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Effect of Contrast Measures on the Performance of No-Reference Image Quality Assessment Algorithm for Contrast-Distorted Images

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Abstract - Most of the no-reference image quality assessment for contrast distorted images (NR-IQA-CDI) algorithms use global standard deviation as a measure for contrast. On the other hand, Michelson and Weber contrast measures - compared to the standard deviation - have lesser computational complexity, and could be considered as potential substitutes if they do not degrade the performance of the NR-IQA-CDI algorithm significantly. In this regard, this paper investigates the effect of substituting the standard deviation with Michelson or Weber contrast measures to find out if the NR-IQA-CDI algorithm could be improved in terms of its computational complexity. The obtained results show that both Michelson and Weber contrast measures, significantly, enhance the performance of NR-IQA-CDI. Consequently, they can easily replace the standard deviation. Moreover, the global Weber contrast measure is found to be the best alternative for the standard deviation since it shows the best improvement in both the overall prediction accuracy and computational complexity.

Keywords— Contrast distortion; Image quality assessment; No-reference image quality assessment; Weber contrast measure; Michelson contrast measure.

1. INTRODUCTION

Contrast is an important measure in the field of contrast-distorted images. Most of the no-reference image quality assessment for contrast distorted images (NR-IQA-CDI) algorithms use global standard deviation – or variance – as a measure for contrast [1]. Enhancing the image could be done globally (i.e. dealing with the item as one unit) or locally (i.e. dividing the item into small units and dealing with each unit alone). So, the contrast of an image could be computed globally for the whole image, or locally for the sub-images - comprising the image - then taking the average of the results [2]. Generally, the measures used in the existing NR-IQA-CDI are global measures that are applied over the entire image. The concept of global and local is applied to contrast measures. Some of the quality measures uses local features such as statistical natural measure (SNM) in tone mapping quality index (TMQI). Local features are useful, especially, for images with uneven contrast. It is therefore interesting to compare global and local contrast measures to determine if NR-IQA-CDI could be improved by means of local measures [3].

In the literature, several contrast measures such as Michelson and Weber contrasts besides standard deviation (or variance) are reported [4]. Michelson and Weber contrast measures had the advantage of lesser computation as compared to standard deviation and could be considered as potential substitutes if they do not degrade the performance of the NR-IQA-CDI algorithm significantly. Hence, it is worthy to study the effect of substituting

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standard deviation with Michelson or Weber contrast measures to find out if the NR-IQA-CDI algorithm could be improved in terms of computational complexity.

For the conducted comprehensive experiment, the following metrics were implemented: mean (the average which indicates the general brightness of the image), standard deviation (the measure of the frequency distribution of a pixel value of an image), skewness (the measure of symmetry, or more precisely, the lack of symmetry), kurtosis (the measure of whether the data are heavy-tailed or light-tailed relative to normal distribution) and entropy that shows how the gray levels are distributed [5, 6].

The rest of the paper is organized as follows: section 2 reviews the contrast measures used in this investigation. Section 3 describes - in detail - the followed research methodology. Section 4 discusses and analyses the obtained results, followed by the conclusions in section 5.

2. LITERATURE REVIEW

The contrast, in general, is the unlikeliness or the difference between two things. In visual perception, contrast is determined by the difference in the brightness and color between the main object and other surrounding objects, and in image processing, contrast is the difference between the lightest and the darkest point in the image. It is the difference in luminance or color that turns the object into the image to be distinct. Brightness always refers to the human determination of how bright an object is, whereas luminance is the amount of reflected light from a surface. Contrast is the measure that distinguishes the object in the image from the background objects; it is adjusted by changing the black level or adjusting the amount of light emitted [7]. Following is a discussion of the three types of contrast used in this investigation.

2.1. Michelson Contrast

Michelson contrast is a global contrast, which is considered as not suitable for measuring natural images, because a point or two of extreme brightness or darkness could determine the whole image contrast [8]. However, it is suitable for patterns that include bright and dark features to be equivalent, taking the same fraction of the area in the image as seen from the following equation:

$$C_M = \frac{I_{max}-I_{min}}{I_{max}+I_{min}} \quad (1)$$

where C_M is the Michelson contrast, and I_{max} and I_{min} represent the highest and lowest luminance, respectively.

2.2. Weber Contrast

Weber contrast is one of the oldest luminance contrast statistics. In Weber's law, the contrast sensitivity is almost independent of background luminance. Weber contrast is used in cases where small features are presented on a large uniform background. It is implemented better over images with small patterns, or sharp-edged graphic objects such as symbols and text characters with larger uniform backgrounds, i.e., the average luminance is approximately equal to the background luminance [9] as can be seen from the following equation:

$$C_W = \frac{I_s-I_b}{I_b} , \quad (2)$$

where C_W is the Weber contrast, and I_s and I_b represent the luminance of the features and the background, respectively.

