Image Quality Assessment using the Versatile Covariance Features: A Review

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Abstract

Image quality assessment is a process of undoing or recovering an image from degraded stage. Knowledge of degradation is needed for successful restoration. The image restoration techniques are used to make the corrupted image as compatible to the original image. Hyper spectral image are alter or corrupted by the mixture of diverse kinds of noise in the acquisition process, which may include stripes, impulse noise, Gaussian noise, deadlines, , and so on. This paper introduces the new image quality assessment methods for the quality semantic gap evaluation for restoration of the image data, which can simultaneously removes the Gaussian noise, impulse noise, deadlines, and stripes. But there is no spatial constraint applied on neighboring pixels that originates large areas of missing pixels. To handle the issue of missing pixels non-reference regularization algorithm has been proposed. The proposed model is projected to improve the overall quality of the image quality assessment methods by correctly analyzing the quality of the image matrix.
Keywords: image quality assessment; adaptive quality measurement; HVS; SSIM; ESSIM; MS-SSIM

I. INTRODUCTION

Image quality assessment means evaluating or estimating the quality of an image and image quality assessment plays a vital role in image processing applications[7]-like image enhancement, image restoration, image acquisition and other fields . The quality of the image degrades from the time when image is captured to the time it is displayed to the human for observation. In image processing, image quality assessment may be significant and difficult problem with several interests during a sort of applications such as composing an image quality, optimization of algorithm, dynamic observation, benchmarking image process system and algorithm, parameter settings of image process system[27][29]. Image quality assessment measures the deterioration in digital images so that the quality of the resultant image can be elaborated [12].

II. OBJECTIVE/NEED OF IMAGE QUALITY ASSESSMENT

Within the whole method of visual information acquisition, processing of information, transmission of information and storage of information, in this whole process some noise or artefacts are introduced to the images which derogate the visual quality of an image. In digital system, the image is captured by digital imaging system and is transformed into signal with the help of sensors. To reduce the noise, this raw signal is processed and compressed for transmission and storage. When the image is displayed to the end user on the screen, then that image is not same as that of original one because image has been exhibited to different kinds of noises or distortion [31] like Gaussian noise, motion blurring, compression, sensor inadequacy, and error during transmission or the combination of many influences. To enhance the achievement of visual information acquisition, transmission, processing, and storage systems, image quality assessment is necessary. It is imperative to determine the visual qualities of the images by the digital imaging system, so that it can maintain, control and improve the quality of an image before storage or transmission [21]. The main objective of image quality assessment is to yield computational models to measure the intuitive quality of a given image.

III. CLASSIFICATION/METHODS OF IMAGE QUALITY ASSESSMENT

To guesstimate the quality of an image, there are two methods namely subjective quality assessment and objective quality assessment [18].

A. *Subjective Quality Assessment:*

In subjective quality assessment, quality of an image is rated by observers [18]. In subjective quality assessment, different viewers have different intuition quality. So rating of an image also vary as different observers rated according to their perception.

Subjective quality assessment method can be categorized into following[30][13]-

1) *Single Stimulus Categorical Rating [30]:*

In this type of subjective assessment, for a fixed amount of time, test images are displayed randomly on the screen. After that, images are vanished and observers will be asked for rating the quality as excellent, good, fair, poor or bad.

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2) Double Stimulus Categorical Rating:
As the name indicates double stimulus means two types of input (images) –namely reference and test images are displayed for fixed amount of time and then vanished from the screen [30]and observers will be asked for rating the image quality.
3) Ordering by force-choice pair- wise comparison:
In this type of comparison, two images of the same scene are displayed and observers are immediately asked to choose the image with higher quality and observers have to choose one even if there is no difference in both the images without time limit. In this type of quality assessment, more analysis is required to compare each pair of conditions [13].
4) Pair-Wise Similarity Judgments[32]:
In this method, observers are asked to choose the image with higher quality and reveal the level of difference between test and reference images. However, these rating results are delusive because observers are credible to assign different quality scales to each scene and type of distortion between both the images.

