

Contrast-distorted image quality assessment based on curvelet domain features

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ABSTRACT

Contrast is one of the most popular forms of distortion. Recently, the existing image quality assessment algorithms (IQAs) works focusing on distorted images by compression, noise and blurring. 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) have been created for CDI. NR-IQA-CDI showed 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, respectively. Spatial domain features are the basis of NR-IQA-CDI architecture. Therefore, in this paper, the spatial domain features are complementary with curvelet domain features, in order to take advantage of the potent properties of the curvelet in extracting information from images such as multiscale and multidirectional. The experimental outcome rely on K-fold cross validation (K ranged 2-10) and statistical test showed that the performance of NR-IQA-CDI rely on curvelet domain features (NR-IQA-CDI-CvT) significantly surpasses those which are rely on five spatial domain features.

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1. INTRODUCTION

Various kinds of distortion such as noise, blurring, fast fading, blocking artifacts and contrast which may appear because of some of certain processes on the image can degrade the quality of images. Subjective and objective methods are two types of IQA or video quality assessment (VQA) used to evaluate the image quality [1, 2]. In real-time applications is impractical to use subjective quality assessment because it takes time and is expensive. Therefore, objective IQA algorithms are the best solution since the role of human is limited in order to predict the quality of image. Objective IQAs can be grouped into full reference (FR), reduce reference (RR) and no reference (NR). These groups require the availability of original image [3-5].

Most of FR-IQA and RR-IQA applications are constrained due to available of original image. Therefore, NR-IQA is the best solution for this case. Recently, the existing NR-IQA works focusing on distorted images by compression, noise and blurring [6, 7]. Contrast is one of the most popular forms of distortion. Figure 1 shows the contrast-distorted image is low gray scale image [8]. poor lighting condition and low quality image acquisition device can produce contrast distortion [9, 10]. Unfortunately, the current work carried out in the area of NR-IQA for CDI is very minimal.

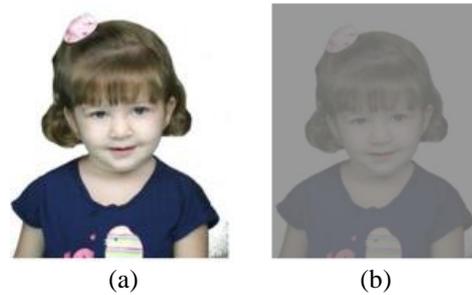


Figure 1. Contrast-distorted image, (a) good contrast image (my lena.bmp), and (b) poor contrast image [8]

Recently, the existing IQAs works for CDI are (1) RIQMC [11] based on entropies and image histogram order statistics; and (2) NR-IQA-CDI [12] which is constructed on the basis of NSS principles such that there are certain regularities in natural scene statistics that may be missing from the statistics of distorted images. Global spatial statistics features are used in NR-IQA-CDI including the mean, standard deviation, entropy, kurtosis and skewness. Regrettably, NR-IQA-CDI performance are not positive in some of test image databases, TID2013 and CSIQ, where the PLCC are only around 0.57 and 0.76, respectively.

The current NR-IQA-CDI is based on global spatial statistics which suffers from three problems. Secondly, spatial domain is lacking of info on scale and orientation which are essential for compact representation of curve which is a common structure in natural image. Compact representation is essential for analysis to be focused on relevant information to reduce confusion by irrelevant info or noise. It has been proven useful in image contrast enhancement and IQA.

Pyramid and wavelet transform is one of multiscale decomposition transform (MSD) has been used successfully in many image processing applications. However, WT lacks directionality. multiscale geometrical analysis (MGA) transforms [13] were proposed to resolve this issue. Curvelet transform (CT) decomposes the original image into set of frequency coefficients of subbands with various scales, orientation and location [14]. In Coarse part, Low-frequency coefficients are distributed. In Fine part, high frequencies coefficients are distributed. And the middle layer are distributed to detail. Curvelet has a common characteristics that distinguishes it from the other types of Transforms are Higher directional sensitivity and lower redundancy [15].