2.3. Standard Deviation Contrast

In this type of contrast, standard deviation computes the root-mean-square (RMS) contrast. This RMS contrast does not depend on the angular frequency content or the spatial distribution of contrast in the image. It is defined as the standard deviation of the pixel intensities [10]:

$$C_S = \sqrt{\frac{1}{MN}\sum_{i=0}^{N-1}\sum_{j=0}^{M-1}(I_{ij}-\bar{I})^2}\,, \tag{3}$$

where I_{ij} intensities present the i^{th} and the j^{th} element of the two-dimensional image. The M by N is the size of the image, and $\bar{I}$ is the average intensity of all pixel values in the image. Image pixels are assumed to be normalized in the range [0, 1].

The contrast could be computed as Weber, Michelson, standard deviation, variance, or just luminance difference. Table 1 summarizes and categorizes the contrast measures used by image quality assessment (IQA) algorithms for contrast distorted images (CDI). It displays a summary of some articles that used different types of contrast measures, and classifies these measures to either global or local.

Table 1. Contrast measures utilized by IQA.

Reference	Contrast measure	Contrast type	
		Global	Local
[11]	Histogram flatness and spread	√	
[12]	Variance		√
[13]	Variance	√	
[14]	Gradient magnitude (GM) map and Laplacian of Gaussian (LOG) response		√
[15]	Variance		√
[16]	Standard deviation	√	
[17]	Variance	√	
[18]	Variance	√	
[19]	Variance	√	
[20]	Modified Michelson	√	√
[21]	Histogram distribution	√	√
[22]	Difference in luminance		√
[23]	Variance	√	√

It is observed from the 2nd column of Table 1 that the variance - or the standard deviation (since both are related to each other) - is the most popular contrast measure. Nevertheless, the definitions of Michelson and Weber contrast measures in Eqs. (1) and (2) indicate that they require far less computation compared to variance or standard deviation, defined in Eq. (3). To address the challenge of fast computation as highlighted by [24], it is therefore important to analyze the effect of substituting standard deviation with Michelson or Weber contrast measures.

Unlike global contrast measure, local contrast measure is computed based on sub-images instead of the entire image as mentioned before. Since local contrast measure is implemented for parts of the image - where there is a difference in the contrast - it became useful for images with uneven contrast. Most of the recent contrast enhancement methods were designed based on local or hybrid (local and global) contrast enhancement. It has also been reported that local contrast measures help improving the performance of IQA [15]. Therefore, this paper argues that it is critical to analyze the effect of substituting global contrast measure with its local counterpart, in addition to finding a substitution for standard deviation contrast measure.

3. RESEARCH METHODOLOGY

In this study, three experiments were conducted. They are described in the following subsections:

3.1. A Comparison between Global and Local Contrast Measures

Contrast measures used in this study are: Standard deviation, Michelson, and Weber contrasts. Global and local measures were computed for these contrasts; so, in total there were six contrast measures. Experiments in this study were conducted in two stages: i) the preliminary stage that used contrasts as a variable (raw data); it is simple and fast and ii) the comprehensive stage that used the NSS contrast measures, namely mean, standard deviation, skewness, kurtosis and entropy.

To compute local contrast measures for the three types of contrasts, SNM [25] was followed. The local measures were computed as follows:

- The image was divided into non-overlapping sub-images of size 11x11.
- The contrast measure was computed for each sub-image.
- The average of the contrast measures was computed for all the sub-images in the image.

SNM suffered from the inconsistent rating across different special resolutions even with identical content and contrast level images.

The root cause of the problem is that the model was developed using sample images with a fixed range of resolution (around 640 x 480). A problem arose when the input image had a resolution that is significantly different from those of the sample images, and the block size used to compute contrast remained the same. The solution was to resize the input image to a standard size - of about 640 x 480 - to avoid a mismatch of resolution during comparison. This method was proven to be statistically effective in reducing the inconsistency in the ratings of images. Therefore, images in this study were resized to have a maximum dimension of 640 x 480 to avoid such inconsistency.

Estimations for each of the six contrast measures (local and global); Michelson, Weber, and standard deviation were done using a big database called SUN2012. The estimation was done using the probability distribution function (PDF) - *dfittool( )*- in MATLAB software. The tool allowed auto distribution fitting to many distributions. Fig. 1 shows that the non-parametric distribution was the best fit for most contrast measures (global and local), except for the global Weber contrast where the best-fit distribution was the piecewise linear distribution.

