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Applicability of Existing Objective Metrics of Perceptual Quality for Adaptive Video Streaming

Jacob Søgaard, Lukáš Krasula,
Muhammad Shahid, Dogancan Temel,
Kjell Brunnström, and Manzoor Razaak



Introduction

- Recently video streaming services has grown in popularity
- Nowadays, most services use HTTP based adaptive streaming
- Degradations quite different from other type of distribution
- Slowly varying quality changes on a fairly long timescale (2 sec – 1 min)

Introduction

- Many objective video quality methods has been proposed
- Performance results have been published
- Their limitations not always clearly known
- This investigation: evaluated some published methods for adaptive video streaming

Metrics

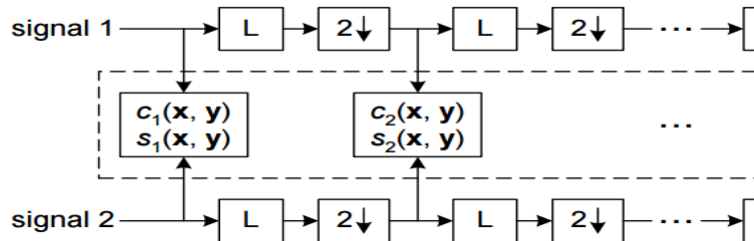
$$PSNR = 10 \cdot \log \left(\frac{MAX^2}{MSE} \right)$$

Luma component used

$$SSIM = \frac{(2\mu_X\mu_Y + c_1)(2\sigma_{XY} + c_2)}{(\mu_X + \mu_Y + c_1)(\sigma_X^2 + \sigma_Y^2 + c_2)}$$

Analyzing structural information. Default parameters used.

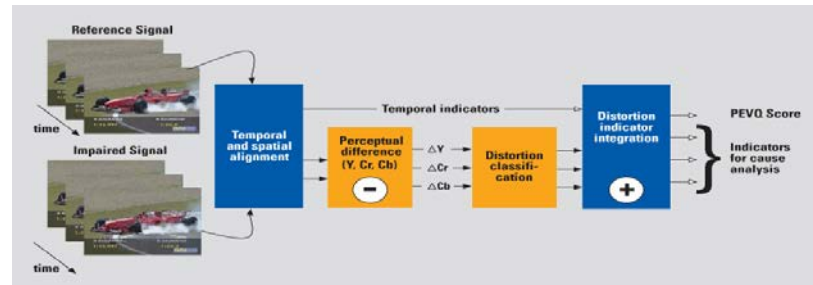
MS-SSIM:



Multiscale version of SSIM. Default parameters used.

PEVQ:

Perceptual Evaluation of Video Quality

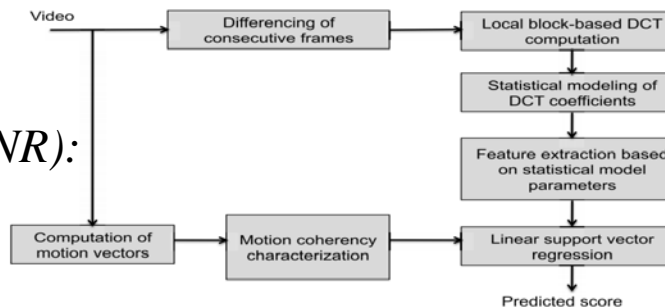


FR metric and part of ITU-T. Rec J.247 – objective metrics for multimedia

Metrics

Standardized ITU-T Rec. J.144 RR-metric

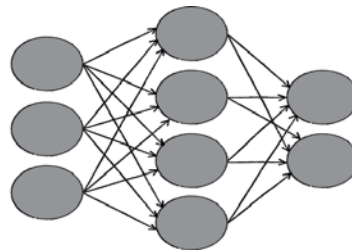
Video BLIINDS (NR):



$$\begin{aligned} VQM = & -0.21 \cdot si_loss \\ & +0.60 \cdot hv_loss \\ & +0.25 \cdot hv_gain \\ & +0.02 \cdot chroma_spread \\ & -2.34 \cdot si_gain \\ & +0.04 \cdot ct_ati_gain \\ & +0.01 \cdot chroma_extreme \end{aligned}$$

