A Comparative Study of Quality and Content-based Spatial Pooling Strategies in Image Quality Assessment

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Outline

1. Pixels to Perception (P2P) Issue
   - In Theory
   - In Practice
2. The Role of Pooling in P2P
   - Spatial Pooling Strategies
   - Proposed Method: Weighted Percentile Pooling (WPP)
   - Pooling in 1D
   - Pooling in 2D
3. Comparison of Spatial Pooling Strategies
4. Conclusion

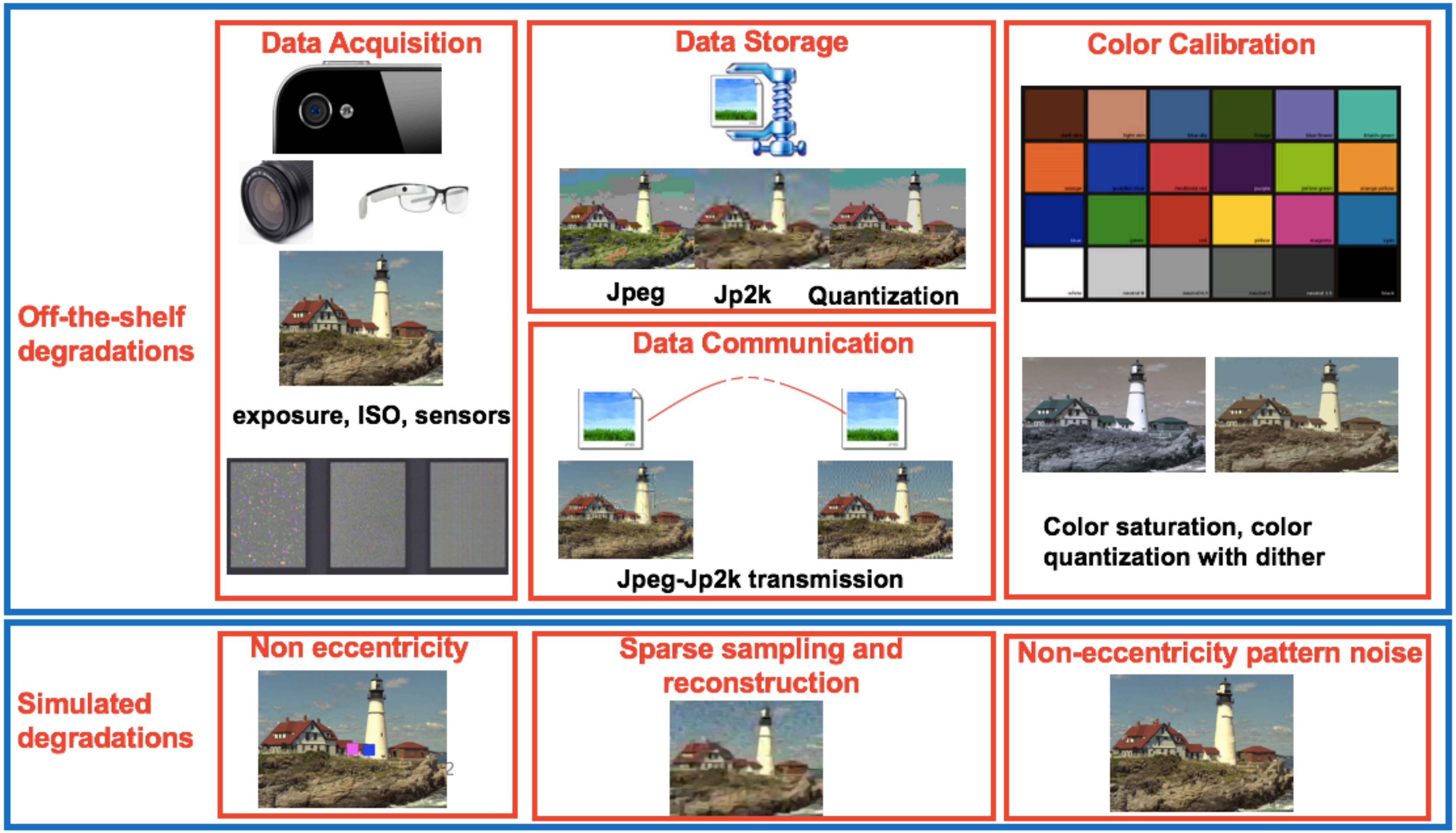
Image Quality Assessment Issue

Capture	Store	Transfer	Display	Perceive
				

P2P

Pixels ⟷ **Perception**

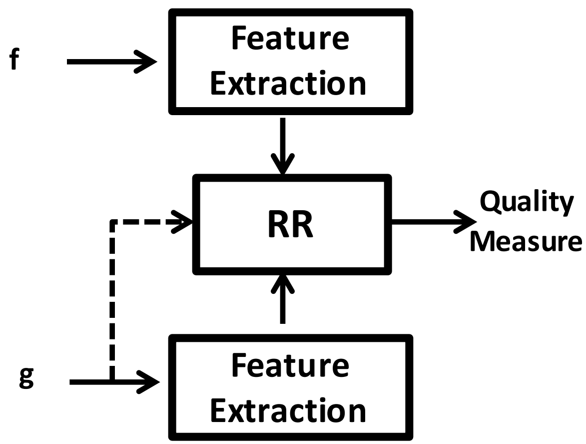
Databases:
Off the shelf and simulated degradations



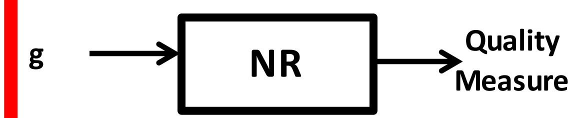
Objective Quality Metric Types

Full Reference (FR)

Reduced Reference (RR)



No Reference (NR)



Literature:
Objective Quality Metric Types

1- Basic statistics	$Mean, Median, Min, Max$
2- Percentile [3]	$\begin{cases} \frac{Q[m,n]}{c_1} z, & Q[m,n] < perc(p,Q) \\ Q[m,n], & otherwise \end{cases}$
3- Five Number Summary[1]	$\frac{mean + perc(25,Q) + median + perc(75,Q) + max}{5}$
