Image Quality Assessment Techniques pn Spatial Domain

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Abstract

Measurement of image quality is important for many image processing applications. Image quality assessment is closely related to image similarity assessment in which quality is based on the differences (or similarity) between a degraded image and the original, unmodified image. There are two ways to measure image quality by subjective or objective assessment. Subjective evaluations are expensive and time-consuming. It is impossible to implement them into automatic real-time systems. Objective evaluations are automatic and mathematical defined algorithms. Subjective measurements can be used to validate the usefulness of objective measurements. Therefore objective methods have attracted more attentions in recent years. Well-known objective evaluation algorithms for measuring image quality include mean squared error (MSE), peak signal-to-noise ratio (PSNR), and structural similarity (SSIM). MSE & PSNR are very simple and easy to use. Various objective evaluation algorithms for measuring image quality like Mean Squared Error (MSE), Peak Signal-To-Noise Ratio (PSNR) and Structural Similarity (SSIM) etc. will be studied and their results will be compared

Keywords

Image Quality, MSE, PSNR, SSIM

I. Introduction

Measurement of image quality is crucial to many image processing systems. Due to inherent physical limitations and economic reasons, the quality of images and videos could visibly degrade right from the point when they are captured to the point when they are viewed by a human observer. Identifying the image quality measures that have highest sensitivity to these distortions would help systematic design of coding, communication and imaging systems and of improving or optimizing the image quality for a desired quality of service at a minimum cost.

A. Background

Digital images are subject to a wide variety of distortions during acquisition, processing, storage, transmission and reproduction, any of which may result in a degradation of visual quality. So, measurement of image quality is very important to numerous image processing applications. Humans are highly visual creatures. The main function of human eye is to extract structural information from the viewing field, and the HVS (human visual system) is highly adapted for this purpose. Therefore, for the applications in which images are ultimately to be viewed by human beings, the only "correct" method of quantifying visual image quality is through subjective evaluation. In practice, however, subjective evaluation is usually too inconvenient, time-consuming and expensive. In recent years, a lot of efforts have been made to develop objective image quality metrics that correlate with perceived quality. MSE, PSNR, and SSIM are some useful and most commonly used objective image quality measures.

B. Image quality

Image quality could degrade in almost all systems of practical importance. Digital images are subject to a wide variety of distortions during acquisition, processing, storage, transmission and reproduction, any of which may result in a degradation of visual quality.

C. Need of Quality Measure

As we know the importance of quality of images and videos and the associated cost-quality balance, the obvious question that arises is why we need to measure quality. The answer is simple and could be illustrated by a few examples. If a designer is designing this high-end television, and wants to know what the quality-cost curve looks like, he obviously needs a mechanism for measuring the quality of the output video when his design is running at certain configuration costing a certain resource. In another scenario, a designer of a medical imaging device may want to decide which of the two alternative X-ray devices gives better results. He too needs a way of scientifically comparing the quality of the two systems. Basically, quality assessment algorithms are needed for mainly three types of applications:

1. For optimization purpose, where one maximize quality at a given cost.
2. For comparative analysis between different alternatives.
3. For quality monitoring in real-time applications.

D. Types of Quality Measure

There are basically two approaches for image Quality measurement:-

1. Objective measurement
2. Subjective measurement

1. Subjective measurement

A number of observers are selected, tested for their visual capabilities, shown a series of test scenes and asked to score the quality of the scenes. It is the only "correct" method of quantifying visual image quality. However, subjective evaluation is usually too inconvenient, time-consuming and expensive.

2. Objective measurement

These are automatic algorithms for quality assessment that could analyse images and report their quality without human involvement. Such methods could eliminate the need for expensive subjective studies. Objective image quality metrics can be classified according to the availability of an original (distortion-free) image, with which the distorted image is to be compared.

Most existing approaches are known as: -

(i) Full-reference: meaning that a complete reference image is assumed to be known.
(ii) No-reference: In many practical applications, however, the reference image is not available, and a no-reference or "blind" quality assessment approach is desirable.
(iii) Reduced-reference: In a third type of method, the reference image is only partially available, in the form of a set of extracted features made available as side information to help evaluate the quality of the distorted image.

The work in this thesis is based on the design of full-reference image quality measure.

