



Trinity  
College  
Dublin

The University of Dublin

# V-SENSE

VIVA-Q: Omnidirectional Video Quality Assessment  
based on Voronoi Patches and Visual Attention

Simone Croci, Emin Zerman, and Aljosa Smolic

# ODV Pipeline



Storytelling/  
Pre-production



Acquisition



Coding

VP9 AV1

H.264  
MPEG-4/AVC

HEVC  
H.265 - HIGH EFFICIENCY VIDEO CODING



Delivery/  
Streaming

MPEG  
DASH



Display



Full-reference  
Quality Assessment

# Unique Aspects of ODV

## 1. Spherical nature but stored in planar representations



Projection



# Unique Aspects of ODV

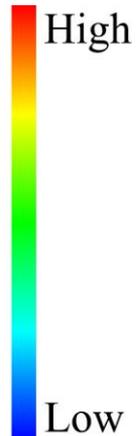
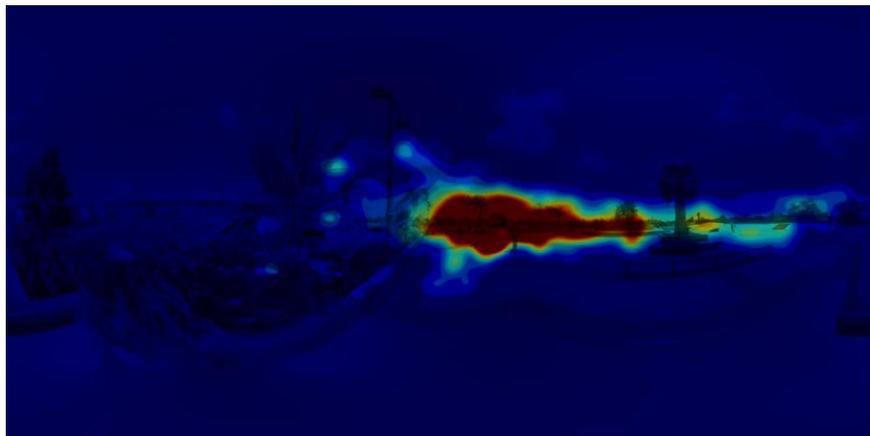
## 2. Viewing characteristics: free look around, only viewport