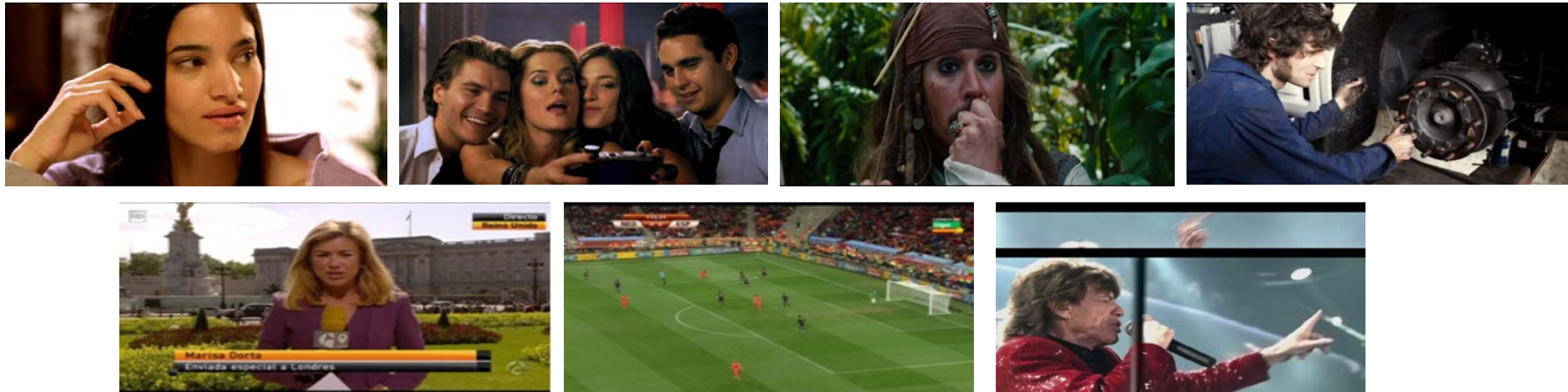
NR machine learning metric natural scene statistics

VQM_VFD:



Improved VQM with Variable
Frame Delays and FR metric

Test video sequences



- 7 commercial content: Movie, Documentary, Sport, News, Music
- 6 min; originally 1080p Bluray video, 24/50 fps
- Different spatial and temporal characteristics

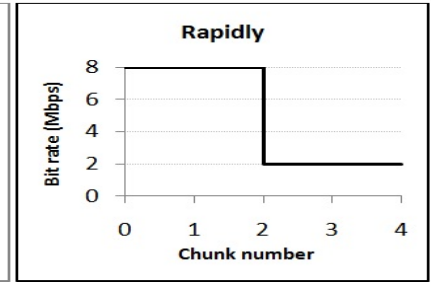
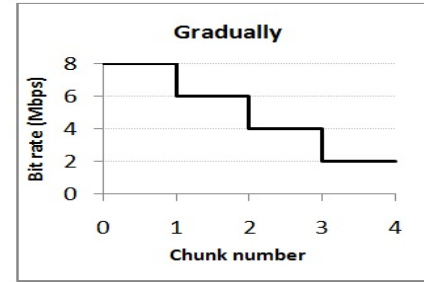
Adaptation study parameters

- Switching behavior

- Period (chunk length): 2 sec and 10 sec
- Amplitude (difference between consecutive quality levels)
gradual vs. rapid switching
- Decreasing and increasing

- Adaptation dimension

- Video quality (QP)
- H.264/AVC
- 4 streams: 5Mbps, 3Mbps, 1Mbps, 600kbps
- 1280x720/ 25fps



