International Journal of Signal Processing, Image Processing and Pattern Recognition
Vol.9, No.4, (2016), pp.347-360
http://dx.doi.org/10.14257/ijsip.2016.9.4.31

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

Aqsa Rashid[1] and Muhammad Khurrum Rahim[2]

Department of Computer Science and Information Technology, The Islamia University of Bahawalpur, Pakistan[1]Department of Electrical Engineering, NUCES, FAST, Pakistan[2]
aqsarashid2@gmail.com[1], aqsa.rashid.pk@ieee.org[1], khurrumrahim@gmail.com[2]

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.

ISSN: 2005-4254 IJSIP
Copyright ⓒ 2016 SERSC

2. Mathematical Forms of Image Quality Measures

This section gives the mathematical definitions and description of the image quality measures used. If $II(x,y), x = 0,1,2,\dots,N-1 \text{ and } y = 0,1,2,\dots,M-1$ and $RI(x,y), x = 0,1,2,\dots,N-1 \text{ and } y = 0,1,2,\dots,M-1$ are the pixel pattern of the input image II and the reference image RI, $N\times M$ represent the dimensions of input and reference image, μ_{II} is the mean of input image, μ_{RI} is the mean of the reference image, σ_{II} is the standard deviation of input image, σ_{RI} is the standard deviation of the reference image, σ^2_{II} is the variance of the input image, σ^2_{RI} is the variance of the reference image, σ_{RIII} is the covariance between input and reference image and H_{II} and H_{IR} 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:

$$L_1 Norm = \sum_{x=0}^{N-1}\sum_{y=0}^{M-1}|II(x,y) - RI(x,y)| \quad (2.1.)$$

2.2 Mean Absolute Error [10]:

$$MAE = {}^1/_{NM} \sum_{x=0}^{N-1}\sum_{y=0}^{M-1}|II(x,y) - RI(x,y)| \quad (2.2)$$

2.3 Peak Absolute Error:

$$PAE = {}^1/_{NM} \frac{\sum_{x=0}^{N-1}\sum_{y=0}^{M-1}|II(x,y) - RI(x,y)|}{\max(II(x,y)) \, for \; x=0,1,2,\dots,N-1 \; and \; y=0,1,2,\dots,M-1} \quad (2.3)$$

2.4 Normalized Absolute Error:

$$NAE = \frac{\sum_{x=0}^{N-1}\sum_{y=0}^{M-1}|II(x,y) - RI(x,y)|}{\sum_{x=0}^{N-1}\sum_{y=0}^{M-1}|II(x,y)|} \quad (2.4)$$

2.5 Maximum Difference [10]:

$$MD = max|II(x,y) - RI(x,y)| \; where \; x = 0,1,2,\dots,N-1, y = 0,1,2,\dots,M-1 \quad (2.5)$$

2.6 Square L_2 Norm:

$$L_2^2 \; Norm = \sum_{x=0}^{N-1}\sum_{y=0}^{M-1}\left(II(x,y) - RI(x,y)\right)^2 \quad (2.6)$$

2.7 Mean Square Error [9, 10]:

$$MSE = {}^1/_{NM} \sum_{x=0}^{N-1}\sum_{y=0}^{M-1}\left(II(x,y) - RI(x,y)\right)^2 \quad (2.7)$$

2.8 Root Mean Square Error:

$$RMSE = \sqrt{{}^1/_{NM} \sum_{x=0}^{N-1}\sum_{y=0}^{M-1}\left(II(x,y) - RI(x,y)\right)^2} \quad (2.8)$$

2.9 Peak Mean Square Error [9]:

Copyright ⓒ 2016 SERSC

$$PMSE = {}^{1}/_{NM}\left(\frac{\sum_{x=0}^{N-1}\sum_{y=0}^{M-1}(II(x,y)-RI(x,y))^{2}}{max(II(x,y))where\ x=0,1,2,\dots,N-1\ and\ y=0,1,\dots,M-1}\right) \quad (2.9)$$

2.10 Normalized Square Error:

$$NSE = \frac{\sum_{x=0}^{N-1}\sum_{y=0}^{M-1}(II(x,y)-RI(x,y))^{2}}{\sum_{x=0}^{N-1}\sum_{y=0}^{M-1}(II(x,y))^{2}} \quad (2.10)$$