4- Minkowski [2]	$\sum_{m=1}^{M} \sum_{n=1}^{N} \frac{Q[m,n]^p}{M\,N}$
5- Quality/Distortion Weighted[2]	$\frac{\sum_{m=1}^{M} \sum_{n=1}^{N} w[m,n] Q[m,n]}{\sum_{m=1}^{M} \sum_{n=1}^{N} w[m,n]}$ $where\;\; w[m,n] = Q[m,n]^p$
5- Information Weighted[2]	$log\left(\left(1 + \frac{\sigma_I[m,n]^2}{c_2}\right)\left(1 + \frac{\sigma_J[m,n]^2}{c_2}\right)\right)$

[1], C.G. Zewdie *et al.*, "A New Pooling Strategy for Image Quality Metrics: Five Number Summary," in *Visual Information Processing (EUVIP), 2014 5th European Workshop on*, vol., no., pp.1-6, 10-12 Dec. 2014
[2] M. Gong and M. Pedersen, "Spatial Pooling for Measuring Color Printing Quality Attributes",in *Journal of Visual Communication and Image Representation*, 23(5), pp. 685-696, Jul. 2012
[3] A.K. Moorthy and A.C. Bovik, "Visual Importance Pooling for Image Quality Assessment," in *Selected Topics in Signal Processing, IEEE Journal of*, vol.3, no.2, pp.193-201, April 2009

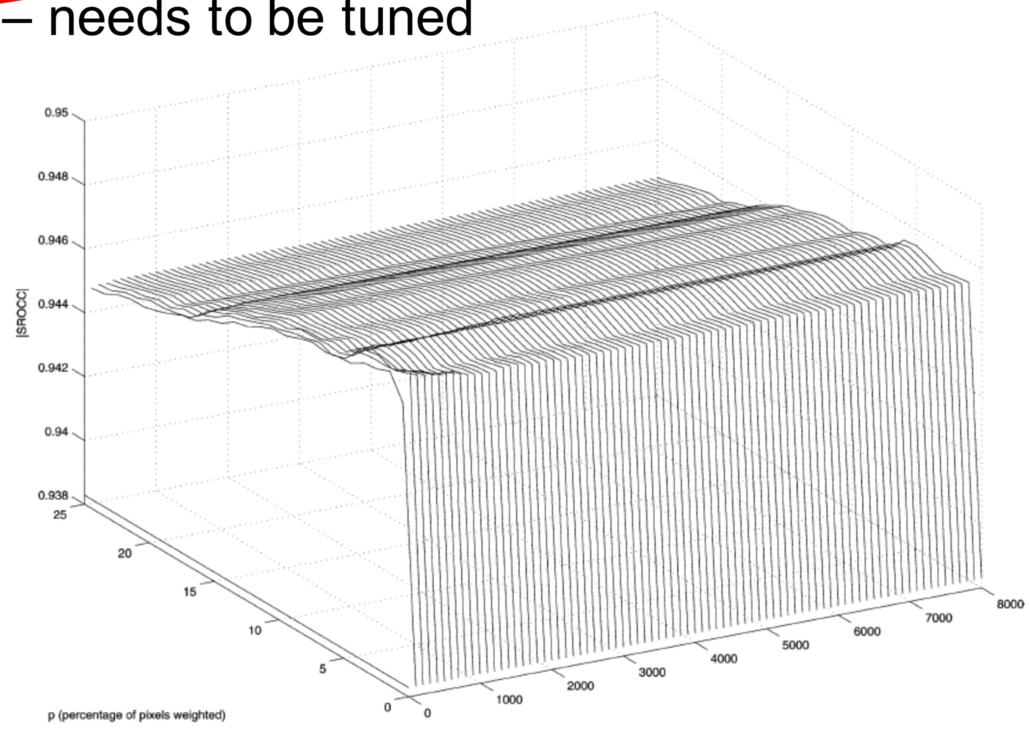
I: Reference image, J: Compared image, Q:Quality map

