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

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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

Pixels  | P2P  | Perception
Databases:
Off the shelf and simulated degradations

Off-the-shelf degradations
- Data Acquisition
  - Exposure, ISO, sensors

Simulated degradations
- Non eccentricity
- Sparse sampling and reconstruction
- Non-eccentricity pattern noise

Data Storage
- Jpeg, Jp2k, Quantization
- Jpeg-Jp2k transmission

Color Calibration
- Color saturation, color quantization with dither
Objective Quality Metric Types

Full Reference (FR)

Reduced Reference (RR)

No Reference (NR)

- Full Reference (FR)
  - $f$ input
  - $g$ input
  - FR output
  - Quality Measure output

- Reduced Reference (RR)
  - $f$ input
  - $g$ input
  - Feature Extraction output
  - RR output
  - Quality Measure output

- No Reference (NR)
  - $g$ input
  - NR output
  - Quality Measure output
<table>
<thead>
<tr>
<th>Literature:</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Objective Quality Metric Types</strong></td>
</tr>
</tbody>
</table>

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

---


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

- One threshold \((p)\) – needs to be tuned
  \[
  \begin{cases}
  Q[m, n] \leq z, & \text{if } Q[m, n] < \text{perc}\{p\} Q \\
  Q[m, n], & \text{otherwise}
  \end{cases}
  \]

- One weight \((c_1)\) – needs to be tuned

Five Number Summary

\[
\text{mean} + \text{perc}(25, Q) + \text{median} + \text{perc}(75, Q) + \text{max} \\
[1] \\
\]

- 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

Proposed pooling strategy: Weighted Percentile Pooling for Quality Maps

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

weight-based normalization

Only one parameter

Automatic percentile adjustment

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

where \( s \in \mathbb{Z} \)
Weighted Percentile Pooling: Quality Versus Distortion Maps

**Quality maps**

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

\[
\sum_{s=1}^{T} \left(1 - \frac{W_q(s)}{100}\right)
\]

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

**Distortion maps**

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

\[
\sum_{s=1}^{T} \left(\frac{W_d(s)}{100}\right)
\]

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

\[s \in \mathbb{Z}\]
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
- Percentile (20,2): 2.95
- Five Number Summary (5Num): 3.42
- Minkowski Distortion:
  - \( \frac{1}{8} \rightarrow 1.14 \)
  - \( \frac{1}{4} \rightarrow 1.30 \)
  - \( \frac{1}{2} \rightarrow 1.72 \)
  - 2 \rightarrow 10.90
  - 4 \rightarrow 166.90
  - 8 \rightarrow 60,743
- Quality Distortion:
  - \( \frac{1}{8} \rightarrow 3.16 \)
  - \( \frac{1}{4} \rightarrow 3.21 \)
  - \( \frac{1}{2} \rightarrow 3.32 \)
  - 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
\frac{1}{8} \rightarrow 0.95
\frac{1}{4} \rightarrow 0.93
\frac{1}{2} \rightarrow 0.92
2 \rightarrow 0.87
4 \rightarrow 0.81
8 \rightarrow 0.73

Quality
/Distortion
\frac{1}{8} \rightarrow 0.94
\frac{1}{4} \rightarrow 0.95
\frac{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

<table>
<thead>
<tr>
<th>Artifact type \ Databases</th>
<th>LIVE</th>
<th>MULTI</th>
<th>TID2013</th>
<th>TOTAL</th>
</tr>
</thead>
<tbody>
<tr>
<td>Compression</td>
<td>460</td>
<td>225</td>
<td>375</td>
<td>1060</td>
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<tr>
<td>Noise</td>
<td>174</td>
<td>225</td>
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<td>Communication</td>
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<tr>
<td>Blur</td>
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<td>450</td>
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<td>Color</td>
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<td>250</td>
<td>250</td>
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<tr>
<td>Local</td>
<td>-</td>
<td>-</td>
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</table>
Quality Metrics: Squared Error, SSIM and PerSIM

Squared Error

\[ \text{Squared Error} = \frac{(\text{Reference} - \text{Distorted})^2}{\text{Reference} + \text{Distorted}} \]

Structural Similarity Metric

Reference

- Luminance measure
- Contrast measure
- Combination

Distorted

- Luminance measure
- Contrast measure
- Combination

\[ \text{SSIM} = \frac{(\text{luminance comp.} + \text{contrast comp.} + \text{structure comp.})}{3} \]

Perceptual Similarity Metric

- Chroma Sensitivity Tuning
- Multi Resolution

\[ \text{PerSIM} = \text{Chroma Subsampling} + \text{4:2:2 Chroma Encoding} + \text{Multi Resolution} \]

Validation metrics: Pearson and correlation coefficient

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

Pearson

Spearman

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

linearity

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

### Results: Statistical Significance

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**Results: Statistical Significance**

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

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<th></th>
<th>SE</th>
<th>SSIM</th>
<th>PerSIM</th>
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<tbody>
<tr>
<td>M-LIVE</td>
<td>26</td>
<td>32</td>
<td>32</td>
</tr>
<tr>
<td>LIVE</td>
<td>8</td>
<td>30</td>
<td>28</td>
</tr>
<tr>
<td>TID 2013</td>
<td>34</td>
<td>38</td>
<td>44</td>
</tr>
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Weighted percentile pooling enhances percentile-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.