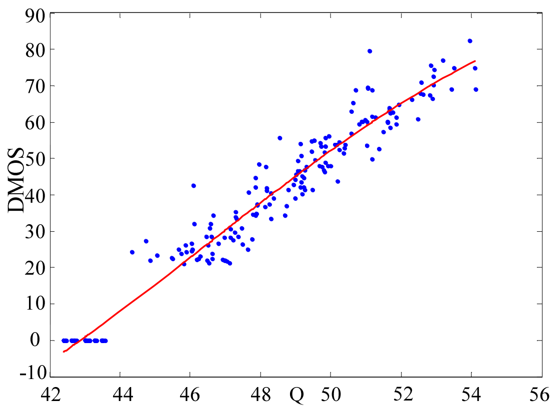
Test Image

$$Q = defuzz(s_t) = \frac{\sum_{i=1}^{5} s_t \mu_i}{\sum_{i=1}^{5} \mu_i}$$

[N. Mei, F. Gao, W. Lu, X.-B. Gao, *IScIDE2013*, 2013]

NR-IQA with Semi-supervised LLE

Experimental Results



Predicted Q vs. subjective DMOS

Median SROCC OF different metrics trained on the LIVE database II and tested on TID2008 database

Metric	JP2K	JPEG	WN	Gblur	All
PSNR	0.8250	0.8760	0.9230	0.9342	0.8700
SSIM	0.9603	0.9354	0.8168	0.9544	0.9016
DIIVINE	0.924	0.966	0.851	0.862	0.889
BLIINDS-II	0.9157	0.901	0.6600	0.8500	0.8442
BRISQUR	0.832	0.924	0.82	0.881	0.896
S2F-I	**0.9115**	**0.9143**	**0.7503**	**0.8422**	**0.8761**

Median LCC and SROCC of different metrics on the LIVE database II

Metric	JP2K		JPEG		WN	
	LCC	SROCC	LCC	SROCC	LCC	SROCC
PSNR	0.8962	0.8726	0.9858	0.8839	0.8895	0.9415
SSIM	0.9367	0.9389	0.9695	0.9283	0.9428	0.9635
DIIVINE	0.9220	0.9130	0.9880	0.9100	0.8880	0.9840
BLIINDS-II	0.9630	0.9293	0.9854	0.9421	0.9436	0.9693
SRNSS	0.9359	0.9283	0.9404	0.9306	0.9473	0.9382
BRISQUR	0.9229	0.9139	0.9851	0.9647	0.9093	0.9786
NIQE	0.9370	0.9172	0.9773	0.9382	0.9128	0.9662
SF100	0.9301	0.9248	0.9782	0.9310	0.8880	0.9622
S^2F-I	**0.9578**	**0.9354**	**0.9668**	**0.9183**	**0.9370**	**0.9710**