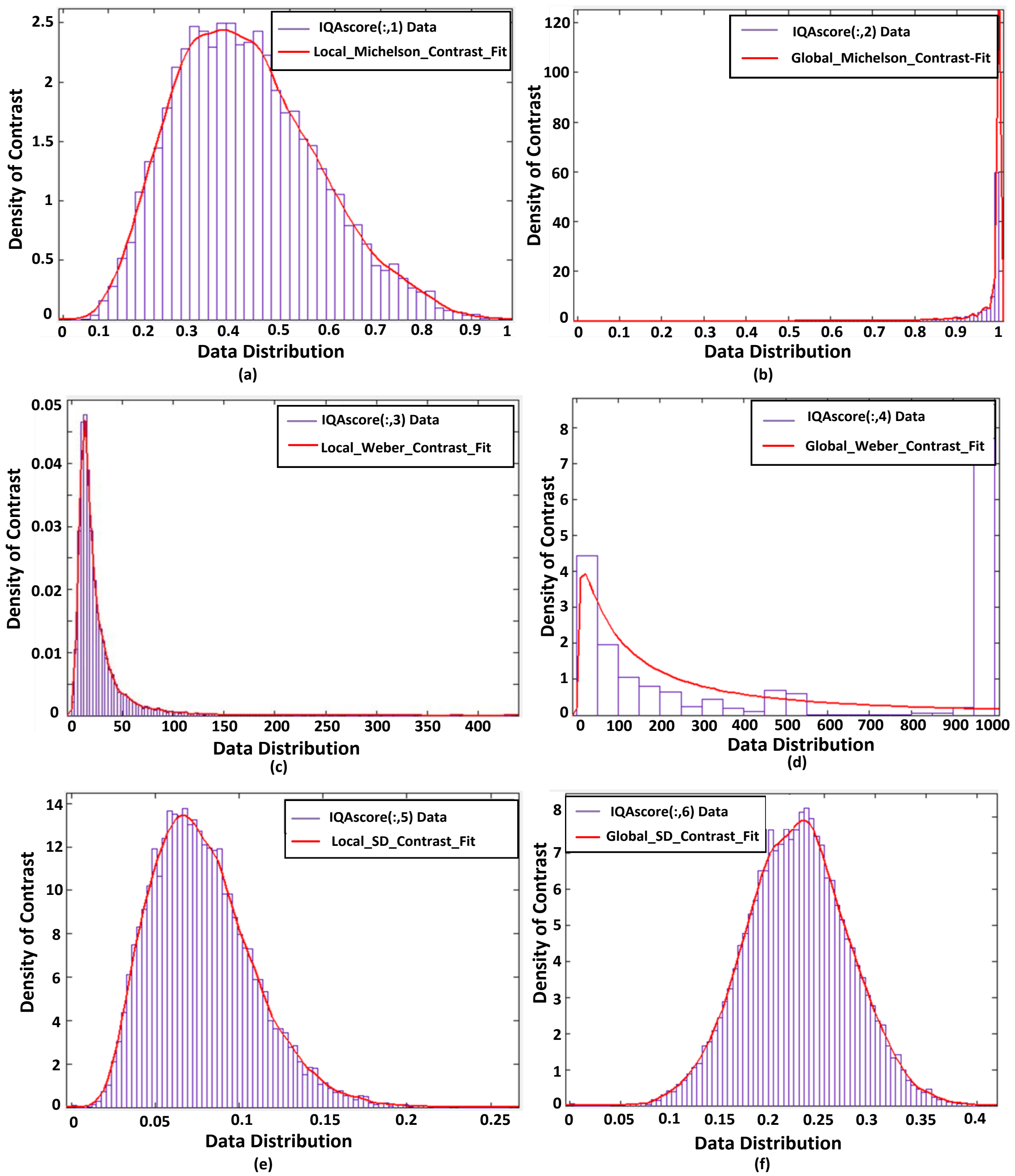

Fig. 1. PDF that best fits each type of contrasts: a) non-parametric distribution for local Michelson contrast; b) non-parametric distribution for global Michelson contrast; c) non-parametric distribution for local Weber contrast; d) non-parametric distribution for global Weber contrast; e) non-parametric distribution for local standard deviation contrast; f) non-parametric distribution for global standard deviation contrast.

UNNATCE database [26] consists of 180 test images with poor, good, and unnatural contrasts. Those images were created by applying the local contrast enhancement method on 60 source images. The source images for the local database were passport photos with good diversity in terms of race, gender, age, hairstyle, and facial expression. This database was added to the experiments to minimize bias because it was observed that the three existing databases consist of only globally contrast-enhanced images. A sample of images used in the study is displayed in Figs. 2 and 3.

Fig. 2. Sample of original (the most left ones) and contrast distorted images (beside). The top row images are from the CSIQ database, the middle row from CID2013, and the bottom row from the TID2013 database [27].

Fig. 3. Sample of original images (upper row), and contrast distorted images (lower row) for the UNNATCE database [26].

3.2. A Comparison Between Raw Values and NSS Values of Contrast Measures

Experiments - that made a comparison between global and local contrast measures, and between Raw values and NSS values of contrast – proceeded as following:

a) Converting images to grayscale using rgb2grey() function in MATLAB.
b) Computing the six types of contrast measures for database images.
c) Getting the raw values of contrasts for the images.
d) Getting the NSS values of contrasts for the images.
e) Comparing computed contrast measures (raw values) to mean opinion score (MOS) of subjective preliminary stage.
f) Comparing computed contrast measures (NSS values) to MOS of subjective comprehensive stage.
g) Using the performance metrics – Pearson linear correlation coefficient (PLCC), Spearman rank order correlation coefficient (SROCC), root mean square error (RMSE), and outlier ratio (OR) – to assess the performance.

h) Comparing the effectiveness of global contrast measures and local contrast measures in predicting image quality.
i) Comparing the effectiveness of raw values and NSS values in predicting image quality. Fig. 4 displays a block diagram for the implemented experiments.