The first NR-IQA [16] used features derived from curvelet transform. Liu *et al.* [17] and Shen *et al.* [18] introduced a new NR-IQA based on CT. The success of all of these works rely on the strength of curvelet, in which CT provides a rich source of orientation information on images. Such info could be used to detect the presence of distortion in the image. Liu *et al.* [17] present an effective NR-IQA using energy features derived from the curvelet domain. These features were found closely related through various types of distortion to the natural image quality. However, all of these works proposed specially for quality evaluation of distorted images due to compression, noise, and blurring. This study is motivated by the strength of curvelet transform in efficient representation of curve, a basic structure often seen in natural scene images. It begins with exploring the use of curvelet domain features in characterizing contrast-distorted images (CDI). Therefore, this paper enhances the existing NR-IQA-CDI using curvelet domain features.

2. CURVELET TRANSFORM

By applying an effective parabolic scaling law: width \cong (length)², the CT can better represent edges and other singularities along curves [13]. Horizontal, vertical and diagonal are limited directional information only captured in Wavelet transform. However, curvelet transform decompose the image with geometric bases in multiple directions and positions [13, 15]. Since the curvelet coefficients are categorized based on orientation and scale, the curvelet edge is smoother than the Wavelet edge. Figure 2 shows the edge representation in curvelet and wavelet transforms. It can be observe that curvelet edge can be represented by smaller amount of large coefficients, while wavelet edge can be represented by a bigger amount of large coefficients in the fine scale.

In last generation of curvelet transform, Cand'es *et al.* proposed a two fast discrete curvelet transforms (FDCT) i.e: Equation (1) unequally-spaced fast fourier transform (USFFT) based curvelet and (2) frequency wrapping based curvelet [15]. The DCT of a 2-D function $f[t_1, t_2]$ is formulated as:

$$C^D(j, \ell, k) := \sum_{0 \leq t_1, t_2 < n} f[t_1, t_2] \overline{\varphi_{j, \ell, k}^D[t_1, t_2]}, \quad (1)$$

where φ, j, ℓ, k are curvelet functions, scale, orientation and position respectively. t_1, t_2 denote coordinates in the spatial domain: $0 \leq t_1, t_2 < n$. $C^D(j, \ell, k)$ denotes curvelet coefficient. In our work, FDCT by wrapping is applied.

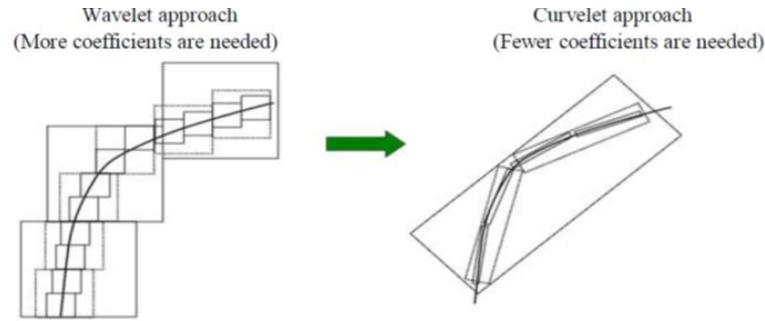


Figure 2. Wavelet and curvelet transforms edge representations [16]

3. APPLICATION OF CURVELET DOMAIN FEATURES IN NR-IQA-CDI

Here, we presents how curvelet domain features are applied in NR-IQA-CDI. It begins with trying to addressing the problems of current NR-IQA-CDI followed by formulating curvelet domain features and predicting image quality using the features.