Percentile Pooling

- One threshold (p) – needs to be tuned

$$\begin{cases} \frac{Q[m,n]}{c_1} z, & Q[m,n] < perc(p, Q) \\ Q[m,n], & otherwise \end{cases}$$ [1]

- One weight (c_1) – needs to be tuned



[1] A.K. Moorthy and A.C. Bovik, "Visual Importance Pooling for Image Quality Assessment," in *Selected Topics in Signal Processing, IEEE Journal of*, vol.3, no.2, pp.193-201, April 2009

Five Number Summary

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$$\frac{mean + perc(25, Q) + median + perc(75, Q) + max}{5} \quad [1]$$

- Two constant percentile thresholds (25, 75) and their contributions are same

Based on percentile pooling and five number summary, we propose

Weighted Percentile Pooling

- *One* parameter (number of percentiles) that automatically adjusts the percentile thresholds and weights

[1] C.G. Zewdie *et al.*, "A New Pooling Strategy for Image Quality Metrics: Five Number Summary," in *Visual Information Processing (EUVIP), 2014 5th European Workshop on*, vol., no., pp.1-6, 10-12 Dec. 2014

Proposed pooling strategy:
Weighted Percentile Pooling for Quality Maps

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weight

$$\frac{\sum_{s=1}^{T}\boxed{\left(1-\frac{W_q(s)}{100}\right)}perc(w_q[s],Q)}{\boxed{\sum_{s=1}^{T}\left(1-\frac{W_q(s)}{100}\right)}}$$

weight-based normalization

Only *one* parameter

Automatic percentile adjustment

$$\boxed{w_q[s]=\begin{cases}1+\frac{100}{N_{bin}}s, & 1+\frac{100}{N_{bin}}s<100\\ 1, & otherwise\end{cases}}$$

$s \in \mathbb{Z}$

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Weighted Percetile Pooling:
Quality Versus Distortion Maps

Quality maps

$$\frac{\sum_{s=1}^{T}\left(1-\frac{W_q(s)}{100}\right)perc(w_q[s],Q)}{\sum_{s=1}^{T}\left(1-\frac{W_q(s)}{100}\right)}$$

$$w_q[s] = \begin{cases} 1+\frac{100}{N_{bin}}\text{s}, & 1+\frac{100}{N_{bin}}\text{s} < 100 \\ 1, & otherwise \end{cases}$$

Distortion maps

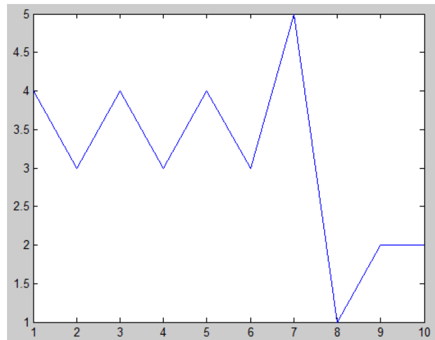
$$\frac{\sum_{s=1}^{T}\left(\frac{W_d(s)}{100}\right)perc(w_d[s],D)}{\sum_{s=1}^{T}\left(\frac{W_d(s)}{100}\right)}$$

$$w_d[s] = \begin{cases} 100-\frac{100}{N_{bin}}\text{s}, & 100-\frac{100}{N_{bin}}\text{s} > 1 \\ 100, & otherwise \end{cases}$$