- **12 Test conditions in total**
- **132 individual events (PVS) rated by test subjects**
- **MOS based on > 60 test subjects**

Performance metrics

Standardized ITU-T Rec. P.1401

$$PLCC = \frac{\sum_{i=1}^N (MOS_i - \overline{MOS}) \times (MOS_{p_i} - \overline{MOS_p})}{\sqrt{\sum_i (MOS_i - \overline{MOS})^2} \times \sqrt{\sum_i (MOS_{p_i} - \overline{MOS_p})^2}}, \quad OR = \frac{n_{\text{outlier}}}{N},$$

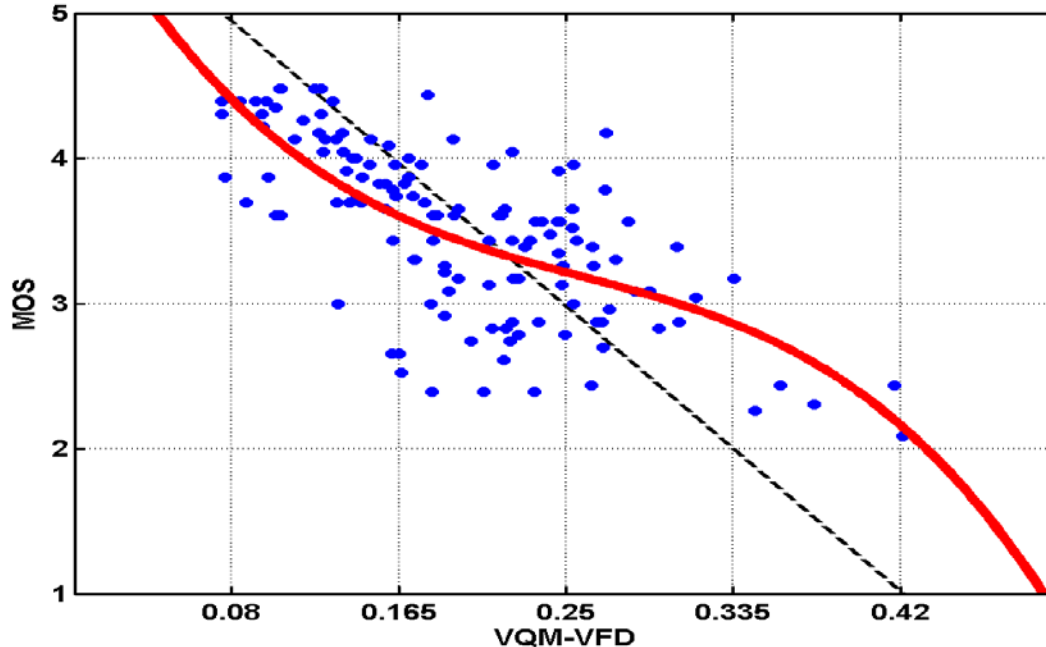
$$SROCC = 1 - \frac{6 \sum_{i=1}^N d_i^2}{N(N^2 - 1)},$$

$$RMSE = \sqrt{\frac{1}{N-1} \sum_{i=1}^N MOS_i - MOS_{p_i}}.$$

Resolving Power (RP): Significance of metric differences for sequences with statistically different MOS. Gives 95% confidence of a difference.