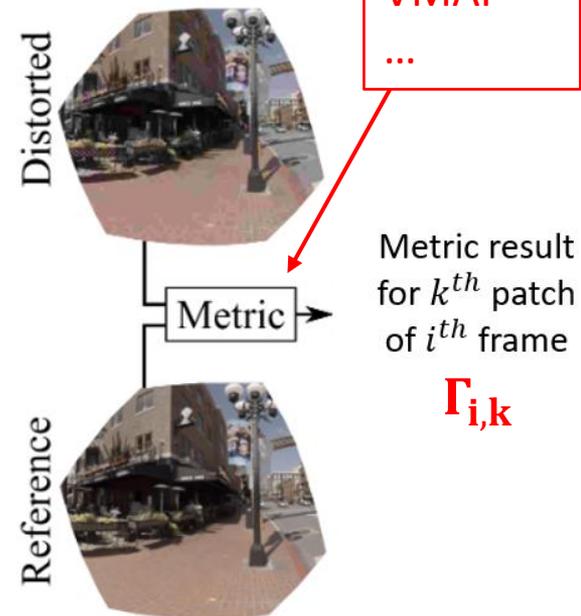
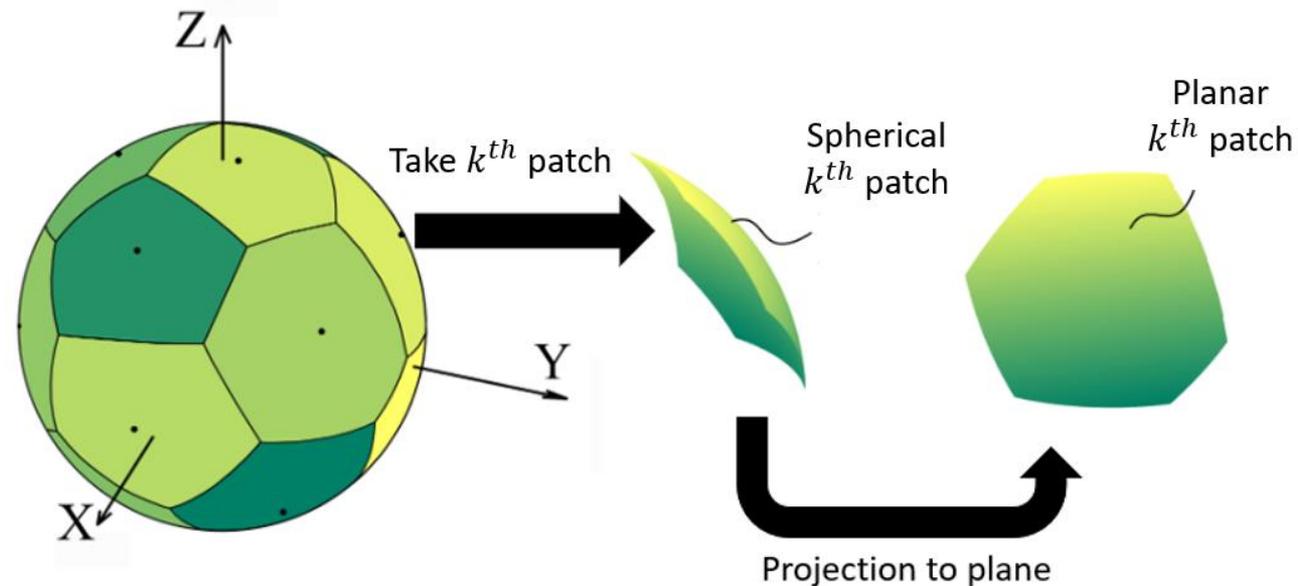
# Unique Aspects of ODV

## 2. Viewing characteristics: free look around, only viewport

Visual Attention



# VIVA-Q Framework



# VIVA-Q Framework

Score of frame  $i$ :

$$T_i = \frac{\sum_{k=1}^M \Gamma_{i,k}}{M}$$

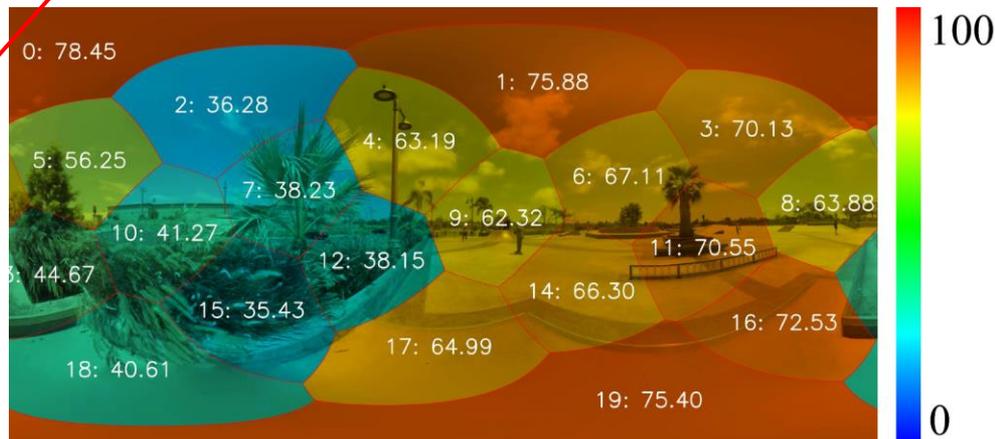
$$T'_i = \frac{\sum_{k=1}^M v_{i,k} \Gamma_{i,k}}{\sum_{k=1}^M v_{i,k}}$$

$\Gamma_{i,k}$  Patch score

$v_{i,k}$  Visual attention weight

Score of patch  $k$  of frame  $i$ :