$$s \in \mathbb{Z}$$

Pooling in 1D

$A = [4\ 3\ 4\ 3\ 4\ 3\ 5\ 1\ 2\ 2]$



$mean$
3.10

$median$
3.00

min
1.00

max
5.00

$prctile(20,2)$
2.95

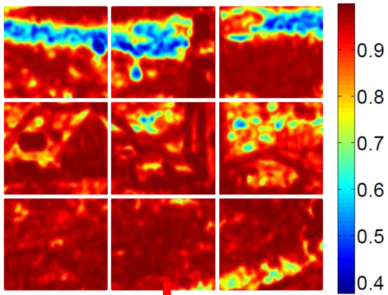
5_{Num}
3.42

$Minkowski$
$^1/_8 \rightarrow 1.14$
$^1/_4 \rightarrow 1.30$
$^1/_2 \rightarrow 1.72$
$2 \rightarrow 10.90$
$4 \rightarrow 166.90$
$8 \rightarrow 60{,}743$

$Qulity$
$/Distortion$
$^1/_8 \rightarrow 3.16$
$^1/_4 \rightarrow 3.21$
$^1/_2 \rightarrow 3.32$
$1 \rightarrow 3.51$
$2 \rightarrow 3.80$
$4 \rightarrow 4.18$
$8 \rightarrow 4.60$

$WPP(5)$
2.13

Pooling in 2D



mean
0.94

median
0.97

min
0.57

max
0.99

prctile
0.90

5_{Num}
0.78

Minkowski
$1/8 \rightarrow 0.95$
$1/4 \rightarrow 0.93$
$1/2 \rightarrow 0.92$
$2 \rightarrow 0.87$
$4 \rightarrow 0.81$
$8 \rightarrow 0.73$

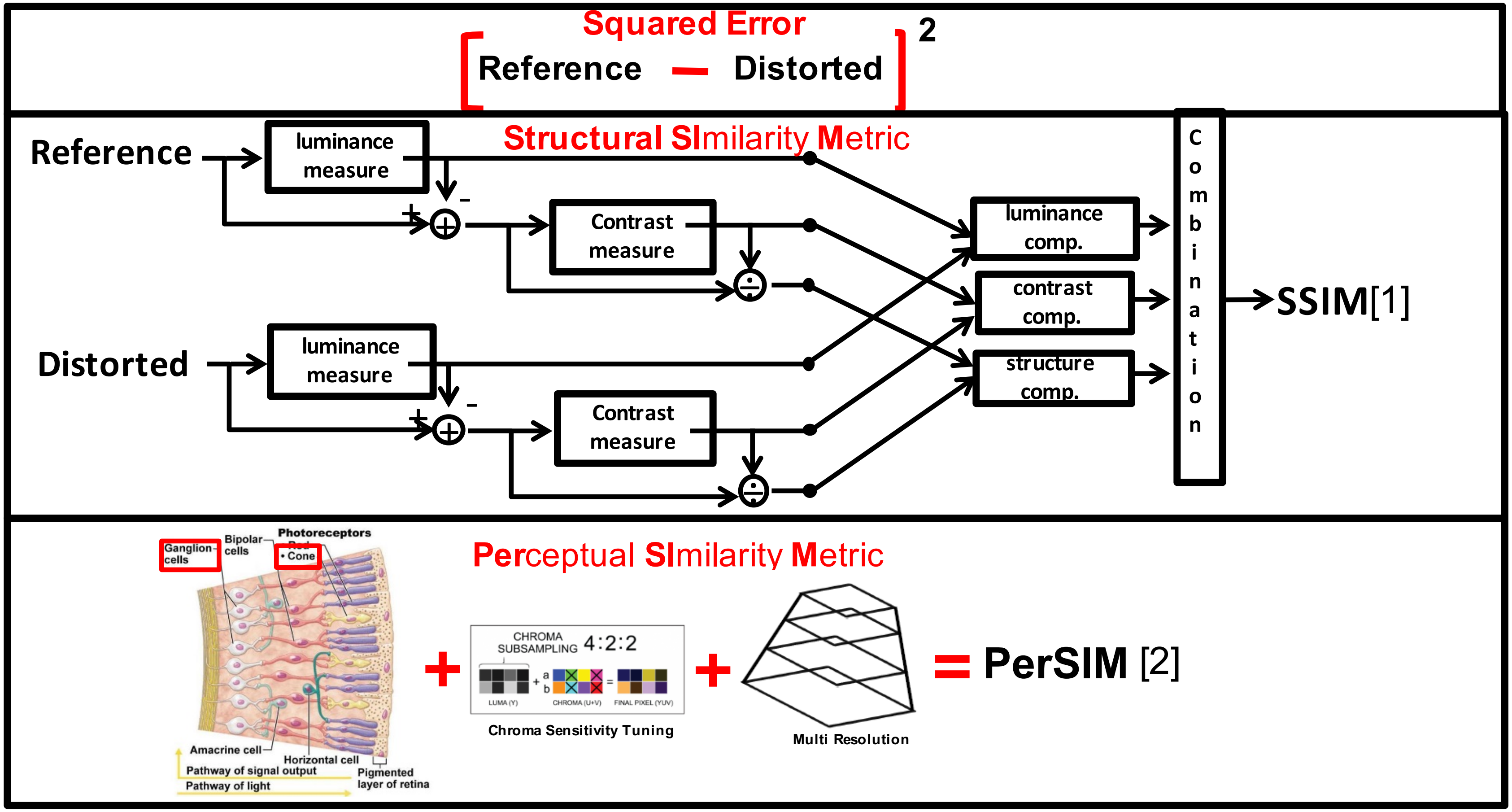
Qulity /Distortion
$1/8 \rightarrow 0.94$
$1/4 \rightarrow 0.95$
$1/2 \rightarrow 0.96$
$1 \rightarrow 0.96$
$2 \rightarrow 0.96$
$4 \rightarrow 0.97$
$8 \rightarrow 0.97$