2.11 Normalized Square L_2 Norm:

$$NL_2^2 = \sum_{x=0}^{N-1}\sum_{y=0}^{M-1}\left(\frac{II(x,y)-\mu_{II}}{\sigma_{II}} - \frac{RI(x,y)-\mu_{RI}}{\sigma_{RI}}\right)^{2} \quad (2.11)$$

2.12 Signal to Noise Ratio:

$$SNR = 10log_{10}\left(\frac{\sum_{x=0}^{N-1}\sum_{y=0}^{M-1}II(x,y)^{2}}{\sum_{x=0}^{N-1}\sum_{y=0}^{M-1}(II(x,y)-RI(x,y))}\right) \quad (2.12)$$

2.13 Peak Signal to Noise Ratio [10]:

$$PSNR = 10log_{10}\left(\frac{(max(x,y))^{2}\ where\ x=0,1,2,\dots N-1\ and\ y=0,1,2,\dots,M-1}{MSE}\right) \quad (2.13)$$

2.14 Intensity Ratio Variance:

$$IR_V = {}^{1}/_{NM}\sum_{x=0}^{N-1}\sum_{y=0}^{M-1}(R(x,y)-\mu_R)^{2} \quad (2.14)$$

$$R(x,y) = \frac{(II(x,y)-\varepsilon)}{(RI(x,y)-\varepsilon)}\ and\ \mu_R = {}^{1}/_{NM}\sum_{x=0}^{N-1}\sum_{y=0}^{M-1}R(x,y) \quad (2.15)$$

2.15 Chi-Square:

$$d_{Chi-square}(H_{II}, H_{RI}) = \sum_{i=1}^{N}\frac{\left(H_{II}(i)-H_{RI}(i)\right)^{2}}{H_{II}+H_{RI}} \quad (2.16)$$

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

2.16 Paterson Cross Correlation [13]:

$$PCC = \frac{\sum_{x=0}^{N-1}\sum_{y=0}^{M-1}(II(x,y)-\mu_{II})(RI(x,y)-\mu_{RI})}{\sqrt{\sum_{x=0}^{N-1}\sum_{y=0}^{M-1}(II(x,y)-\mu_{II})^{2}\sum_{x=0}^{N-1}\sum_{y=0}^{M-1}(RI(x,y)-\mu_{RI})^{2}}} \quad (2.17)$$

Copyright ⓒ 2016 SERSC

2.17 Spearman's Rank Correlation:

$$SRCC = 1 - \frac{6\sum_{x=0}^{N-1}\sum_{y=0}^{M-1}\left(Rank_{II}(x,y) - Rank_{RI}(x,y)\right)^2}{N \times M\left((N \times M)^2 - 1\right)} \tag{2.18}$$

$$SRCC = \frac{\sum_{x=0}^{N-1}\sum_{y=0}^{M-1}(II(x,y) - \mu_{II})(RI(x,y) - \mu_{RI})}{\sqrt{\sum_{x=0}^{N-1}\sum_{y=0}^{M-1}(II(x,y) - \mu_{II})^2 \sum_{x=0}^{N-1}\sum_{y=0}^{M-1}(RI(x,y) - \mu_{RI})^2}} \tag{2.19}$$

2.18 Minimum Ratio:

$$MIN_r = {}^{1}/_{NM}\sum_{x=0}^{N-1}\sum_{y=0}^{M-1} r(x,y) \text{ where } r(x,y) = min\left(\frac{II(x,y)}{RI(x,y)}, \frac{RI(x,y)}{II(x,y)}\right) \tag{2.20}$$

2.19 Jaccard Measure [13]:

$$d_{Jaccard}(H_{II}, H_{RI}) = \frac{\sum_{x=0}^{N-1}\sum_{y=0}^{M-1} H_{II}(x,y)H_{RI}(x,y)}{\sum_{x=0}^{N-1}\sum_{y=0}^{M-1}\left(H_{II}(x,y)\right)^2 + \sum_{x=0}^{N-1}\sum_{y=0}^{M-1}\left(H_{RI}(x,y)\right)^2 - \sum_{x=0}^{N-1}\sum_{y=0}^{M-1} H_{II}(x,y)H_{RI}(x,y)} \tag{2.21}$$