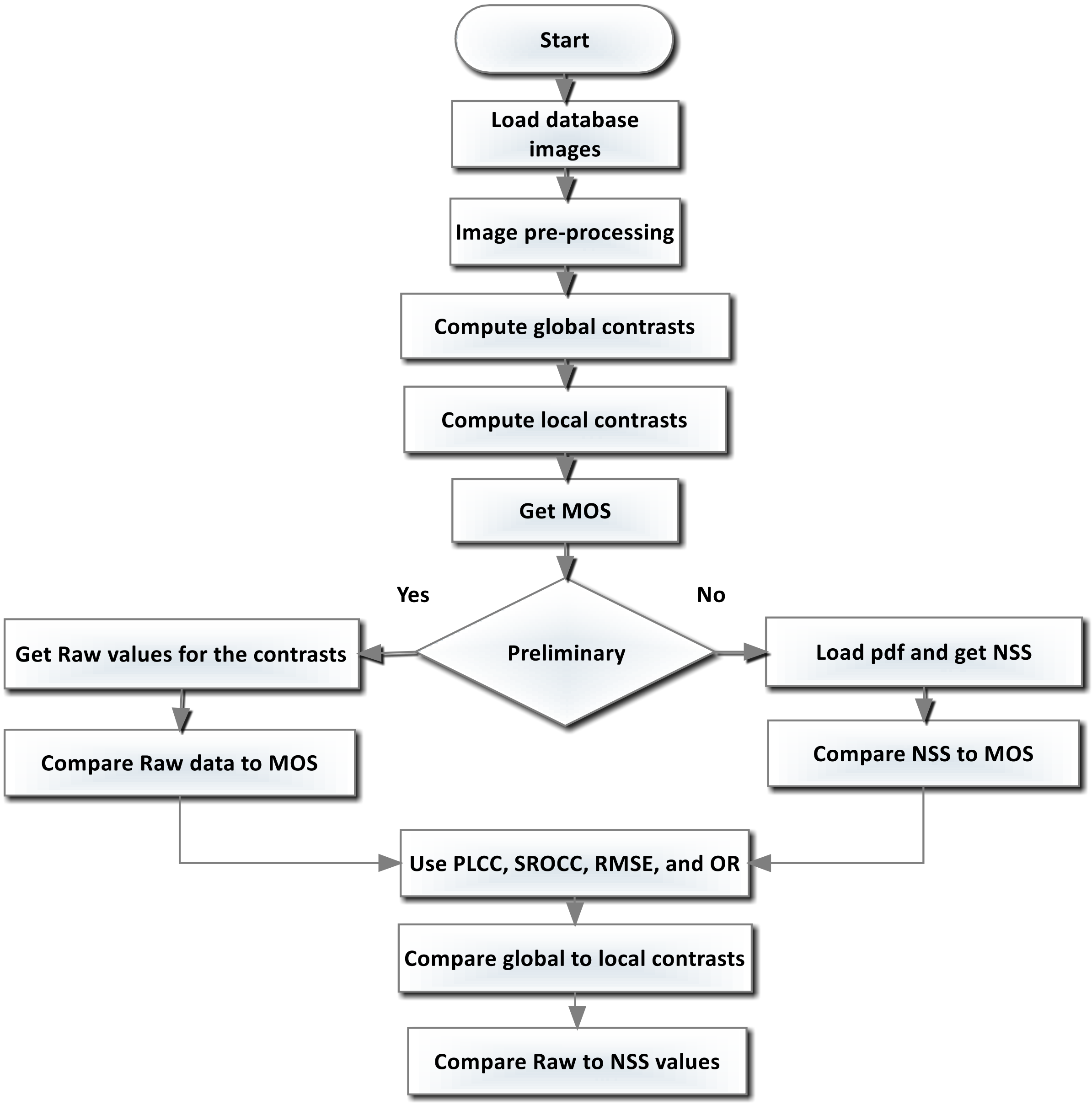

Fig. 4. Experiments block diagram.

3.3. Analysing the Effect of Using Alternative Contrast Measures

This section describes our efforts to find an alternative contrast measure, which could replace that of NR-IQA-CDI, i.e., the NSS of global standard deviation. The alternative contrast measures in this study included Michelson and Weber, besides standard deviation. These measures were compared in both local and global modes as well as in NSS and raw value mode. In total, five alternative contrast measures to NSS global standard deviation were investigated. The UNNATCE database was also included in the study besides the existing three databases to minimize bias based on the finding of the previous section.

This experiment was divided into the three following parts:

Part 1: Compares the raw values with the NSS values; this was motivated by the findings from a previous study which indicated that NSS of contrast was not always the best. The percentage of the difference between raw values (VC) and NSS values was first computed by:

$$\%dif = (VC - NSS)/NSS \quad (4)$$

then the average difference for each type of contrast was computed.

Part 2: Compares the five alternative contrast measures based on either raw or NSS values (depending on which one showed better performance in part 1).

Part 3: Compares Michelson and Weber contrast measures depending on the results from part 2.

4. RESULTS AND DISCUSSION

This section presents and discusses the results of the three carried out investigations.

