Perceptual Quality Assessment of UHD-HDR-WCG Videos

Shahrukh Athar[1], Thilan Costa[1], Kai Zeng[2] and Zhou Wang[1]

[1]University of Waterloo, Canada

[2]SSIMWAVE Inc., Canada

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Outline

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Perceptual Video Quality Assessment (VQA)

Purpose

Development of quantitative measures that can automatically predict the *perceived* quality of videos

Objective VQA

Types of Objective VQA Models:

- Full-Reference (FR) VQA
- Reduced-Reference (RR) VQA
- No-Reference (NR) VQA

Development of objective VQA models requires subject-rated databases

Limitations of Existing Work

Existing subject-rated databases for High Dynamic Range (HDR) videos [Banitalebi-Dehkordi, 2014], [Narwaria, 2015], [Rerabek, 2015], [Minoo, 2015], [Mukherjee, 2016], [Azimi, 2018] have the following limitations:

- Maximum spatial resolution is Full High Definition (FHD)
- Color gamut of content/displays is limited to BT.709
- Maximum temporal resolution is usually 30 frames per second (fps)
- Fixed distortion levels (bit rates) regardless of content complexity are used
- Evaluation of state-of-the-art FR and NR methods is missing

Outline

Waterloo UHD-HDR-WCG Database

Reference Content Characteristics

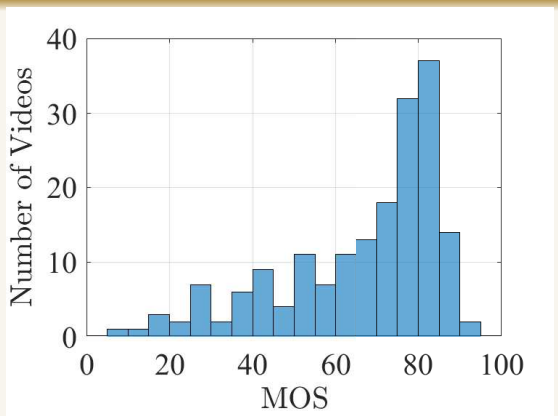
- 14 high-quality reference videos in YUV file format
- Length of each video: 10 seconds
- Ultra High Definition (UHD) resolution (3840 x 2160)
- Bit depth: 10 bits (Luma)
- Wide Color Gamut (WCG): BT.2020 color primaries
- YUV 4:2:0 chroma format
- SMPTE ST 2084 (PQ) transfer function
- Frame rate: 59.94 fps (9 videos) and 24 fps (5 videos)

Waterloo UHD-HDR-WCG Database

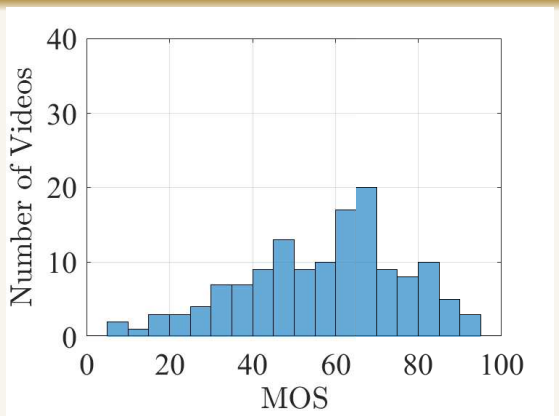
Distorted Content Characteristics

- Focus: To study the impact of compression on UHD-HDR-WCG content
- Two encoders used (H.264 and HEVC)
- Five content-adaptive distortion levels (bitrates) for each encoder
- Overall 140 distorted videos in YUV file format

Impact of Content-Adaptive Distortion Levels



(a) Preliminary FHD database with fixed bitrates



(b) Waterloo UHD-HDR-WCG database with content-adaptive bitrates

Hardware Setup

Canon DP-V2420 Reference Display

- 4K/UHD HDR Mastering monitor
- Screen Size: 24 inch
- Compatible with Academy Color Encoding System (ACES)
- Supports WCG (BT.2020)
- Peak Luminance: 1000 cd/m^2
- Minimum black level: 0.005 cd/m^2
- Supports SMPTE ST 2084 (PQ) transfer function
- Quad 3G Serial Digital Interface (SDI) with throughput of 12 Gbits/s

Hardware Setup

Dedicated Hardware Pipeline

- Maximum throughput requirement: 11.12 Gbits/s
- Workstation
  - Stores the entire database (1.64 TBytes) in a 2 TByte Samsung 960 Pro SSD (read speed up to 3.5 GBytes/s)
  - 32 GBytes 3000 MHz DDR4 RAM (holds each video while playing)
- Blackmagic Design Ultrastudio 4K Extreme 3
  - Connected to the workstation through a Blackmagic Design PCI Express Cable Kit
  - Splits single input data stream into four streams connected to a Quad SDI output interface
  - Output of Ultrastudio connected to the Canon Reference Display
- Customized video playback software developed using Blackmagic Design Software Development Kit (SDK)