$\Gamma_{i,k}$



# VIVA-Q Framework

Score of frame  $i$ :

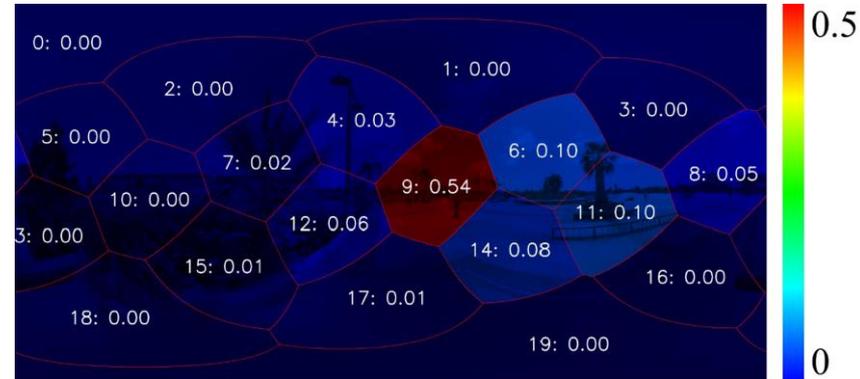
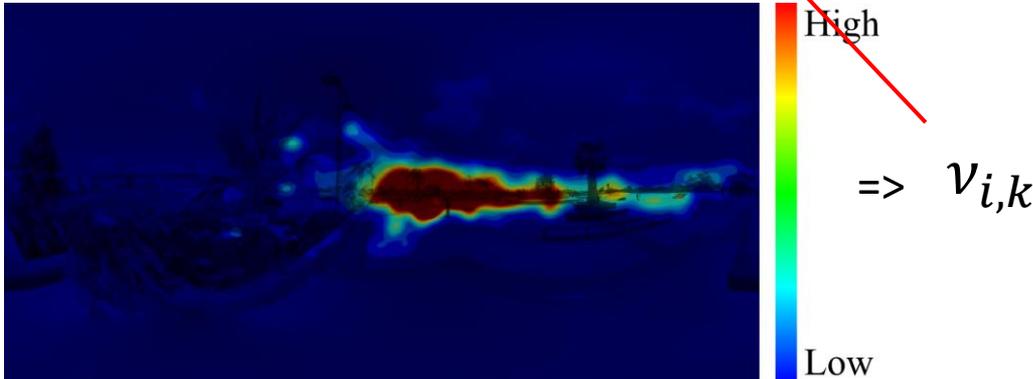
$$T_i = \frac{\sum_{k=1}^M \Gamma_{i,k}}{M}$$

$\Gamma_{i,k}$  Patch score

$$T'_i = \frac{\sum_{k=1}^M v_{i,k} \Gamma_{i,k}}{\sum_{k=1}^M v_{i,k}}$$

$v_{i,k}$  Visual attention weight

Visual attention weight of patch  $k$  of frame  $i$ :



# VIVA-Q Framework

Final score from temporal pooling  $P$  of frame scores

$$\text{VI-Q} = P(T_1, T_2, \dots, T_N)$$

$$\text{VIVA-Q} = P(T'_1, T'_2, \dots, T'_N)$$

$P$ : arithmetic mean, harmonic mean, min, median, p-th percentile, ...

# ODV Dataset and Subjective Experiments

- **Goal: metric evaluation**
- **ODV Dataset**
  - 8 reference and 120 distorted ODVs
  - Scaling and compression distortions
- **Subjective Experiments**
  - Subjective scores (DMOS) and visual attention data

# ODV Dataset

- 8K x 4K ERP
- YUV420p
- 10 sec.



