No-reference HDR Image Quality Assessment Method Based on Tensor Space

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- Methodology
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Introduction

Traditional LDR Image:

- Dynamic range **10^2: 1**
- Much smaller than **real world**

➢ *Image Information Loss*

➢ *Poor Watching Experience*

HDR Image:

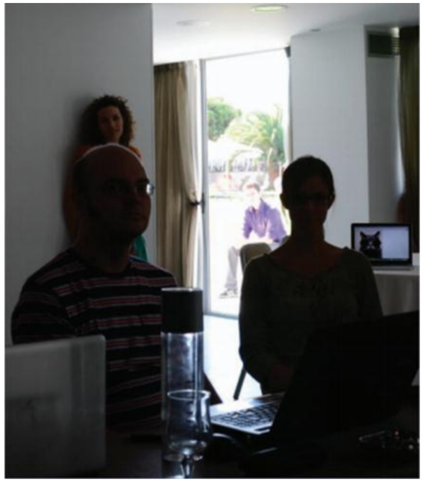
- Dynamic range **10^{10}: 1** or higher
- Details in dark/bright regions
- Much close to **real world**

➢ *More Information*

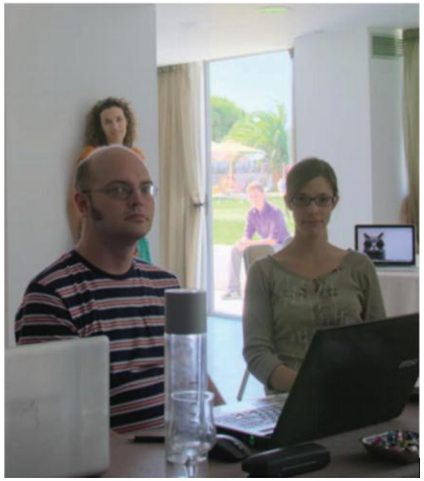
➢ *Better Watching Experience*

LDR

HDR



LDR



HDR

Introduction

HDR Coding Framework:

HDR Image → Encoder → network → Decoder → Recovered HDR Image

Quality Degradation

Quality Assessment

Importance of HDR-IQA Method

- ✓**Optimize** HDR Imaging System
- ✓ **Promote** HDR Imaging Techniques

*HDR-IQA = High Dynamic Range Image Quality Assessment

Introduction

Motivation:

Original and distorted HDR image

Causes of quality degradation:

- Structure be destroyed
- Detail information loss
- Unable to get reference image

⇩

Solution:

- Extract quality features
- No-reference (NR)