Subjective quality assessment methods indulge rigorous and predictable measurements of the quality of the observable signal, however it's time intense and conjointly an expensive method [8]and they cannot be amalgamate into applications like compression and transmission systems and also their results rely on physical condition and emotion. These are basic reasons for the evaluation of objective image quality assessment algorithms that will forecast the quality of the image automatically.

B. Objective Image Quality Assessment:

Objective IQA can be grouped into three categories on the basis of reference image named as- full-reference, reduced-reference and no-reference[12]. The main motive of objective image quality assessment models is to significantly evaluate the non cognitive quality of images, which are correlated with the human testimonial or recognition. Objective IQA strategies were based on mathematical measures like Euclidean distance between the pixels of the original image and its distorted version.
1) Full-Reference:
When complete reference image is known to compare with the distorted image[12].
2) No-Reference:
When reference image is not available. No- reference method is also labeled as blind quality assessment[12].
3) Reduced-Reference:
When some restricted information is known as a side information of reference image for evaluation [12].
a) Applications of Objective Image Quality Assessment:
Objective IQA methods have a wide variety of applications [24]:
- To upgrade image processing and transmission systems. For example, for upgrading algorithms like pre-filtering and bit assignment at encoder side and also algorithms like post-filtering and reconstruction at the decoder [24] in a visual communication network, an objective IQA can be used.
- To monitor the quality of an image in a quality control system, objective IQA is used. For example, an objective IQA can be employed in image acquisition system to guide and consequently adjust them to obtain the best quality image data [24].
- To benchmark image processing algorithms. For example, when various algorithms on image enhancement are available, then objective IQA metric is used to choose the algorithm which contributes higher quality of an image [24].

4) Metrics:
a) Mathematical Metrics:
1) PSNR: The Peak Signal to Noise Ratio [18] is widely used metrics because of its standardized and computing simplicity. Peak Signal to Noise Ratio may be a classical index which is outlined as the ratio between the ultimate desirable power of a signal and the power of noxious noise which influence the morality and authenticity of its representation. It is inclined as:

$$PSNR = 10\log_{10} 255^2 / MSE$$

Where, 255 is the maximum gray level of a 8bits/pixel monotonic image.

The calculated PSNR embrace dB value for intuition of the quality of an image. The image quality depends upon the PSNR. If the value of PSNR is high then the quality of an image will also be higher and vice-versa.
2) MSE: MSE stands for the mean squared error .It is exemplify as the divergence or variation between the original image and distorted image[17]. The mathematical interpretation for MSE is

$$MSE = \left(1 / M \times N\right)\sum_{i=1}^{M} \sum_{j=1}^{N} (a_{ij} - b_{ij})^2$$

Where, in the original image , *aij* means the pixel value at position (i, j)and in the distorted image bij means the pixel value at position(i, j). All the equations of these mathematical metrics are taken from[17] [18].
b) HVS based metrics
In HVS based approach, the error signal is defined as the difference between the reference and the distorted image, is normalized according to its visibility [28].
Some HVS features which are commonly used in IQM are:

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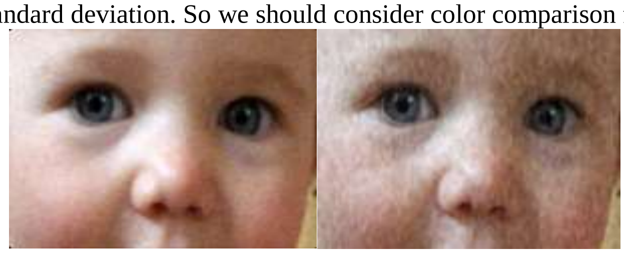
1) Contrast Sensitivity Function (CSF): As Human Judgment Is More Responsive To Lower Spatial Frequency As Compared To Higher One. Hence, Some IQM Models Implement CSF As Weighting Factors For Sub Bands After Decomposition Of Frequency[28] And Some IQM Models Implement CSF As The Low-Pass (Or Band-Pass) Filter.
2) Luminance contrast sensitivity: As human eyes are very sensitive to luminance contrast as compared to absolute luminance value. By Weber's law, the magnitude relation ΔL/L of simply notable brightness or luminance difference ΔL and the luminance L is constant for large range of luminance. For low background luminance (e.g. dark), when the background luminance decreases, this ratio increases. This impact is sculptured as luminance masking in numerous IQM [33].
3) Contrast masking: Contrast masking invokes to the reduction in the visibility of one image element by the presence of another element.