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

2.20 Intersection [13]:

$$d_{Intersection}(H_{II}, H_{RI}) = \sum_{x=0}^{N-1}\sum_{y=0}^{M-1} min\left(H_{II}(x,y), H_{RI}(x,y)\right) \tag{2.22}$$

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

2.21 Bhattacharya [13]:

$$d_{Bhattacharya}(H_{II}, H_{RI}) = \sqrt{1 - \frac{1}{\sqrt{{}^{1}/_{NM}\sum_{x=0}^{N-1}\sum_{y=0}^{M-1} H_{II}(x,y) \sum_{x=0}^{N-1}\sum_{y=0}^{M-1} H_{RI}(x,y)}}\sum_{x=0}^{N-1}\sum_{y=0}^{M-1}\sqrt{H_{II}(x,y)H_{RI}(x,y)}} \tag{2.23}$$

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

2.22 Contrast:

$$Contrast = C(II, RI) = \frac{2\sigma_{II}\sigma_{RI}}{\sigma^2_{II} + \sigma^2_{RI}} \tag{2.24}$$

2.23 Luminance:

$$Luminance = l(II, RI) = \frac{2\mu_{II}\mu_{RI}}{\mu^2_{II} + \mu^2_{RI}} \tag{2.25}$$

2.24 Structural Information:

 Copyright ⓒ 2016 SERSC

$$Structural\ Information = SI(II, RI) = \frac{2\sigma_{IIRI}}{\sigma_{II} + \sigma_{RI}} \tag{2.26}$$

2.25 Image Fidelity:

$$IF = 1 - \frac{\sum_{x=0}^{N-1}\sum_{y=0}^{M-1}\left(II(x,y) - RI(x,y)\right)^2}{\sum_{x=0}^{N-1}\sum_{y=0}^{M-1}\left(II(x,y)\right)^2} \tag{2.27}$$

2.26 Normalized Cross Correlation [10]:

$$NCC = \frac{\sum_{x=0}^{N-1}\sum_{y=0}^{M-1}\left(II(x,y) * RI(x,y)\right)}{\sum_{x=0}^{N-1}\sum_{y=0}^{M-1}\left(II(x,y)\right)^2} \tag{2.28}$$

2.27 Structural Content [10]:

$$SC = \frac{\sum_{x=0}^{N-1}\sum_{y=0}^{M-1}\left(RI(x,y)\right)^2}{\sum_{x=0}^{N-1}\sum_{y=0}^{M-1}\left(II(x,y)\right)^2} \tag{2.29}$$

2.28 Average Difference [10]:

$$AD = {}^{1}/_{NM} \sum_{x=0}^{N-1}\sum_{y=0}^{M-1}\left(II(x,y) - RI(x,y)\right) \tag{2.30}$$

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

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

$$UIQI(II, RI) = l(II, RI) * C(II, RI) * SI(II, RI) \tag{2.31}$$

It can also be defines as:

$$UIQI(II, RI) = \frac{4\mu_{II}\mu_{RI}\mu_{IIRI}}{({\mu^2}_{II} + {\mu^2}_{RI})({\sigma^2}_{II} + {\sigma^2}_{RI})} \tag{2.32}$$

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

$$SSIM(II, RI) = \frac{(2\mu_{II}\mu_{RI} + C_1)(2\sigma_{IIRI} + C_2)}{({\mu^2}_{II} + {\mu^2}_{RI} + C_1)({\sigma^2}_{II} + {\sigma^2}_{RI} + C_2)} \tag{2.33}$$

Where C_1 and C_2 are constant defined as:

$$C_1 = (K_1 L)^2\ where\ K_1 = 0.01\ and\ L = 2^{\#\ of\ bits\ per\ pixel} \tag{2.34}$$

$$C_2 = (K_2 L)^2\ where\ K_2 = 0.03\ and\ L = 2^{\#\ of\ bits\ per\ pixel} \tag{2.35}$$

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 1. Comparison of Subjective and Objective Quality Measures

Feature	Subjective measure (SM)	Objective measure (OM)
Human involvement (observer)	Yes	No
Automatic	No	Yes
Mathematically defined algorithms	No	Yes
Expensive evaluation	Yes	No
Computational complexity	No	Yes
Inconvenient	Yes	No
Time consuming	Yes	No

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].

