# Analysis of Global Spatial Statistics Features in Existing Contrast Image Quality Assessment Algorithm

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***Abstract*—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. Contrast distortion may be caused by poor lighting condition and poor-quality image acquisition device. No Reference-Image Quality Assessment (NR-IQA) for Contrast-Distorted Images (NR-IQA-CDI) is one of these few IQAs. 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. 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 presents the reason which led to poor results in existing NR-IQA-CDI. This paper also can address the problem of existing NR-IQA-CDI which the weakness of the global features in assessing images with uneven contrast.**

***Keywords—Contrast-distorted image (CDI), No Reference-Image Quality Assessment (NR-IQA) for Contrast-Distorted Images (NR-IQA-CDI), Uneven Contrast, global spatial statistics, local spatial statistics.***

## I. INTRODUCTION

Various types of distortion such as noise, blurring, fast fading, blocking artifacts and contrast distortion can degraded the quality of an image. These distortions may occur during operations such as acquisition, compression, storage, transmission, display and post-processing. 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. Contrast distortion is among the most common and fundamental distortion [1,2]. In order to measure the change in image quality, two Image Quality Assessment (IQA) approaches can be adopted: Two Image Quality Assessment (IQA) approaches can be adopted to measure the change in image quality. (1) subjective IQA and (2) objective IQA. The former is computationally expensive and it is impractical for real-time applications. Hence, 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].

(a) (b)

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

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However, the current IQA algorithms dedicated for CDI are very few. The RR image quality metric for contrast-changed images (RIQMC) [6] worked based on entropies and order statistics of the image histograms. By using the principle of natural scene statistics (NSS), the no-reference (NR) IQA method for contrast enhancement (NR-IQA-CDI) was developed by [7]. The contrast quality was assessed by two metrics [8], i.e. histogram flatness (HFM) and spread (HS). The Reduced-reference Contrast-changed image Quality Index (RCIQM) was developed by [9] via integrating both bottom-up and top-down strategies. A local patch-based FR-IQA method was proposed by [10] for evaluating contrast quality. Their algorithm employed an adaptive representation of local patch structure. Although [8,9,10] it can have achieved impressive performance. However, these techniques have certain limitations. Most of them require partial access to the reference image, which is unavailable in practice. We can note that few NR-IQA metrics exist for Contrast-Distorted Images (CDI) in the literature. NR-IQA-CDI [7] are used five global spatial statistics features of an image including the mean, standard deviation, entropy, kurtosis and skewness. 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 limitation in existing NR-IQA-CDI. In the next section (Section 2), overview on existing NR-IQA-CDI. Section 3 Analyse of the global spatial statistics features in existing NR-IQA-CDI. Section 4 concludes the current work.

## II. Overview on Existing NR-IQA-CDI

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) [7]. NR-IQA-CDI based on hypotheses that contrast distortion would temper the statistical regularities of natural images, leading to unnatural appearance that degrades perceived image quality [11], [12]. Based on these hypotheses, they choose the moment features to evaluate the distortion of statistical regularities of contrast-distorted images, and use the entropy metric to measure the image contrast.

In many studies related to image contrast, moment features of images have been widely used. It is demonstrated that the first raw moment (mean) of image intensity can be used to evaluate the overall brightness of images [13], and utilize the second central moment (variance) of images to represent the dispersion of image pixel intensity. The third central moment (skewness) is also used to describe the surface gloss and surface albedo of images [14], and the fourth central moment (kurtosis) is employed to estimate the standard noise deviation in corrupted natural images [11].

For the image *I* in the SUN2012 database [15], 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 ith 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 with large number of natural scene images (SUN2012 database) [15] which includes 16873 images that cover a large variety of image content. 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 quality of the image is predicted based on this feature set. This is a regression problem and we adopt SVR 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 metric: CID2013 [6], TID2013 [16], and CSIQ [17]. They used 10-fold leave one out cross validation only, results for TID2013 database was not the best which called for more researches.

## III. Analyse of The Global Spatial Statistics Features in Existing NR-IQA-CDI

The existing NR-IQA-CDI relies only on global spatial statistics of an image including the mean, standard deviation, entropy, kurtosis and skewness. In order to analyze the Global Spatial Statistics in Existing NR-IQA-CDI, we will conduct the following experiment.

In an image with uneven contrast, some regions of the image show good contrast but other regions show poor contrast. Fig 2 shows two images with uneven contrast (image (a), Boat and image (b), Girl) and two images with even contrast (image (c), Racing and image (d), Mountain). Notice that in image Boat, the contrast of sky and sea is good but the contrast within the boat is relatively poor. In image Girl, the contrast between the girl and the background is good. However, the contrast within the face of the girl, especially the right region of the face, is relatively poor. Such uneven contrast distribution is not observed in both Racing and Mountain images. Notice that most regions in the two images show equally good contrast.

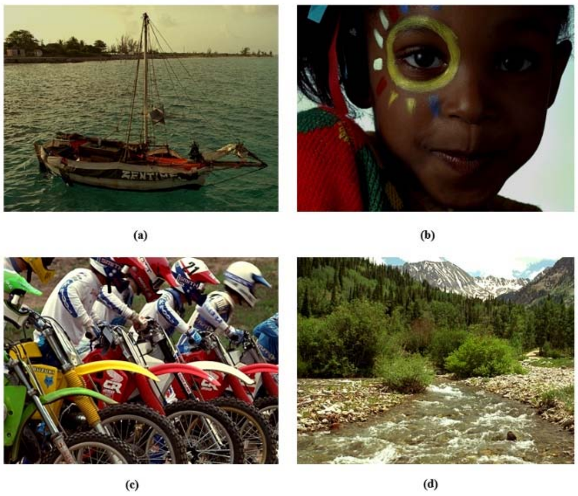


Figure. 2. First row (a, b) is two uneven contrast image samples, Second row (c, d) is two good contrast image samples. Both are from TID2013 Database [16].

