Classification, Analysis and Comparison of Non-Blind Image Quality Measure

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Abstract

Computation of extent of image visual excellence is of essential importance for many image and video processing appliances, where the objective of quality evaluation algorithms is to automatically evaluate the excellence of images. This paper is the detailed experimental study, classification, analysis and comparison of the subjective non-blind image quality measures. After analysis, evaluation and comparison, these schemes are classified into two groups on the basis of similarity and dissimilarity check. It also scrutinizes the statistical recital of all the quality measures.

Keywords: Image Quality Assessment, Subjective Measure, Objective Measure, Blind Measures, Non-blind Measures, Similarity Measure, Dissimilarity Measure

1. Introduction

Image quality evaluation (IQM) \([1]\) is an essential but intricate concern in image processing appliances \([6]\). There has been capricious intensification in the use of multimedia tools and appliances specially images and videos etc. But regrettably, these are subjected to extensive diversity of misrepresentation during its acquisition, processing, communication, consequent compression and then imitation, which corrupt visual quality. So, extent of image quality is vital for many image and video processing system relevance including monitoring of image quality in quality control computer vision systems, selection of capturing device on the basis of good quality image, Steganalysis \([12]\) etc., where the objective of quality estimation algorithms is to automatically evaluate the quality of images or videos in accord with human quality conclusion.

To classify the image quality measures into similarity and dissimilarity measures is very important and useful in many images processing application. Image similarity and dissimilarity evaluations are strongly correlated to image quality evaluation in terms of that the quality is based on the perceptible differences or similarities between a degraded, reference image and the original, unmodified input image.

This paper is an attempt to provide the detail study, classification, analysis and comparison of many image quality evaluation methods with experimental analysis and results. The rest of paper is arranged as second section provides the mathematical definition of image quality measures; third section discusses the different types of existing classification and properties of similarity and dissimilarity for classification. Forth section gives the experimental results and conclusion and references are in the last.
2. Mathematical Forms of Image Quality Measures

This section gives the mathematical definitions and description of the image quality measures used. If \( I(x,y), x = 0,1,2,\ldots,N-1 \) and \( R(x,y), x = 0,1,2,\ldots,N-1 \) are the pixel pattern of the input image \( I \) and the reference image \( R \), \( N \times M \) represent the dimensions of input and reference image, \( \mu_I \) is the mean of input image, \( \mu_R \) is the mean of the reference image, \( \sigma_I \) is the standard deviation of input image, \( \sigma_R \) is the standard deviation of the reference image, \( \sigma_{II} \) is the variance of the input image, \( \sigma_{RR} \) is the variance of the reference image, \( \sigma_{RI} \) is the covariance between input and reference image and \( H_I \) and \( H_R \) are the value of bin of histogram of input image and reference image respectively. Then image quality measures can be defined as following:

2.1 L1 Norm:

\[
L_1 Norm = \sum_{x=0}^{N-1} \sum_{y=0}^{M-1} |I(x,y) - R(x,y)|
\]  
(2.1)

2.2 Mean Absolute Error [10]:

\[
MAE = \frac{1}{NM} \sum_{x=0}^{N-1} \sum_{y=0}^{M-1} |I(x,y) - R(x,y)|
\]  
(2.2)

2.3 Peak Absolute Error:

\[
PAE = \frac{\max_{x=0,1,2,\ldots,N-1, y=0,1,2,\ldots,M-1} |I(x,y) - R(x,y)|}{\max_{x=0,1,2,\ldots,N-1, y=0,1,2,\ldots,M-1} |I(x,y)|}
\]  
(2.3)

2.4 Normalized Absolute Error:

\[
NAE = \frac{\sum_{x=0}^{N-1} \sum_{y=0}^{M-1} |I(x,y) - R(x,y)|}{\sum_{x=0}^{N-1} \sum_{y=0}^{M-1} |I(x,y)|}
\]  
(2.4)