WPP
$1 \rightarrow 0.99$
$10 \rightarrow 0.98$
$20 \rightarrow 0.97$

Validation Set

Artifact type \ Databases	LIVE	MULTI	TID2013	TOTAL
Compression	460	225	375	1060
Noise	174	225	1375	1774
Communication	174	-	250	424
Blur	174	450	250	874
Color	-	-	375	375
Global	-	-	250	250
Local	-	-	250	250

Quality Metrics:
Squared Error, SSIM and PerSIM



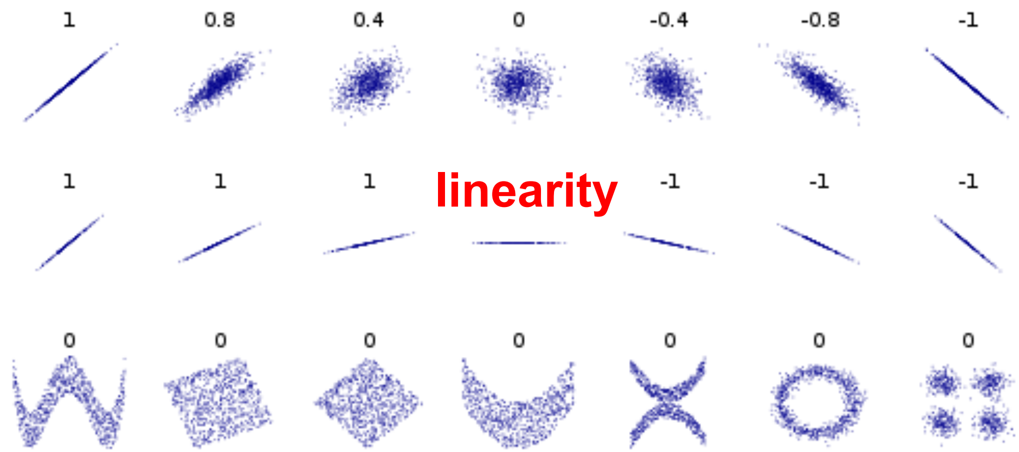
[1] Z. Wang *et al.*, "Image Quality Assessment: From Error Visibility to Structural Similarity," in *Image Processing, IEEE Transactions on*, vol.13, no.4, pp.600-612, April 2004

[2] D. Temel and G. AlRegib, "PerSIM: Multi-Resolution Image Quality Assessment in the Perceptually Uniform Color Domain," Image Processing (ICIP), 2015 22th IEEE International Conference on , 2015.

