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Opinion Unaware Blind Image Quality Assessment

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ABSTRACT

Human society is living in the age of high speed development and increase of high volume of visual data. It has become a highly desirable goal to be able to faithfully evaluate the quality of these visual data or images in many applications. Users are in demand of good quality digital visual content and monitoring the quality of digital images is becoming quite puzzling. The quality of images can be worsened due to image enhancement, noise corruption, blur, compression, etc. Therefore, blindly evaluating the quality of an image has been increasingly significant. Applications mostly will be dealing with distorted images and not always with their originals and hence Non Reference or Blind Image Quality Assessment Method demands high interest in real world. An analysis of opinion unaware blind quality assessment technique is discussed in this paper.

***Index Terms*:** Gaussian distribution, Normalized luminance, quality Assessment, statistical properties.

1. INTRODUCTION

The modern era where we live in is an increasingly digital epoch. Progresses in technology have made it easy to capture, store and transmit images and videos. All these types of manipulations happening to the image gradually leads to reduction in quality or content in the image. This led to an increase in development of tools for assessing image quality. Image Quality Assessment tools help in rating the way humans perceive quality of images. It is now a challenge for research community to develop the most accurate quality assessment tool. Investigators in quality assessment have attempted to study and analyze how the existence of these distortions disturbs the viewing experience. The ideal approach to measure the effect of distortions on the quality of viewing experience is to collect opinions from a sufficiently large sample of the human population. Taking an average of those opinions will give the perceived average quality measure denoted by subjective assessment. In objective assessment, the evaluation of quality is done by means of algorithms. Of the two, collecting the subjective opinion of image quality is the best gauge of how distortions affect perceived quality, but tit consumes more time and is inefficient. Existing IQA metrics can be classified into three categories according to the availability of the original image: 1) full-reference IQA; 2) reduced-reference IQA; and 3) no-reference/ blind IQA (BIQA). Of these approaches, BIQA does not require any reference information, which enhances its applicability remarkably and renders it significantly in practice[7]. Objective quality assessment is a very complicated task, and even full-reference QA methods have had only limited success in making accurate quality predictions.

Human beings can easily recognize the distortions or noises in natural images and there exists certain structures that discriminate the unnatural from the natural. Such structures are called Natural Scene Statistics, NSS [13]. Also natural images are highly non-random with interdependencies within them[9].

Earlier work in BIQA was based on knowledge of the type of distortion happened to the image and then, as developments happened, the distortion detecting algorithm determined the type of distortion and

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based on that, quality was assessed[1][7]. A technique has been established to directly map image features to subjective quality without distinguishing the type of distortion [11]. Saad et al. [1] formulated BLIINDS and BLIINDS-II using NSS. Li et al. [10] used a regression network to regress the image features to quality scores.

2. REVIEW OF STATE OF THE ART METHODS

Quality Assessment Based on DCT: Michele Saad, Alan C. Bovik, Christophe Charrier developed a method called by the name BLIINDS [1] to effectively assess quality in NSS images. The algorithm relies on discrete cosine transform for feature extraction. The local DCT contrast value is calculated and is used for determining the distortion. The histogram pattern of undistorted and distorted images shows a major difference. The distorted images exhibit a higher peak at 0 and the variance value also gets changed accordingly. The DCT coefficient Kurtosis value is computed for this. The degree of this peak and tail weight are quantified to get the distortion value. The result is further enhanced by including the image details in multi scales.

Anush Krishna Moorthy and Alan C. Bovik[4] in 2011 devised a method using wavelet transform coefficients for blind image quality assessment (DIIVINE). Here a loose wavelet transform is applied on to the image and the scale-space-orientation of the image is noted. These supply a set of statistical features and those are stacked to form a vector. By means of this feature vector, the distortion type is determined and the quality score is calculated. Here, a regression model is developed for each category of distortion and mapping is done from distortion to quality value. Hence a probabilistic distortion identification is combined with distortion specific quality score to produce a final quality value for the image.

