# Analysis of Probability Density Functions in Existing No-Reference Image Quality Assessment Algorithm for Contrast-Distorted Images

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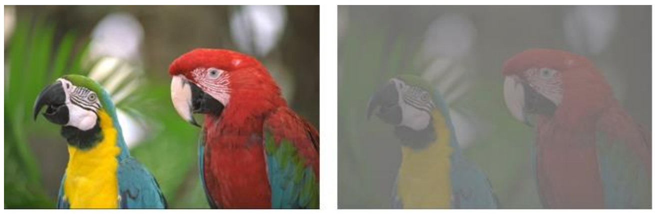
***Abstract*— Amongst all distortion types, contrast change is very crucial for visual perception of image quality. Contrast distortion may be caused by poor lighting condition and poor quality image acquisition device. Contrast-distorted image (CDI) is defined as image with low dynamic range of brightness. Most of existing image quality assessment algorithms (IQAs) have been developed during the past decade. However, most of them are designed for images distorted by compression, noise and blurring. There are very few IQAs designed specifically for CDI, e.g. Reduced-reference Image Quality Metric for Contrast-changed images (RIQMC) and No Reference-Image Quality Assessment (NR-IQA) for Contrast-Distorted Images (NR-IQA-CDI). The five features used in NR-IQA-CDI are the global spatial statistics of an image including the mean, standard deviation, entropy, kurtosis and skewness. The statistical model or the Probability Density Function (PDF) for each of the given moment features were estimated using a public image database with large number of natural scene images. Because of poor performance in two out of three image databases, where the Pearson Correlation Coefficient (PLCC) were only 0.5739 and 0.7623 in TID2013 and CSIQ database, thus motivate us to further investigated to detect the gabs in existing NR-IQA-CDI. The paper can address the problem of existing NR-IQA-CDI which the bell-curve like probability density function (pdf) of the contrast related features like standard deviation and entropy does not correlate well with the monotonic relation between the contrast features and the perceived contrast level.**

***Keywords*— Contrast-distorted image (CDI), image quality assessment algorithms (IQAs), No Reference-Image Quality Assessment (NR-IQA) for Contrast-Distorted Images (NR-IQA-CDI), Probability Density Function (PDF), bell-curve.***

## I. INTRODUCTION

Image can be effected by different kinds of distortion through various process. Problems such as poor illumination and lighting condition, limited dynamic range in image sensor, incorrect setting of lens aperture during image acquisition, limitation of the acquisition device, etc. may lead to loss of contrast and visible details in an original image. Contrast distortion is among the most common and fundamental distortion. Contrast-distorted image (CDI) is an image with low range of grayscale as shown in Fig. 1 [1,2].

There is two Image Quality Assessment (IQA) measures can be used: (1) subjective measures and (2) objective measures. Due to computationally expensive of subjective IQA, the objective IQA algorithms are commonly used for image analysis and quality prediction. Objective IQA can be broadly classified into a few categories such as full reference (FR) IQA, reduced-reference (RR) IQA and no-reference (NR)/blind image quality assessment (BIQA) [3,4,5,6].



(a) (b)

Fig. 1. (a) Good Contrast Image; (b) Poor Contrast Image.

No-Reference Image Quality Assessment Algorithm (NR-IQA) has been seen as the ideal solution for most practical applications where an original image is not available. The issue of reference image is even more compelling in the enhancement of CDI. In this case, it is altogether impossible

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to have a reference image because the original image is of poor contrast which requires contrast enhancement; the output image must show improved contrast so it is meant to be different from the original image as shown in Fig. 2.

Fig. 2. (a) A contrast-distorted image and (b) its contrast-enhanced image.

Many image quality assessment algorithms (IQAs) have been developed during the past decade. However, most of them are designed for images distorted by compression, noise and blurring. Such distortions cause structural change in image which does not happen in contrast distortion. Hence, it is not suitable to use the above mentioned IQAs to assess contrast-distorted images (CDI).

There are very few IQAs designed specifically for CDI. The first IQA for CDI is a Reduced-Reference IQA (RR-IQA) called RIQMC [7]. RIQMC used histogram features (Mean, Standard Deviation, Entropy, Skewness, and Kurtosis of image's grey level) for evaluation. The disadvantage of RIQMC is that it requires partial access to original image, which is impractical in real-life application. Unlike distortion caused by image compression where the original image could be used as reference image, contrast distortion is caused by poor image acquisition conditions such as poor lighting or poor device so the original image itself is distorted and reference image is practically not available.

