Boosting in Image Quality Assessment

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Outline

I. Introduction
   - Image Quality Assessment
   - Boosting

II. Experimental Setup
   - Image Quality Estimators
   - Boosting Methods and Test Setup

III. Experimental Analysis
   - Performance Comparison of Existing, Regressed, and Boosted Methods
   - Boosting Performance with respect to Number of Fused Methods

IV. Conclusion
I. Introduction

Image Quality Assessment: Why?

<table>
<thead>
<tr>
<th>Application</th>
<th>Average daily shared photos</th>
</tr>
</thead>
<tbody>
<tr>
<td>Facebook</td>
<td>390 Million</td>
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<tr>
<td>WhatsApp</td>
<td>700 Million</td>
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<tr>
<td>Instagram</td>
<td>70 Million</td>
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<tr>
<td>Snapchat</td>
<td>760 Million</td>
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</table>

Remote assistance

Smart capturing

I. Introduction

Image Quality Assessment: How?

Test setup

Reference images [1]

Distorted images [1] Subjective Scores

P2P pipeline

Image 1

Image 2

Image N

Score 1

Score 2

Score N

Mean opinion scores

I. Introduction
Image Quality Assessment: How?

Is it possible to obtain **strong** learners from **weak learners**?

*Kearns, 1988  Kearns and Valiant, 1994*
I. Introduction

Boosting

<table>
<thead>
<tr>
<th>YEAR</th>
<th>2008</th>
<th>2011</th>
<th>2013</th>
<th>2015</th>
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<td>QUALITY ESTIMATORS</td>
<td>Liu and Yang</td>
<td>Liu et al.</td>
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<tr>
<td>Fidelity</td>
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<tr>
<td>Structure</td>
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<td>Scale Space</td>
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<td>Boosting Method</td>
<td>SVR</td>
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<td>Others</td>
<td>Canonical Correlation Analysis</td>
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</table>

### Generalizability

- Boosting > regression ?
- Boosting performance (number of fused methods) ?

### Superiority

- An alternative approach >SVR ?
II. Experimental Setup
Boosting Methods and Test Setup

Boosting Methods
- Support Vector Machines (SVM)
- Neural Networks (NN)

Databases

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<th>LIVE</th>
<th>MULTI</th>
<th>TID13</th>
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<tr>
<td>Local</td>
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Performance Metrics

- RMSE: $\sqrt{E[(X - Y)^2]}$
- Pearson Correlation: $\frac{E[(X - \mu_X)(Y - \mu_Y)]}{\sigma_X \sigma_Y}$
- Spearman Correlation: $1 - \frac{6 \sum_{i=1}^{N}(x_i - y_i)^2}{N(N^2 - 1)}$
II. Experimental Setup

Image Quality Estimators

1. Fidelity: MSE, PSNR
2. Perceptually-extended fidelity: PSNR-HA, PSNR-HMA
3. Structure: SSIM, MS-SSIM, CW-SSIM, IW-SSIM, SR-SIM (Spectral)
4. Color: FSIMc, PerSIM
5. Learning: UNIQUE
III. Experiments
Part I: Performance comparison of existing, regressed, and boosted quality estimators

Experimental Procedure

Support Vector Machines (SVM)  |  Neural Networks (NN)

Existing methods  |  Regressed methods  |  Boosted methods
III. Experiments

Part I: Performance comparison of existing, regressed, and boosted quality estimators

\[ \text{RMSE} = \sqrt{E[(X - Y)^2]} \]

\[ \text{Pearson Correlation} = \frac{E[(X - \mu_X)(Y - \mu_Y)]}{\sigma_X \sigma_Y} \]

\[ X_i, Y_i \rightarrow x_i, y_i \]

\[ \text{Spearman Correlation} = 1 - \frac{6 \sum_{i=1}^{N}(x_i - y_i)^2}{N(N^2 - 1)} \]
III. Experiments
Part I: Performance comparison of existing, regressed, and boosted quality estimators

**Generalizability**
- Boosting > regression?

**Superiority**
- An alternative approach > SVR?

<table>
<thead>
<tr>
<th>RMSE</th>
<th>LIVE</th>
<th>MULTI</th>
<th>TID13</th>
</tr>
</thead>
<tbody>
<tr>
<td>√E[(X − Y)^2]</td>
<td>6.00</td>
<td>8.50</td>
<td>0.60</td>
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<tr>
<td>Pearson Correlation</td>
<td>0.97</td>
<td>0.92</td>
<td>0.91</td>
</tr>
<tr>
<td>Spearman Correlation</td>
<td>0.95</td>
<td>0.87</td>
<td>0.86</td>
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**Pearson**
\[
\rho = \frac{\sum_{i=1}^{N}(x_i - \mu_x)(y_i - \mu_y)}{\sigma_x \sigma_y}
\]

**Spearman**
\[
\rho_s = 1 - \frac{6 \sum_{i=1}^{N}(x_i - y_i)^2}{N(N^2 - 1)}
\]
Sort existing methods with respect to their performance from the worst to the best.

Regress the worst performing method (with respect to each performance metric).

Boost with the next best performing method until all the methods are utilized.
III. Experiments
Part II: Boosting Performance versus Number of Fused Methods

\[ \text{RMSE} = \sqrt{E[(X - Y)^2]} \]

\[ E[(X - \mu_X)(Y - \mu_Y)] \]
\[ \frac{\sigma_X \sigma_Y}{\sigma_X \sigma_Y} \]

\[ x_i, y_i \rightarrow X_i, Y_i \]
\[ 1 - \frac{6 \sum_{i=1}^{N}(x_i - y_i)^2}{N(N^2 - 1)} \]
III. Experiments
Part II: Boosting Performance with respect to Number of Fused Methods

**Generalizability**

- Boosting performance (number of fused methods)?

**Superiority**

- An alternative approach > SVR?

\[
\text{RMSE} = \sqrt{E[(X - Y)^2]}
\]

\[
\text{Pearson Correlation} = \frac{E[(X - \mu_X)(Y - \mu_Y)]}{\sigma_X \sigma_Y}
\]

\[
\text{Spearman Correlation} = 1 - \frac{6 \sum_{i=1}^{N} (x_i - y_i)^2}{N(N^2 - 1)}
\]
IV. Conclusion

Findings

- **Boosting**-based methods generally **outperform existing** best performing methods.

- **Boosting** the **worst** performing quality estimator with two or more additional methods leads to statistically **significant improvements** in all the test scenarios (independent of the boosting technique).

- Boosting-based performance enhancement **level** depends on the **type** of the boosting **strategy**.

- **Neural network**-based boosting outperforms **support vector machine**-based boosting (when two or more methods are fused).
IV. Conclusion
Prospective Research Directions

- The *complexity* of the estimators can be considered while boosting.

- The *relationship* between the characteristics of quality estimators and the distortion types can be analyzed through boosting.

- Instead of boosting final scores, *feature maps* can be boosted to obtain hybrid methods.

- *Deep* architectures can be used for boosting feature maps.