Validation metrics: Pearson and correlation coefficient

Pearson

$$\frac{Cov(X,Y)}{\sigma_X \sigma_Y} = \frac{E[(X-\mu_X)(Y-\mu_Y)]}{\sigma_X \sigma_Y} = \frac{\sum_{i=1}^{N}(X_i-\mu_X)(Y_i-\mu_Y)}{\sqrt{\sum_{i=1}^{N}(X_i-\mu_X)^2}\sqrt{\sum_{i=1}^{N}(Y_i-\mu_Y)^2}}$$



Spearman

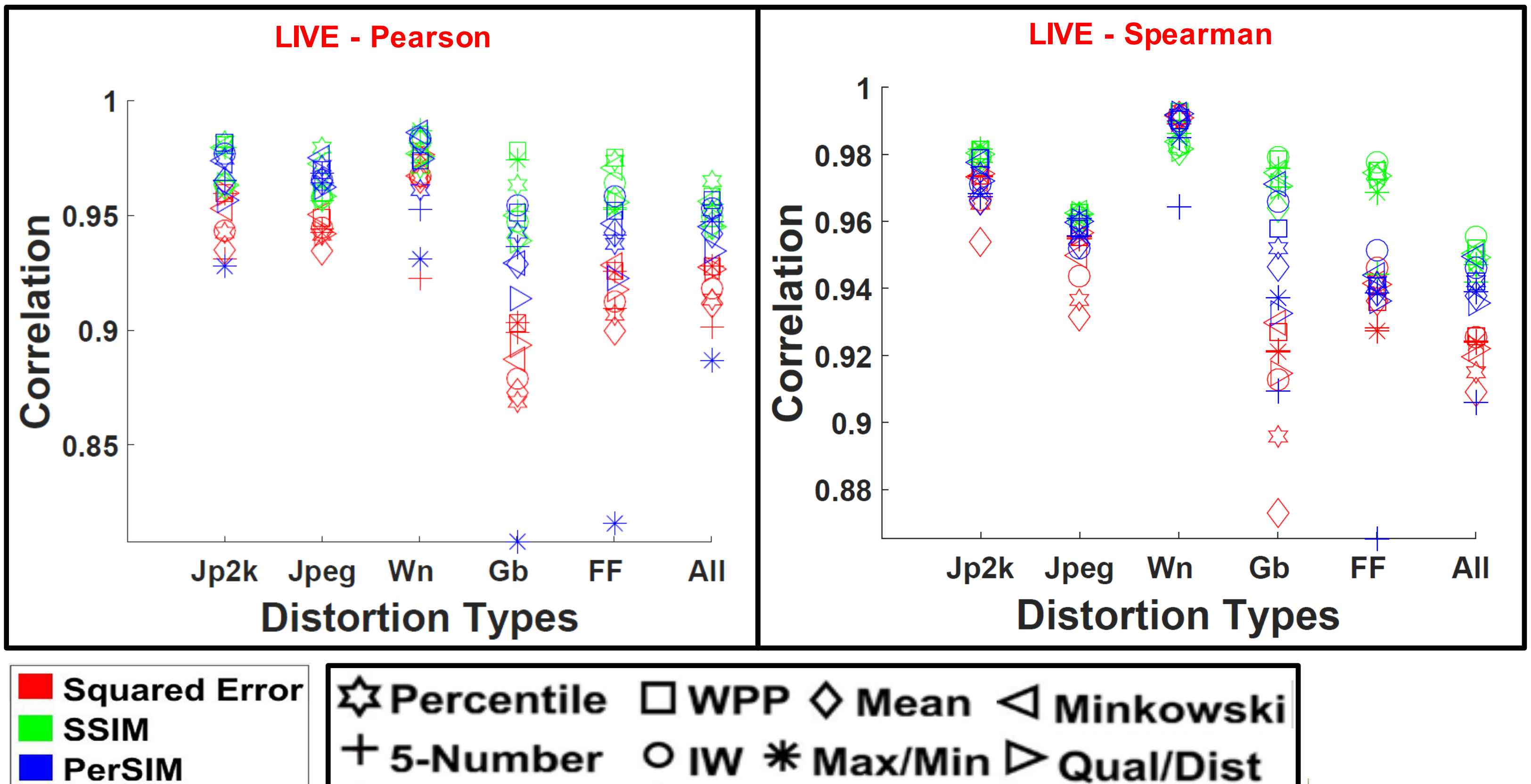