Peng Ye, Jayant Kumar and Le Kang suggested a method of Image Quality Assessment using code book[5] in 2012. In this method of NR-IQA(CORNIA), raw-image-patches local descriptors instead of hand-crafted features, which are more efficient and easily computable are used. Then, a codebook based approach which allows to learn highly effective features automatically is adopted.

The method CORNIA was tested on LIVE IQA and TID2008. Performance of this system improved as the number of code-words in codebook was increased.

In 2013, Xinbo Gao and Xuelong Li[12] successfully implemented a method of Image Quality Analysis by multiple Kernel Learning[12] . This paper uses the secondary and tertiary properties of wavelet transform to get the features of NSS images. Secondary properties of Wavelet transform gives Non-Gaussianity, Clustering and Persistency. Tertiary properties give EDC and strong persistency at finer scales.

Another assessment algorithm using Deep Learning was developed recently by Weilong Hou and Xinbo Gao,-This paper[8] inspects how to assess the visual quality of an image by learning rules from linguistic explanations. Normally, subjects are used for providing linguistic descriptions, here this method learns the qualitative evaluations and provides numerical marks for comparison [16]. The exponential decay characteristic of wavelet coefficients are used to represent the image. The magnitudes of the wavelet coefficients decay exponentially across scale for natural images. Besides, the exponential decay is not dependent on particular image content and is hence appropriate for making a universal BIQA method.

The image is decomposed into 3 scales and the values of magnitudes and entropy in these sub-bands are calculated. . In this framework, a four-layer deep model is used to assign image representation to five ratings corresponding to the five adjective labels in the LIVE II database [18], i.e., excellent, good, fair, poor, and bad. The discriminative deep model is pre-trained by DBN and back-propagation is used for fine-tuned. The input image is classified into one among the five grades based on the corresponding probabilistic confidence P(L|X). These grades are then converted to numerical scores by taking the mean of marginal distribution.

Next section discusses about opinion unaware blind quality assessment method. Opinion unaware indicates that meta data is not available in the dataset.

3. QUALITY ASSESSMENT IN NATURAL IMAGES

Most of the existing quality assessment methods concentrate mapping the image domain from spatial to another and doing processing on that. We are concentrating and processing in spatial domain since we think that the visual cortex of human beings respond well in spatial domain. The normalized luminance value of the image offers a good knowledge about the amount of distortion happened to the image and also the amount of naturalness presented in the image under consideration. In this paper, we examine the quality of an NSS image by inspecting the normalized luminance value and then pairwise product of these coefficients are modelled to compute the quality score[14]. Opinion-unaware methods do not need human subjective scores for training and thus the practical applicability of such methods are more compared to opinion aware quality assessment methods. Also they do not depend on training samples and hence the outcome is purely an independent value.

We made an attempt to check the versatility of this kind of quality prediction. The inspiration for creating such a model is based on the fact that NSS images possess some statistical properties and the amount of distortion happened to the image can be found by collecting together this variations from original distribution.

We then demonstrate how the statistical features obtained from the image can represent quality and that the representation confirms well with human perception of quality.

3.1. Finding the normalized luminance

a) $$\overline{I}(i,j) = {}^{I(i,j)-\mu(i,j)} /_{\sigma(i,j)+c} \tag{1}$$

Where I and j are spatial indices and i =1, 2, ... M and n = 1, 2, … N. μ(i, j) represents the mean and is taken as