2.5 Maximum Difference [10]:

\[
MD = \max_{x=0,1,2,\ldots,N-1, y=0,1,2,\ldots,M-1} |I(x,y) - R(x,y)|
\]  
(2.5)

2.6 Square L2 Norm:

\[
L_2^2 Norm = \sum_{x=0}^{N-1} \sum_{y=0}^{M-1} (I(x,y) - R(x,y))^2
\]  
(2.6)

2.7 Mean Square Error [9, 10]:

\[
MSE = \frac{1}{NM} \sum_{x=0}^{N-1} \sum_{y=0}^{M-1} (I(x,y) - R(x,y))^2
\]  
(2.7)

2.8 Root Mean Square Error:

\[
RMSE = \sqrt{\frac{1}{NM} \sum_{x=0}^{N-1} \sum_{y=0}^{M-1} (I(x,y) - R(x,y))^2}
\]  
(2.8)

2.9 Peak Mean Square Error [9]:

\[
\text{Peak MSE} = \max_{x=0,1,2,\ldots,N-1, y=0,1,2,\ldots,M-1} (I(x,y) - R(x,y))^2
\]
2.10 Normalized Square Error:

\[
PMSE = \frac{1}{NM} \frac{\sum_{x=0}^{N-1} \sum_{y=0}^{M-1} (I(x,y) - \bar{R}(x,y))^2}{\max(I(x,y)) \text{ where } x=0,1,..N-1 \text{ and } y=0,1,..M-1}
\]  

(2.9)

2.11 Normalized Square L2 Norm:

\[
NL2 = \sum_{x=0}^{N-1} \sum_{y=0}^{M-1} \left( \frac{(I(x,y) - \bar{H}(x,y))}{\sigma_H} \right)^2
\]  

(2.11)

2.12 Signal to Noise Ratio:

\[
SNR = 10 \log_{10} \left( \frac{\sum_{x=0}^{N-1} \sum_{y=0}^{M-1} (I(x,y))^2}{\sum_{x=0}^{N-1} \sum_{y=0}^{M-1} (I(x,y) - \bar{R}(x,y))^2} \right)
\]  

(2.12)

2.13 Peak Signal to Noise Ratio [10]:

\[
PSNR = 10 \log_{10} \left( \frac{\max(I(x,y))^2 \text{ where } x=0,1,..N-1 \text{ and } y=0,1,..M-1}{MSE} \right)
\]  

(2.13)

2.14 Intensity Ratio Variance:

\[
IRV = \frac{1}{NM} \sum_{x=0}^{N-1} \sum_{y=0}^{M-1} (R(x,y) - \mu_R)^2
\]  

(2.14)

2.15 Chi-Square:

\[
d_{\chi^2}(H_{II}, H_{RI}) = \sum_{i=1}^{N} \frac{(H_{II}(i) - H_{RI}(i))^2}{H_{II} + H_{RI}}
\]  

(2.16)

Where \(d\) is function that computes Chi-square between \(H_{II}\) and \(H_{RI}\).

2.16 Paterson Cross Correlation [13]:

\[
PCC = \frac{\sum_{x=0}^{N-1} \sum_{y=0}^{M-1} (I(x,y) - \mu_I)(R(x,y) - \mu_R)}{\sqrt{\sum_{x=0}^{N-1} \sum_{y=0}^{M-1} (I(x,y) - \mu_I)^2 \sum_{x=0}^{N-1} \sum_{y=0}^{M-1} (R(x,y) - \mu_R)^2}}
\]  

(2.17)
2.17 Spearman’s Rank Correlation:

\[
SRCC = 1 - \frac{6 \sum_{xy} (rank_H(xy) - rank_RI(xy))^2}{MN(N^2-1)}
\]  

(2.18)

\[
SRCC = \frac{\sum_{xy} (R_H(xy) - \mu_H)M_RI(xy) - \mu_{RI}}{\sum_{xy} (R_H(xy) - \mu_H)^2 + \sum_{xy} (R_{RI}(xy) - \mu_{RI})^2}
\]  

(2.19)