4.1. Global Vs. Local Contrast Measures

4.1.1. Preliminary Experiment Results

Before starting to analyze the results, it is worth clearing that the OR for the CID2013 database was unavailable because the database did not provide the standard deviation of MOS. Tables 2 and 3 show the results of the preliminary investigation. Table 2 shows the percentage of difference (global measures – local measures) for each of the performance metrics. Table 3 shows the p-values of the paired t-tests. As for the TID2013 database, Table 2 shows that global measures have higher PLCC and SROCC by 146% and 214%, respectively. They also show lesser RMSE and OR by 26% and 16%, respectively. From Table 3, all the four p-values for the TID2013 database were less than 0.05 indicating that the differences in all the four-performance metrics were statistically significant.

For the CID2013 database, there was an increment in PLCC by 13%. The p-values for PLCC and SROCC in Table 3 were more than 0.05, indicating that the differences in these two-performance metrics were not statistically significant. The global measures showed lower RMSE by 5% with a p-value of less than 0.05.

Table 2. Percentage of difference (global – local) in each performance metric.

Database	Performance metric			
	PLCC	SROCC	RMSE	OR
TID2013	146%	214%	-26%	-16%
CID2013	13%	-7%	-4%	NA
CSIQ	50%	53%	-43%	-49%
Overall databases	70%	87%	-24%	-33%

For the CSIQ database, the global measures showed higher PLCC and SROCC by 50% and 53%, respectively. They also showed lower RMSE and OR by 43% and 49%, respectively. As seen in Table 3, all four p-values for CSIQ were less than 0.05 indicating that the differences in all of the four-performance metrics were statistically significant.

For the average results over the three databases, global measures showed an increase in PLCC and SROCC by 70% and 87%, respectively. They also showed lower RMSE and OR by 24% and 33%, respectively. Statistical test results indicated that the differences in PLCC, SROCC, RMSE, and OR were significant because the p-values were less than 0.05.

Table 3. *p*-values for paired *t*-test of global contrasts over the three public databases.

Database	Performance metric			
	PLCC	SROCC	RMSE	OR
TID2013	$2.52\text{x}10^{-16}$	$4.24\text{x}10^{-15}$	$4.14\text{x}10^{-11}$	$5.73\text{x}10^{-07}$
CID2013	$2.83\text{x}10^{-01}$	$2.08\text{x}10^{-01}$	$7.89\text{x}10^{-03}$	NA
CSIQ	$1.68\text{x}10^{-14}$	$9.95\text{x}10^{-16}$	$3.40\text{x}10^{-22}$	$1.20\text{x}10^{-17}$
Overall database	$1.97\text{x}10^{-16}$	$7.06\text{x}10^{-11}$	$7.10\text{x}10^{-12}$	$7.28\text{x}10^{-18}$

Overall, the results indicated that global contrast measures demonstrate better performance using TID2013 and CSIQ databases. However, this paper argued that this occurred because the images in the three databases (TID2013, CID2013, and CSIQ) experienced the same type of contrast distortion which was global contrast change. In the comprehensive stage, the UNNATCE database consisting of test images - with local contrast change - was used besides the three databases.

4.1.2. Comprehensive Experiment Results

Tables 4 and 5 show the results of the comprehensive investigation. Table 4 shows the percentage of difference (global measures – local measures) in each of the performance metrics. Table 5 shows the p-values of the paired t-tests. As for the TID2013 database, Table 4 exhibits that the global measures showed higher PLCC and SROCC by 205% and 255%, respectively. They also showed lesser RMSE and OR by 5% and 1%, respectively. As depicted in Table 5, all of the four p-values for TID2013 were less than 0.05 indicating that the differences in the three-performance metrics were statistically significant.

As for the CID2013 database, there was an increase in PLCC and SROCC by 29% and 30%, respectively. They also decreased in RMSE by 6%. The p-values for PLCC and RMSE were less than 0.05 indicating that the differences in their performance metrics were statistically significant. The SROCC p-value was more than 0.05 indicating that the difference in the performance metric was not statistically significant.

For the CSIQ database, there were an increase in PLCC and SROCC by 136% and 155% respectively, with a decrease in RMSE by 4%. As revealed by Table 5, the p-value for PLCC and SROCC were less than 0.05 indicating that the differences in these performance metrics were statistically significant, while the p-values for RMSE and OR were more than 0.05 indicating that the differences in these two-performance metrics were not statistically significant.

For the average results over the three databases, global measures showed an increase in PLCC, and SROCC by 123% and 146%, respectively. They also showed lower RMSE by 5%. The results of statistical tests showed that the differences in PLCC, SROCC, and RMSE were statistically significant where the p-values were less than 0.05, whereas the difference in OR was not statistically significant.

As for the UNNATCE database, and as exhibited in Table 4, the global measures showed lower PLCC and SROCC by 23% and 22%, respectively; they also showed higher RMSE and OR by 11% and 50%, respectively.

Table 4. Percentage of difference for all four data sets using NSS.

Database	Performance metric			
	PLCC	SROCC	RMSE	OR
TID2013	205%	255%	-5%	-1%
CID2013	29%	30%	-6%	NA
CSIQ	136%	155%	-4%	6%
Overall databases	123%	146%	-5%	2%
UNNATCE	-23%	-22%	11%	50%

The statistical tests indicated that the differences in the four-performance metrics were statistically significant since the p-values were less than 0.05. These results were due to the locally enhancement of the UNNATCE database.