E. Full-Reference Image Quality Measure

Researchers in the field of image quality measurement have attempted to measure quality using the so-called full-reference (FR) framework. This framework is a consequence of our limited

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understanding of human perceptions of quality. It involves the following hypothesis: The quality of an image could be evaluated by comparing it against a reference signal of perfect quality. A measure of the similarity between the reference image and the image being evaluated could be calibrated to serve as a measure of perceptual quality. There are basically two general classes of objective quality or distortion assessment approaches.

- Simple statistics error metrics
- HVS feature based metric

1. Simple Statistics Error and Correlation Based Metrics

There are large varieties of these metrics. Some of existing measures of image quality are listed below.

(i) Mean Squared Error (MSE): One obvious way of measuring this similarity is to compute an error signal by subtracting the test signal from the reference, and then computing the average energy of the error signal. The mean-squared-error (MSE) is the simplest, and the most widely used, full-reference image quality measurement.

This metric is frequently used in signal processing and is defined as follows [1] :-

$$MSE = \frac{1}{MN}\sum_{i=1}^{M}\sum_{j=1}^{N}(x(i,j)-y(i,j))^2 \qquad (1.1)$$

Where $x(i,j)$ represents the original (reference) image and $y(i,j)$ represents the distorted (modified) image and i and j are the pixel position of the M×N image.

MSE is zero when $x(i,j)=y(i,j)$.

(ii) Peak Signal to Noise Ratio (PSNR): The PSNR is evaluated in decibels and is inversely proportional the Mean Squared Error. It is given by the equation [1]:-

$$PSNR = 10\log_{10}\frac{(2^n-1)^2}{\sqrt{MSE}} \qquad (1.2)$$

(iii) Average Difference (AD): AD is simply the average of difference between the reference signal and test image. It is given by the equation [1]:-

$$AD = \frac{1}{MN}\sum_{i=1}^{M}\sum_{j=1}^{N}(x(i,j)-y(i,j)) \qquad (1.3)$$

(iv) Maximum Difference (MD): MD is the maximum of the error signal (difference between the reference signal and test image) [1].

$$MD = MAX\left|x(i,j)-y(i,j)\right| \qquad (1.4)$$

(v) Mean Absolute Error (MAE): MAE is average of absolute difference between the reference signal and test image. It is given by the equation [1]:-

$$MAE = \frac{1}{MN}\sum_{i=1}^{M}\sum_{j=1}^{N}\left|(x(i,j)-y(i,j)\right| \qquad (1.5)$$

(vi)Peak Mean Square Error (PMSE): It is given by the following equation [1]:-

$$PMSE = \frac{1}{MN}\times\frac{\sum_{i=1}^{M}\sum_{j=1}^{N}(x(i,j)-y(i,j))^2}{(MAX(x(i,j))^2} \qquad (1.6)$$

(vii) Normalized Cross-Correlation (NK): The closeness between two digital images can also be quantified in terms of correlation function. Normalized Cross-Correlation (NK) measures the similarity between two images and is given by the equation [1]:-

$$NK = \frac{\sum_{i=1}^{M}\sum_{j=1}^{N}(x(i,j)\times y(i,j))}{\sum_{i=1}^{M}\sum_{j=1}^{N}(x(i,j))^2} \qquad (1.7)$$

(viii) Structural Content (SC): SC is also correlation based measure and measures the similarity between two images.

Structural Content (SC) is given by the equation [1] :-

$$SC = \frac{\sum_{i=1}^{M}\sum_{j=1}^{N}(y(i,j))^2}{\sum_{i=1}^{M}\sum_{j=1}^{N}(x(i,j))^2} \qquad (1.8)$$

Where $x(i,j)$ represents the original (reference) image and $y(i,j)$ represents the distorted (modified) image.

The simplest and most widely used full-reference image quality measure is the MSE and PSNR. These are appealing because they are simple to calculate, have clear physical meanings, and are mathematically convenient in the context of optimization. MSE and PSNR lack a critical feature: the ability to assess image similarity across distortion types. They both have low computational complexities MSE and PSNR are acceptable image similarity measures when the images in question differ by simply increasing distortion of a certain type. These mathematical measures fail to capture image quality when they are used to measure across distortion types. MSE and PSNR do not model the human visual system. Advantage of MSE and PSNR are that they are very fast and easy to implement. However, they simply and objectively quantify the error signal. With PSNR, greater values indicate greater image similarity, while with MSE greater values indicate lower image similarity.