2.18 Minimum Ratio:

\[
MIN_r = \frac{1}{MN} \sum_{xy=0}^{N-1} \sum_{y=0}^{M-1} r(x, y) \text{ where } r(x, y) = \min\left(\frac{H_{II}(x, y)}{H_RI(x, y)}, \frac{R_H(x, y)}{H_{II}(x, y)}\right)
\]  

(2.20)

2.19 Jaccard Measure [13]:

\[
d_{Jaccard}(H_{II}, H_{RI}) = \frac{\sum_{xy} H_{II}(x, y)H_{RI}(x, y)}{\sum_{xy} H_{II}(x, y)^2 + \sum_{xy} H_{RI}(x, y)^2 - \sum_{xy} H_{II}(x, y)H_{RI}(x, y)}
\]  

Where \( d \) is function that computes Jaccard coefficient between \( H_{II} \) and \( H_{RI} \).

2.20 Intersection [13]:

\[
d_{Intersection}(H_{II}, H_{RI}) = \sum_{xy=0}^{N-1} \sum_{y=0}^{M-1} \min(H_{II}(x, y), H_{RI}(x, y))
\]  

(2.22)

Where \( d \) is function that computes Intersection between \( H_{II} \) and \( H_{RI} \).

2.21 Bhattacharya [13]:

\[
d_{Bhattacharya}(H_{II}, H_{RI}) = \sqrt{1 - \frac{1}{\sqrt{\sum_{xy} H_{II}(x, y)H_{II}(x, y)^2 \sum_{xy} H_{RI}(x, y)H_{RI}(x, y)}}}
\]  

(2.23)

Where \( d \) is function that computes Bhattacharya between \( H_{II} \) and \( H_{RI} \).

2.22 Contrast:

\[
Contrast = C(HII, HRI) = \frac{2\mu_H \mu_{RI}}{\sigma_{HII}^2 + \sigma_{HRI}^2}
\]  

(2.2)

4

2.23 Luminance:

\[
Luminance = l(HII, HRI) = \frac{2\mu_H \mu_{RI}}{\mu_{HII}^2 + \mu_{HRI}^2}
\]  

(2.2)

5

2.24 Structural Information:
2.25 Image Fidelity:

\[
IF = 1 - \frac{\sum_{x=0}^{N-1} \sum_{y=0}^{M-1} (I(x,y) - RL(x,y))^2}{\sum_{x=0}^{N-1} \sum_{y=0}^{M-1} (I(x,y))^2}
\]  

(2.27)

2.26 Normalized Cross Correlation [10]:

\[
NCC = \frac{\sum_{x=0}^{N-1} \sum_{y=0}^{M-1} (I(x,y) \cdot RL(x,y))}{\sum_{x=0}^{N-1} \sum_{y=0}^{M-1} (I(x,y))^2}
\]  

(2.28)

2.27 Structural Content [10]:

\[
SC = \frac{\sum_{x=0}^{N-1} \sum_{y=0}^{M-1} (RL(x,y))^2}{\sum_{x=0}^{N-1} \sum_{y=0}^{M-1} (I(x,y))^2}
\]

(2.29)

2.28 Average Difference [10]:

\[
AD = \frac{1}{NM} \sum_{x=0}^{N-1} \sum_{y=0}^{M-1} (I(x,y) - RL(x,y))
\]

(2.30)

2.29 Universal Image Quality Index: [7, 9, 11]

On the basis of luminance, contrast and structural information UIQI is:

\[
UIQI(I, RL) = i(I, RL) \cdot C[I, RL] \cdot SI(I, RL)
\]  

(2.31)

It can also be defines as:

\[
UIQI(I, RL) = \frac{4\mu_I\mu_RL(\mu_{RL})^2}{(\mu_I^2 + \mu_RL^2)(\sigma_{II}^2 + \sigma_{RL}^2)}
\]  

(2.32)