From Tables 4 and 5, it becomes obvious that the global contrast measures are better for images with a global contrast change, whereas local contrast measures were better for images with local contrast change. There was an interesting observation that the results in the preliminary stage were better than those of the comprehensive stage.

Table 5. *p*-values for paired *t*-test for each of the public data sets using NSS.

Database	Performance metric			
	PLCC	SROCC	RMSE	OR
TID2013	5.69×10^{-03}	1.78×10^{-04}	5.65×10^{-04}	1.75×10^{-03}
CID2013	1.00×10^{-02}	7.81×10^{-02}	4.95×10^{-04}	NA
CSIQ	2.75×10^{-11}	8.11×10^{-18}	1.00×10^{-01}	3.45×10^{-01}
Overall public databases	9.49×10^{-11}	5.95×10^{-12}	1.50×10^{-06}	4.37×10^{-01}
UNNATCE	4.90×10^{-03}	3.74×10^{-03}	7.50×10^{-04}	1.50×10^{-02}

4.2. Raw Values Vs. NSS Values of Contrast Measures

Table 6 shows the results of comparing raw with NSS values in replacing standard deviation in NR-IQA-CDI. It shows the percentage of difference (raw values of contrast – NSS values of contrast) for global and local contrasts, in each of the performance metrics for each database.

In general, raw values of global contrast were significantly better than NSS values except for the CID2013 database with a very marginal difference. In general, NSS values of local contrast showed better performance than raw values of local contrast except for CSIQ.

However, the magnitude of the difference was very marginal as compared to those of global contrast. The overall results indicated that there was an advantage of using raw values to using NSS values of contrast.

Table 6. Percentage of difference in performance metrics for raw and NSS values of contrast measures.

Measure	Database	% of difference (raw values – NSS values)			
		PLCC	SROCC	RMSE	OR
Global	CSIQ	35%	40%	-35%	-36%
	CID2013	-4%	-3%	8%	NA
	TID2013	35%	29%	-18%	-14%
	UNNATCE	56%	41%	-5%	-13%
	ALL	31%	27%	-12%	-21%
Local	CSIQ	2%	5%	-2%	-7%
	CID2013	-7%	-6%	14%	NA
	TID2013	-2%	-7%	1%	1%
	UNNATCE	59%	35%	-5%	-15%
	ALL	13%	7%	2%	-7%
Overall		22%	17%	-5%	-14%

4.3. Alternative Contrast Measure for Standard Deviation

Fig. 5 shows the average performance improvement of NR-IQA-CDI by alternative contrast measures using the three public databases (CSIQ, CID2013, and TID2013), Fig. 6 shows the average performance improvement using the UNNATCE database, and Fig. 7 shows the average performance improvement of NR-IQA-CDI by alternative contrast measures using all the four databases.