$$\mu(i,j) = \sum_{k=-k}^{K} \sum_{i=-L}^{L} W_{ki} I_{ki}(i,j) \tag{2}$$

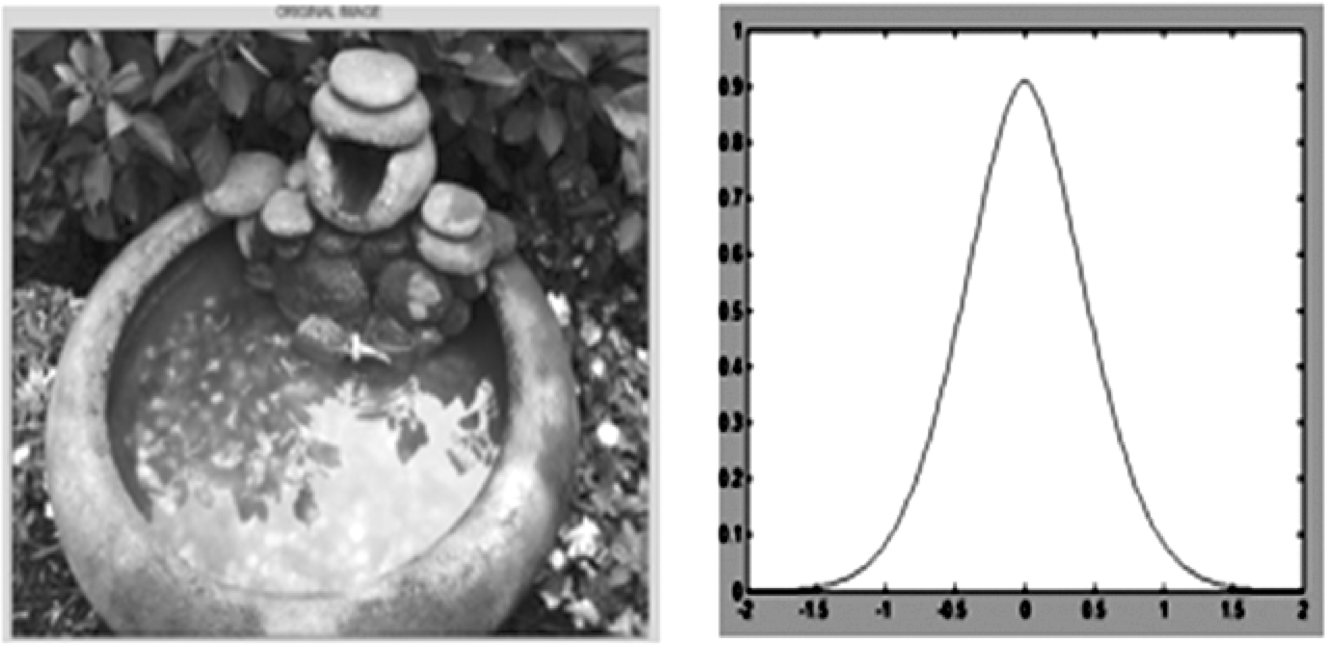
Variance, σ(i ,j) is obtained as

$$\sigma(i,j) = \sqrt{\sum_{k=-K}^{K} . \sum_{l=-L}^{L} w_{ki} I_{ki}(i,j) - \mu(i,j)2} \tag{3}$$