2.30 Structural Similarity Index Measure: [7, 9, 11]

\[
SSIM(I, RL) = \frac{(2\mu_I\mu_RL + C_1)(2\sigma_{IL} + C_2)}{\mu_I^2 + \mu_RL^2 + C_1(\sigma_{II}^2 + \sigma_{RL}^2) + C_2}
\]  

(2.33)

Where \(C_1\) and \(C_2\) are constant defined as:

\[
C_1 = (K_1L)^2 \text{ where } K_1 = 0.01 \text{ and } L = 2^{\text{bits per pixel}}
\]  

(2.34)

\[
C_2 = (K_2L)^2 \text{ where } K_2 = 0.03 \text{ and } L = 2^{\text{bits per pixel}}
\]  

(2.35)
3. Different Types of Classification of Image Quality Measure

During the past years lots of classification has been made for image quality measures [3].

3.1 Subjective/Objective Quality Measures [8, 9, 10]

Subjective excellence measures are based on the perception of human on the image quality. The most dependable way of evaluating the quality of an image is by subjective estimation.

Subjective measures are used in the Mean Opinion Score (MOS) manner where the excellence of the image is umpired by the group of human spectators and then Mean Opinion Score is used as the image quality measure.

On the other hand, objective image quality measures are quantitative in nature that can envisage the apparent image excellence automatically and have a standard mathematical description. Table 1 shows the comparison of these measures.

<table>
<thead>
<tr>
<th>Feature</th>
<th>Subjective measure (SM)</th>
<th>Objective measure (OM)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Human involvement (observer)</td>
<td>Yes</td>
<td>No</td>
</tr>
<tr>
<td>Automatic</td>
<td>No</td>
<td>Yes</td>
</tr>
<tr>
<td>Mathematically defined</td>
<td>No</td>
<td>Yes</td>
</tr>
<tr>
<td>algorithms</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Expensive evaluation</td>
<td>Yes</td>
<td>No</td>
</tr>
<tr>
<td>Computational complexity</td>
<td>No</td>
<td>Yes</td>
</tr>
<tr>
<td>Inconvenient</td>
<td>Yes</td>
<td>No</td>
</tr>
<tr>
<td>Time consuming</td>
<td>Yes</td>
<td>No</td>
</tr>
</tbody>
</table>

3.2 Blind/Semi-Blind/Non-Blind [8, 9, 10]:

Depending upon the availability of original un-modified image, it is classified into three groups.

Non-Blind image quality measures are full-reference based measures [4] or binary measures. This type of measure required the original and modified image for evaluating the quality i.e., a complete reference image is tacit to be known and input image is compared against it to assess the closeness of input image to a reference image.

Blind image quality measures are no-reference based. For such measures the reference image is not available.

Semi-Blind are Reduced-reference image quality measures. The reference image is only partly accessible, in the form of a set of extorted features made available as side information to help evaluate the quality of the distorted image.

3.3 Based on Type of Information Image Quality Measure (IQM) used [8]:

This type of classification is based on the type of information the quality measure use to compute the results. This includes the Pixel Difference Based (PDB), Correlation Based (CB), Edge Based (EB), Spectral Distance Based (SDB), Context Measure (CM) and Human Visual System Based (HVSB). The first five of them are statistics based and last is human visual system featured based. Table 2 shows the image quality measures classification based on the type of information they used for evaluating quality [5].
Table 2. Classification Based on Type of Information Used by IQM