(a) *Basketball*



(b) *Dancing*



(c) *Harbor*



(d) *JamSession*



(e) *KiteFlite*



(f) *Gaslamp*



(g) *SkateboardTrick*



(h) *Trolley*

# ODV Dataset

## Adaptive Streaming System Distortions

1. Scaling: 8128 x 4064, 3600 x 1800, 2032 x 1016
2. Compression:
  - HEVC/H.265 (libx265 codec): two-pass encoding with the video buffering verifier method
  - Five target bitrates selected by experts

=> 120 distorted ODVs

# Subjective Experiments

- **M-ACR-HR**<sup>1</sup>

Stimulus (10 sec)	Mid-Gray (3 sec)	Stimulus (10 sec)	Voting
----------------------	---------------------	----------------------	--------

  - [0,100] continuous grading scale
- **Apparatus:** HTC Vive + Virtual Desktop

<sup>1</sup> Singla et al., “Comparison of subjective quality evaluation for HEVC encoded omnidirectional videos at different bit-rates for UHD and FHD resolution”, Proceedings of the on Thematic Workshops of ACM Multimedia, 2017

# Comparative Analysis

- **Metrics:**

- **VI-Q:** VI-PSNR, VI-SSIM, VI-MS-SSIM, VI-VMAF

**VIVA-Q:** VIVA-PSNR, VIVA-SSIM, VIVA-MS-SSIM, VIVA-VMAF

- 20 patches with 10 pix/deg resolution
- Traditional video: PSNR, SSIM, MS-SSIM, VMAF<sup>1</sup>
- Formats: equirectangular proj. (ERP), cubemap proj. (CMP)
- ODV: S-PSNR-I<sup>2</sup>, S-PSNR-NN<sup>2</sup>, WS-PSNR<sup>3</sup>, CPP-PSNR<sup>4</sup>

<sup>1</sup>Li et al., “Toward a practical perceptual video quality metric”, Netflix Tech Blog, 2019

<sup>2</sup>Yu et al., “A framework to evaluate omnidirectional video coding schemes”, ISMAR, 2015

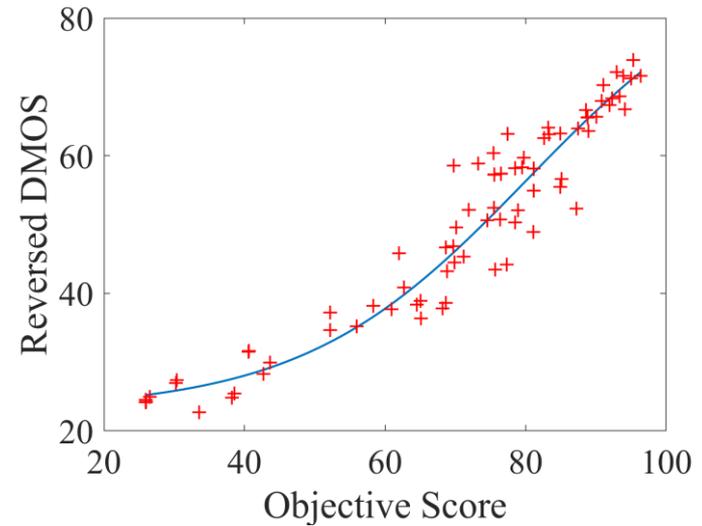
<sup>3</sup>Sun et al., “Weighted-to-spherically-uniform quality evaluation for omnidirectional video”, Signal Process. Lett., 2017

<sup>4</sup>Zakharchenko et al., “Quality metric for spherical panoramic video”, Proc. SPIE, 2016