$$X_i, Y_i \longrightarrow x_i, y_i$$

monotonicity

$$1 - \frac{6\sum_{i=1}^{N}(x_i - y_i)^2}{N(N^2-1)}$$

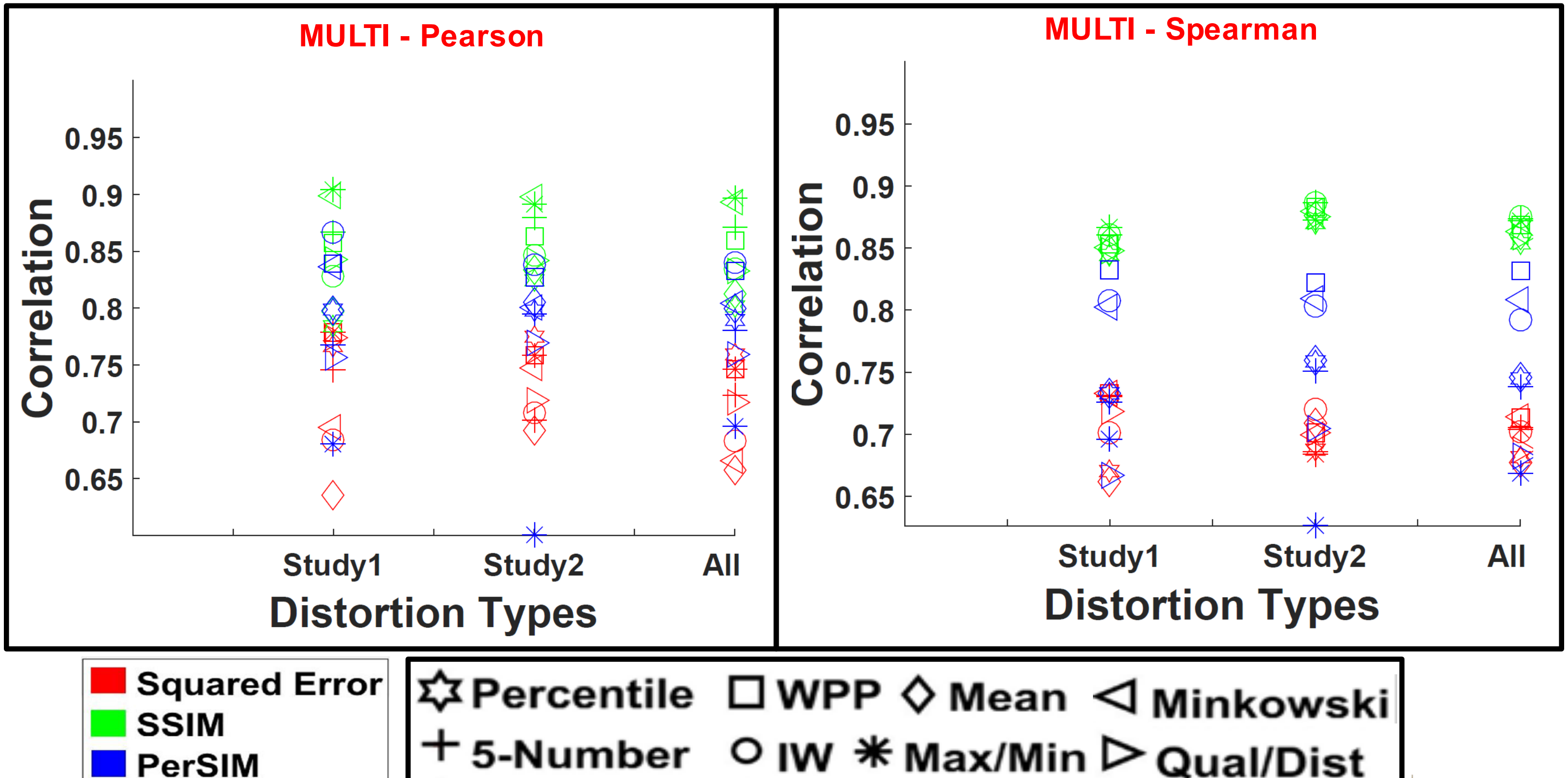
Results: LIVE database

- **Pearson:** Percentile and weighted percentile pooling are the best in the full database
- **Spearman:** Information weighted and weighted percentile pooling using SSIM are the best