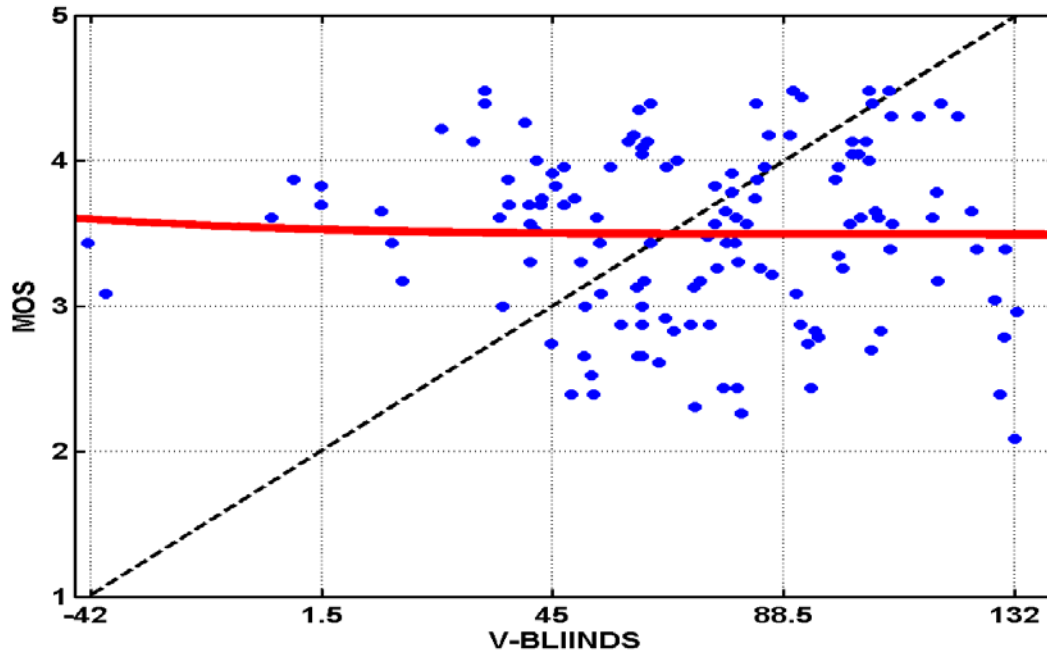
ITU-T Rec. J.149

SCATTER PLOT: VQM-VFD



monotonic regression with 3rd order polynomial function

SCATTER PLOT: VIDEO BLINDS



monotonic regression with 3rd order polynomial function

Performance

Table 1: Measures of performance.

	PLCC	SROCC	OR	RMSE	RP
PSNR	0.46	0.39	0.50	0.53	0.31
SSIM	0.55	0.54	0.47	0.49	0.25
MSSSIM	0.64	0.64	0.39	0.45	0.28
VQM	0.56	0.54	0.40	0.49	0.26
VQM-VFD	0.69	0.67	0.30	0.43	0.23
PEVQ	0.33	0.19	0.51	0.56	0.23
V-BLIINDS	0.02	0.02	0.54	0.59	1.00

Performance

Table 2: Test of significant differences for SROCC.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
PSNR (1)					-		+
SSIM (2)						+	+
MS-SSIM (3)						+	+
VQM (4)						+	+
VQM-VFD (5)	+					+	+
PEVQ (6)		-	-	-	-		
V-BLIINDS (7)	-	-	-	-	-		

Significance test ITU-T Rec P.1401 and
Bonferroni multiple-comparison compensation

Performance

Table 3: Test of significant differences for RMSE.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
PSNR (1)							
SSIM (2)							
MS-SSIM (3)							+
VQM (4)							
VQM-VFD (5)						+	+
PEVQ (6)					-		
V-BLIINDS (7)			-		-		

Discussion

- No method performs well
- SSIM, MS-SSIM perform slightly better than PSNR
 - but not significantly
- VQM-VFD performs overall best

Discussion

- V-BLIINDS are NR models based on machine learning not trained for this case
- PEVQ – dataset definitely out of scope trained on much severe transmission errors
- Videos varying length up to 40 sec – additional challenge for the methods

Conclusion

- No method performed well
- Caution should be used when using metrics not designed for a particular scope

More on this topic

- Subjective Analysis and Objective Characterization of Adaptive Bitrate Videos
- [HVEI@4.30pm](#) later today