c) Other Metrics

1) SSIM**:** SSIM stands for **S**tructural Similarity Index which measures the similarity between two images [24]. The SSIM index is a full reference metric [18]. SSIM is accomplished to upgrade conventional methods like PSNR and MSE [18]**.**
2) ESSIM: ESSIM stands for Edge–based Structural Similarity. As SSIM declines in mapping badly blurred images. To map badly blurred images ESSIM has been developed. ESSIM can be denominated as the method of correlating quantity metrics which measures the edge information between the original image and the distorted image block and replaces the structure comparison of SSIM with the edge based structure comparison [26].To get edge information some ways are edge detection algorithm and local gradients.
3) MS-SSIM: MS-SSIM stands for Multi Scale Structural similarity. As SSIM and ESSIM are single scale methods but MS-SSIM is multi scale and hence more flexible. The two main operations used in MS-SSIM are low-pass filtering and down sampling [11].Both the original and distorted images are attractively low-pass filtered and after that down sampling will be performed on that by the factor of 2. For multi scale operation, the original image is taken as scale1. In multi scale structure similarity three comparisons have been performed. The one comparison is performed on scale M is luminance comparison. Other two comparisons are performed on the intermediate scale and after all these the final quality measurement [11] metric is the combination of these three comparisons.
4) FSIM: FSIM stands for Feature Similarity. This full reference metric is proposed on the basis of HVS, as human visual system (HVS) gets an image in agreement to its low-level features rather than high level features [34]. The two features which can be viewed as FSIM are- Phase congruency and Gradient magnitude.

The extensive used strategies of full-reference quality assessment are error sensitivity based strategies. By considering the test image signal as the sum of the original image signal and an error signal. One problem with these strategies is that larger visible variations might not essentially embody lower noncognitive quality. Canonical quality measures, such as MSE, WMSE or PSNR, are straightforward to calculate, are mathematically convenient in the direction of optimization [1] and have clear physical meanings. However, they are all error sensitivity based strategies and that's why they are not invariably correlate with visual observations. It is additionally vital to yield their drawback, such as the natural image complexity problem, supra-threshold problem[1].

In last three decades, great attempts have been made to flourish new objective video or image quality methods which incorporate non cognitive quality measures in view of HVS characteristics. Structural similarity is presented as an innovative philosophy for objective QA methods. It is different from the typical HVS-based approaches, which typically consider signal difference between the test and reference images, and attempts to quantify the difference non cognitive by associating accepted HVS properties. In order to incorporate perceptual quality measures, Zhou Wang [26] first proposed a structural similarity (SSIM) measurement system for image quality assessment. The system includes three comparisons: structure, contrast and luminance. By deeply studying the SSIM, Guan-Hao Chen et al.[25] found it fails in measuring the badly blurred images, and develop a reformed method which is termed as Edge-based Structural Similarity (ESSIM). Although the values of mean structural similarity (MSSIM)[9] show much better consistency with the qualitative visual appearance than other image quality methods which are based on error sensitivity, only the luminance component is used for color image quality assessment. An example is shown in Fig. 1, where the original image is distorted by different noise, each to provide nearly identical standard deviation relative to the original image. Fig. 1(a) is the original image, Fig. 1(b) is distorted by uncolored noise, while Fig. 1(c) is distorted by some color noise and Fig. 1(d) is distorted by more color noise, respectively. Except for the different color of the noise, Fig. 1(b) and (c) almost have the same noise, but we can see that the two images have hugely different perceptual quality. As shown in Fig.1, color difference makes the images look different with same standard deviation. So we should consider color comparison for measuring color image quality.



(a) (b)

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(c) (d)

Fig. 1: Different looks with same standard deviation ($\sigma = 8$). (a) Original image (b) Uncolored noise distorted image (c) Some color noise distorted image (d) More color noise distorted image

IV. Literature review

El-Abed et al.[2] has proposed a generic methodology for assessing the quality of an image on the basis of biometric information by combining two types of information-The first information is image quality and the other one is pattern based quality by using the descriptor named as-Scale Invariant Feature Transformation (SIFT) . To depict the benefits of the proposed cadent, one verification system and six benchmark databases are used. This measured has the advantage of being both multinodal and independent from used system. Three types of alterations –Gaussian noise, blurring, resolution are detected in this metric.