Outline

Subjective Study

Salient Features

- 51 subjects aged between 18 and 35
  - 29 males and 22 females
  - 43 naïve and 8 experts
- Single stimulus with hidden reference methodology
- Viewing distance approximately twice the screen height
- Two 30-minutes rating sessions with a mandatory break in-between
- Dark room environment
- Scores range: 0 to 100 (higher for better quality)
- Scoring GUI allowed selection of integers through sliding bar
- Training session preceded the study
  - Five training videos (No overlap with test set)

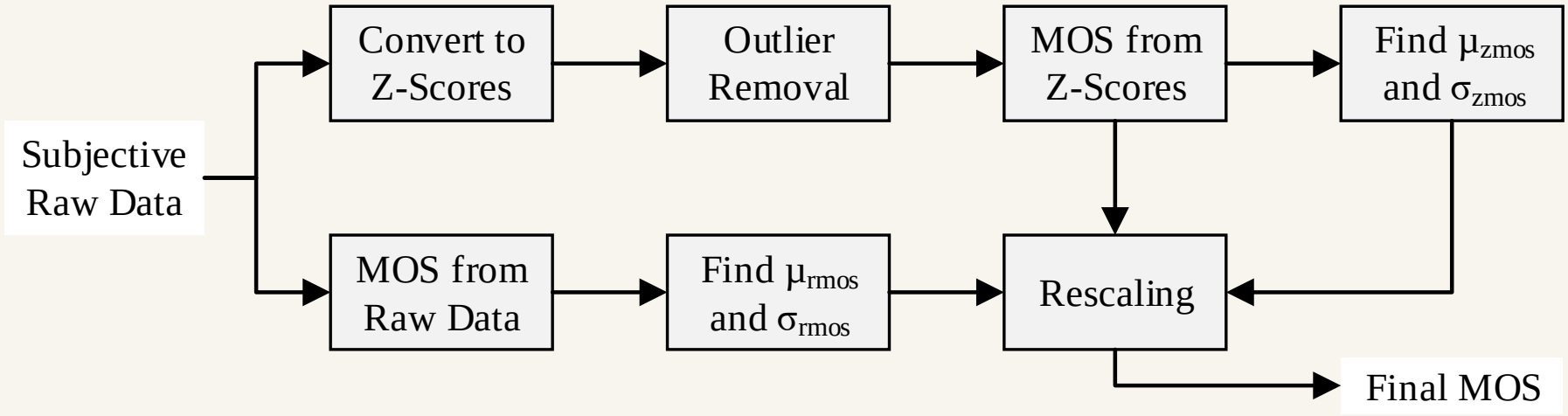
Data Processing

Steps

1. Raw scores converted to Z-scores
   - Accounts for the quality scale variations between subjects
2. Outlier removal procedure according to Rec. ITU-R BT.500-13
   - 9 subjects removed
3. Mean Opinion Score (MOS) for each content computed from Z-scores
4. MOS rescaled to the 0 to 100 range
   - MOS distribution is preserved
   - Maintains overall mean and variance of raw scores