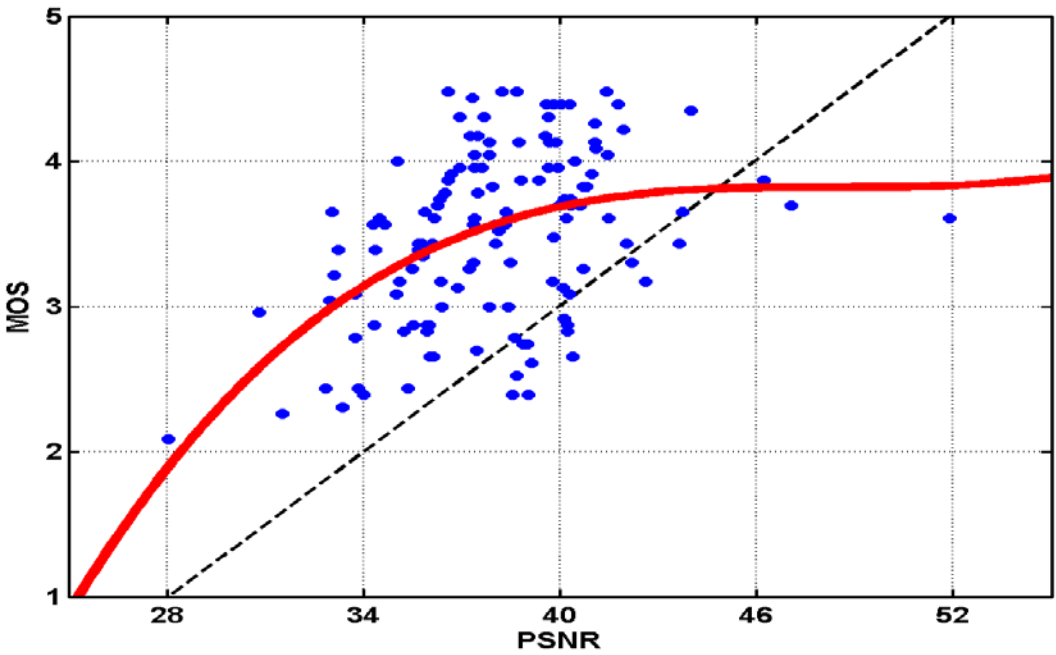
THANK YOU



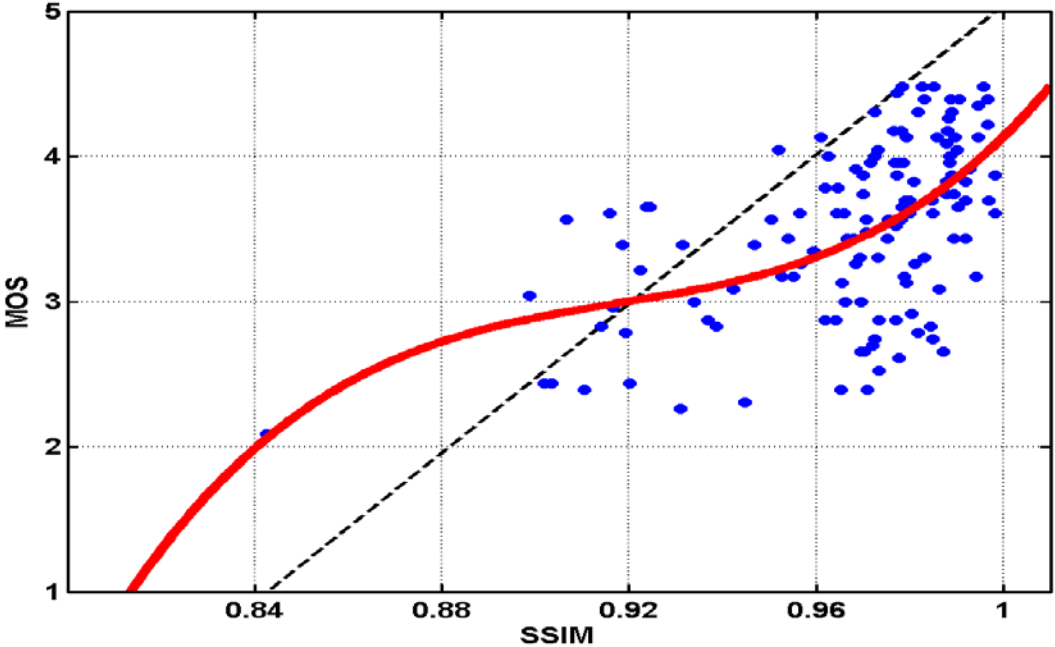
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- The support of Multimedia and Sensors lab (MSL) of Center for Signal and Information processing group at Georgia Tech is also gratefully acknowledged.