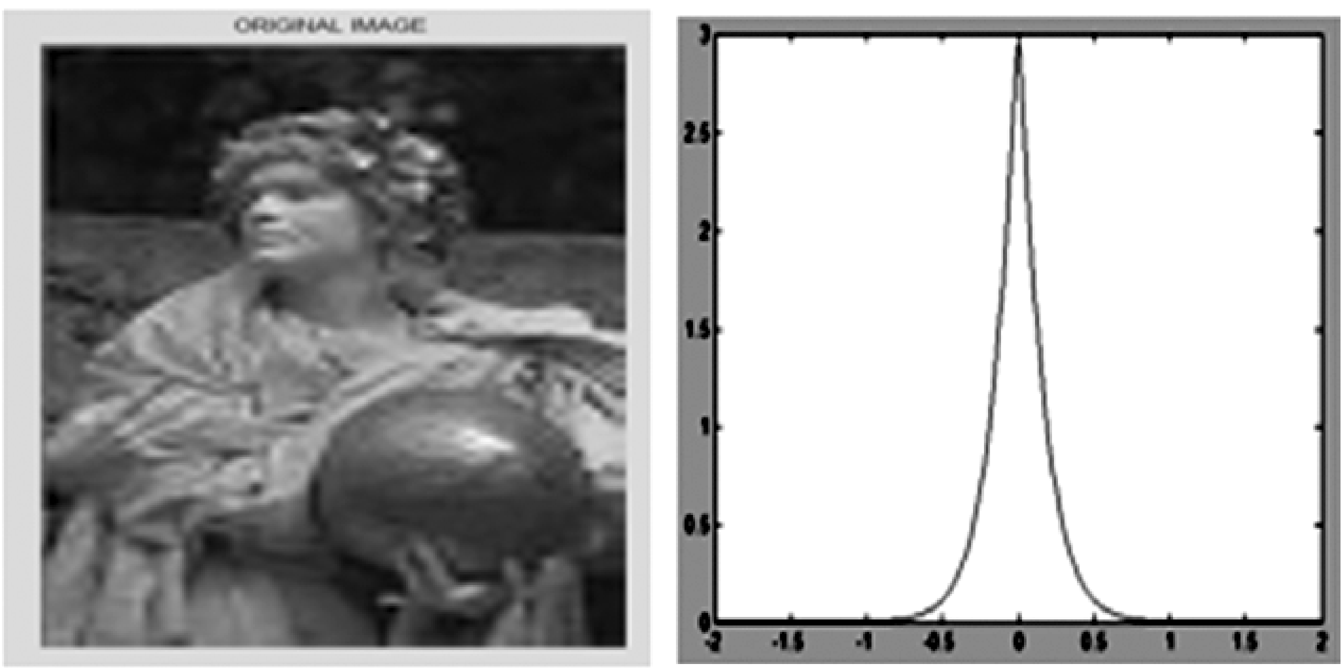
Where $w = \{w\ k, l\ |k = -K, \ldots, K, l = -L, \ldots L\}$ is a 2D circularly-symmetric Gaussian weighting function. In our implementation, K and L are taken as 3.

Analysis has shown that these normalized luminance values portrays a unit Gaussian distribution in the absence of any distortion for NSS images. These normalized luminance values are also named as Mean Subtracted Contrast Normalized(MSCN) values.

Our experiments are based on the theory that the MSCN coefficients have specific statistical properties that are altered by the presence of distortion, and that collecting together these differences will make it possible to predict the type of distortion affecting an image as well as its perceptual quality[2][13]. In order to visualize how the MSCN coefficient distributions vary as a function of distortion, the coefficient values were plotted for an undistorted pristine image and for a distorted low quality image. As Fig 1 shows, the MSCN coefficients clearly indicates the distinction between a good quality undistorted natural image and a low quality distorted image.



(a) (b)



(c) (d)

Figure 1(a)and 1(b) shows the Good Quality undistorted natural image and its MSCN coefficient.
Fig 1(c) and 1(d) shows Low Quality –FF(Rayleigh fast-fading) distorted image and its MSCN coefficient..

The shape of the MSCN curve is perfectly Gaussian for an undistorted version and is exhibiting peak around zero for its distorted version. The shape of the curve varies based on the type of distortion happening to the image ie each type of distortion changes the shape in its own characteristic way [4].

Studies have shown that a GGD or generalized Gaussian Distribution is able to capture distorted image characteristics from the MSCN coefficients. A GGD with mean zero is

$$f\left(x;\alpha,\sigma^2\right)=\frac{\alpha}{2\beta\Gamma\left(\frac{1}{\alpha}\right)}\exp\left(-\left(\frac{|x|}{\beta}\right)^{\alpha}\right) \tag{4}$$

Where

$$\beta = \sigma \sqrt{\frac{\Gamma\left(\frac{1}{\alpha}\right)}{\Gamma\left(\frac{3}{\alpha}\right)}} \tag{5}$$