3.1. CDI distinguish

CT is an effective image representation by smaller amount of large coefficients as compared to those in the spatial domain as mention in [19]. Large-magnitude coefficients only occur in regions of the image that contain fine details; fine scales coefficients show the existence local info in an image. But in the coarsest scale consists of mainly large-magnitude coefficients and matches the image in low spatial resolution. Overall contrast and brightness of an image are depends on the distribution of the coefficients. In an image with good contrast must be included a powerful overall contrast, relatively bright appearance and fine details. In order to represent the characteristics, easily can be accomplished by using distribution of curvelet coefficients. In good overall contrast and bright appearance, a distribution of coefficients at coarsest scale with high dispersion and high central tendency. While in presence of fine details, a distribution of coefficients at finer scale with high central tendency. Briefly, from the observation of the distributions of curvelet coefficients at the coarsest and finest scales can be achieved by generate possible features in characterizing good contrast images and also CDI [19]. Therefore, in the next section, the details about formulating the features from the curvelet coefficients will be presented.

3.2. Formulating curvelet domain features

This section presents the two main processes in the proposed NR-IQA-CDI rely on curvelet domain features (NR-IQA-CDI-CvT). The first process is for computing curvelet features and the second one is for predicting image quality using the statistics as explained in the sub-sections.

3.2.1. Computing curvelet features

There are 3 steps in computing curvelet features as shown in Figure 3.

Step 1: Pre-processing

In this step, Colour images are converted to grayscale image using (2), where $I_{gray}, I_{red}, I_{green}$ and I_{blue} are the grayscale image, and red, green and blue channel of the original RGB image, respectively. MATLAB[®] function `rgb2gray()` is used to perform the conversion.

$$I_{gray} = 0.2989I_{red} + 0.5870I_{green} + 0.1140I_{blue} \quad (2)$$

In addition, resize step was used to normalize the size of the input image to have the size of minimum dimension fixed to 256 in order to avoid mismatch of resolution during comparison.

Step 2: Fast discrete curvelet transform

Using FDCT, The grayscale image is partitioned into groups of curvelet coefficients $C(j, l, k_1, k_2)$ as defined by (3). The curvelet transformation was done using the curvelet 2.1.2 toolbox, available from <http://www.curvelet.org>.

$$C^D(j, l, k_1, k_2) = \sum_{\substack{0 \leq m < M \\ 0 \leq n < N}} f[m, n] \varphi_{j,l,k_1,k_2}^D[m, n] \quad (3)$$

where φ_{j,l,k_1,k_2}^D is a curvelet coefficients at different scales, j , orientations, l and location, (k_1, k_2) [20].

Step 3: Extract features from curvelet coefficients

First, the magnitude of coefficients at each scale j , $|\theta_j|$ were computed. Coefficients from same scale but different orientations were grouped together. Next, the mean, $\mu()$ and standard deviation, $\sigma()$ of the curvelet coefficients at the two coarsest scales $j=\{1, 2\}$ were extracted as the four features, f_1, f_2, f_3 and f_4 as defined by (4)-(7).

$$f_1 = \mu(|\theta_1|) \quad (4)$$

$$f_2 = \mu(|\theta_2|) \quad (5)$$

$$f_3 = \sigma(|\theta_1|) \quad (6)$$

$$f_4 = \sigma(|\theta_2|) \quad (7)$$

The last feature, f_5 , is the mean, $\mu()$ of the highest 1% curvelet coefficients, θ'_j at the finest scale, $j=5$ as defined by (8):

$$f_5 = \mu(|\theta'_5|) \quad (8)$$

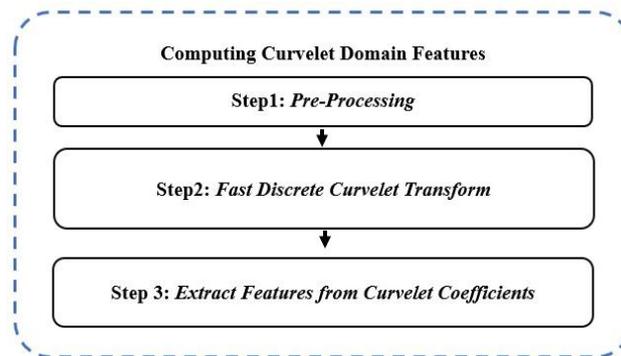


Figure 3. Flowchart of computing curvelet domain features

3.2.2. Predicting image quality

The steps for predicting image quality are shown in Figure 4.