<table>
<thead>
<tr>
<th>PDB</th>
<th>CB</th>
<th>EB</th>
<th>SDB</th>
<th>CM</th>
<th>HVSB</th>
</tr>
</thead>
<tbody>
<tr>
<td>Mean Square Error</td>
<td>Normalized Cross Correlation</td>
<td>Pratt Edge Measure</td>
<td>Spectral Phase Error</td>
<td>Rate Distortion Measure</td>
<td>HVS Absolute Norm</td>
</tr>
<tr>
<td>Mean Absolute Error</td>
<td>Image Fidelity</td>
<td>Edge Stability Measure</td>
<td>Spectral Phase-Magnitude Error</td>
<td>Hellinger Distance</td>
<td>HVS L₂ Norm</td>
</tr>
<tr>
<td>Modified Infinity Norm</td>
<td>Czekonowski Correlation</td>
<td>Block Spectral Phase Error</td>
<td>Generalized Matusita Distance</td>
<td>Browsing Similarity</td>
<td>Block Spectral Phase Error</td>
</tr>
<tr>
<td>L’A’B’ Perceptual Error</td>
<td>Mean Angle Similarity</td>
<td>Block Spectral Phase Error</td>
<td>Spearman Rank Correlation</td>
<td>DCTune</td>
<td>Block Spectral Phase Error</td>
</tr>
<tr>
<td>Neighborhood Error</td>
<td>Mean Angle Magnitude Similarity</td>
<td>Spectral Phase-Magnitude Error</td>
<td>Block Spectral Phase Error</td>
<td></td>
<td>Block Spectral Phase Error</td>
</tr>
<tr>
<td>Multi-Resolution Error</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

3.4 Similarity and Dissimilarity Based Classification

To classify the image quality measures, following properties are used.

Similarity based image quality measures persuades the following properties:

- Limited Range: \( \text{Min} - \text{Range} \leq \text{Similarity}(II,RI) \leq \text{Max} - \text{Range} \)
- Reflexive property: \( \text{Similarity}(II,RI) = \text{ideal value if and only if } II = RI \) or sometimes some condition.
- Symmetric property: \( \text{Similarity}(II,RI) = \text{Similarity}(RI,II) \)

Dissimilarity based image quality measures persuades the following properties:

- Non-negativity: \( \text{Dissimilarity}(II,RI) \geq 0 \)
- Reflexive property: \( \text{Similarity}(II,RI) = \text{ideal value if and only if } II = RI \)
- Symmetric property: \( \text{Similarity}(II,RI) = \text{Similarity}(RI,II) \)

4. Experimental Results and Discussion

IQEM software is implemented in C# (.Net Framework 3.5) and MATLAB. Both shows the same results for all image quality measure methods. For evaluating the results and performance, different operations are performed on the original, unmodified, input image and then these modified images are compared with input images for image quality. Operations include the following:

- Addition of different types of noise
  - Salt and Pepper Noise
  - Gamma Noise
  - Gaussian Noise
  - Exponential Noise
  - Uniform Noise
- Contrast Enhancement
- Basic Filtration
Mean Filter
Median Filter
Sharpening
Steganography [14, 15, 16, 17, 18, 19, 20]
LSB Matching [21]
LSB Substitution [22]

Experiment are performed on many standard images including Barbara, Lena, Baboon, Pepper, Boat, Stream and Bridge, Airport, General Test Pattern etc. Only the results of Barbara are included in the paper. Discussion and conclusion are based on the experimental results of almost 50 standard images.

Figure 1 shows Barbara image after applying different operations. (a) is the original input image II and (b-l) are the reference image RI used during experiment.

Figure 1. Input Image and Images after Performing Different Operations

Experimental result section is divided into two subsections. First subsection gives the results of similarity and dissimilarity classification, second scrutinize the statistical recital.
4.1 Results of Classification of IQMs in Similarity and Dissimilarity Measure:

To classify the image quality measures, properties of similarity and dissimilarity are checked in between input image II and reference image RI.

4.1.1 Similarity Based Classification: Table 3 shows the similarity based image quality measures. It also includes the range of these measures, ideal value and behavior when these measures show the ideal value.