2. HVS Feature Based Metric

A major emphasis in recent research has been given to a deeper analysis of the Human Visual System (HVS) features. Researchers assume that incorporating knowledge of the human visual system (HVS) and human perception into objective quality assessment algorithms could increase their accuracy. This HVS-based FR paradigm has been the dominant paradigm for the last three decades. The underlying premise is that humans do not perceive images as signals in a high-dimensional space, but are interested in various attributes of those images, such as brightness, contrast, shape and texture of objects, orientations, smoothness, etc. Since the sensitivity of the HVS is different for different aspects of images, it makes sense to account for these sensitivities while making a comparison between the test and the reference signal. There are a lot of HVS characteristics that may influence the human visual perception on image quality. Although HVS is

too complex to fully understand with present psychophysical means, the incorporation of even a simplified model into objective measures reportedly leads to a better correlation with the response of the human observers. Human Visual System (HVS) has been extensively exposed to the natural visual environment, and a variety of evidence has shown that the HVS is highly adapted to extract useful information from natural scenes.Two Human visual systems (HVS) based image quality measures are given below:-
(i) Universal Image Quality Index (UIQI)
(ii) Structural Similarity Index Metric (SSIM).

(i) UIQI (Universal Image Quality Index)

Let x = { xi | i= 1,2,3,..., N} , y= { yi | i= 1,2,3,..., N }
be the original and the test images, respectively[1]:

$$Q = \frac{4 \times \sigma_{xy} \times \bar{x} \times \bar{y}}{(\sigma_x^2 + \sigma_y^2) \times ((\bar{x})^2 + (\bar{y})^2)} \qquad (1.9)$$

$\bar{x}$, $\bar{y}$, σ_x^2 , σ_y^2 and σ_{xy} are given as:

$$\bar{x} = \frac{1}{N}\sum_{i=1}^{N} x_i \qquad (1.9.1)$$

$$\bar{y} = \frac{1}{N}\sum_{i=1}^{N} y_i \qquad (1.9.2)$$

$$\sigma_x^2 = \frac{1}{N-1}\sum_{i=1}^{N} (x_i - \bar{x})^2 \qquad (1.9.3)$$

$$\sigma_y^2 = \frac{1}{N-1}\sum_{i=1}^{N} (y_i - \bar{y})^2 \qquad (1.9.4)$$

$$\sigma_{xy} = \frac{1}{N-1}\sum_{i=1}^{N} (x_i - \bar{x})(y_i - \bar{y}) \qquad (1.9.5)$$

The dynamic range of Q is [0, 1]
Best value Q=1, is achieved when $y_i = x_i$, i = 1, 2,…, n.
This quality index models any distortion as a combination of three different factors: loss of correlation, luminance distortion, and contrast distortion. In order to understand this, rewriting the definition of Q as a product of three components:

$$Q = Q_1 \times Q_2 \times Q_3 \qquad (1.10)$$

$$Q_1 = \frac{\sigma_{xy}}{\sigma_x \times \sigma_y} \qquad (1.10.1)$$

$$Q_2 = \frac{2 \times \bar{x} \times \bar{y}}{((\bar{x})^2 + (\bar{y})^2)} \qquad (1.10.2)$$

$$Q_3 = \frac{2 \times \sigma_x \times \sigma_y}{(\sigma_x^2 + \sigma_y^2)} \qquad (1.10.3)$$

$$Q = \frac{\sigma_{xy}}{\sigma_x \times \sigma_y} \times \frac{2 \times \bar{x} \times \bar{y}}{((\bar{x})^2 + (\bar{y})^2)} \times \frac{2 \times \sigma_x \times \sigma_y}{(\sigma_x^2 + \sigma_y^2)} \qquad (1.11)$$

The first component is the correlation coefficient between x and y, which measures the degree of linear correlation between x and y. The best value 1 is obtained when for $y_i = ax_i + b$ for all i=1, 2... N, where a and b are constants. Even if x and y are linearly related, there still might be relative distortions between them, which are evaluated in the second and third components.The second component, with a value range of [0, 1], measures how much the x and y are close in luminance. It equals to 1 if $\bar{x} = \bar{y}$. σ_x and σ_y can be viewed as an estimate of the contrast of x and y, and the third component measures the similarities between the contrasts of the images. Its range of values is also [0, 1], where the best value 1 is achieved if and only if $\sigma_x = \sigma_y$.