Step 1 : Modelling using curvelet domain features

Step 1.1 : Compute curvelet domain features from training images

The step to compute curvelet domain features is as explained in section 3.2. The images used were from training set for modelling purposes.

Step 1.2 : Perform feature normalization and regression

In feature normalization, the values of each feature f_i are normalized against their mean, μ_f and standard deviation, σ_f such that the normalized values, Z_i will have zero mean and unit standard deviation as defined in (9). Feature normalization is important before performing any machine learning such as regression because it tends to increase the accuracy.

$$Z_i = \frac{f_i - \mu_f}{\sigma_f} \quad (9)$$

The mean, μ_f and standard deviation, σ_f and the regression function derived from this step will be used later in Step 2.2. Regression aims to find the mapping function, or better known as regression function, which map independent variables to dependent variables. In this work, the independent variables are the features and the dependent variable is the subjective mean opinion score (MOS). Regression is important in

this work to remove non-linearity to improve the linear correlation between the features and MOS. In this work, support vector regression (SVR) (via LIBSVM-3.12 package [21]) is used to find the regression function, similar to what has been used in the current NR-IQA-CDI for fair comparison. In SVR, regression function is determined through the approach of supervised machine learning.

Step 2 : Computing image quality

Step 2.1 : Compute curvelet domain features from input image

The step to compute curvelet domain features is as explained in section 3.2. The image used is the input image which the quality is to be assessed.

Step 2.2 : Compute image quality using the mean and standard deviation for feature normalization and regression function obtained from step 1.2

In this step, the curvelet domain features were normalized using the mean, μ_f and standard deviation, σ_f , obtained from Step 1.2. Next, they were plugged into the regression function obtained from Step 1.2 to compute the final image quality score.

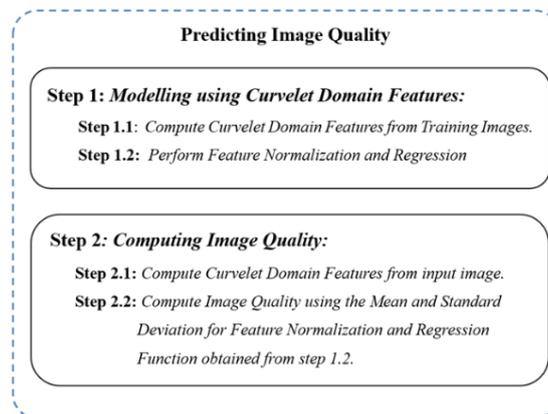


Figure 4. Flowchart of the predicting image quality

4. EXPERIMENTAL RESULTS AND DISCUSSION

Here, the NR-IQA-CDI rely on curvelet features (NR-IQA-CDI-CvT) performance is evaluated. The evaluation procedure, discussions, and conclusions was described.

4.1. Evaluation procedure

To evaluate our proposed, the same test image databases used by NR-IQA-CDI were used. Only contrast distorted images (116, 250, and 400) were chosen from CSIQ [22], TID2013 [23], and CID2013 [11], respectively. Mean opinion score (MOS) or differential mean opinion score (DMOS) are used to represent the Subjective scores. In order to evaluate the IQA accuracy, K-fold cross validation (CV) was used to determine how well the IQA could be generalized to independent data groups while decrease bias, since regression is essentially a learning algorithm that requires training.