Data Processing

Mean Opinion Score (MOS) Generation Mechanism

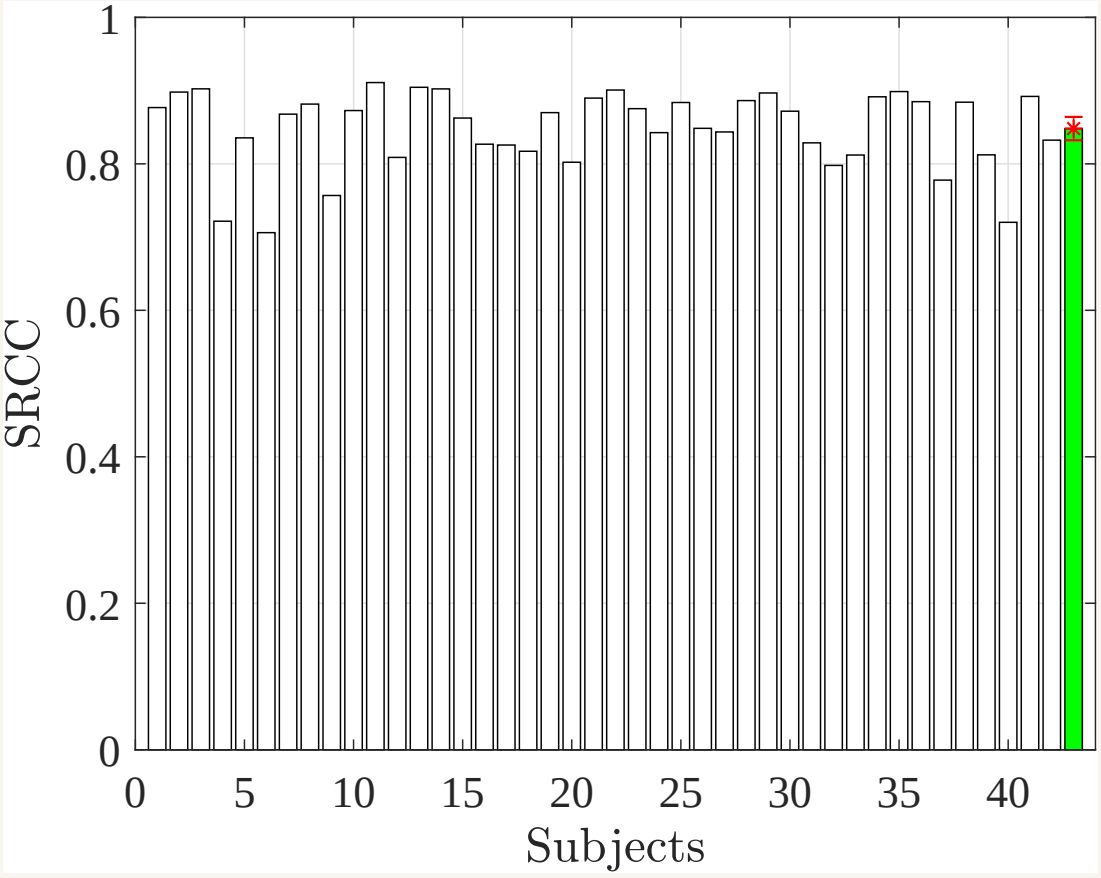


Rescaling

$$MOS = \sigma_{rmos}\left[\frac{MOS_z - \mu_{zmos}}{\sigma_{zmos}}\right] + \mu_{rmos} \quad (1)$$

Data Processing

Spearman Rank Correlation Coefficient between MOS and Individual Subjects



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Performance of Objective Models

Evaluation Criteria

- Prediction Accuracy
  - Pearson Linear Correlation Coefficient (PLCC)
  - Root Mean Square Error (RMSE)
- Prediction Monotonicity
  - Spearman Rank order Correlation Coefficient (SRCC)
- Statistical Significance Testing on prediction residuals
  - Jarque-Bera test to determine Gaussianity of residuals
  - Hypothesis testing through the F-test

Number of Objective Models Evaluated

- 11 FR Models
  - Including HDRVDP2 and HDRVQM (designed for HDR content)
- 7 NR Models

Performance of Objective Models

Category	Method	PLCC	SRCC	RMSE
FR	DSS [Balanov, 2015]	0.7685	0.7456	12.3718
	ESSIM [Zhang, 2013]	0.8512	0.8389	10.1485
	FSIM [Zhang, 2011]	0.8693	0.8564	9.5568
	GMSD [Xue, 2014]	0.7366	0.7045	13.0781
	GSIM [Liu, 2012]	0.8596	0.8453	9.8812
	HDRVDP2 [Mantiuk, 2011]	0.7035	0.6703	13.7423
	HDRVQM [Narwaria, 2015]	0.7783	0.7759	12.1428
	IWSSIM [Wang, 2011]	0.8088	0.7861	11.3730
	PSNR	0.5113	0.4615	16.6185
	SRSIM [Zhang, 2012]	**0.8726**	**0.8630**	**9.4462**
	VIFDWT [Rezazadeh, 2013]	0.6809	0.6748	14.1612
NR	BRISQUE [Mittal, 2012]	0.3622	0.3271	18.0241
	CORNIA [Ye, 2012]	**0.6497**	**0.6296**	**14.7003**
	dipIQ [Ma, 2017]	0.6192	0.5560	15.1845
	HOSA [Xu, 2016]	0.5379	0.5138	16.3015
	LPSI [Wu, 2015]	0.3941	0.3820	17.7718
	NIQE [Mittal, 2013]	0.5286	0.4922	16.4152
	VMEON [Liu, 2018]	0.5776	0.5308	15.7845