They apply their quality measurement method to local region using a sliding window approach. Starting from top-left corner of the image, a sliding window of size B x B moves pixel by pixel horizontally and vertically through all the row and column of the image until the bottom-right corner is reached. The index is computed for each window, leading to a quality map of the image.

The overall quality index is the average of all the Q values in the quality map:

$$Q = \frac{1}{M}\sum_{j=1}^{M} Q_j \qquad (1.12)$$

M = total number of windows.

(ii) SSIM (Structural Similarity Index Metric)

In Universal image quality index, Q produces unstable results when either $((\bar{x})^2 + (\bar{y})^2)$ or $(\sigma_x^2 + \sigma_y^2)$ is very close to zero.

The SSIM is given by equation below.

$$SSIM = \frac{(2 \times \bar{x} \times \bar{y} + C1)(2 \times \sigma_{xy} + C2)}{(\sigma_x^2 + \sigma_y^2 + C2) \times ((\bar{x})^2 + (\bar{y})^2 + C1)} \qquad (1.13)$$

Where C1 and C2 are constants. $\bar{x}$, $\bar{y}$, σ_x^2 , σ_y^2 and σ_{xy} are given as:

$$\bar{x} = \frac{1}{N}\sum_{i=1}^{N} x_i \qquad (1.13.1)$$

$$\bar{y} = \frac{1}{N}\sum_{i=1}^{N} y_i \qquad (1.13.2)$$

$$\sigma_x^2 = \frac{1}{N-1}\sum_{i=1}^{N} (x_i - \bar{x})^2 \qquad (1.13.3)$$

$$\sigma_y^2 = \frac{1}{N-1}\sum_{i=1}^{N} (y_i - \bar{y})^2 \qquad (1.13.4)$$

$$\sigma_{xy} = \frac{1}{N-1}\sum_{i=1}^{N} (x_i - \bar{x})(y_i - \bar{y}) \qquad (1.13.5)$$

Similar to the case of UIQI, in SSIM, they apply their quality measurement method to local region using a sliding window approach. Starting from top-left corner of the image, a sliding window of size B x B moves Pixel by pixel horizontally and vertically through all the row and column of the image until the bottom-right corner is reached. The overall image quality MSSIM is obtained by computing the average of SSIM values over all windows:

$$MSSIM = \frac{1}{M}\sum_{j=1}^{M} SSIM_j \tag{1.14}$$

M = total number of windows.
UIQI and SSIM greater values indicate greater image similarity. Both UIQI and SSIM measure similarity with greater accuracy and consistency than MSE and PSNR, but incur greater computational cost. Therefore, main focus is on MSE and PSNR due to their commonness and SSIM due to its high performance.

II. Problem Formulation

Measurement of visual quality is of fundamental importance to numerous image processing applications. Due to inherent physical limitations and economic reasons, the quality of images and videos could visibly degrade right from the point when they are captured to the point when they are viewed by a human observer. Identifying the image quality measures that have highest sensitivity to these distortions would help systematic design of coding, communication and imaging systems and of improving or optimizing the image quality for a desired quality of service at a minimum cost i.e. image and video quality could degrade in almost all systems of practical importance, it is crucial for designers and developers to keep the tradeoffs between visual quality and system cost in mind, and to optimize systems for providing maximum visual quality at a minimum cost.Very often the quality of an image needs to be quantified. Optimizing the performance of digital imaging systems with respect to a wide variety of distortions during acquisition, processing, storage, transmission and reproduction, any of which may result in a degradation of visual quality. So, measurement of image quality is very important to numerous image processing applications in this domain. Any imaging system can use the quality metric to adjust itself automatically for obtaining improved quality images. It can be used to compare and evaluate image processing systems and algorithms. This can be done by subjective testing sessions, or by objective – computational metrics. The only "correct" method of quantifying visual image quality is through subjective evaluation. In subjective evaluation, a number of observers are selected, tested for their visual capabilities, shown a series of test scenes and asked to score the quality of the scenes. It is the only "correct" method of quantifying visual image quality. However, subjective evaluation is usually too inconvenient, time-consuming and expensive.On the other hand objective evaluations are automatic algorithms for quality assessment that could analyse images and report their quality without human involvement. Such methods could eliminate the need for expensive subjective studies