The first practical solution is proposed by Yaming et al. which is called No-Reference IQA for CDI (NR-IQA-CDI) [8]. It is develop based on the principles of Natural Scene Statistics (NSS) in that there are certain regularities in the statistics of natural scenes which could be missing from the statistics distorted images. The five features used in NR-IQA-CDI are the global spatial statistics of an image including the mean, standard deviation, entropy, kurtosis and skewness. The statistical model or the Probability Density Function (PDF) for each of the given moment features were estimated using a public image database with large number of natural scene images. The distortion of an image was measured by likelihood of being a natural scene image based on the PDF. The feature set can be used in image quality prediction. To solve the regression problem, SVR can be used to find the mapping function between the feature set and perceptual quality score.

Unfortunately, the performance of NR-IQA-CDI are not encouraging in two of the three test image databases, TID2013 and CSIQ, where the Pearson Linear Correlation Coefficients are only around 0.57 and 0.76, respectively. Therefore, we analyze and investigate to detect the reasons and gabs in existing NR-IQA-CDI. In the next section (Section 2), overview on NR-IQA-CDI. Section 3 Disadvantage of the Existing PDFs of Contrast Features. Section 4 concludes the current work.

## II. NR-IQA-CDI Overviwe

Contrast distortion is caused by poor image acquisition conditions such as poor lighting or poor device so the original image itself is distorted and reference image is practically not available. The first practical solution is proposed by Yaming et al. which is called No-Reference IQA for CDI (NR-IQA-CDI) [8]. NR-IQA-CDI based on assumption that natural images are statistically regular and contrast distortion tend to break such statistics and make the images unnatural that degrades perceived image quality [9], [10]. They choose the moment features to evaluate the distortion of statistical properties of contrast-distorted images, and the entropy to measure the image contrast.

Among the various features, moment features of images have been widely used in many studies related to image contrast. First raw moment (mean) of image intensity can be used to evaluate the overall brightness of images [11], and to represent the dispersion of image pixel intensity, the second central moment (variance) of images can be used. The third central moment (skewness) can be used to describe the surface gloss and surface albedo of images [12], and to estimate the standard noise deviation in corrupted natural images, the fourth central moment (kurtosis) is employed [9].

For the image I in the SUN2012 database [13], They compute global features. Let μ denotes the sample mean operator. Then, for each image patch, five features such as sample mean me(I), standard deviation std(I), entropy ent(I), kurtosis ku(I), and skewness sk(I) are computed as:

$$me(I) = \mu(I), \tag{1}$$

$$std(I) = \sqrt{\mu[(I - \mu(I))^2]} \ , \tag{2}$$

$$sk(I) = \frac{\mu[\,(I-\mu(I))^3]}{std(I)^3}, \tag{3}$$

$$ku(I) = \frac{\mu[(I-\mu(I))^4]}{std(I)^4} - 3 \ , \tag{4}$$

$$ent(I) = -\sum_j p_j(I) log_2 p_j(I), \tag{5}$$

where $I^h$ indicates the histogram of the image *I, Pi (I)* indicates the probability density of $i^{th}$ grayscale in the image *I* and log (.) has base two.

The statistical model or the Probability Density Function (PDF) for each of the given moment features were estimated using a public image database (SUN2012 database) with large number of natural scene images (16873 images) **[13].** And show that the statistical features correlate with HV perception of contrast distortion. The empirical distribution or histogram of each of the five features of the images in SUN2012 database are used to perform distribution fitting with various parametric and non-parametric distribution. The best-fit distribution is the one which best match the empirical distribution visually. Notice that the best-fit distribution for $me, std, sk, ku$ and $ent$ is Gaussian distribution, Gaussian distribution, Gaussian distribution, inverse Gaussian probability density function, and Extreme Value Distribution respectively.

The feature set can be used in image quality prediction. To solve the regression problem, SVR can be used to find the mapping function between the feature set and perceptual quality score. They used three databases to validate the performance of the proposed NR-IQA-CDI: CID2013 **[7],** TID2013 **[14],** and CSIQ [**15**]. They used 10-fold leave one out cross validation only, results for TID2013 database was not the best which called for more researches.

## III. Disadvantage of the Existing PDFs of Contrast Features

The five features used in NR-IQA-CDI are the global spatial statistics of an image. The statistical model or the Probability Density Function (PDF) for each of the given moment features were estimated using a public image database with large number of natural scene images. The distortion of an image was measured by likelihood of being a natural scene image based on the PDF.

In order to investigate the monotonic relation between the above contrast features and the perceived contrast level, we deducing the following experiment.