# Comparative Analysis

## Correlation Analysis:

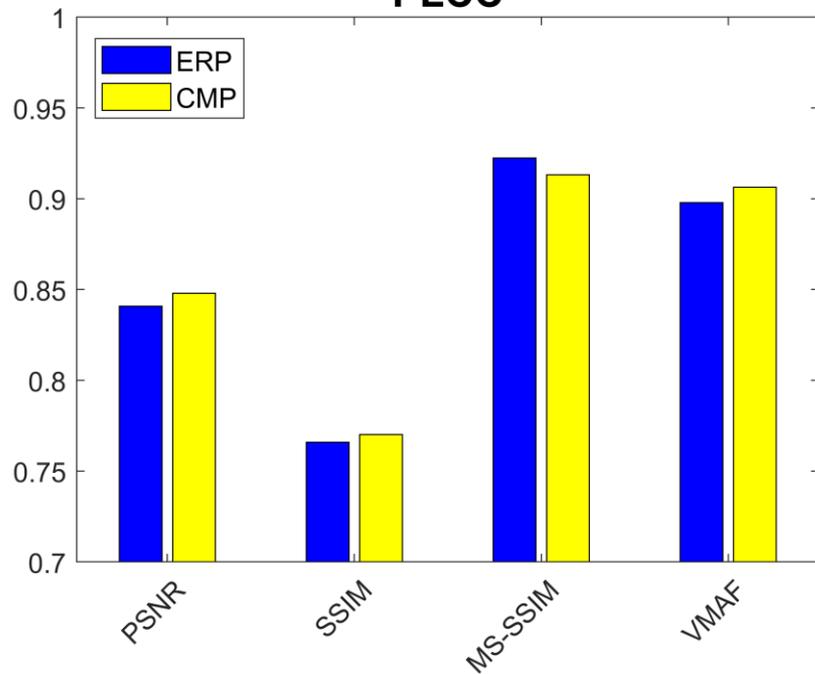
- **Logistic function:** 
$$S' = \frac{\beta_1 - \beta_2}{1 + e^{-\frac{S - \beta_3}{\|\beta_4\|}}} + \beta_2$$
- **Performance metrics**
  - Pearson's linear correlation coefficient (PLCC)
  - Spearman's rank ordered correlation coefficient (SROCC)
  - Root mean squared prediction error (RMSE)
  - Mean absolute prediction error (MAE)



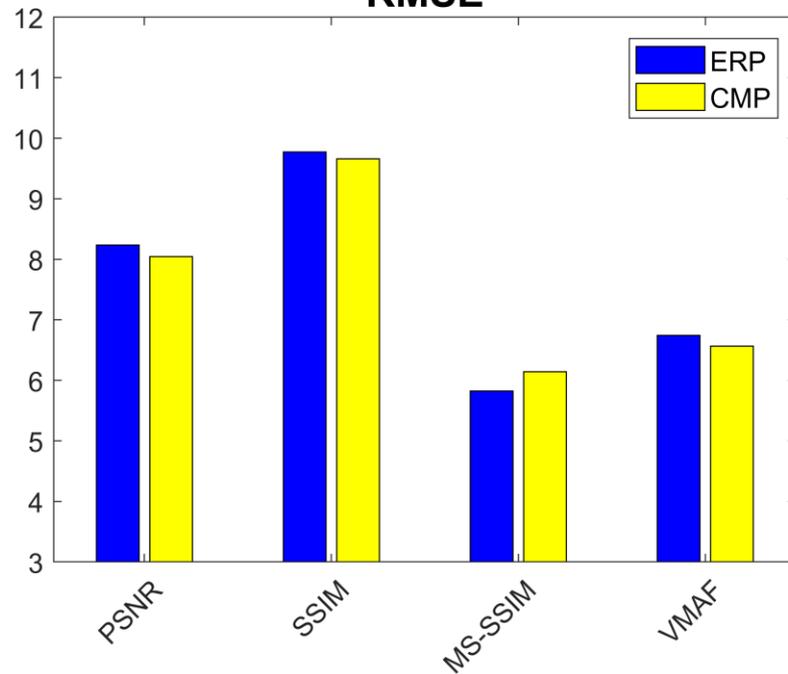
Metrics	PLCC	SROCC	RMSE	MAE
PSNR <sub>ERP</sub>	0.8408	0.8237	8.2326	6.3169
PSNR <sub>CMP</sub>	0.8480	0.8323	8.0419	6.2085
S-PSNR-I	0.8580	0.8438	7.8207	5.9715
S-PSNR-NN	0.8584	0.8433	7.8066	5.9648
WS-PSNR	0.8582	0.8430	7.8107	5.9772
CPP-PSNR	0.8579	0.8439	7.8200	5.9779
SSIM <sub>ERP</sub>	0.7659	0.7551	9.7734	7.7396
SSIM <sub>CMP</sub>	0.7701	0.7546	9.6583	7.6036
MS-SSIM <sub>ERP</sub>	0.9224	0.9160	5.8232	4.4205
MS-SSIM <sub>CMP</sub>	0.9132	0.9081	6.1422	4.7378
VMAF <sub>ERP</sub>	0.8978	0.8864	6.7433	5.3631
VMAF <sub>CMP</sub>	0.9063	0.8945	6.5630	5.2229
VI-PSNR	0.8676	0.8551	7.5743	5.8377
VI-SSIM	0.8823	0.8763	7.1172	5.2867
VI-MS-SSIM	0.9486	0.9450	4.8743	3.8475
VI-VMAF	0.9646	0.9581	4.2096	3.1548
VIVA-PSNR	0.8876	0.8712	7.1818	5.5072
VIVA-SSIM	0.9106	0.9007	6.4345	4.8097
VIVA-MS-SSIM	0.9676	0.9635	3.8982	3.1526
VIVA-VMAF	<b>0.9773</b>	<b>0.9717</b>	<b>3.3753</b>	<b>2.5948</b>