Copyright ⓒ 2016 SERSC

Table 2. Classification Based on Type of Information Used by IQM

PDB	CB	EB	SDB	CM	HVSB
Mean Square Error	Normalized Cross Correlation	Pratt Edge Measure	Spectral Phase Error	Rate Distortion Measure	HVS Absolute Norm
Mean Absolute Error	Image Fidelity	Edge Stability Measure	Spectral Phase-Magnitude Error	Hellinger Distance	HVS L_2 Norm
Modified Infinity Norm	Czekonowski Correlation		Block Spectral Magnitude Error	Generalized Matusita Distance	Browsing Similarity
$L^* A^* B^*$ Perceptual Error	Mean Angle Similarity		Block Spectral Phase Error	Spearman Rank Correlation	DCTune
Neighborhood Error	Mean Angle Magnitude Similarity		Block Spectral Phase-Magnitude Error		
Multi-Resolution Error					

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

Dissimilarity based image quality measures persuades the following properties:

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

4. Experimental Results and Discussion

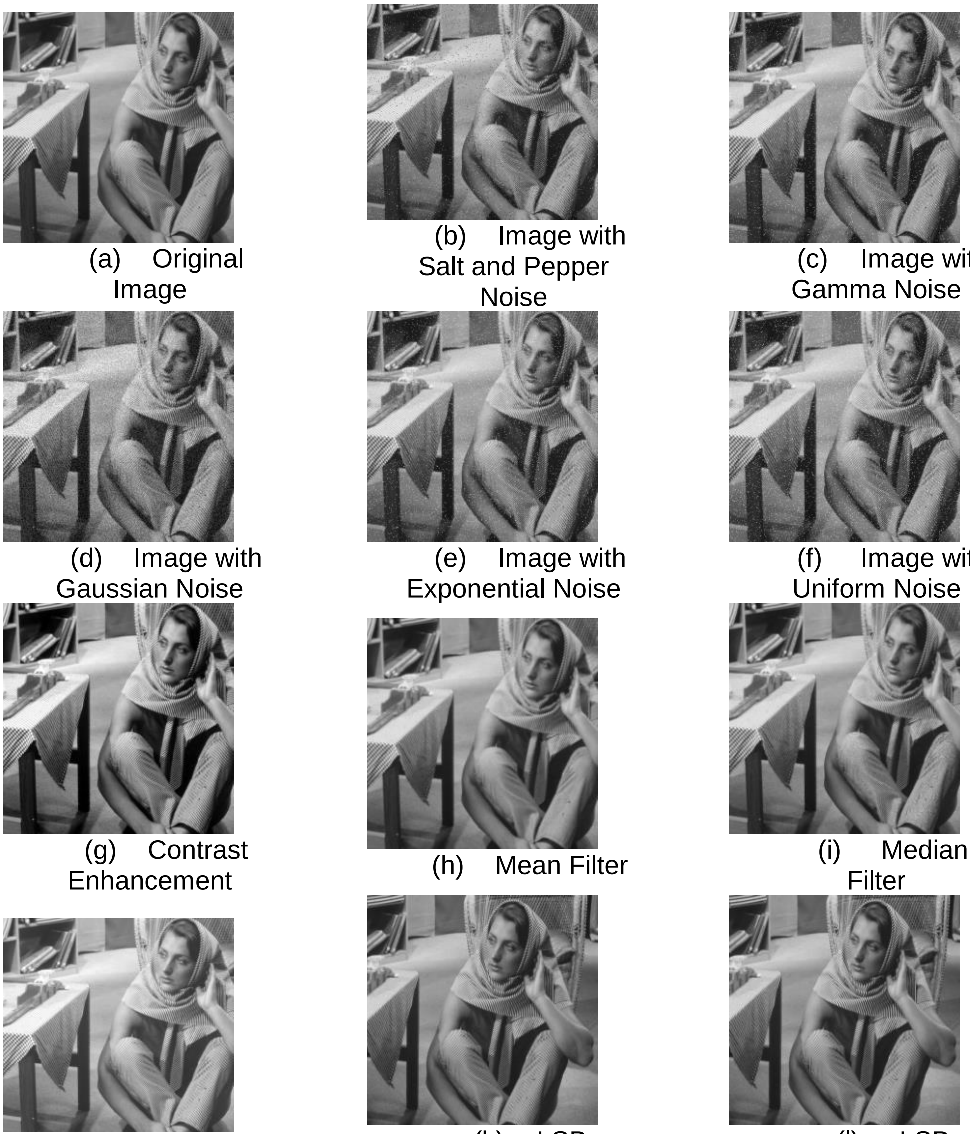
IQEM software is implemented in C# (.Net Framework 3.5) and MATLAB. Both shows the same results for all image quality measure methods. For evaluating the results and performance, different operations are performed on the original, unmodified, input image and then these modified images are compared with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