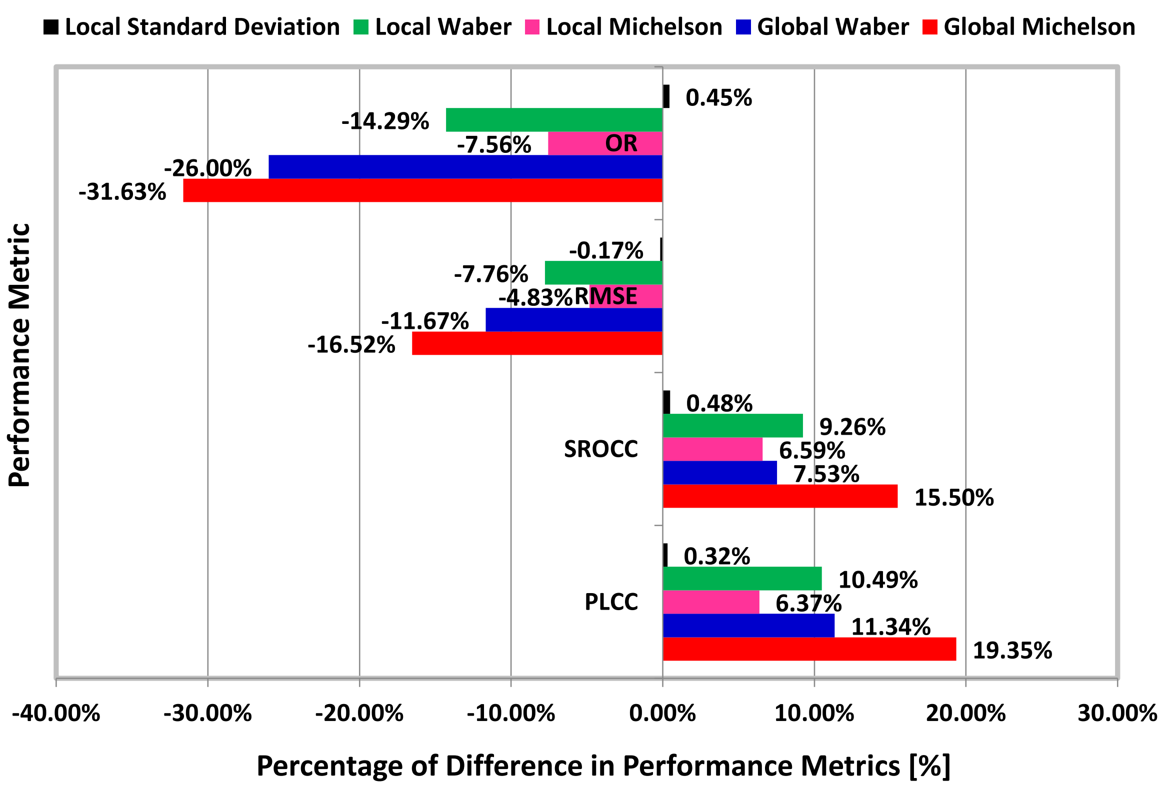

Fig. 5. Percentage of difference in performance metrics of NR-IQA-CDI by alternative contrast measures using CSIQ, CID2013, and TID2013 databases.

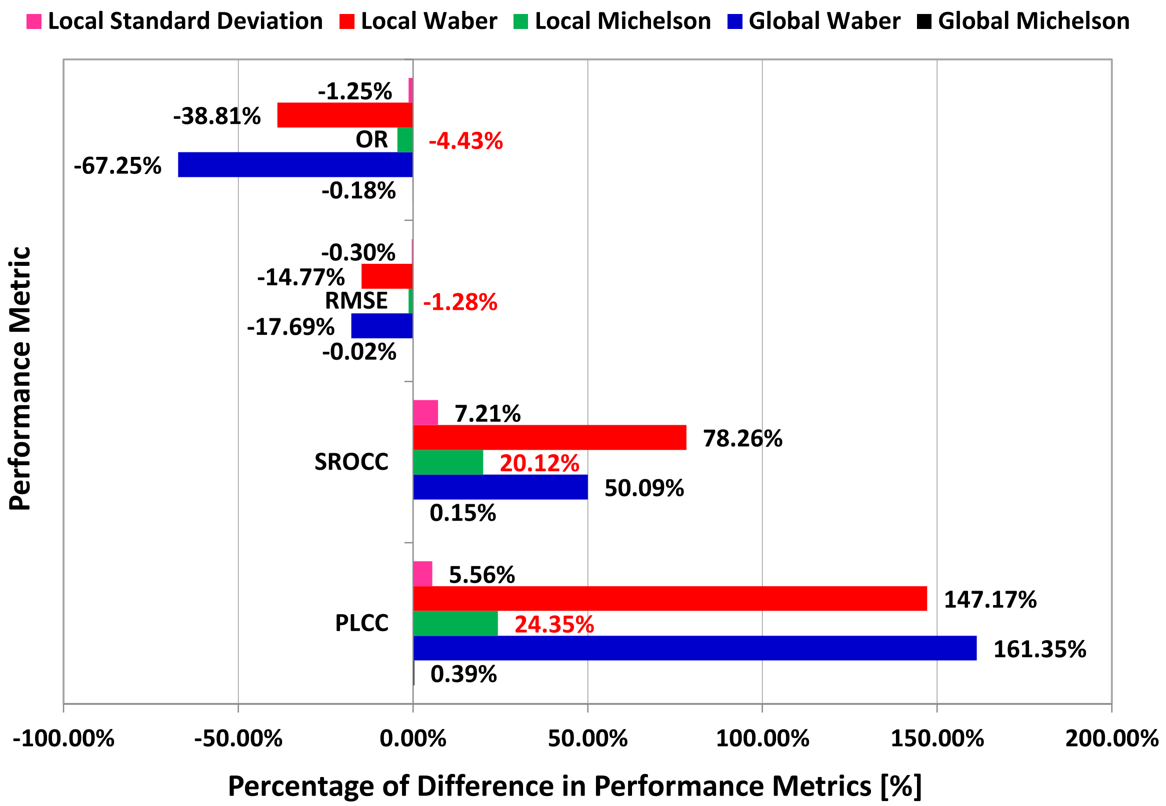

Fig. 6. Percentage of difference in performance metrics of NR-IQA-CDI by alternative contrast measures using UNNATCE database.