A. Objective

On the bases of these ideas the goal of this thesis work is to compare objective image quality matrices for image assessment and their analysis that can automatically predict image quality. Image quality assessment is closely related to image similarity assessment. So, the emphasis in this thesis will be on image fidelity, i.e., how close an image to given original or reference image. Some commonly used methods to evaluate image quality are given below:

(i) Mean Squared Error (MSE)

One obvious way of measuring this similarity is to compute an error signal by subtracting the test signal from the reference, and then computing the average energy of the error signal. The mean-squared-error (MSE) is the simplest, and the most widely used, full-reference image quality measurement. This metric is frequently used in signal processing and is defined as follows [2]:-

$$MSE = \frac{1}{MN}\sum_{i=1}^{M}\sum_{j=1}^{N}(x(i,j) - y(i,j))^2 \tag{2.1}$$

Where $x(i,j)$ represents the original (reference) image and $y(i,j)$ represents the distorted (modified) image and i and j are the pixel position of the M×N image.
MSE is zero when $x(i,j) = y(i,j)$.

(ii) Peak Signal to Noise Ratio (PSNR)

The PSNR is evaluated in decibels and is inversely proportional the Mean Squared Error. It is given by the equation [2]:-

$$PSNR = 10\log_{10}\frac{(2^n - 1)^2}{\sqrt{MSE}} \tag{2.2}$$

(iii) SSIM (Structural Similarity Index Metric)

The SSIM is the best method to evaluate image quality and the SSIM is given by equation 2.3 below [2].

$$SSIM = \frac{(2\times\bar{x}\times\bar{y} + C1)(2\times\sigma_{xy} + C2)}{(\sigma_x^2 + \sigma_y^2 + C2)\times((\bar{x})^2 + (\bar{y})^2 + C1)} \tag{2.3}$$

Where C1 and C2 are constants. $\bar{x}$, $\bar{y}$, σ_x^2, σ_y^2 and σ_{xy} are given as:

$$\bar{x} = \frac{1}{N}\sum_{i=1}^{N} x_i \tag{2.3.1}$$

$$\bar{y} = \frac{1}{N}\sum_{i=1}^{N} y_i \tag{2.3.2}$$

$$\sigma_x^2 = \frac{1}{N-1}\sum_{i=1}^{N}(x_i - \bar{x})^2 \tag{2.3.3}$$

$$\sigma_y^2 = \frac{1}{N-1}\sum_{i=1}^{N}(y_i - \bar{y})^2 \tag{2.3.4}$$

$$\sigma_{xy} = \frac{1}{N-1}\sum_{i=1}^{N}(x_i - \bar{x})(y_i - \bar{y}) \tag{2.3.5}$$

III. Methodology

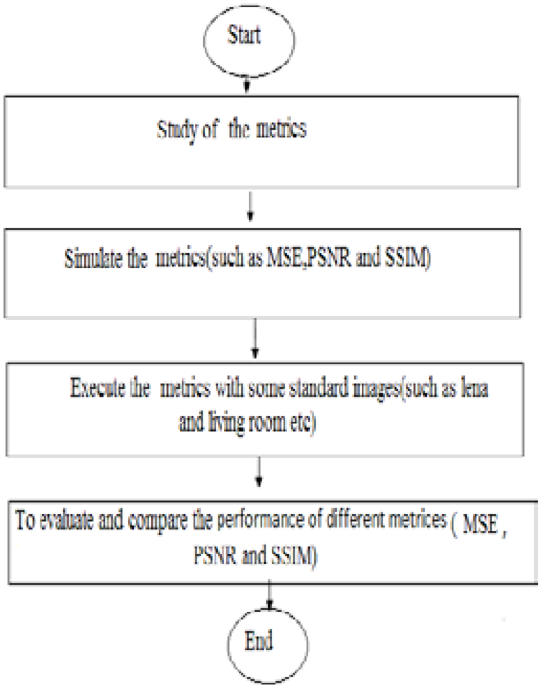
The new image quality metric has been designed using MATLAB software. MATLAB is a powerful, general-purpose, mathematical software package. MATLAB possesses excellent graphics and matrix handling capabilities. It integrates mathematical computing in a powerful language to provide a flexible environment for technical computing. The salient features of MATLAB are its in-built mathematical toolboxes and graphic functions. Additionally, external routines that are written in other languages such as C, C++, FORTRAN and Java, can be integrated with MATLAB applications. MATLAB also supports importing data from files and other external devices. Most of the functions in MATLAB are matrix-oriented and can act on arrays of any appropriate dimension. MATLAB also has a separate toolbox for image processing applications, which provided simpler solutions for many of the problems encountered in this research.