Figure 3 shows the contrast measure based on spatial statistics (standard deviation of brightness, σ) of two selected regions in image Girl. Notice that contrast between the face and the background is good with higher σ=43 while the contrast of the right eye is relatively poor with lower σ=12.

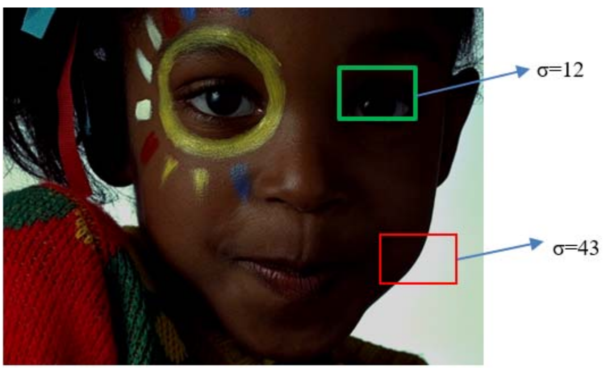


Figure. 3. Uneven Contrast Image sample divided into block images.

Perceptually, images Racing and Mountain in Fig 2 show much better contrast than images Boat and Girl. Unfortunately, this fact is not well reflected by contrast measures based on global spatial statistics as shown in the figures in Table 1. Notice that the contrast measures in terms of the standard deviation of the brightness of the entire image, σglobal are not of much difference among the four images, especially between images Girl and Mountain where the difference is only 6%.

TABLE I. GLOBAL AND LOCAL STANDARD DEVIATION RESULTS ACROSS DIFFERENT BLOCK SIZE AND DIFFERENT PERCENTAGE BETWEEN THEM.

| | Image | $\sigma_{global}$ | $\sigma_{local}$ | | | |
|---|---|---|---|---|---|---|
| | | | *128x128* | *64x64* | *32x32* | *16x16* |
| **Uneven Contrast** | *(a)Boat* | 59.63 | 35.81 (-40%) | 28.19 (-53%) | 23.44 (-61%) | 19.65 (-67%) |
| | *(b)Girl* | 62.59 | 41.16 (-34%) | 27.34 (-56%) | 18.05 (-71%) | 11.67 (-81%) |
| **Even Contrast** | *(c)Racing* | 71.03 | 66 (-7%) | 61.07 (-14%) | 52.98 (-25%) | 44.25 (-38%) |
| | *(d)Mountain* | 66.5 | 52.96 (-20%) | 45.81 (-31%) | 39.86 (-40%) | 34.93 (-47%) |

Nevertheless, contrast measure local spatial statistics shows advantage in addressing this problem. In order to calculate contrast measure based on local spatial statistics, an image is first divided into non-overlapping sub-images as shown in Fig 2. Next, the contrast measure of each sub-image is calculated. Finally, the contrast measures of all the sub-images are aggregated. In Table 1, σlocal is obtained by averaging the standard deviation of the brightness of all the sub-images of size N×N, N={128, 64, 32, 16}). Notice that the σlocal of images with uneven contrast are significantly lower than those with even contrast; these measures are more consistent to the perceptual contrast. Notice also from Fig 4 that the difference between contrast measures derived from local and global spatial statistics, Δσ (as defined by Equation 6) of images with uneven contrast tend to be higher than those of images with even contrast. This shows that local spatial statistics can reflect the regional contrast of image better than its global counterpart, especially for image with uneven contrast.

$$\Delta_{\sigma} = \left(\frac{\sigma_{local} - \sigma_{global}}{\sigma_{global}}\right) \times 100\% \qquad (6)$$

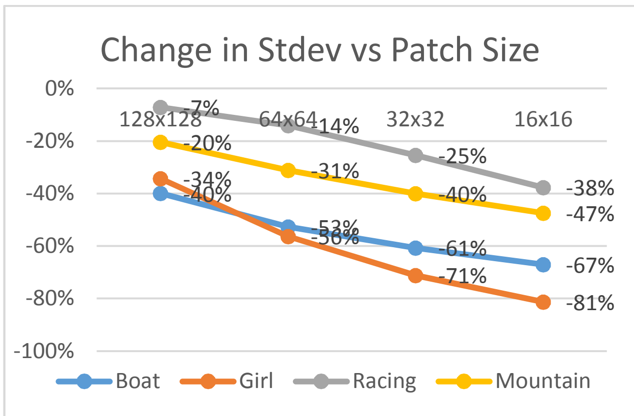


Figure. 4. Percentage different of change in Stdev across different block size.

Hence, the following problem can be address: The existing NR-IQA-CDI relies only on global spatial statistics, global statistics may not be effective in assessing images with uneven contrast distribution where some regions have better or poorer contrast than others.

## IV. Conclusion

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. 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 analyze the global spatial statistics features in existing NR-IQA-CDI. This paper can be addressing the problem of existing NR-IQA-CDI which the weakness of the global features in assessing images with uneven contrast. In other words, the advantage of local spatial statistics lies on the ability to reflect the regional contrast of image in a more consistent manner with human visual perceptual than its global counterpart, especially for image with uneven contrast.

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