Zhang, Peng et al. [3] has proposed a no-reference quality assessment for image on the basis of semantic obviousness. Algorithm which is based on the semantic obviousness measures the quality of an image from both semantic sense and signal level. The concluded quality of an image of semantic obviousness illustrates high flexibility with human perceptual quality. For evaluating distortion–specific and non-distortion specific experiments of NR-IQA method, LIVE dataset is used. Semantic obviousness method is compared to full-reference image quality assessment methods and surpass the state-of-art non-reference image quality assessment method.

Zhang, Min et al. [4] has proposed the blind image quality assessment of generalized local binary pattern using the joint statistics. The new quality-aware feature is emerged from the recommended joint generalized local binary pattern (GLBP) statistics. By using the Laplacian of Gaussian (LOG) filters, firstly the images are decomposed into multi-scale subband images. After that, the subband images are encoded with the GLBP operator and the quality-aware features are devised from the joint GLBP histograms from the encoding maps of each subband image. By using support vector regression(SVR), the quality-aware features are epitomized to the image’s subjective quality score NR-IQA .

Shahid, Muhammad, et al.[6] has reviewed and classified approaches for no-reference image and video quality assessment on the basis of methodologies used for the hidden processing which is utilized for quality estimation. In this paper, authors classified NR image and video quality assessment into three methods. The first method is based on pixel-which is further classified on the measures of artifacts and features. The second method is based on bit stream –which is further categorized as parametric planning and packet layer model and bitstream layer model. The third method is the combination of first method and second method –which consists of artifacts and features based on pixel and bitstream and also consists of statistics of transform coefficients.

Nisha, et al. [10] has reviewed various kinds of techniques which are used for assessing the quality of an image. In this paper, subjective and objective methods are described .In Subjective methods humans vote for the quality of an image, so it varies from one human to another. So this method is not applicable in real time environment because it is tedious and expensive while objective methods are based on the intensity of two images. Three kinds of methods are described such as full reference, no-reference and reduced reference. Objective based metrics are described i.e. Statistics error metrics and HVS based metrics. HVS metrics such as SSIM, MSSIM, DSSIM are more efficient than statistics error metrics such as PSNR, MSE because PSNR, MSE become unstable when the image is depraved by certain amount.

Anish Mittal et al.[15] has worked on blind image quality assessment (IQA) model that percolates in the spatial domain. The new model, named blind/referenceless image spatial quality evaluator (BRISQUE) does not estimate distortion-specific features, such as blur, blocking ,or ringing, but preferably uses scene statistics of locally standardized brightness coefficients to strength possible losses of “naturalness” in the image due to the existence of distortions, thereby leading to a holistic measure of quality. No transformation to another coordinate frame (DCT, wavelet, etc.) is required, categorizing it from preceding NR IQA approach. BRISQUE is statistically preferable than the full-reference structural similarity index metric and PSNR due to its simplicity. BRISQUE has very low computational complexity. BRISQUE features may be used to identify distortion and well suited for real time applications.

Michele A. Saad et al. [16] has worked on the blind image quality assessment algorithm by using a model named as natural scene statistics of DCT(discrete cosine transform) coefficients. The algorithm is computationally attractive, given the availability of platforms expansion for DCT computation . The approach forecast image quality scores on the basis of Bayesian inference model .The features are based on DCT coefficients of the image on an NSS model . The predicted parameters of the model are employed to form features which are demonstrative of intuitive quality. These features are used to predict quality scores in a simple Bayesian inference approach.

Benoit, Aleixandre, et al.[19] has proposed an objective quality cadent for assessment of stereo pairs by using the depth information and 2D quality metric and also reviews diverse problems that are linked with 3D visualization. For subjective

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assessment, the suggested metric is criticized using a methodology named as Subjective Assessment Methodology for Video Quality (SAMVIQ). In this paper, according to results, quality metric can be improved by depth information.

