Enhancement of No-Reference Image Quality Assessment for Contrast-Distorted Images using Natural Scene Statistics features in Curvelet Domain

ISMAIL TAHA AHMED [1,3], Chen Soong Der [2].
1: College of Computer Science and Information Technology, Universiti Tenaga Nasional, Malaysia.
2: College of Graduate Studies, Universiti Tenaga Nasional, Malaysia.
3: College of Computer Sciences and Information Technology, University of Anbar, Anbar, Iraq.
E-mail: esmaeel006@yahoo.com, Chensoong@uniten.edu.my

***Abstract*-- Contrast is a very important characteristic for visual perception of image quality. Some No-Reference Image Quality Assessment Algorithm NR-IQA metrics for Contrast-Distorted Images (CDI) have been proposed in the literature, e.g. Reduced-reference Image Quality Metric for Contrast-changed images (RIQMC) and NR-IQA for Contrast-Distorted Images (NR-IQACDI). Here, we intend to improve the assessment results of images available in databases such as TID2013 and CSIQ. Most of the NR-IQA metrics (e.g. NR-IQACDI) designed for CDI adopt features available in the spatial domain. This paper proposes to compliment it with feature in Curvelet domain which is powerful in capturing multiscale and multidirectional information in an image. We employed the Natural Scene Statistics (NSS) features in Curvelet domain originally recommended by Liu et al. (2014) which were found useful in the assessment of the quality of image distorted by compression, noise and blurring. Experiments were then conducted to assess the effect of incorporating these NSS features. The experimental results based on K-fold cross validation (K ranged from 2 to 10) and statistical test showed that the performance of NRIQACDI was improved. Future works include improvements of NRIQACDI, exploration of feature fusion methods and using a suitable feature selection method.**

Keywords-- Image quality assessment (IQA), Contrast-Distorted Images(CDI), No Reference Image quality assessment (NR-IQA), Curvelet Domain, NSS.

I. INTRODUCTION

Image distortion occurs due to processes such as acquisition, processing, compression, storage, transmission, reproduction and sharing. In order to measure the change in image quality, two Image Quality Assessment (IQA) approaches can be adopted: (1) subjective measures and (2) objective measures [1].

Subjective quality assessment is impractical because it is computationally expensive. Therefore, Objective IQA algorithms are preferable in analyzing images and predicting image qualities. With original image (having "ideal quality"), Objective IQA algorithms are preferable when one intends to analyze images and predict their qualities. Depending on the availability of an "ideal quality" original image, objective IQAs are further classified into Full Reference (FR), Reduce Reference (RR) and No Reference (NR) [2]. For more Review and details on the general taxonomy of IQA/ Video Quality Assessment (VQA) can be found in [3]. In many applications, FR-IQA and RR-IQA are restricted by the requirement of a reference image. Therefore, No-Reference Image Quality Assessment (NRIQA) metrics are preferable whenever a reference image is unavailable.

Currently, most of the existing NR-IQA metrics are used to evaluate the qualities of distorted images due to compression, noise and blurring. The related work performed in the area of NR-IQA for CDI is quite limited unfortunately. Figure 1 illustrates the reference image with CDI [4]. Recently, the two state-of-the-art IQA algorithms for CDI are: (1) Reduced-reference Image Quality Metric for Contrast-changed images (RIQMC) [5] which is devised based on entropies and order statistics of the image histograms; and (2) No-Reference Quality metric for Contrast-Distorted Images (NR-IQACDI) [6] which is developed based on the idea of Natural Scene Statistics (NSS). From our opinion, the performances of NR-IQACDI on CSIQ and TID2013 databases can be further improved.

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Fig. 1: Some sample of Contrast Distortion Images [4].

Multiscale Decomposition Transform (MSD) such as pyramid transform and Wavelet Transform (WT) have been successfully applied in numerous image processing applications. However, WT is lack of directionality. To address this issue, Multiscale Geometrical Analysis (MGA) transforms [7] such as Ridgelets, Curvelets, Wave atoms, Contourlets, etc. have been proposed recently.

Liu et al. [8], Wen et al. [9] and Fang et al. [10] have built the NR-IQA metric based on NSS in Curvelet, Contourlet and Steerable Pyramid Decomposition domains. We have noticed that most of the existing NR-IQA metrics were developed based on MGA transforms catered for general applications. However, the related studies of NR-IQA metric (developed based on MGA transforms) specifically designed for CDI are somehow limited. In [11] propose enhancement of existing (NR-CDIQA) [6] based on direction contrast in curvelet domain.