Performance Analysis

FR Methods

- SRSIM is the top performing FR method
- Performance of ESSIM, GSIM, and FSIM is statistically indistinguishable from SRSIM
- Above methods are developed for Low Dynamic Range (LDR) content and inherit a similar formulation of signal fidelity measurement from SSIM [Wang, 2004]
- HDR specific FR methods (HDRVDP2 and HDRVQM) do not offer superior performance
- LDR FR methods may be extended for HDR VQA

Performance Analysis

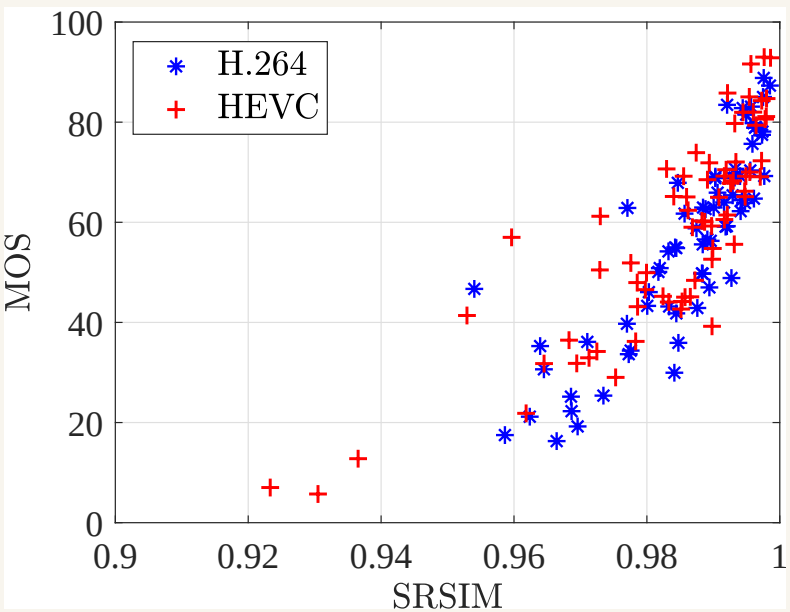
NR Methods

- All NR methods perform inadequately
- CORNIA is the top performing NR method
- All NR methods under test were developed for LDR content
- There is significant room for improvement in HDR specific design innovations

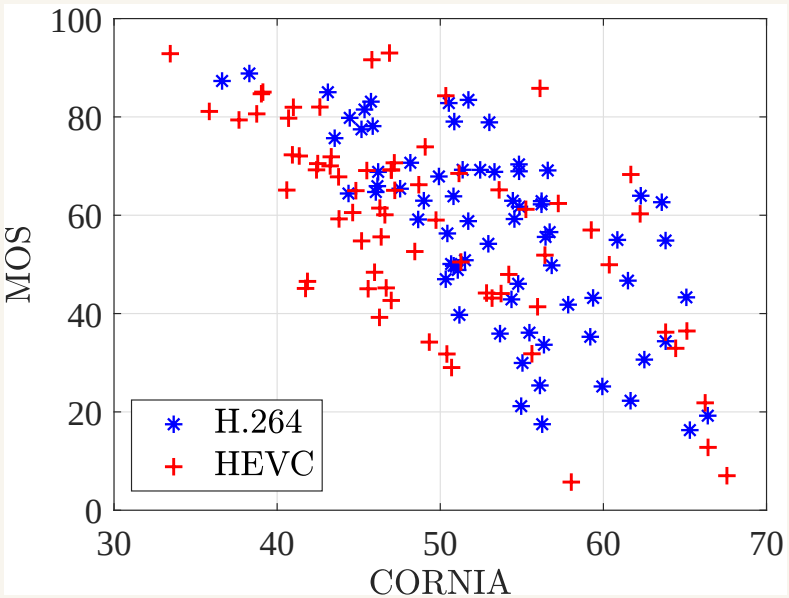
Performance Analysis

Objective Model Performance on Individual Distortion Types

- Models perform similarly on H.264 and HEVC compression
- Example below shows scatter plots for top performing FR (SRSIM) and NR (CORNIA) models



(a)



(b)

Outline

Summary

Contributions

- Constructed a first-of-its-kind Waterloo UHD-HDR-WCG database
- Carried out a first-of-its-kind subjective study on a professional HDR Reference Display with a dedicated hardware pipeline
- Proposed a novel method to process subjective data
  - Accounts for subject quality scale variations
  - Preserves distribution of data and keeps the overall mean and standard deviation of subjective scores unchanged
- Evaluated the performance of 11 FR and 7 NR objective models
  - FR models developed for LDR content can be used as a basis for new UHD-HDR-WCG FR VQA models
  - Substantial room for improvement exists when it comes to NR VQA of UHD-HDR-WCG content

QUESTIONS

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