Three databases were split randomly into 10 subgroups when performing the K-fold cross validation. To test the proposed metric, the method named 10-fold leave-one-out CV was used. By using K times, the result of the assessment were averaged. To decrease the variability, repeated rounds of cross-validation ($k = 2$ to 10) were accomplished through various partitions [8, 24]. The above cross-validation has been iterated hundred times (to prevent bias). Tables 1 and 2 show the average results. To evaluate IQA performance, three metric were used between the estimated objective scores and the subjective mean opinion scores (MOS). The metrics are (1) SROCC, (2) PLCC and (3) RMSE. The effective performance in case of correlation with human awareness if SROCC~1, PLCC~1 and RMSE~0 [8, 24].

4.2. NR-IQA-CDI-CvT evaluation

Tables 1 and 2 lists the three-performance metrics used to evaluate the current NR-IQA-CDI and the proposed NR-IQA-CDI-CvT with the three test image databases and k -fold cross-validation with k range from 2 to 10. Figure 5 shows the bar chart graph comparing the average values of each of the three-performance metrics of the two NR-IQA-CDI for each of the three databases. At a glance, NR-IQA-CDI-CvT outperformed the current NR-IQA-CDI in all the three-performance metrics using CSIQ and TID2013.

Table 1. The PLCC, SROCC and RMSE across 100 train-test iteration via NR-IQA-CDI [12] (five global NSS features)

k	CSIQ			TID2013			CID2013		
	PLCC	SROCC	RMSE	PLCC	SROCC	RMSE	PLCC	SROCC	RMSE
2	0.6849	0.7093	0.1233	0.5111	0.4450	0.8608	0.8685	0.8711	0.3090
3	0.7518	0.7619	0.1121	0.5698	0.4886	0.8112	0.8844	0.8874	0.2945
4	0.7389	0.7522	0.1133	0.5785	0.4992	0.8266	0.8799	0.8797	0.2970
5	0.7923	0.7818	0.1092	0.5762	0.4957	0.8091	0.8738	0.8743	0.3035
6	0.7601	0.7683	0.1097	0.5911	0.5173	0.7923	0.8804	0.8829	0.2979
7	0.7840	0.7775	0.1045	0.5812	0.5024	0.8141	0.8857	0.8816	0.2917
8	0.7724	0.7846	0.1070	0.5900	0.5028	0.8089	0.8818	0.8817	0.2961
9	0.7788	0.7803	0.1054	0.5870	0.4932	0.8064	0.8844	0.8833	0.2962
10	0.7978	0.7751	0.1076	0.5799	0.5048	0.8019	0.8789	0.8765	0.2974
Av	0.7623	0.7657	0.1102	0.5739	0.4943	0.8146	0.8797	0.8798	0.2981

Table 2. The average PLCC, SROCC and RMSE across 100 train-test iteration via the NR-IQA-CDI-CvT (5 features)

k	CSIQ			TID2013			CID2013		
	PLCC	SROCC	RMSE	PLCC	SROCC	RMSE	PLCC	SROCC	RMSE
2	0.8078	0.8076	0.1024	0.6681	0.5887	0.7360	0.8522	0.8566	0.3280
3	0.8384	0.8354	0.0962	0.6875	0.6259	0.7144	0.8848	0.8882	0.2936
4	0.8301	0.8358	0.0950	0.6881	0.6211	0.7213	0.8769	0.8823	0.3023
5	0.8547	0.8417	0.0903	0.6882	0.6220	0.7242	0.8808	0.8866	0.2965
6	0.8487	0.8396	0.0943	0.6955	0.6309	0.7095	0.8863	0.8896	0.2908
7	0.8475	0.8351	0.0910	0.7044	0.6295	0.7073	0.8860	0.8880	0.2922
8	0.8564	0.8473	0.0893	0.6914	0.6268	0.7177	0.8850	0.8890	0.2948
9	0.8535	0.8396	0.0922	0.6991	0.6313	0.7024	0.8900	0.8926	0.2821
10	0.8693	0.8536	0.0870	0.6928	0.6164	0.7197	0.8851	0.8954	0.2856
Av	0.8451	0.8373	0.0931	0.6906	0.6214	0.7169	0.8808	0.8854	0.2962