(a) Original Image
(b) Image with Salt and Pepper Noise
(c) Image with Gamma Noise
(d) Image with Gaussian Noise
(e) Image with Exponential Noise
(f) Image with Uniform Noise
(g) Contrast Enhancement
(h) Mean Filter
(i) Median Filter
(j) Sharpen
(k) LSB Matching
(l) LSB Substitution

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.

 Copyright ⓒ 2016 SERSC

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 3. Similarity Based Image Quality Measures (IQM)

	Image Quality Measure	Range	Ideal Value	Behavior to show ideal value
1	Pearson Correlation Coefficient	[-1,+1]	1	If and only if $\mu_{II} = \mu_{RI}$
2	Spearman's Rank Correlation	[-1,+1]	1	If and only if $\mu_{II} = \mu_{RI}$
3	Minimum Ratio	[0,1]	1	If and only if II=RI
4	Jaccard Measure	[0,1]	1	If and only if II=RI
5	Normalized Histogram Intersection Coefficient	[0,1]	1	If and only if II=RI
6	Bhattacharya	[0,1]	1	If and only if II=RI
7	Contrast	[0,1]	1	If and only if II=RI
8	Luminance	[0,1]	1	If and only if $\mu_{II} = \mu_{RI}$
9	Structural information	[0,1]	1	If and only if $\sigma_{II=}\sigma_{RI}$
10	Image Fidelity	[0,1]	1	If and only if II=RI
11	Normalized Cross Correlation	[0,1]	1	If and only if II=RI
12	Structural Content	[0,1]	1	If and only if $\sigma_{II=}\sigma_{RI}$
13	Average Difference	[0,1]	0	If and only if II=RI
14	UIQI	[-1,+1]	1	If and only if II=RI
15	SSIM	[-1,+1]	1	If and only if II=RI

4.1.2 Dissimilarity Based Classification:

Table 4 shows the dissimilarity based image quality measures.

Table 4. Dissimilarity Based Image Quality Measures (IQM)

	Image Quality Measure	Ideal Value	Behavior to show ideal value
1	L_1 Norm	0	If and only if II=RI
2	Mean Absolute Error	0	If and only if II=RI
3	Peak Absolute Error	0	If and only if II=RI
4	Normalized Absolute Error	0	If and only if II=RI
5	Maximum Difference	0	If and only if II=RI
6	Square L_2 Norm	0	If and only if II=RI
7	Mean Square Error	0	If and only if II=RI
8	Root Mean Square Error	0	If and only if II=RI
9	Peak Mean Square Error	0	If and only if II=RI
10	Normalize Square Error	0	If and only if II=RI
11	Normalized Square L_2 Norm	0	If and only if II=RI
12	Signal to Noise Ratio	Infinity	If and only if II=RI
13	Peak Signal to Noise Ratio	Infinity	If and only if II=RI
14	Intensity Ratio Variance	0	If and only if II=RI
15	Chi-Square	0	If and only if II=RI