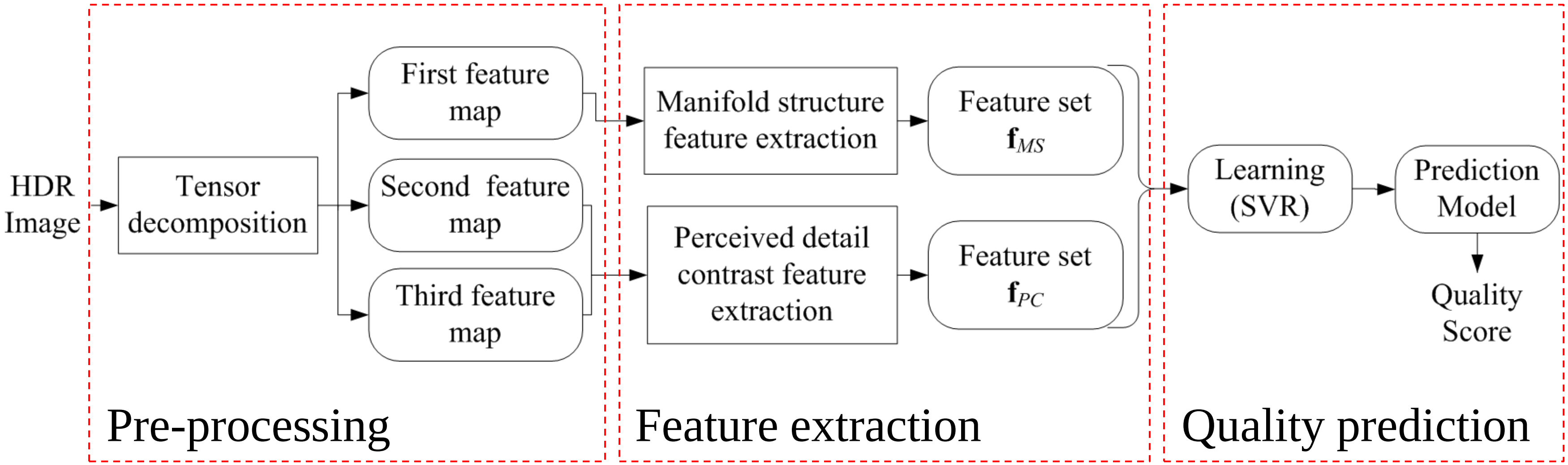
⇩

Approach:

✓ NR HDR-IQA method

Methodology

Framework:



NR HDR IQA Method

Methodology

Pre-processing—Tensor space:

Purpose:

- ✓ Represent high-dimensional data
- ✓ Color information of an HDR image

Tucker decomposition:

$$\mathcal{I} = \zeta \times_1 \mathbf{U}^{(1)} \times_2 \mathbf{U}^{(2)} \times_3 \mathbf{U}^{(3)} = \xi \times_3 \mathbf{U}^{(3)}$$

$$\Downarrow$$

$$\mathbf{I}_t = \mathbf{U}_{t,1}^{(3)} \boldsymbol{\theta}_1 + \mathbf{U}_{t,2}^{(3)} \boldsymbol{\theta}_2 + \mathbf{U}_{t,3}^{(3)} \boldsymbol{\theta}_3 = \sum_{i=1}^{3} \mathbf{U}_{t,i}^{(3)} \boldsymbol{\theta}_i$$

$$\|\mathcal{I}\|^2 = \|\xi\|^2 = \sum_{i=1}^{3} \|\boldsymbol{\theta}_i\|^2, \ \|\boldsymbol{\theta}_1\|^2 \geq \|\boldsymbol{\theta}_2\|^2 \geq \|\boldsymbol{\theta}_3\|^2$$

The HDR image can then be represented by a third-order tensor $\mathcal{I}$ of the size $M \times N \times 3$, ξ is the core tensor;

$\boldsymbol{\theta}_i$ ($1 \leq i \leq 3$) is the i-th channel matrix of size $M \times N$ of the core tensor. Here, $\{\boldsymbol{\theta}_i | i=1,2,3\}$ represents a set of feature maps, and these three feature maps are collectively called the **tensor space**.

$\|\cdot\|$ represents the Frobenus norm.

Methodology

Feature extraction—Structure:

Purpose:

✓ First feature map contains main energy of an HDR image

✓ **Manifold learning** can find the inherent geometric structure

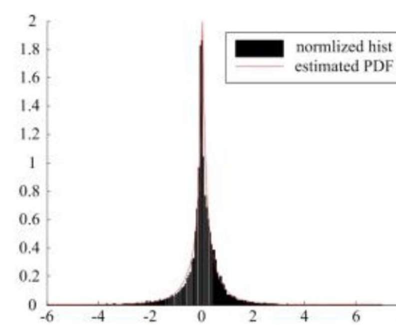
Training database → Tensor decomposition → First feature map → Establish the training sample → PCA/ Whitening → OLPP → Best Projection Matrix **W**

$$\mathbf{d}_k = \mathbf{W} \times \mathbf{y}_k$$

$$\mathbf{D} = \left[\mathbf{d}_1, \mathbf{d}_2, \ldots, \mathbf{d}_k\right]$$

The first feature map of the test HDR image is divided into a plurality of 8×8 non-overlapping image blocks, $\mathbf{y}_k$ is zero mean column vector of the k-th image block, $\mathbf{D}$ is the manifold structure feature matrix of the test HDR image.