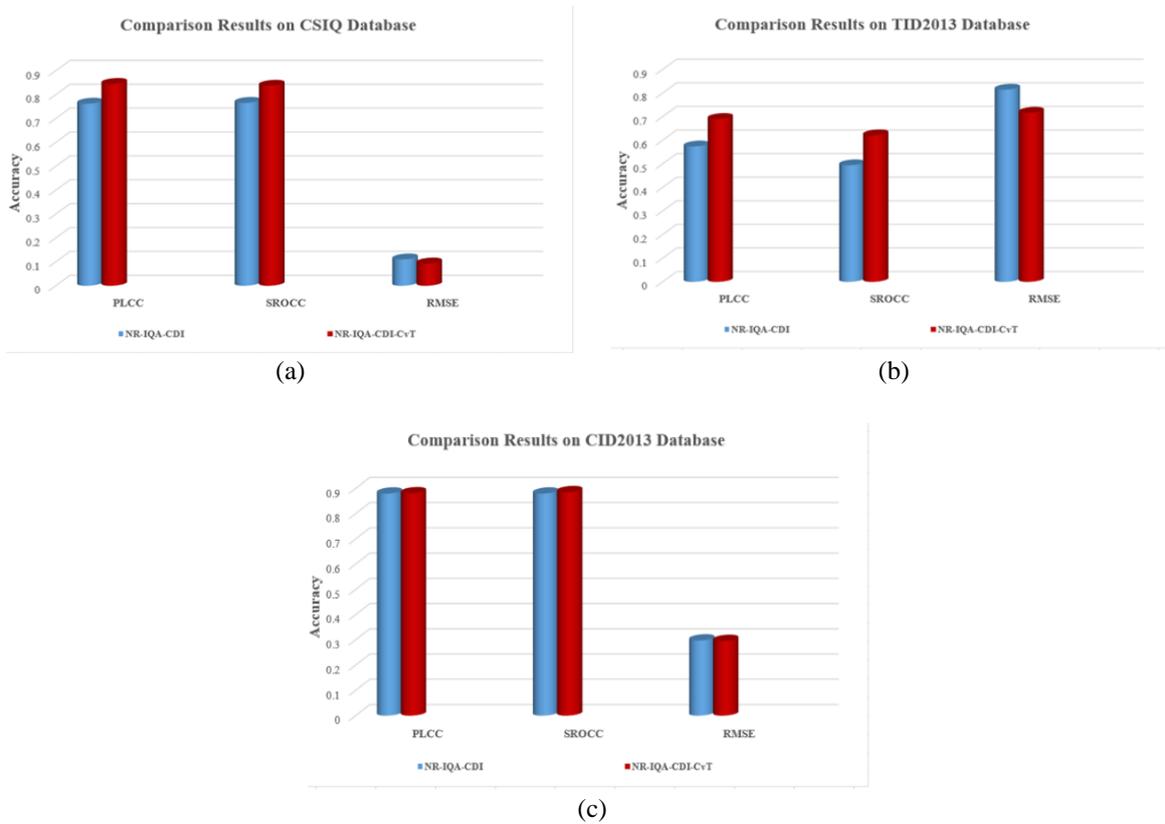


Figure 5. Comparison of SROCC, PLCC, and RMSE of NR-IQA-CDI, NR-IQA-CDI-CvT on; (a) CSIQ database, (b) TID2013 database, (c) CID2013 database

4.2.1. Statistical performance analysis

a. Percentage of difference

Each k in each of the databases, the difference between the two-performance metrics are calculated by (10):

$$d_i = cvt c_i - c_i \quad (10)$$

Where c_i corresponds to the first metric values without using features in curvelet domain and $cvt c_i$ corresponds to the second metric values by using features in curvelet domain. Then the average percentage of differences is calculated for all the k values and databases. The percentage is calculated by dividing the performance difference by the absolute first metric value of c_i .

$$dp = \frac{1}{n} (\sum_{i=1}^n d_i / abs(c_i)) \quad (11)$$

Where n corresponds to the total number k across all databases. The absolute value is used to keep the percentage (increment or decrement) sign of difference in performance. The percentage of difference is shown in Table 3.