And and Γ(.) is the gamma function:

$$\Gamma(a) = \int_0^{\infty} t^{a-1} e^{-t} dt \tag{6}$$

The 'shape' of the distribution is controlled by the parameter α and the parameter σ^2 control the variance. The shape parameter α denotes the rate of decay: the smaller α, the more peaked is the distribution, and the larger α, the flatter is the distribution, so it is also called as the decay rate. NSS images ensure certain dependencies between neighbouring pixels and these dependencies alters due to distortion. We can model this by computing the pairwise products of neighboring MSCN coefficients along four orientations – horizontal (H), vertical (V), main-diagonal (D1) and secondary diagonal (D2).

$$\begin{aligned} H(\imath, j) &= I(\imath, j) I(i, j+1) \\ V(\imath, j) &= I(\imath, j) I(i+1, j) \\ D1(\imath, j) &= I(\imath, j) I(i+1, j+1) \\ D2(\imath, j) &= I(\imath, j) I(i+1, j-1) \end{aligned} \tag{7–10}$$

for i ∈ {1, 2 . . . M} and j ∈ {1, 2 . . . N}.

The variations of these pairwise products are better represented using the commonly available Asymetric Generalized Gaussian distribution function. To perceive the dissimilarity, we plot histograms of paired products for a reference image and for distorted versions of it along each of four orientations.

$$f\left(x; v, \sigma l^2, \sigma r^2\right) = \left\{ \frac{v}{(\beta l + \beta r)\Gamma\left(\frac{1}{v}\right)} \exp\left(-\left(\frac{-x}{\beta l}\right)^{v}\right) \right\} \quad where\ x < 0$$

$$= \left\{ \frac{v}{(\beta l + \beta r)\Gamma\left(\frac{1}{v}\right)} \exp\left(-\left(\frac{x}{\beta l}\right)^{v}\right) \right\} \quad where\ x \geq 0 \tag{11}$$

Where

$$\beta l = \sigma l \sqrt{\frac{\Gamma\left(\frac{1}{\alpha}\right)}{\Gamma\left(\frac{3}{\alpha}\right)}} \beta r = \sigma r \sqrt{\frac{\Gamma\left(\frac{1}{\alpha}\right)}{\Gamma\left(\frac{3}{\alpha}\right)}} \tag{12–13}$$

The shape parameter í controls the 'shape' of the distribution while σ_l^2 and σ_r^2 are scale parameters that control the spread on each side of the mode, respectively. The skew [3] of the distribution is a function of the left and right scale parameters. If $\sigma^2 l = \sigma^2 r$ sthen the AGGD reduces to GGD.

AGGD is usually used to model skewed heavy tailed distributions.

3.2. Finding the MSCN Coefficients

These coefficients express a very high correlation among adjacent pixels and the correlation gets altered in the presence of distortion. Hence the above discussed equation(7) to (10)are applied here and the powerful

Figure 2: An NSS undistorted image and its MSCN coefficients.