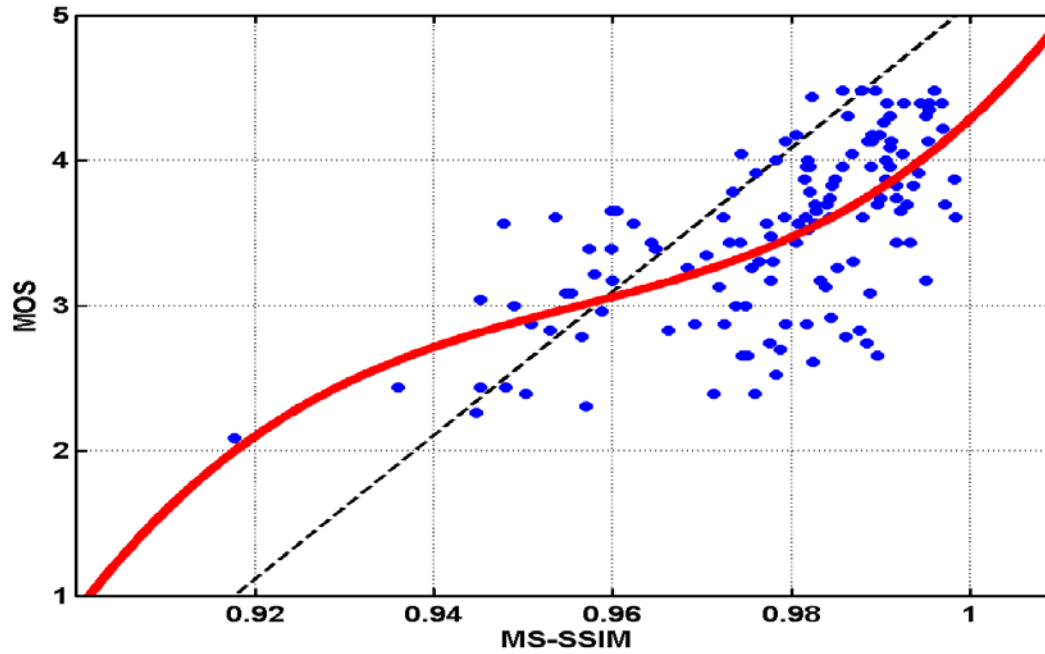
SCATTER PLOT: PSNR



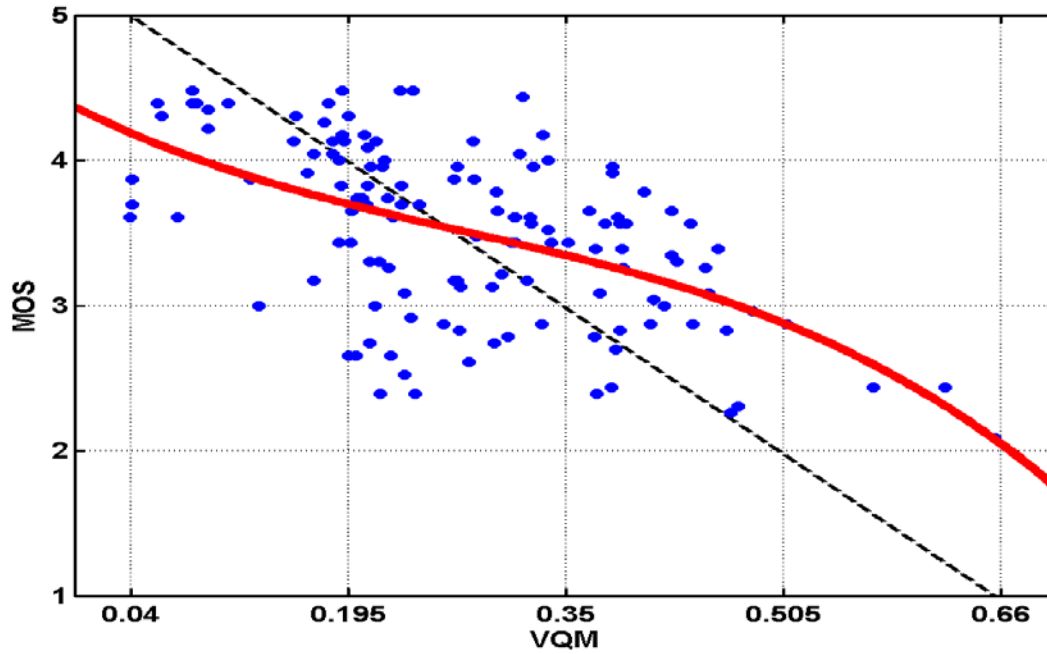
SCATTER PLOT: SSIM