Table 3. Percentage difference results for NR-IQA-CDI-CvT-NR-IQA-CDI

Image Database	PLCC	SROCC	RMSE
TID2013	20.49 %	25.81 %	-11.96 %
CID2013	0.11 %	0.63 %	-0.67 %
CSIQ	10.99 %	9.41 %	-15.53 %
All Databases	10.53 %	11.95 %	-9.39 %

b. Statistical significance

A paired T-test hypothesis test [25, 26] is implemented to the performance metric value calculated before and after adding curvelet features to produce the p-value as shown in Table 4. Generally, p-value of less than 0.05 implies that a significant difference appear within the values. Tables 4 and 5 displays the P-values of the paired T-tests for adding curvelet feature.

Table 4. P-values of differences between NR-IQA-CDI & NR-IQA-CDI-CvT

Image Database	PLCC	SROCC	RMSE
TID2013	1.24×10^{-08}	2.54×10^{-10}	1.48×10^{-08}
CID2013	3.41×10^{-01}	5.43×10^{-02}	2.88×10^{-01}
CSIQ	4.34×10^{-07}	1.25×10^{-07}	4.32×10^{-08}
All Databases	1.85×10^{-07}	1.49×10^{-07}	4.73×10^{-05}

Table 5. P-values of differences between NR-IQA-CDI & NR-IQA-CDI-CvT If p -value ≤ 0.05 : the observed difference is "significant"

Image Database	PLCC	SROCC	RMSE
TID2013	Significant	Significant	Significant
CID2013	Insignificant	Insignificant	Insignificant
CSIQ	Significant	Significant	Significant
All Databases	Significant	Significant	Significant

4.2.2. Discussion

The discussion on the results in Tables 3, 4, and 5 are as:

- Table 3 indicates that the findings using the TID2013 have improved, that was our main aim for enhancement. There was a significant increase in PLCC and SROCC by 20.49% and 25.81%, respectively. The RMSE decreased noticeably by 11.96 %. The 3 p-values for TID2013 were below than 0.05, meaning significant differences in those three performance measures as shown in Tables 4 and 5.
- For CID2013, PLCC and SROCC increased very marginally by 0.11% and 0.63%, respectively. The RMSE also decreased very marginally by 0.67%. The 3 p-values for CID2013 indicate that the differences in these three measures were not statistically significant as shown in Tables 4 and 5.

- For the CSIQ, there was a moderate increase in PLCC and SROCC by 10.99% and 9.41%, respectively. The RMSE decreased moderately by 15.53%. The 3 p -values for CSIQ below than 0.05, indicate that the differences in these three measures were statistically significant as shown in Tables 4 and 5.

For the average results of the three databases, there were moderate increase in PLCC and SROCC by 10.53% and 11.95%, respectively. The RMSE decreased moderately by 9.39%. The three p -values for all databases below than 0.05, indicate that the differences in these three performance matrices were statistically significant as shown in Tables 4 and 5.

5. CONCLUSION

In this paper, the existing NR-IQA-CDI was enhanced using curvelet domain features. In characterizing a good contrast image and contrast-distorted image at various scales, distributions of curvelet coefficients were found to be accurate. The five curvelet domain features proposed were derived from the distribution of the curvelet coefficients across the two coarsest scales and the finest scale. The performance evaluation indicated that NR-IQA-CDI-CvT significantly outperformed the existing NR-IQA-CDI in database TID2013 and CSIQ, which were the primary target for improvement of this work, although there wasn't much performance difference in database CID2013.

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