<table>
<thead>
<tr>
<th>Image Quality Measure</th>
<th>Range</th>
<th>Ideal Value</th>
<th>Behavior to show ideal value</th>
</tr>
</thead>
<tbody>
<tr>
<td>1 Pearson Correlation Coefficient</td>
<td>[-1,+1]</td>
<td>1</td>
<td>If and only if µII =µRI</td>
</tr>
<tr>
<td>2 Spearman’s Rank Correlation</td>
<td>[-1,+1]</td>
<td>1</td>
<td>If and only if µII =µRI</td>
</tr>
<tr>
<td>3 Minimum Ratio</td>
<td>[0,1]</td>
<td>1</td>
<td>If and only if II=RI</td>
</tr>
<tr>
<td>4 Jaccard Measure</td>
<td>[0,1]</td>
<td>1</td>
<td>If and only if II=RI</td>
</tr>
<tr>
<td>5 Normalized Histogram Intersection Coefficient</td>
<td>[0,1]</td>
<td>1</td>
<td>If and only if II=RI</td>
</tr>
<tr>
<td>6 Bhattacharya</td>
<td>[0,1]</td>
<td>1</td>
<td>If and only if II=RI</td>
</tr>
<tr>
<td>7 Contrast</td>
<td>[0,1]</td>
<td>1</td>
<td>If and only if II=RI</td>
</tr>
<tr>
<td>8 Luminance</td>
<td>[0,1]</td>
<td>1</td>
<td>If and only if µII =µRI</td>
</tr>
<tr>
<td>9 Structural information</td>
<td>[0,1]</td>
<td>1</td>
<td>If and only if σII=σRI</td>
</tr>
<tr>
<td>10 Image Fidelity</td>
<td>[0,1]</td>
<td>1</td>
<td>If and only if II=RI</td>
</tr>
<tr>
<td>11 Normalized Cross Correlation</td>
<td>[0,1]</td>
<td>1</td>
<td>If and only if II=RI</td>
</tr>
<tr>
<td>12 Structural Content</td>
<td>[0,1]</td>
<td>1</td>
<td>If and only if σII=σRI</td>
</tr>
<tr>
<td>13 Average Difference</td>
<td>[0,1]</td>
<td>0</td>
<td>If and only if II=RI</td>
</tr>
<tr>
<td>14 UIQI</td>
<td>[-1,+1]</td>
<td>1</td>
<td>If and only if II=RI</td>
</tr>
<tr>
<td>15 SSIM</td>
<td>[-1,+1]</td>
<td>1</td>
<td>If and only if II=RI</td>
</tr>
</tbody>
</table>

4.1.2 Dissimilarity Based Classification:

Table 4 shows the dissimilarity based image quality measures.

<table>
<thead>
<tr>
<th>Image Quality Measure</th>
<th>Ideal Value</th>
<th>Behavior to show ideal value</th>
</tr>
</thead>
<tbody>
<tr>
<td>1 L1 Norm</td>
<td>0</td>
<td>If and only if II=RI</td>
</tr>
<tr>
<td>2 Mean Absolute Error</td>
<td>0</td>
<td>If and only if II=RI</td>
</tr>
<tr>
<td>3 Peak Absolute Error</td>
<td>0</td>
<td>If and only if II=RI</td>
</tr>
<tr>
<td>4 Normalized Absolute Error</td>
<td>0</td>
<td>If and only if II=RI</td>
</tr>
<tr>
<td>5 Maximum Difference</td>
<td>0</td>
<td>If and only if II=RI</td>
</tr>
<tr>
<td>6 Square L2 Norm</td>
<td>0</td>
<td>If and only if II=RI</td>
</tr>
<tr>
<td>7 Mean Square Error</td>
<td>0</td>
<td>If and only if II=RI</td>
</tr>
<tr>
<td>8 Root Mean Square Error</td>
<td>0</td>
<td>If and only if II=RI</td>
</tr>
<tr>
<td>9 Peak Mean Square Error</td>
<td>0</td>
<td>If and only if II=RI</td>
</tr>
<tr>
<td>10 Normalize Square Error</td>
<td>0</td>
<td>If and only if II=RI</td>
</tr>
<tr>
<td>11 Normalized Square L2 Norm</td>
<td>0</td>
<td>If and only if II=RI</td>
</tr>
<tr>
<td>12 Signal to Noise Ratio</td>
<td>Infinity</td>
<td>If and only if II=RI</td>
</tr>
<tr>
<td>13 Peak Signal to Noise Ratio</td>
<td>Infinity</td>
<td>If and only if II=RI</td>
</tr>
<tr>
<td>14 Intensity Ratio Variance</td>
<td>0</td>
<td>If and only if II=RI</td>
</tr>
<tr>
<td>15 Chi-Square</td>
<td>0</td>
<td>If and only if II=RI</td>
</tr>
</tbody>
</table>

4.2 Analysis of Statistical Recital

This section checks the statistical performance of the similarity and dissimilarity measures. Input image is the original Barbara image and reference images are the images after applying different operation as given in Figure 1.