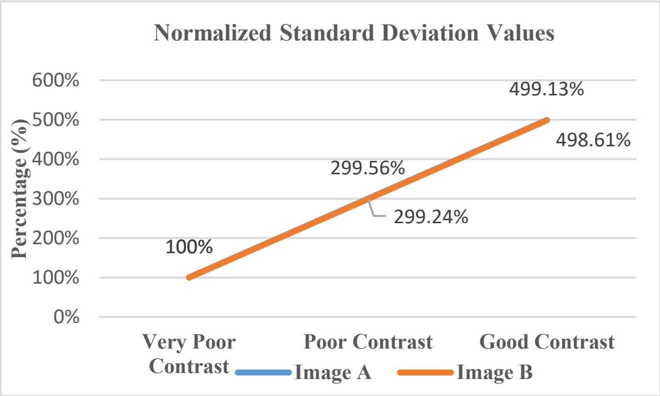
Fig. 3 shows two sets of images (Parrot and House), with increasing level of perceptual contrast and hence better image quality from left to right. Table I lists the values (top) and the normalized values (bottom) of the five features used in the existing NR-IQA-CDI for each of the images.


Fig. 3. First row (a1, a2, a3) is very poor, poor, and good contrast image, second row (b1, b2, b3) is very poor, poor, and good contrast image. Both good images are from CID2013 database [7].

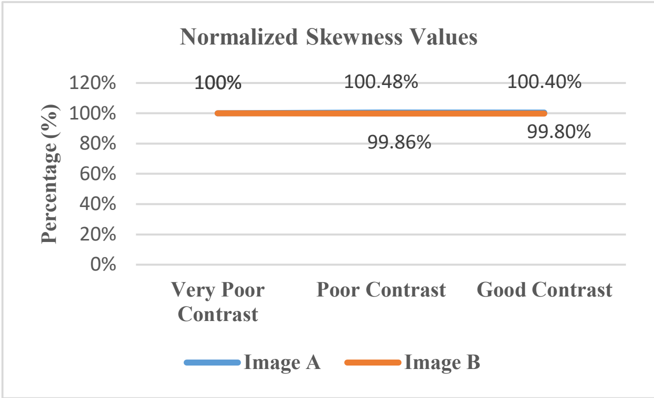
TABLE I. Five Features Results for Images in Fig. 3 and Percentage change of Five Features.

| **Feature** | **Image A** | | | **Image B** | | |
|---|---|---|---|---|---|---|
| | ***Very Poor Contrast (a1)*** | ***Poor Contrast (a2)*** | ***Good Contrast (a3)*** | ***Very Poor Contrast (b1)*** | ***Poor Contrast (b2)*** | ***Good Contrast (b3)*** |
| Standard Deviation | 9.22 100% | 27.62 299.56 % | 46.02 499.13 % | 7.92 100% | 23.70 299.24 % | 39.49 498.61% |
| Entropy | 4.98 100% | 6.56 131.72 % | 7.29 146.38 % | 4.87 100% | 6.45 132.44 % | 7.18 147.43% |
| Kurtosis | 3.4527 100% | 3.4536 100.02 % | 3.4483 99.87% | 3.4064 100% | 3.4027 99.89% | 3.4052 99.96 % |
| Skewed | 1.0185 100% | 1.0234 100.48 % | 1.0226 100.40 % | 0.6568 100% | 0.6559 99.86% | 0.6555 99.80% |
| Mean | 123.89 100% | 116.62 94.13% | 109.37 88.27% | 124.51 100% | 118.50 95.17% | 112.52 90.37% |

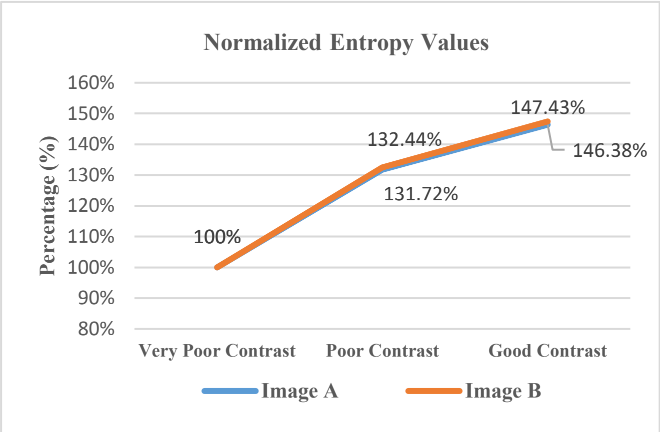
Fig. 4 shows the graphs of the normalized values of each feature for both sets of images. Notice that the normalized values of contrast related features like standard deviation and entropy increase monotonically while there is no significant change in other feature (kurtosis, skewness and mean) with increasing level of perceptual image quality.