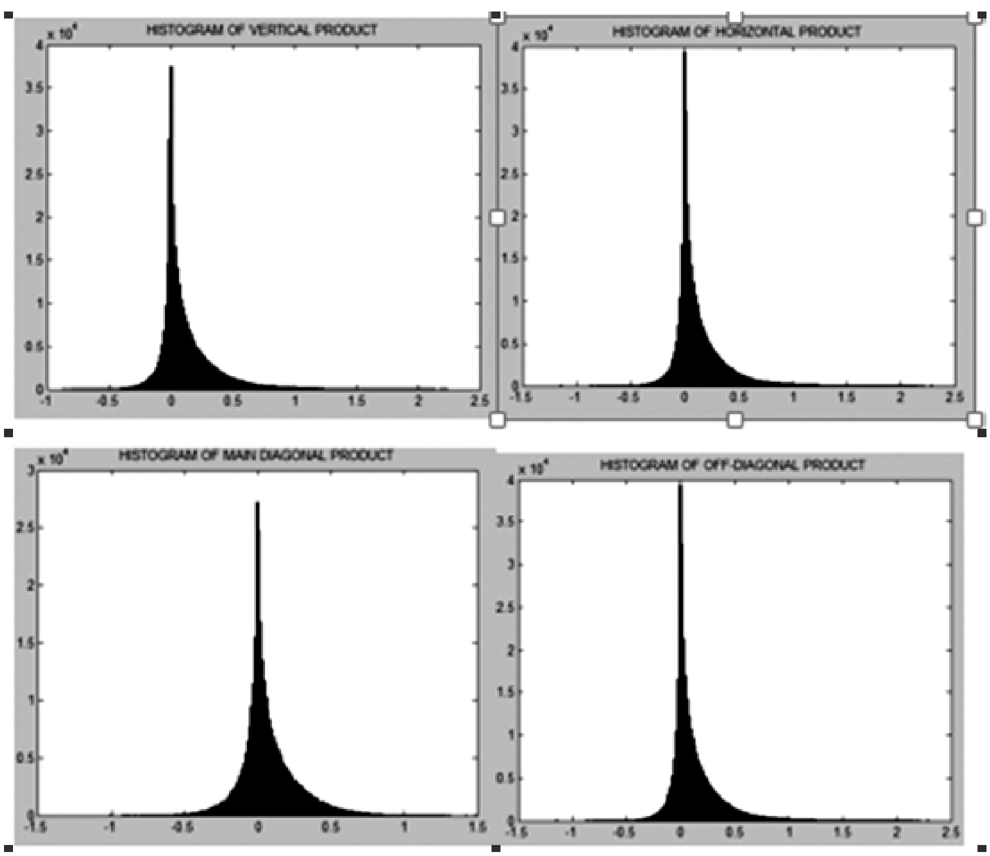


Figure 3(a), 3(b),3(c), 3(d) shows the MSCN coefficients, horizontal product, vertical product, main diagonal and off diagonal product values of the original image of fig 2.

features Shape, mean, left variance, right variance are extracted in all four orientations by using an AGGD fit.

3.3. Computing Gradient statistics

Gradient statistics of an image is a local descriptor and is able to reflect the quality of the image effectively.

The presence of distortions changes the distribution of gradient components and gradient magnitudes. Hence information about distortion can be represented effectively by means of gradient statistics. The (smoothed) gradient components of images, along the horizontal and vertical direction denoted, by *Imgh* and *Imgv*, is obtained by convolving *I* with two Gaussian derivative filters along the horizontal and vertical directions, respectively. It has been found that natural (smoothed) image gradient components are well modelled as following a GGD [16] and the gradient magnitude component by Weibull distribution[15]. Gradient magnitude is computed by

$$GM = \sqrt{Imgh^2 + Imgv^2}$$

Weibull distribution is given by

$$p(x;a,b) = \begin{cases} \dfrac{a}{b^a} x^{a-1} \exp\left(-\left(\dfrac{x}{b}\right)^a\right), x \geq 0 \\ 0,\ x < 0 \end{cases} \tag{14}$$

Studies have shown that larger values of the parameter *a* roughly correspond to more texture in the gradient magnitude map, while larger values of *b* imply greater local contrast. Latest studies in neuroscience recommend that the responses of visual neurons intensely correlate with Weibull statistics when processing images [15]. Degradations in quality alters the gradient magnitudes of an image, hence we use the parameters *a* and *b* of empirical fits of the Weibull distribution as highly relevant quality-aware NSS features. The color image in RGB space is converted to opponent color space for better expression of parameters. It is done before calculating the gradient parameters. The conversion followed is,

$$\begin{bmatrix} o1 \\ o2 \\ o3 \end{bmatrix} = \begin{bmatrix} 0.06 & 0.63 & 0.27 \\ 0.30 & 0.04 & -0.35 \\ 0.34 & -0.6 & 0.17 \end{bmatrix} \begin{bmatrix} R \\ G \\ B \end{bmatrix} \tag{15}$$

3.4. Log Gabor filter

Multi scale, multi orientation features of an image can also deliver the quality specific information. The 2D log Gabor filter in fourier domain is used for collecting related features. Applying log-Gabor filters having *N* different centre frequencies and *J* different orientations to filter an image $f(\mathbf{x})$ yields a set of $2NJ$ responses,

$$\{(en, j\ (\mathbf{x}), on, j\ (\mathbf{x})) : |n = 0, \ldots, N-1, j = 0, \ldots, J-1\},$$

where $en, j(\mathbf{x})$ and $on, j(\mathbf{x})$ are the responses of the real and imaginary parts of a log-Gabor filter. A GGD is used to model these values and the coefficients α and β were extracted.