# Standard Video Metrics

## PLCC

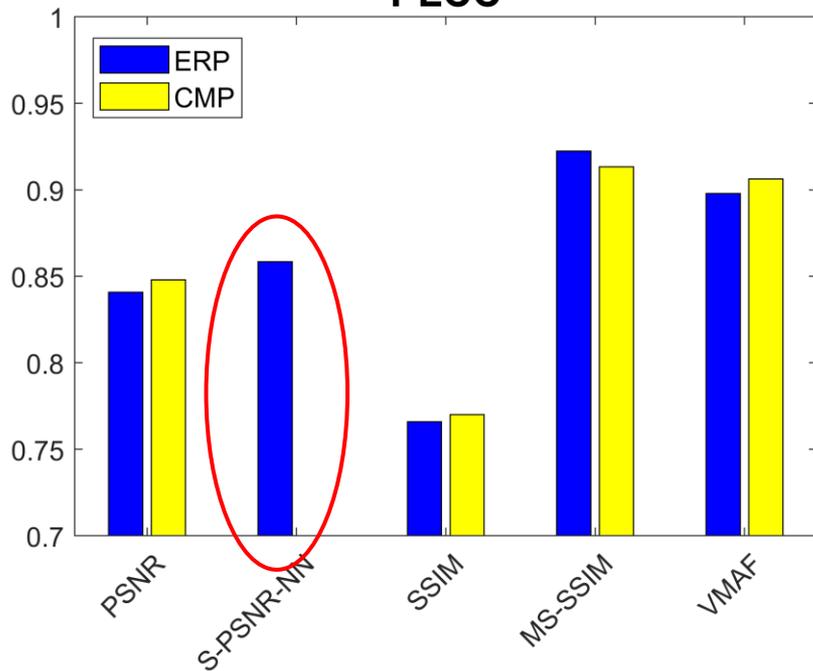


## RMSE

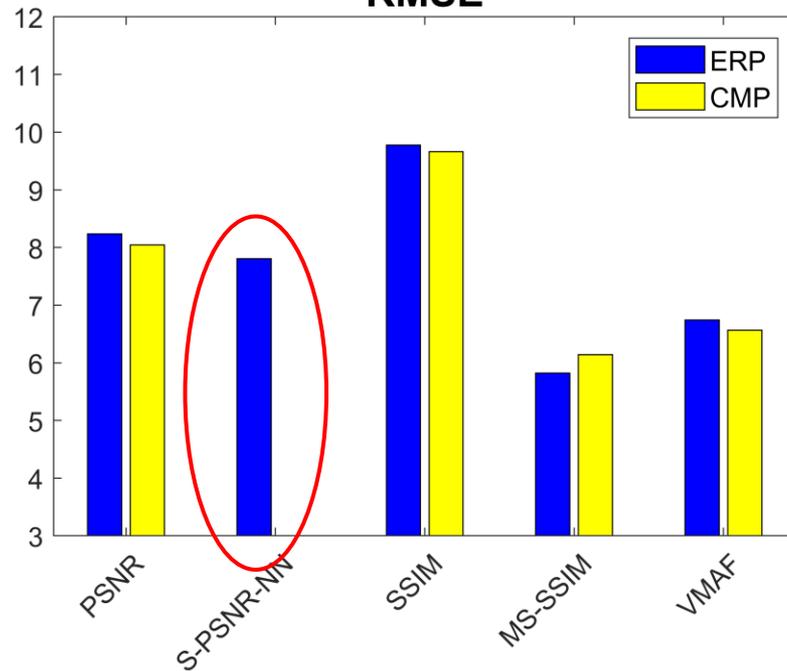


# S-PSNR-NN

## PLCC

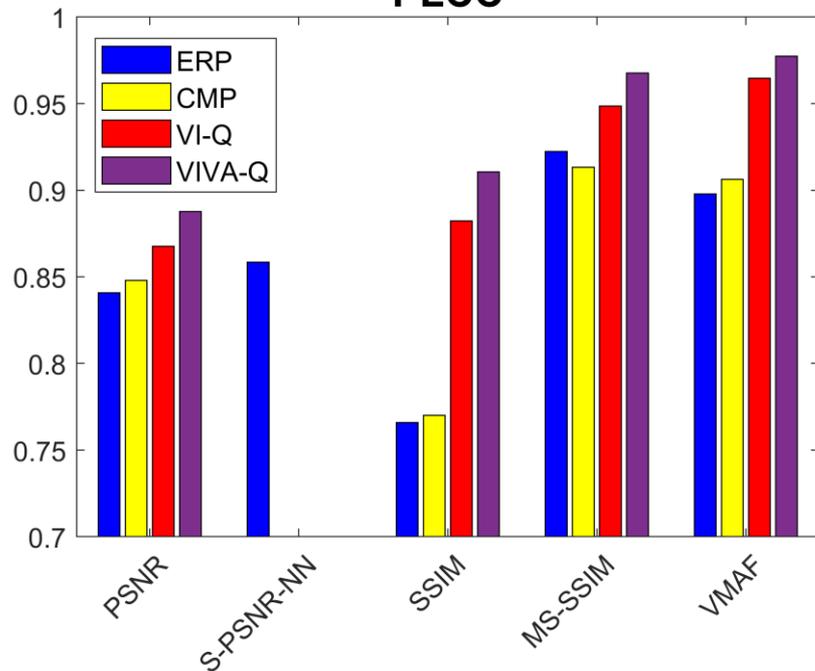


## RMSE

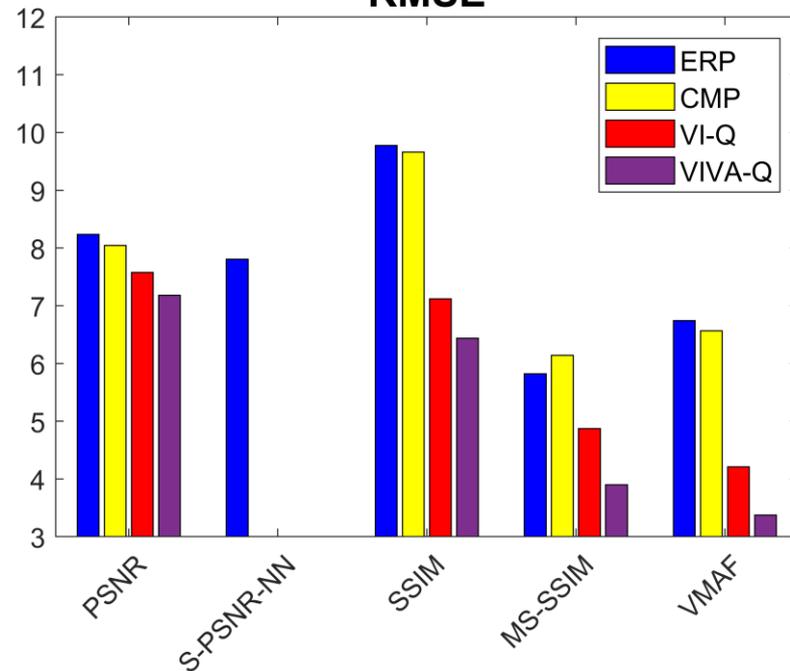


# Voronoi patches and Visual Attention

## PLCC



## RMSE



Metrics	2K		4K		8K	
	PLCC	SROCC	PLCC	SROCC	PLCC	SROCC
PSNR <sub>ERP</sub>	0.7388	0.6139	0.8360	0.8343	0.9202	0.9183
PSNR <sub>CMP</sub>	0.7517	0.6203	0.8431	0.8450	0.9221	0.9163
S-PSNR-I	0.7634	0.6469	0.8568	0.8615	0.9304	0.9228
S-PSNR-NN	0.7649	0.6433	0.8570	0.8574	0.9300	0.9227
WS-PSNR	0.7650	0.6366	0.8570	0.8574	0.9299	0.9230
CPP-PSNR	0.7638	0.6432	0.8567	0.8615	0.9302	0.9230
SSIM <sub>ERP</sub>	0.6996	0.5570	0.7703	0.7951	0.8600	0.8482
SSIM <sub>CMP</sub>	0.7011	0.5591	0.7714	0.7878	0.8565	0.8484
MS-SSIM <sub>ERP</sub>	0.8841	0.7992	0.9150	0.9351	0.9652	0.9478