(a) An HDR image



(b) Histogram distribution

Methodology

Feature extraction—Contrast:

Purpose:

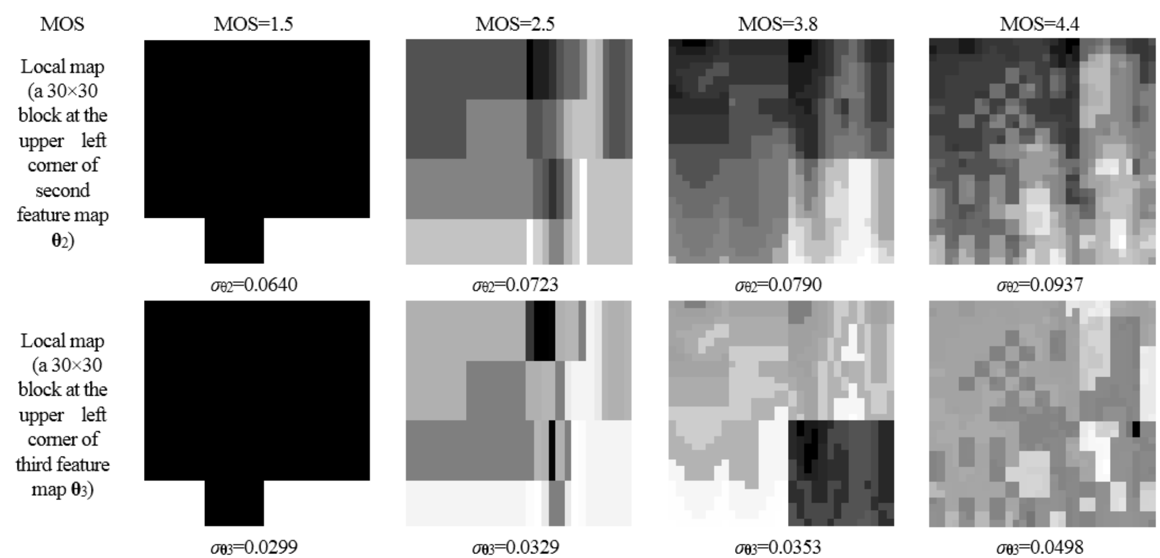
- ✓ Second and third feature map shows the details information
- ✓ As complementary feature, Contrast information is important

Standard deviation

$$\sigma = \frac{1}{P}\sum_{P}\left(\frac{1}{p-1}\sum_{j=1}^{p}\left(x_j - \bar{x}\right)^2\right)^{1/2}$$

$$\bar{x} = \frac{1}{p}\sum_{j=1}^{p} x_j$$

p represents the number of pixels in each image block, P is the total number of blocks, and $\bar{x}$ is the mean intensity of the pixels.



Methodology

Quality prediction:

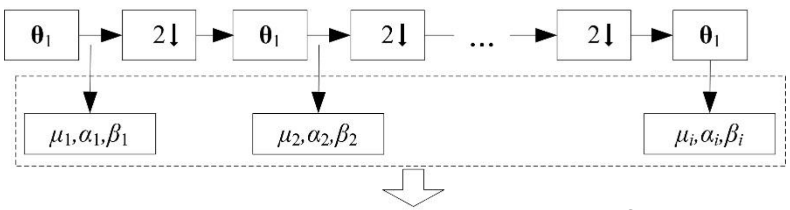
Manifold structure feature matrix **D**

GGD

$$g(x;\mu,\alpha,\beta)=\frac{\alpha}{2\beta\Gamma(1/\alpha)}\exp\left(-\left(\frac{|x|}{\beta}\right)^{\alpha}\right)$$

$$\Gamma(x)=\int_0^{\infty}t^{x-1}e^{-t}dt,\ x>0$$

μ,α,β (Quality-aware features)