Han, Ho-Sung, et al.[20] has proposed image quality assessment algorithm for assessing structural information using LU factorization . LU factorization also called MLU is suggested to assess the structural information of distorted image. In suggested algorithm, firstly LU factorization is performed in both reference and distorted image. Then, for measuring the quality of distorted image, a distortion map is enumerated. After determining distortion map, the suggested image quality metric is calculated from two –dimensional distortion map. The quality of an image is assessed by enumerating L2 norm of the distinction of diagonal component vectors. Experimental results of the suggested algorithm with LIVE database shows that MLU is better than SSIM, MSE, MSVD. MLU can be adapted to various applications such as monitoring the network, for assessing the quality of compressed web content / monitor, etc.

Yi, Yaohua, et al. [22] developed an image quality assessment on the basis of structural distortion and image definition. In this paper, author proposed a unique index of image quality assessment. The aspect of image quality assessment embrace gradation, consistency and definition. The image quality assessment methodology supported structural distortion which conclude distortion issue into three totally different factors i.e. mean distortion, variance distortion and loss of correlation .So, the image definition drawback is not taken under consideration. Experimental results of the suggested method will be more persistent with human perception.

Sheikh, et al.[23] has recommended relationship between image info and visual quality and additionally presents a VIF criterion for full reference IQA. VIF comes from quantification of two mutual information quantities .The first amount is the mutual information between input and output of HVS channel when no distortion is present and also the second amount is the mutual information between the input of the distortion channel and the output of HVS channel for test image. During this paper, main contribution is to quantify the information| present within the reference image and conjointly to quantify what proportion information is extracted from distorted image. By combining such the quantities, author recommended a visible information fidelity measure for assessing the standard of a picture. By testing during this analysis, VIF was incontestable to be higher than SSIM index, progressive HVS technique, structural fidelity criterion, the Sarnoff 's JND matrix.

V. FINDINGS OF LITERATURE STUDY

The existing model has not been found able to perform well on the asymmetric distorted stereoscopic image database (ADSID) [5], which carries the random distortion in the stereoscopic images in non-referenced patterns. The existing methods evaluate the image quality over the symmetric distorted stereoscopic image with its state-of-the-art methodology. The existing model has not been found sufficient to explore the robust relevance evaluation for the sparse properties of an image against its left-right images. The evaluation of sparse image matrix against the left-right image matrices can produce the better results with the in-depth image quality assessment (IQA) methods. The existing model also lacks in utilizing the blind quality assessment, which are the useful non-reference image quality assessment (NR-IQA) methods [5].

VI. METHODOLOGY

Digital images are [14] apparent to a vast variety of distortions during acquisition, storage, processing, transmission and reproduction, which may outgrowth in a disgrace of perceptible quality. So, measurement of image quality is very significant to diverse image processing applications. Humans are highly perceptible creatures. The main objective of human eye is to choose structural information from the viewing field, and the HVS (human visual system) is highly acceptable for this purpose.

Image Acquisition
Preprocessing to denoise
Image Quality Feature Extraction
Image Quality Feature Evaluation and Comparison
Image Quality Assessment report with useful parameters

Fig. 2: Flow of proposed model

So the applications in which images are eventually viewed by human beings, the only "appropriate" method of quantifying perceptible image quality is concluded by subjective evaluation. In manner, subjective evaluation is too embarrassing, immoderate and tedious [7].In recent years, a lot of attempts have been made to develop objective image quality metrics that associate with perceived quality. MSE, PSNR, and SSIM are advantageous and most commonly used objective image quality measures. These are automatic algorithms for assessing the quality that could analyze images and hustle their quality without human intervention. Such methods could remove the need for excessive subjective studies.

VII. CONCLUSION

The proposed image quality assessment method is based upon the blind quality assessment methodology which incorporates the in-image properties for the evaluation of the quality of the given image. This project proposed an improved quality assessment

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method by calculating color comparison into structural similarity measurement system for evaluating color image quality. After that disparate the task of similarity measurement into four comparisons i.e. luminance, color, structure and contrast. Five different distortion types of image sets are used to evaluate the performance of the proposed method. The experimental results will be obtained for predicted quality scores are projected to be more effective and consistent with visual quality based proposed in the form of PSNR, MSSIM and ESSIM for color images.

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