Comparing Different objective image quality matrices step by step.

Step 1: There are many algorithms already developed for measuring image quality. Mean Squared Error (MSE), Peak Signal to Noise Ratio (PSNR), Average Difference (AD), Maximum Difference (MD), Universal image quality index (UIQI) and Structural Similarity Index Metric (SSIM) are some of them. So, first step is to study of the metrics. This is done by a through literature survey. This step is to analyse their significance. This is a detailed study of the parameters used, their individual contribution to the overall formula and the advantages and disadvantages of method, etc.

Step 2: The second step is to simulate the methods (MSE, PSNR & SSIM)

Step 3: Execute the methods with some standard images (such as Lena and Baboon etc.).The images are first corrupted with different kind of noises.



Flowchart for comparing objective image quality metric

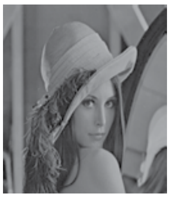
Step 4: The final step is to critically analyse the pros & cons of different methods.

IV. Results

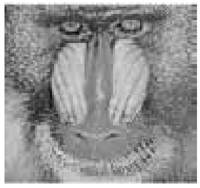
Image quality assessment can be done either by subjective or objective assessment. Subjective evaluations are expensive and time-consuming. It is impossible to implement Subjective evaluations into automatic real-time systems. Objective evaluations which are automatic and mathematical defined algorithms are used for the experiment. Well-known objective evaluation algorithms for measuring image quality such as mean squared error (MSE), peak signal-to-noise ratio (PSNR), and structural similarity index metric (SSIM) have been used. Leena, Living room, Baboon and Bridge have been used as standard test images. Different operations have been applied on the standard test images of Leena ,Living room, Baboon and Bridge and then these images are assessed for image quality. Following operations are applied on the original standard test images:

1) Compression
2) Change in Contrast
3) Add Blur
4) Addition of Gaussian Noise

After applying these operations on standard test images. MSE, PSNR, SSIM are calculated and the results are compared.




Leena Image Living Room

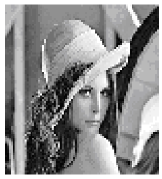



Bridge Image Baboon Image

Fig. 1: Original Images

Results





Original Image Compressed image Contrast Image


Blurred Image Gaussian Noise Image

Fig.2: Different operations on the standard Lena Image

Table1: COMPARISON OF MSE, PSNR, SSIM FOR LEENA IMAGE

ORIGINAL IMAGE		
S.NO	QUALITY MEASUREMENT PARAMETER	QUALITY VALUE
1.	MSE	0
2.	PSNR	∞
3.	SSIM	1
COMPRESSED IMAGE		
1.	MSE	35.4032
2.	PSNR	40.3856
3.	SSIM	0.8719(1st)
CONTRAST IMAGE		
1.	MSE	3.0664
2.	PSNR	45.6976
3.	SSIM	0.8323(2nd)
BLURRED IMAGE		
1.	MSE	30.0145
2.	PSNR	40.7441
3.	SSIM	0.7606(3rd)
GAUSSIAN NOISED IMAGE		
1.	MSE	49.2451
2.	PSNR	39.6690
3.	SSIM	0.1359(4th)