3.5. Color statistics

In order to further capture the statistical properties, the RGB channels were converted to logarithmic signals with their mean subtracted.

$$R(i,j) = \log R(i,j) - \mu R$$
$$G(i,j) = \log G(i,j) - \mu G$$
$$B(i,j) = \log B(i,j) - \mu B \qquad (16)-(18)$$

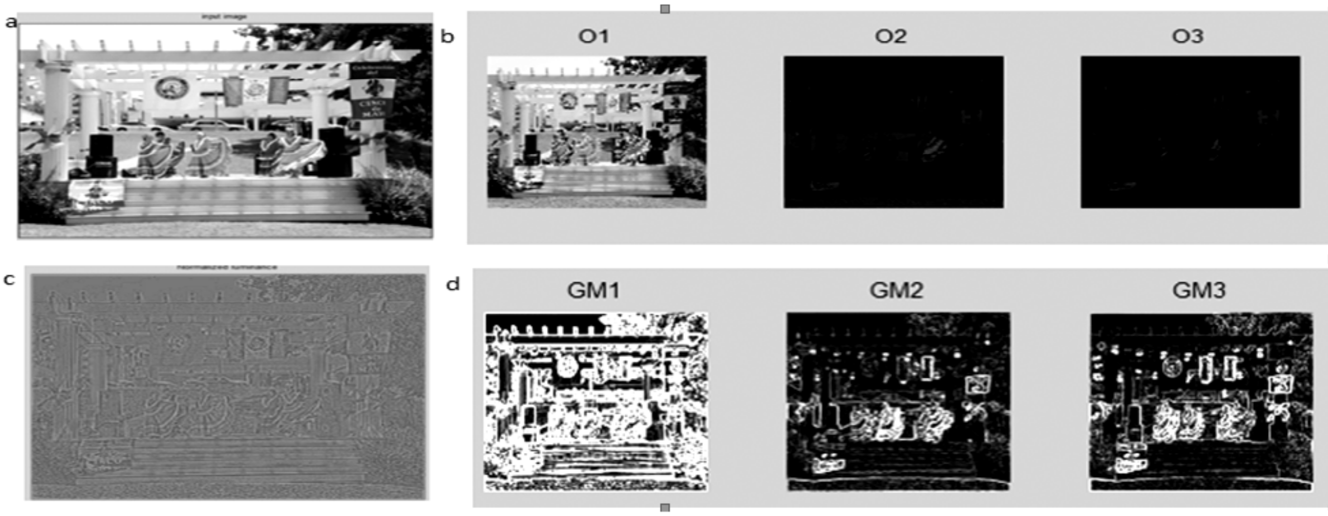


Figure 4: (a) shows the original distorted image and (b) shows its opponent color space channel representations Figure 4 (c) shows its MSCN coefficient and fig 4(d) the Gaussian Magnitude values along 3 channels

Table 1
Result of applying 5 different images, each with 17 types of distortions like Additive Gaussian noise, Additive noise in color components, Spatially correlated noise, Masked noise, High frequency noise, Impulse noise, Quantization noise, Gaussian blur, Image de-noising, JPEG compression, JPEG2000 compression, JPEG transmission errors, JPEG2000 transmission errors, Non eccentricity pattern noise, Local block-wise distortions of different intensity, Mean shift (intensity shift) and Contrast change.