Table 5 shows the result of IQMs when the reference image contain some noise.
Table 5. Analysis of Image Quality Measure when Reference Image

<table>
<thead>
<tr>
<th>Image Quality Measure</th>
<th>Salt &amp; Pepper Noise</th>
<th>Gamma Noise</th>
<th>Gaussian Noise</th>
<th>Exponential Noise</th>
<th>Uniform Noise</th>
</tr>
</thead>
<tbody>
<tr>
<td>1 L₁ Norm</td>
<td>2036483</td>
<td>2079004</td>
<td>5667653</td>
<td>2203776</td>
<td>2716989</td>
</tr>
<tr>
<td>2 Mean Absolute Error</td>
<td>7.7685</td>
<td>7.93077</td>
<td>21.6203</td>
<td>8.40673</td>
<td>10.36449</td>
</tr>
<tr>
<td>3 Peak Absolute Error</td>
<td>0.03946</td>
<td>0.03110</td>
<td>0.08478</td>
<td>0.03296</td>
<td>0.040645</td>
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<tr>
<td>4 Normalized Absolute Error</td>
<td>0.06617</td>
<td>0.06755</td>
<td>0.18416</td>
<td>0.07161</td>
<td>0.088286</td>
</tr>
<tr>
<td>5 Maximum Difference</td>
<td>80.6666</td>
<td>82.3333</td>
<td>60.3333</td>
<td>85.3333</td>
<td>83.3333</td>
</tr>
<tr>
<td>6 Square L₂ Norm</td>
<td>1130538</td>
<td>12340336</td>
<td>19058407</td>
<td>13368956</td>
<td>183373335</td>
</tr>
<tr>
<td>7 Mean Square Error</td>
<td>431.266</td>
<td>470.746</td>
<td>727.020</td>
<td>509.985</td>
<td>699.5137</td>
</tr>
<tr>
<td>8 Root Mean Square Error</td>
<td>20.1669</td>
<td>21.6966</td>
<td>26.9633</td>
<td>22.5828</td>
<td>26.44832</td>
</tr>
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<td>9 Peak Mean Square Error</td>
<td>1.69124</td>
<td>1.84606</td>
<td>2.85106</td>
<td>1.99994</td>
<td>2.743191</td>
</tr>
<tr>
<td>10 Normalize Square Error</td>
<td>0.02572</td>
<td>0.02807</td>
<td>0.04336</td>
<td>0.03041</td>
<td>0.041719</td>
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<tr>
<td>11 Normalized Square L₂ Norm</td>
<td>23671.7</td>
<td>25217.5</td>
<td>36804.6</td>
<td>27132.7</td>
<td>36014.987</td>
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<tr>
<td>12 Signal To Noise Ratio</td>
<td>15.8970</td>
<td>15.5166</td>
<td>13.6290</td>
<td>13.79656</td>
<td>13.79656</td>
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<tr>
<td>14 Intensity Ratio Variance</td>
<td>87.3982</td>
<td>0.42750</td>
<td>20.7588</td>
<td>0.40991</td>
<td>0.425447</td>
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<tr>
<td>15 Chi-Square</td>
<td>1.83527</td>
<td>1.98264</td>
<td>3.09498</td>
<td>2.14583</td>
<td>2.929299</td>
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<td>16 Pearson Correlation Coefficient</td>
<td>0.93227</td>
<td>0.92785</td>
<td>0.89470</td>
<td>0.92237</td>
<td>0.896959</td>
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<td>17 Spearman’s Rank Correlation</td>
<td>0.93227</td>
<td>0.92785</td>
<td>0.89470</td>
<td>0.92237</td>
<td>0.896959</td>
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<tr>
<td>18 Minimum Ratio</td>
<td>0.31190</td>
<td>0.30947</td>
<td>0.01470</td>
<td>0.28160</td>
<td>0.179141</td>
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<tr>
<td>19 Jaccard Measure</td>
<td>0.97486</td>
<td>0.97307</td>
<td>0.95838</td>
<td>0.97093</td>
<td>0.960797</td>
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<td>20 Normalized Intersection Coefficient</td>
<td>0.96774</td>
<td>0.97747</td>
<td>0.90838</td>
<td>0.97642</td>
<td>0.972924</td>
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<tr>
<td>21 Bhattacharya</td>
<td>0.07801</td>
<td>0.06180</td>
<td>0.10349</td>
<td>0.06403</td>
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<tr>
<td>22 Contrast</td>
<td>0.99886</td>
<td>0.99854</td>
<td>0.99507</td>
<td>0.99832</td>
<td>0.997048</td>
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<tr>
<td>23 Luminance</td>
<td>0.99999</td>
<td>0.99999</td>
<td>0.99999</td>
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<td>0.999999</td>
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<tr>
<td>24 Structural Information</td>
<td>0.93227</td>
<td>0.92785</td>
<td>0.89470</td>
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<td>0.896859</td>
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<td>25 Image Fidelity</td>
<td>0.97427</td>
<td>0.97192</td>
<td>0.95663</td>
<td>0.96958</td>
<td>0.958280</td>
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<td>26 Normalized Cross Correlation</td>
<td>0.99742</td>
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<td>0.99868</td>
<td>1</td>
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<td>27 Structural Content</td>
<td>0.97983</td>
<td>0.94546</td>
<td>0.90686</td>
<td>0.94110</td>
<td>0.920229</td>
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<tr>
<td>28 Average Difference</td>
<td>-0.19624</td>
<td>-2.64150</td>
<td>-0.11087</td>
<td>-2.87092</td>
<td>-4.07350</td>
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<tr>
<td>29 UIQI</td>
<td>0.93121</td>
<td>0.92627</td>
<td>0.89089</td>
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<td>0.893808</td>
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<tr>
<td>30 SSIM</td>
<td>0.93129</td>
<td>0.92636</td>
<td>0.89042</td>
<td>0.92065</td>
<td>0.893933</td>
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</table>