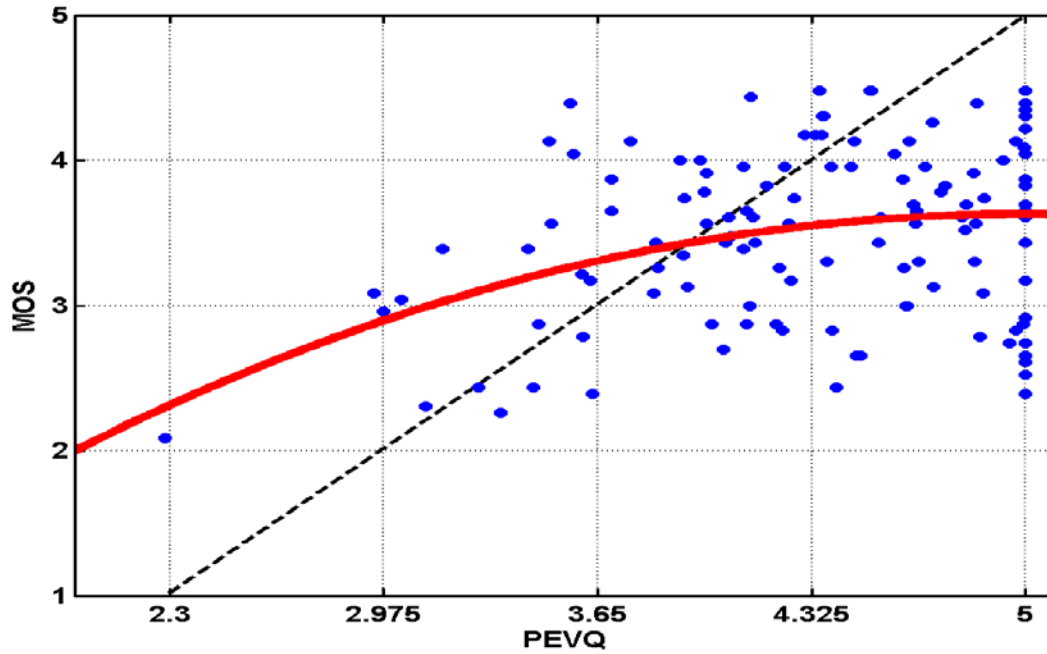
SCATTER PLOT: MS-SSIM



SCATTER PLOT: VQM



SCATTER PLOT: PEVQ



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