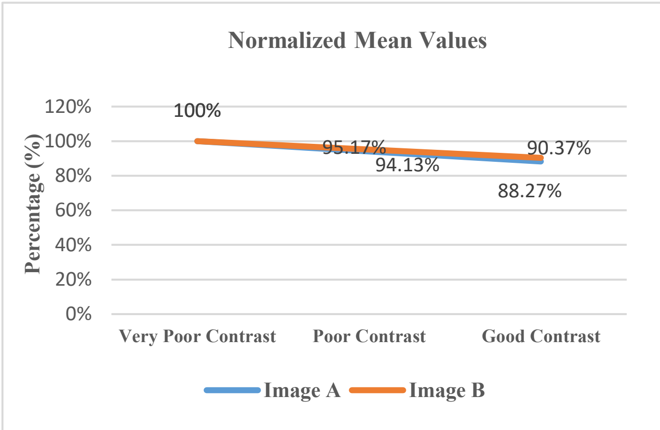

**(a)**



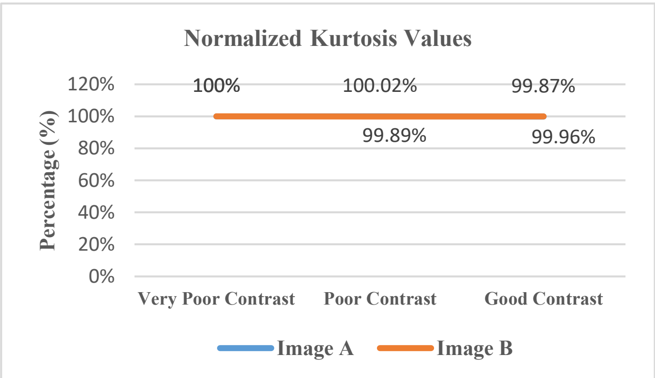

**(d)**




**(b)**




**(e)**




**(c)**

Fig. 4. (a, b, c, d, e) are Percentage of Standard deviation, entropy, kurtosis, skewness, and mean for two original images with poor and very poor contrast version.

However, such monotonic relation is not well reflected by bell-curve-like PDF as shown in Fig. 5. This is true especially for the right half of the curve (red line) where the slope is negative, which imply lower image quality with the increase of the contrast feature value, $f > fo$.

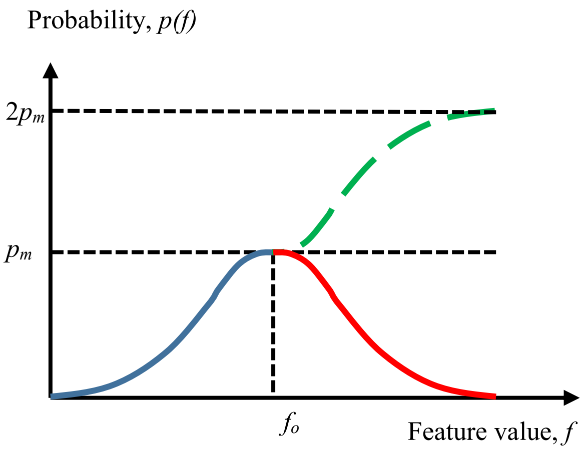



Fig. 5. Bell-curve-like pdf.

So, we can address the following problem in the existing NR-IQA-CDI which the bell-curve like probability density function (pdf) of the contrast related features like standard deviation and entropy does not correlate well with the monotonic relation between the contrast features and the perceived contrast level.

## IV. Conclusion

No-Reference IQA for CDI (NR-IQA-CDI) is develop based on the principles of Natural Scene Statistics (NSS) in that there are certain regularities in the statistics of natural scenes which could be missing from the statistics distorted images. The five features used in NR-IQA-CDI are the global spatial statistics of an image. Unfortunately, the performance of NR-IQA-CDI are not encouraging in two of the three test image databases, TID2013 and CSIQ, where the Pearson Linear Correlation Coefficients are only around 0.57 and 0.76, respectively. Therefore, this paper can analyze and investigate to detect the gabs in existing NR-IQA-CDI. The paper can address the problem of existing NR-IQA-CDI which the bell-curve like probability density function (pdf) of the contrast related features like standard deviation and entropy does not correlate well with the monotonic relation between the contrast features and the perceived contrast level. In other words, the disadvantage of existing NR-IQA-CDI is bell-curve-like PDF of contrast related features which cannot reflect the monotonic relation between values of contrast feature and perceptual image quality.

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