Table 6 shows the result of image quality measures when the reference image is enhanced in contrast, sharpened filtered and steganography is applied. For Steganography, the least significant bit (LSB) matching steganography [22] and least significant bit (LSB) substitution Steganography shows the same result therefore the results for steganography are included only once in the table.
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4. Conclusions and Future Work

This paper provides the detail study and classification of image quality measures. From the experimental results, it is clear that the similarity measures are more accurate, consistent and static as compare to dissimilarity measures. Mostly mean square error and peak signal to noise ratio have been used for evaluating the quality of the images. Experimental results show that mean square error and peak signal to noise ratio are exceptionally uncomplicated, easy to execute and have low computational complication. But the result shown by these measures is not good. Mostly the dissimilarity measures are satisfactory for evaluating the difference in images when the images are at variance by just increasing alteration of a certain kind. But these are unsuccessful to confine image quality when they are employed to compute across alteration types. Similarity measures can evaluate the quality across alteration types, are more static, accurate and consistent as compare to that of dissimilarity measures but they are unsuccessful in case of extremely vague image. So depending upon the domain of the problem, image quality measure can be selected for evaluating the quality of the image.

Future work of this contribution, towards the scientific community, will include the evaluation of these similarity and dissimilarity based image quality measures on some...
more real time applications of image processing, pattern recognition and computer vision. Efficiency of similarity and dissimilarity, based on the result of applied domain, will also be the part of future contribution.

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**References**


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