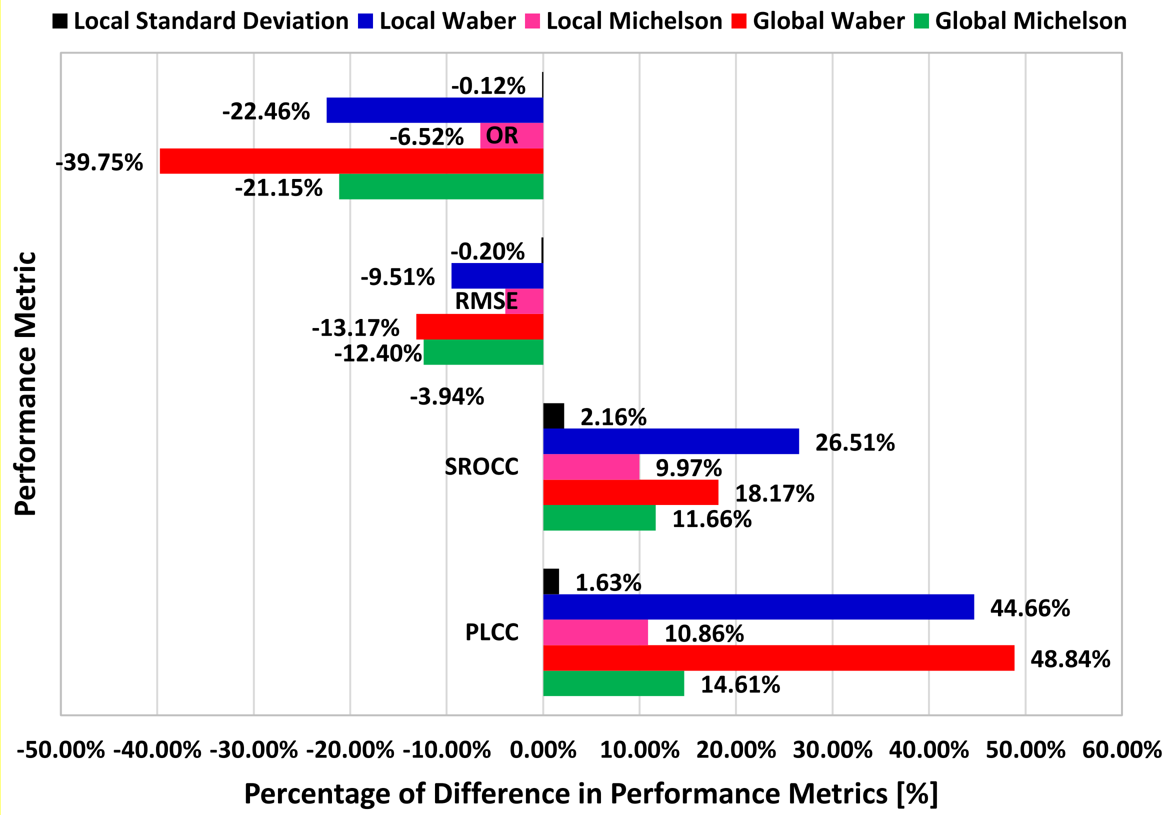

Fig. 7. Percentage of difference in performance metrics of NR-IQA-CDI by alternative contrast measures using all of the four databases.

In general, global contrast measures showed better performance with the three databases while local contrast measures showed better performance using the UNNATCE database. This finding was consistent with the finding of the investigation presented earlier. There were only very few exceptional cases. For example, global Weber contrast showed better performance in PLCC, RMSE, and OR with the UNNATCE database.

It is clear from the figures that both Michelson and Weber contrast measures could help - significantly - improving the performance of NR-IQA-CDI. Hence, they could replace standard deviation which required more computation. Michelson contrast measures showed better performance than Weber contrast measures when the assessment involved only the three databases. Nevertheless, Weber contrast measures showed better performance when the UNNATCE database was included. Such finding again showed the importance to include both test images with global and local contrast change in the experiments conducted.

Overall, global Weber contrast showed the best performance among all other alternative contrast measures. This finding showed that NR-IQA-CDI could be improved not only in terms of accuracy but also computation complexity by replacing global standard deviation with global Weber contrast. A more detailed comparison between Weber and Michelson contrast measures is presented in Table 7.

Table 7. Percentage of difference in performance metrics for Weber and Michelson.

Measure	Database	Percentage of difference (Weber - Michelson)			
		PLCC	SROCC	RMSE	OR
Global	CSIQ	-9.62%	-9.19%	30.30%	62.08%
	CID2013	0.78%	-0.21%	-1.99%	NA
	TID2013	-9.67%	-3.63%	5.69%	-0.04%
	UNNATCE	160.40%	109.15%	-14.85%	-39.79%
	ALL	35.47%	24.03%	4.79%	7.42%
Local	CSIQ	4.41%	4.82%	-5.85%	-13.49%
	CID2013	0.34%	0.25%	-0.89%	NA
	TID2013	6.73%	1.95%	-2.84%	-2.07%
	UNNATCE	97.71%	47.33%	-13.66%	-35.96%
	ALL	27.30%	13.59%	-5.81%	-17.17%
Overall		31.39%	18.81%	-0.51%	-4.88%

Table 7 shows the percentage of the difference between Weber and Michelson measures (global and local) in each of the performance metrics for each database. In general, Weber contrast measures showed better performance than Michelson contrast measures of global and local contrast, especially for the UNNATCE database.

The overall results indicated that there was an advantage of replacing standard deviation with Weber contrast measure in NR-IQA-CDI algorithms.

5. CONCLUSIONS

The following conclusions can be drawn from the three conducted investigations:

- NSS values of contrast measures were not always better than the raw values; hence, it is highly recommended to make a comparison between the two before including any new measure in NR-IQA-CDI.

- Both Weber and Michelson contrast measures could replace the standard deviation since they could improve both the prediction accuracy and computation complexity.
- Global Weber contrast measure is recommended as the best alternative since it showed the best improvement in the overall prediction accuracy.
- Since Weber contrast measure was derived from the Weber-Fechner law, the results were in-line with this famous psychophysics law which defines the relation between the actual changes in a physical stimulus and perceived changes.

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