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

	Image Quality Measure	Salt & Pepper Noise	Gamma Noise	Gaussian Noise	Exponential Noise	Uniform Noise
1	L_1 Norm	2036483	2079004	5667653	2203776	2716989
2	Mean Absolute Error	7.7685	7.93077	21.6203	8.40673	10.36449
3	Peak Absolute Error	0.03046	0.03110	0.08478	0.03296	0.040645
4	Normalized Absolute Error	0.06617	0.06755	0.18416	0.07161	0.088286
5	Maximum Difference	80.6666	82.3333	60.3333	85.3333	83.33333
6	Square L_2 Norm	1130538	12340336	19058407	13368956	183373335
7	Mean Square Error	431.266	470.746	727.020	509.985	699.5137
8	Root Mean Square Error	20.1669	21.6966	26.9633	22.5828	26.44832
9	Peak Mean Square Error	1.69124	1.84606	2.85106	1.99994	2.743191
10	Normalize Square Error	0.02572	0.02807	0.04336	0.03041	0.041719
11	Normalized Square L_2 Norm	23671.7	25217.5	36804.6	27132.7	36014.987
12	Signal To Noise Ratio	15.8970	15.5166	13.6290	15.1689	13.79656
13	Peak Signal To Noise Ratio	21.7833	21.4029	19.5153	21.0552	19.68284
14	Intensity Ratio Variance	87.3982	0.42750	20.7588	0.40991	0.425447
15	Chi-Square	1.83527	1.98264	3.09498	2.14583	2.929299
16	Pearson Correlation Coefficient	0.93227	0.92785	0.89470	0.92237	0.896959
17	Spearman’s Rank Correlation	0.93227	0.92785	0.89470	0.92237	0.896959
18	Minimum Ratio	0.31190	0.30947	0.01470	0.28160	0.179141
19	Jaccard Measure	0.97486	0.97307	0.95838	0.97093	0.960797
20	Normalized Intersection Coefficient	0.96774	0.97747	0.90838	0.97642	0.972924
21	Bhattacharya	0.07801	0.06180	0.10349	0.06403	0.073759
22	Contrast	0.99886	0.99854	0.99507	0.99832	0.997048
23	Luminance	0.99999	0.99975	0.99999	0.99970	0.999436
24	Structural Information	0.93227	0.92785	0.89470	0.92237	0.896859
25	Image Fidelity	0.97427	0.97192	0.95663	0.96958	0.958280
26	Normalized Cross Correlation	0.99742	1	0.99868	1	1
27	Structural Content	0.97983	0.94546	0.96086	0.94110	0.920229
28	Average Difference	-0.19624	-2.64150	-0.11087	-2.87092	-4.007350
29	UIQI	0.93121	0.92627	0.89089	0.92055	0.893808
30	SSIM	0.93129	0.92636	0.89042	0.92065	0.893933

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.

Copyright ⓒ 2016 SERSC

Table 6. Analysis of Image Quality Measure when the Contrast of Reference Image RI is Enhanced Sharpened, Filtered and Steganography is Applied

	Image Quality Measure	Contrast	Mean Filter	Median Filter	Sharpen	Stegano-Graphy
1	L_1 Norm	3082261	1982704	1694489	6544662	15967.333
2	Mean Absolute Error	11.7589	7.56341	6.46396	24.965904	0.4608842
3	Peak Absolute Error	0.04610	0.02966	0.02534	0.0097905	0.0020179
4	Normalized Absolute Error	0.10015	0.06442	0.05506	0.2126643	0.0082330
5	Maximum Difference	14.3333	39.6666	52.3333	18.666666	0.6666666
6	Square L_2 Norm	50960263	51125194	49360433	163459188	15967.333
7	Mean Square Error	194.397	195.027	188.295	623.54731	0.4608842
8	Root Mean Square Error	13.9426	13.96521	13.7220	24.970929	0.6788820
9	Peak Mean Square Error	0.76234	0.764812	0.73841	2.4452835	0.0018073
10	Normalize Square Error	0.01159	0.011631	0.01123	0.0371891	0.0001111
11	Normalized Square L_2 Norm	212.102	11557.46	11199.59	14.429146	10.876697
12	Signal To Noise Ratio	19.3576	19.34357	19.4961	14.295633	39.545987
13	Peak Signal To Noise Ratio	25.2438	25.22985	25.3824	20.182109	51.510033
14	Intensity Ratio Variance	6.09167	0.229154	0.22532	3.8146827	0.1633088
15	Chi-Square	0.83879	0.932134	0.80219	2.4004973	0.0738829
16	Pearson Correlation Coefficient	0.99939	0.966933	0.96797	0.9999587	0.9873204
17	Spearman's Rank Correlation	0.99939	0.966933	0.96797	0.9999587	0.9873204
18	Minimum Ratio	0.02213	0.171607	0.31547	3.8146972	0.5391157
19	Jaccard Measure	0.98878	0.988303	0.98875	0.9693097	0.998965
20	Normalized Intersection Coefficient	0.93700	0.965989	0.97219	1	0.9873204
21	Bhattacharya	0.07759	0.965989	0.04135	0.0360383	0.0141812
22	Contrast	0.97628	0.998772	0.99931	0.9999999	0.9999999
23	Luminance	0.99965	0.999999	0.99999	0.9816939	0.9999999
24	Structural Information	0.99939	0.966933	0.96795	0.9999587	0.9997724
25	Image Fidelity	0.98840	0.988368	0.98876	0.9628108	0.9998888
26	Normalized Cross Correlation	1	0.982831	0.98876	1	0.9921465
27	Structural Content	0.94657	1	1	0.7213299	1
28	Average Difference	3.03372	0.421936	0.06556	-24.965904	0.04993505
29	UIQI	0.97536	0.965740	0.96729	0.9816526	0.9997719
30	SSIM	0.97538	0.965789	0.96733	0.9816540	0.99977280