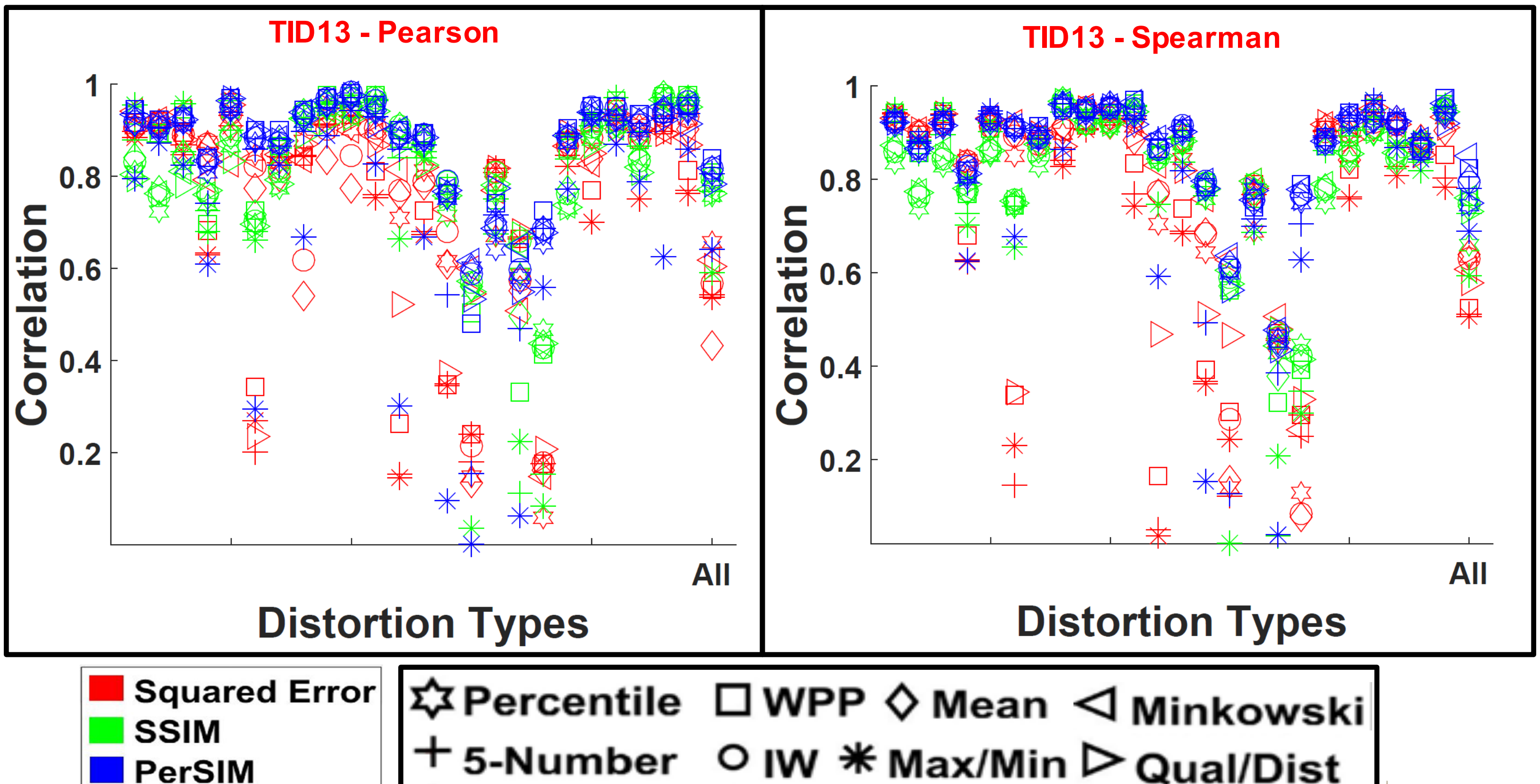
Results: MULTI database

- **Pearson:** Minkowski and Max/min are the best for SSIM, information-weighted and weighted percentile pooling are the best for PerSIM, percentile is the best for squared error
- **Spearman:** Information weighted and max/min are the best for SSIM, weighted percentile pooling is the best for PerSIM



Results: TID13 database

- **Pearson:** Weighted percentile pooling is the best for PerSIM
- **Spearman:** Monkowski pooling is the best for PerSIM followed by weighted percentile pooling



Results: Statistical Significance

- The effect of pooling strategy selection is more significant when there are more distortion types in the validation database.

Artifact type \ Databases	LIVE	MULTI	TID2013
Compression	460	225	375
Noise	174	225	1375
Communication	174	-	250
Blur	174	450	250
Color	-	-	375
Global	-	-	250
Local	-	-	250

3 types of artifacts → **M-LIVE**: 66

4 types of artifacts → **LIVE**: 90

7 types of artifacts → **TID13**: 116

Results: Statistical Significance

- Structural and perceptual similarity metrics are better for differentiating pooling strategies compared to pixel-wise squared error

	SE	SSIM	PerSIM
M-LIVE	26	32	32
LIVE	8	30	28
TID 2013	34	38	44

Conclusions

- Weighted percentile pooling enhances percenile-based methods by automatically adjusting thresholds and weights.
- Pooling matters, but not as much as quality attribute design.
- Structural and perceptual similarity metrics are better for differentiating pooling strategies compared to pixel-wise squared error.
- Pooling strategy and quality attributes can not be considered as independent processes.
- The effect of pooling strategy is more significant when the distortion types are diverse.