$\mathbf{f}_i=(\mu_i,\alpha_i,\beta_i)\quad i=1,2,\cdots,5$ (*five scales*)

Multi-scale manifold structure feature set $\mathbf{f}_{MS}$ of the HDR image is produced as follows:

$$\mathbf{f}_{MS}=[\mathbf{f}_1,\mathbf{f}_2,\mathbf{f}_3,\mathbf{f}_4,\mathbf{f}_5]$$

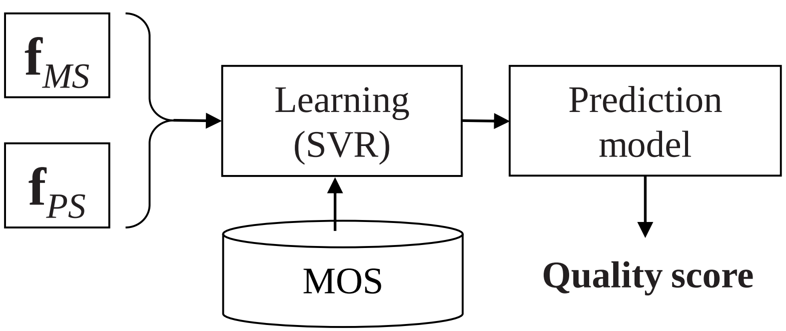
Perceived detail contrast feature

σ (Quality-aware feature)

$\mathbf{f}_{i+5}=(\sigma_{\boldsymbol{\theta}_2}(i),\sigma_{\boldsymbol{\theta}_3}(i))$ (*five scales*)

Multi-scale perceived detail contrast feature set is produced as:

$$\mathbf{f}_{PC}=[\mathbf{f}_6,\mathbf{f}_7,\mathbf{f}_8,\mathbf{f}_9,\mathbf{f}_{10}]$$



Experiments

Performance Indexes in Nantes* & EPFL* database:

Databa -ses	Indexes	PU-MSE	PU-SSIM	PU-DIIVI-NE	HDR-VDP-2.2	Propo-sed
Nantes	PLCC	0.4471	0.6056	0.2613	0.7329	**0.9269**
	SROCC	0.4197	0.6528	0.2271	0.7047	**0.9153**
	RMSE	0.9019	0.8006	0.9712	0.6485	**0.3671**
EFPL	PLCC	0.8241	0.9178	0.5892	**0.9500**	**0.9015**
	SROCC	0.8385	0.9191	0.5081	**0.9419**	**0.8740**
	RMSE	0.6798	0.4750	0.9668	**0.3736**	**0.5016**

MSE, **SSIM** and **DIIVINE** are representative LDR IQA methods, **HDR-VDP-2.2** is considered the state-of-the-art FR HDR IQA method.

*PU=Perceptually Uniform

*Nantes HDR image database
Narwaria M, *et al*.2013.

*EPFL HDR image database
Pavel Korshunov, *et al*.2015.

- **Traditional LDR-IQA method**: *not competent for HDR image*
- **Existing HDR-IQA method**: *accurate but can be better*
- **Proposed NR HDR-IQA method**: *fully consideration of typical distortion in HDR image*

Conclusions

Contributions of this work:

- Proposed a **NR HDR image quality assessment method**
- A new HDR feature representation space, named **tensor space**, is constructed and used to define and extract the new features of an HDR image effectively
- Applying the image **manifold** feature to visual quality assessment

Conclusions

Future Work:

- ***Improvement of proposed method***
  - Better quality feature for NR HDR IQA
- ***Application of proposed method***
  - Guidance in designing of new HDR video coding scheme
  - Concentrating on HDR video quality assessment

Thank you !