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 pack 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

Copyright ⓒ 2016 SERSC

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.

Acknowledgements

We are very thankful to **Sir Dr. Malik Muhammad Saad Missen**, Director Weekend Program at the Department of CS&IT, The Islamia University of Bahawalpur, Pakistan, and **Sir Dr. Nadeem Salamat**, Associate Professor at the Department of Basic Sciences, KFITU, R.Y.Khan, Pakistan, for help.

Thanks to “The USC-SIPI Image Database” and “Photo database provided by Fabien a. P. Petitcolas” for providing the images (Cover Images only remaining are the results of experiments) and facility of conversion of image into different format for research and experiments.

References

[1] D. M. Chandler, “Review Article Seven Challenges in Image Quality Assessment: Past, Present, and Future Research”, Hindawi Publishing Corporation ISRN Signal Processing, Article ID 905685, ,http://dx.doi.org/10.1155/2013/905685, **(2013)**, pp. 53.

[2] R. Kumar and M. Rattan, “Analysis of Various Quality Metrics for Medical Image Processing”, International Journal of Advanced Research in Computer Science and Software Engineering, vol. 2, no. 2, **(2012)**, pp. 137-144.

[3] A. G. George and A. K. Prabavathy, “A Survey on Different Approaches Used in Image Quality Assessment”, International Journal of Emerging Technology and Advanced Engineering, vol. 3, no. 2, **(2013)**, pp. 197-203.

[4] A. George and S. J. Livingston, “A Survey on Full Reference Image Quality Assessment Algorithms”, International Journal of Research in Engineering and Technology, vol. 2, no. 12, **(2013)**, pp. 303-307.

[5] Z. Wang and Qiang Li, “Information Content Weighting for Perceptual Image Quality Assessment”, IEEE TRANSACTIONS ON IMAGE PROCESSING, vol. 20, no. 5, May **(2011)**, pp. 1185-1198,

[6] A. Saffor, A. R. Ramli and K.H. Ng, “A COMPARATIVE STUDY OF IMAGE COMPRESSION BETWEEN JPEG AND WAVELET”, Malaysian Journal of Computer Science, vol. 14, no. 1, **(2001),** pp. 39-45.

[7] N. Thakur and S. Devi, “A New Method for Color Image Quality Assessment”, International Journal of Computer Applications (0975 – 8887) , vol. 15, no. 2, **(2011),** pp. 10-17.

[8] I. Avcıbas, B. Sankur and K. Sayood, “Statistical evaluation of image quality measures”, Journal of Electronic Imaging, vol. 11, no. 2, **(2002)** ,pp. 206–223.

[9] Y. A. Y. Al. Najjar and Dr. D. C. Soong, “Comparison of image quality assessment: PSNR, HVS, UIQI, SSIM”, IJSER, vol. 3, no. 8, **(2012)**, pp.1-5.

[10] C. S. Varnan, A. Jagan, J. Kaur, D. Jyoti and D. S.Rao, “Image Quality Assessment Techniques pn Spatial Domain”, International Journal of Computer Science and Technology (IJCST), vol. 2, no. 3, **(2011)**, pp. 177- 184.