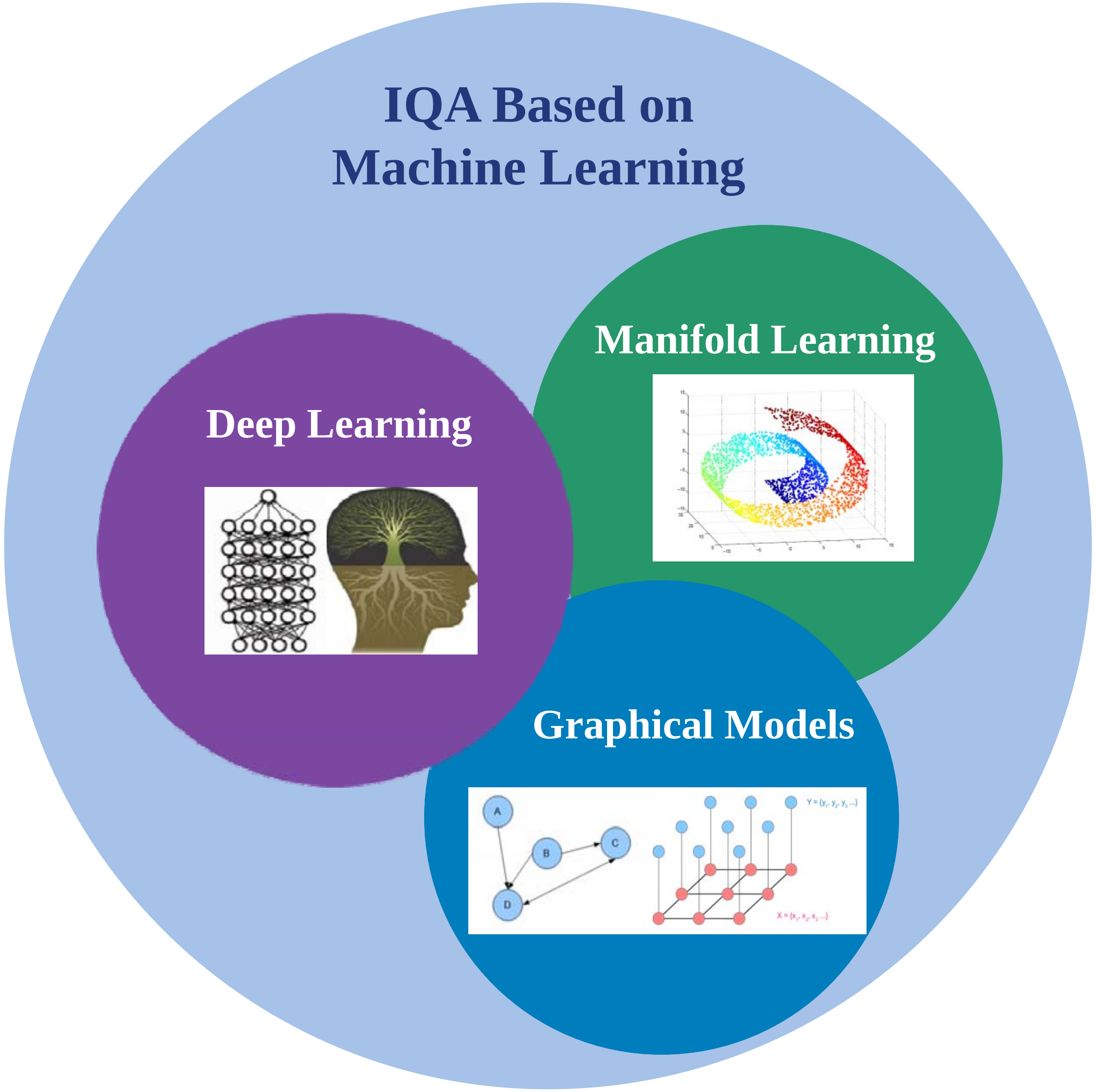
Metric	Gblur		FF		All	
	LCC	SROCC	LCC	SROCC	LCC	SROCC
PSNR	0.7834	0.8839	0.8895	0.7646	0.8240	0.8636
SSIM	0.8740	0.9283	0.9428	0.8942	0.8634	0.8834
DIIVINE	0.9230	0.9100	0.8880	0.9210	0.9170	0.9170
BLIINDS-II	0.9481	0.9421	0.9436	0.9232	0.9232	0.9202
SRNSS	0.9356	0.9306	0.9473	0.9327	0.9318	0.9304
BRISQUR	0.9506	0.9647	0.9093	0.9511	0.9424	0.9395
NIQE	0.9525	0.9382	0.9128	0.9341	0.9147	0.9135
SF100	0.9516	0.9310	0.8880	0.9614	0.9213	0.9214
S^2F-I	**0.9556**	**0.9183**	**0.9370**	**0.9367**	**0.9464**	**0.9412**

[N. Mei, F. Gao, W. Lu, X.-B. Gao, *IScIDE2013*, 2013]

Outline

- Image Quality Assessment (IQA)
- IQA Based on Machine Learning
- Some Work of My Group
- Opening Issues

Opening Issues



Opening Issues


Thank you !