Original Image

Compressed Image

Contrast Image

Blurred Image

Gaussian Noise Image

Fig.3 : Different operations on the standard Living Room image

Table 2: COMPARISON OF MSE, PSNR, SSIM FOR LIVING ROOM IMAGE

ORIGINAL IMAGE		
S. NO	QUALITY MEASUREMENT PARAMETER	QUALITY VALUE
1.	MSE	0
2.	PSNR	∞
3.	SSIM	1
COMPRESSED IMAGE		
1.	MSE	76.7929
2.	PSNR	38.7042
3.	SSIM	0.7468(2nd)
CONTRAST IMAGE		
1.	MSE	3.5898
2.	PSNR	45.3554
3.	SSIM	0.9716(1st)
BLURRED IMAGE		
1.	MSE	58.1150
2.	PSNR	39.3094
3.	SSIM	0.5003(3rd)
GAUSSIAN NOISE IMAGE		
1.	MSE	49.4759
2.	PSNR	39.6588
3.	SSIM	0.2494(4th)


Original Image

Compressed Image

Contrast Image

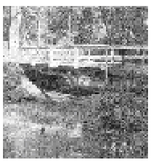
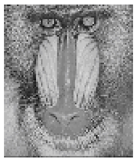
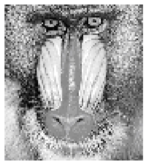
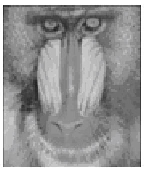
Blurred Image

Gaussian Noise Image

Fig.4 : Different operations on the standard Bridge image

Table : COMPARISON OF MSE, PSNR, SSIM FOR BRIDGE IMAGE

ORIGINAL IMAGE		
S. NO	QUALITY MEASUREMENT PARAMETER	QUALITY VALUE
1.	MSE	0
2.	PSNR	∞
3.	SSIM	1
COMPRESSED IMAGE		
1.	MSE	88.1564
2.	PSNR	38.4045
3.	SSIM	0.6377 (2nd)
CONTRAST IMAGE		
1.	MSE	20.4841
2.	PSNR	41.5737
3.	SSIM	0.9896 (1st)
BLURRED IMAGE		
1.	MSE	73.2754
2.	PSNR	38.8060
3.	SSIM	0.3628 (3rd)
GAUSSIAN NOISE IMAGE		
1.	MSE	49.5933
2.	PSNR	39.6537
3.	SSIM	0.3545 (4th)


Original Image

Compressed Image

Contrast Image

Blurred Image

Gaussian Noise Image

Fig.5 : Different operations on the standard Baboon image

Table 4: COMPARISON OF MSE, PSNR, SSIM FOR BABOON IMAGE

ORIGINAL IMAGE		
S. NO	QUALITY MEASUREMENT PARAMETER	QUALITY VALUE
1.	MSE	0
2.	PSNR	∞
3.	SSIM	1
COMPRESSED IMAGE		
1.	MSE	97.9318
2.	PSNR	38.1762
3.	SSIM	0.5413 (2nd)
CONTRAST IMAGE		
1.	MSE	34.1263
2.	PSNR	40.4654
3.	SSIM	0.9149 (1st)
BLURRED IMAGE		
1.	MSE	75.4143
2.	PSNR	38.7435
3.	SSIM	0.3082 (4th)
GAUSSIAN NOISE IMAGE		
1.	MSE	49.9410
2.	PSNR	39.6385
3.	SSIM	0.3923 (3rd)

V. Conclusions

Image quality measurement plays an important role in various image processing application. A great deal of effort has been made in recent years to develop objective image quality metrics. Unfortunately, only limited success has been achieved. In this thesis some insights on why image quality is so difficult by pointing out weakness of existing image quality measurement approaches in the literature. Experimental results indicate that MSE and PSNR are very simple, easy to implement and have low computational complexities. But these methods do not show good results. MSE and PSNR are acceptable for image similarity measure only when the images differ by simply increasing distortion of a certain type. But they fail to capture image quality when they are used to measure across distortion types. SSIM is widely used method for measurement of image quality. It works accurately can measure better across distortion types as compared to MSE and PSNR, but fails in case of highly blurred image.

VI. Future Work

The SSIM formula works accurately to measure the quality of the still black and white images, but this formula can be modified for color images and video quality measurement. This method focuses on full-reference image quality assessment, means that a complete reference image is assumed to be known. In many practical applications, however, the reference image is not available, and a no-reference or "blind" quality assessment approach is desirable. So, there may be some other method to support this kind of assessment.

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