[11] Z. Wang, A. C. Bovik, H. R. Sheikh and E. P. Simoncelli, “Image Quality Assessment: From Error Visibility to Structural Similarity”, IEEE TRANSACTIONS ON IMAGE PROCESSING, vol. 13, no. 4, **(2004)**, pp. 1-14 .

[12] I. Avcıbas, N. Memon and B. Sankur, “Steganalysis Using Image Quality Metrics”, IEEE TRANSACTIONS ON IMAGE PROCESSING, vol. 12, no. 2, **(2003)**, pp. 221-229.

[13] A. P. Nagabhushan and N. U. Bhajantri, “Similarity Measures For Automatic Defect Detection on Patterned Textures”, International Journal of Image Processing and Vision Sciences (Ijipvs), vol. 1, no. 1, **(2012)**, pp.18-24.

[14] M.K. Rahim, N.Slamat, S. Missen and A.Rashid, “Robust Increased Capacity Image Steganograpgy Scheme”, International Journal of Advanced Computer Science and Applications, vol. 5, no. 11, **(2014)**, pp. 125-131.

[15] A. Rashid, “Robust Electronic Communication Scheme in Spatial Domain”, British Journal of Mathematics and Computer Science, vol. 7, no. 3, **(2015)** , pp. 218-228.

[16] A. Rashid, M. M. S. Missen and N. Slamat, “Analysis of Steganography Technique using Least Significant Bit in Graysclae Images and their ectension to Colour Images”, Journal of Scientific Research and Report, vol. 9, no. 3, **(2016)**, pp. 1-14.

[17] A. Rashid and M. K. Rahim, “Experimental Review of Steganography Method that uses 5^{th}, 6^{th} and 7^{th} Bit of a Pixel”, International Journal of Computer Applications, vol. 121, no. 1, **(2015)**, pp. 41-45.

[18] A. Rashid and M. K. Rahim, “Experimental Analysis and Review of Increased Capacity of Information Hinding” , International Journal of Security and its Applications, vol. 9, no. 12, **(2015)**, pp. 221-230.

 Copyright ⓒ 2016 SERSC

[19] A. Rashid and M. K. Rahim, "Experimental Review of "Grey Level Modification" Steganography", International Journal of Signal Processing, Image Processing and Pattern Recognition, vol. 8, no.11, **(2015),** pp. 256-272.
[20] A. Rashid and M. K. Rahim, "Stego-Scheme for Secret Communication in Grayscale and RGB Images", British Journal of Mathematics and Computer Science, vol. 10, no. 1, **(2015)**, pp. 1-9.
[21] A. Rashid, "Experimental Analysis and Comparison of LSB substitution and LSB Matching Method of Information Security", IJCSI International Journal of Computer Science Issues, vol. 12, Issue 1, no. 1, **(2015)**, pp. 91-100,
[22] K. R. Rashid, A. Rashid, N. Salamat and S. Missen, "EXPERIMENTAL ANALYSIS OF MATCHING TECHNIQUE OF STEGANOGRAPHY FOR GREYSCALE AND COLOUR IMAGE", International Journal of Computer Science & Information Technology (IJCSIT) , vol. 6, no. 6, **(2014)**, pp. 157-166.

Authors

Muhammad Khurrum Rahim currently is a student of Electrical Engineering BS (EE) in NUSES FAST Islamabad, Pakistan for the session 2013-2017. He has won the competition of English Creative writing in 2007 held in Pano Akil Region, Pakistan by APS&CS. He has one gold and three silver medals in Inter School Mega Competition 2012 and Inter School Mega Competition 2013 in Pano Akil Region, Pakistan by APS&CS. His fields of interest include Robotics, Image Processing, Signal Processing, Circuit theory, Differential and Telecommunication

Aqsa Rashid received her MSCS degree in 2015 from The Islamia University of Bahawalpur, Pakistan. She attended The Islamia University of Bahawalpur, Pakistan for her MCS degree and completed in November, 2012 with a Gold Medal and specialization in Digital image processing and Information security. Her fields of interest include Information security, Robotics, Digital image Processing, Artificial Intelligence, Pattern recognition, Data Mining and Web Designing and Development. Currently she is engaged in real time image processing and computer vision projects.

Copyright ⓒ 2016 SERSC

Copyright ⓒ 2016 SERSC