MS-SSIM <sub>CMP</sub>	0.8673	0.7824	0.9071	0.9276	0.9583	0.9446
VMAF <sub>ERP</sub>	0.9202	0.8735	0.9203	0.9071	0.9515	0.9240
VMAF <sub>CMP</sub>	0.9226	0.8790	0.9309	0.9156	0.9567	0.9285
VI-PSNR	0.7640	0.6321	0.8660	0.8769	0.9358	0.9247
VI-SSIM	0.8346	0.7109	0.8794	0.9060	0.9367	0.9249
VI-MS-SSIM	0.8642	0.8807	0.8140	0.9437	0.9767	0.9557
VI-VMAF	0.9627	0.9287	0.9577	0.9458	0.9789	0.9500
VIVA-PSNR	0.7960	0.6644	0.9050	0.9006	0.9451	0.9321
VIVA-SSIM	0.8434	0.7326	0.9200	0.9321	0.9593	0.9392
VIVA-MS-SSIM	0.9529	0.9105	0.8332	<b>0.9674</b>	0.9829	<b>0.9634</b>
VIVA-VMAF	<b>0.9762</b>	<b>0.9493</b>	<b>0.9737</b>	0.9625	<b>0.9862</b>	0.9593

# Findings

- **VI-Q and VIVA-Q better than ERP and CMP**
  - Low projection distortion of Voronoi patches
- **VIVA-Q better than VI-Q**
  - Visual attention is important
- **Best: VIVA-VMAF**

# Conclusions

- **VIVA-Q framework**
  - Metrics based on Voronoi patches and visual attention
- **ODV Dataset with 8 reference and 120 distorted ODVs**
  - Subjective scores and visual attention data
- **Comparative analysis**
  - VIVA-VMAF achieves state-of-the-art performance

# Suggestions

- **VIVA-Q as standard recommendation**
- **Extension of ODV Dataset**
  - More contents
  - Different types of distortions
  - Subjective quality scores and visual attention data



Trinity  
College  
Dublin

The University of Dublin

# V-SENSE

## Many Thanks!

- Contact: [crocis@tcd.ie](mailto:crocis@tcd.ie)
- Paper: Croci et al., “Visual Attention-Aware Quality Estimation Framework for Omnidirectional Video using Spherical Voronoi Diagram”, QUX 2020
- Code & Dataset: <https://v-sense.scss.tcd.ie/research/voronoi-based-objective-metrics/>