No.	01	02	03	04	05	06	07	08	09	10	11	12	13	14	15	16	17
1	13.301	13.392	20.664	12.222	12.087	13.131	13.972	11.609	12.357	12.474	12.413	12.418	11.569	12.313	11.803	12.272	12.567
2	13.621	13.222	20.300	12.493	12.701	13.183	12.943	13.017	13.266	13.038	11.267	12.626	13.495	12.914	9.970	13.304	11.238
3	12.826	12.422	17.518	11.717	11.910	13.218	13.321	12.580	14.267	10.789	9.936	12.523	11.404	11.774	10.880	14.453	10.393
4	12.668	12.858	19.934	11.951	11.827	13.313	16.121	12.583	13.331	12.438	12.007	11.890	10.249	12.533	10.274	12.584	10.849
5	12.054	12.136	18.347	10.422	10.666	11.225	12.212	10.935	11.577	10.561	10.430	10.313	10.887	10.334	9.054	11.421	10.323

where μR, μG and μB are the mean values of log $R(i, j)$, log $G(i, j)$ and log $B(i, j)$, respectively, over the entire image. And then these image pixels expressed in RGB space are projected onto an opponent colour space,

$$I1(x,y) = (R+G+B)/\sqrt{3}$$

$$I2(x,y) = \frac{R+G-2B}{\sqrt{6}}$$

$$I3(x,y) = (R-G)/\sqrt{2} \qquad (19)\text{-}(21)$$

Now we have decided on a set of features that can be extracted out of any image for quality comparison. This feature set is extracted out of a collection of pristine images and is fitted on a Multivariate Gaussian Model and the pair (μ, Σ) is extracted and stored. This collection of pristine natural image set serves as a reference for quality assessment process. The test image is divided into patches and these NSS features are extracted from each of the patches. It is then fitted in to MVG distribution and the value pair (μ, Σ) is extracted. It is then compared with the pair (μ, Σ) of pristine images. The distortion level in patch I is obtained by following the modified Bhattacharya distance measure, Qi. The distributions of these coefficients follow a Gaussian probability pattern for natural undistorted images. Hence the channels *l1*, *l2* and *l3* are fitted on a Gaussian function,

$$f\left(x;\varsigma,\rho^2\right)=\frac{1}{\rho\sqrt{2\Pi}}\exp\left(\frac{-\left(x-\varsigma\right)^2}{2\rho^2}\right) \tag{22}$$

The final quality score of the image is taken by averaging the quality values of all patches [11][6].

4. ANALYSIS OF RESULT

Two different datasets were selected for performance analysis. One is TID 2008[17] and the other is LIVE Release 2[18]. From the TID 2008 dataset, 17 types of distortions were chosen and performance of the system was evaluated based on those distortions. Table 1 shows the results obtained for five different images on 17 distortion (85 samples). These five images were acted on with 17 different types of distortions. Quality value of the result is expressed as a number in the range 0 to 20.

The table shows that the result is comparable with human judgment. Excellent results (score between 17 and 20) are obtained for certain distortions like spatially correlated noise in TID2008 database. Higher values indicate that the system recognizes distortions well. The method suffers to detect certain Distortions like Local block-wise distortions of different intensity. Most of the other distortions have score ranging between 10 and 14. All the distortion types given in the LIVE dataset is identified by the system. The method works well with LIVE 2 dataset.

The same images when given to an opinion aware quality assessment gave results in the range analogous to opinion unaware method, which promotes the scope of proposed method.

5. CONCLUSION

In this paper we discussed about an opinion-unaware method to estimate the quality of a certain set of 85 sample images. Objective analysis result can be taken into account only by verifying its comparison with subjective assessment. In some cases, the system self learns the quality values without taking into account the opinion values. The efficiency of opinion unaware method depends greatly on the feature set extracted from image. Here, we found that this method gives promising result and is comparable with human perception of quality. Our experiments validate that the new features can significantly improve image quality prediction performance. A lot more future work is vacant where the result can be enhanced by selecting a better strong set of features.

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