Curvelet transform is a new and special type of MGA transform, which is designed to represent edges and other singularities along curves in a more efficient manner owing to its high directional sensitivity, high anisotropy and less redundancy [12]. Therefore, it is widely applied in many image processing applications such as contrast enhancement [13] and IQA [8].

The first NSS-based NR-IQA method applied in Curvelet domain was proposed in [14]. Thereafter, Liu et al. [8] and Shen et al. [15] introduced a new NR-IQA metric based on Curvelet Transform and NSS. Liu et al [8] proposed a promising NR-IQA metric from their experimental results. The produced energy features extracted from the Curvelet domain were closely linked to the natural image quality across multiple distortion categories. Therefore, it has been regarded as one of the best examples of NSS. Owing to the inherent benefits of Curvelet Transform, it is applied in the current work.

In this work, we propose to compliment the NR-IQACDI which uses only features based on NSS in spatial domain with features based on NSS in Curvelet domain proposed by Liu et al. We assess the effect of adding NSS features in Curvelet domain based on k-fold cross validation with k range from 2 to 10 and statistical test.

In the next section (Section II), the Curvelet transform is described. Section III describes the phases of the proposed improvement, including Feature Extraction, and Learning Image Quality. Section IV describes the experimental results, and Section V concludes the current work.

II. CURVELET TRANSFORM

The Curvelet transform, which is one of the members in Multiscale Geometrical Analysis (MGA) transform, is designed to better represent edges and other singularities along curves via the implementation of an effective parabolic scaling law: width $\cong (\text{length})^2$ on the sub-bands appeared in the frequency domain. Curvelet transform is well known for its higher directional sensitivity, higher anisotropy and lesser redundancy [12]. Fig. 2 shows the edge representations by using both Wavelet and Curvelet Transforms.

Cand`es et al (2006) [16] have proposed two Fast Discrete Curvelet Transforms (FDCT) i.e. Unequally-Spaced Fast Fourier Transform (USFFT) Based Curvelet and Frequency Wrapping Based Curvelet. Curvelets appear as needle-shaped element and non-directional coarse element at higher and lower scales, respectively. The parameters are bounded by two constraints, i.e. the maximum number of resolutions depending on the original image size and the number of angle at the second coarsest level. The number of angle must be a multiple of 4.0 ($\geq$8). The discrete Curvelet transform of a 2-D function f [t1, t2] is defined as follows:

$$C^D(j,\ell,k) := \sum_{0\leq t1,t2<n} f[t1,t2]\,\overline{\varphi^D_{j,\ell,k}[t1,t2]}, \qquad (1)$$

where φ, j, ℓ, k are Curvelet functions, scale, orientation and position respectively. t1, t2 denote coordinates in the spatial domain: 0 ≤ t1, t2 < n. $C^D(j,\ell,k)$ denotes Curvelet coefficient. FDCT is more efficient as compared to its previous generation. Owing to this reason, FDCT via wrapping is implemented in the current work.

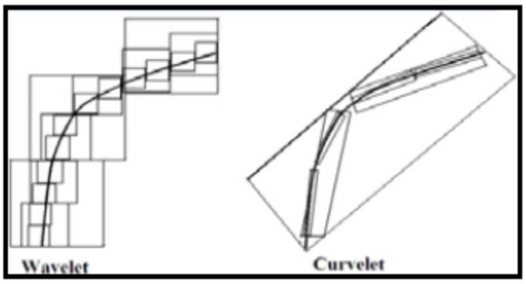

Fig.2: Edge Representations by both Wavelet and Curvelet Transforms [16].

III. Proposed Improvement Phases

The proposed improvement method consists of two steps. The details of each step are elaborated in the next sections. The block diagram of the proposed enhanced method is illustrated in Figure 3.

A. *Feature Extraction Phase*

In the current work, a set of feature vectors was extracted from various domains in CDI databases such as CID2013, TID2013 and CSIQ. It is important to note that the five NSS features employed in NR-IQACDI [6] were obtained from spatial domain. Statistical image features such as mean, standard deviation, kurtosis, skewness and entropy are extracted directly from each distorted image. In this study, we proposed to add NSS features which are available in the Curvelet domain (e.g. the 12 NSS features used in the general-purpose NR-IQA algorithm [8]) to NR-IQACDI features~~.~~ The dimensions of CurveletQA and NR-IQACDI features are 12 and 5, respectively.

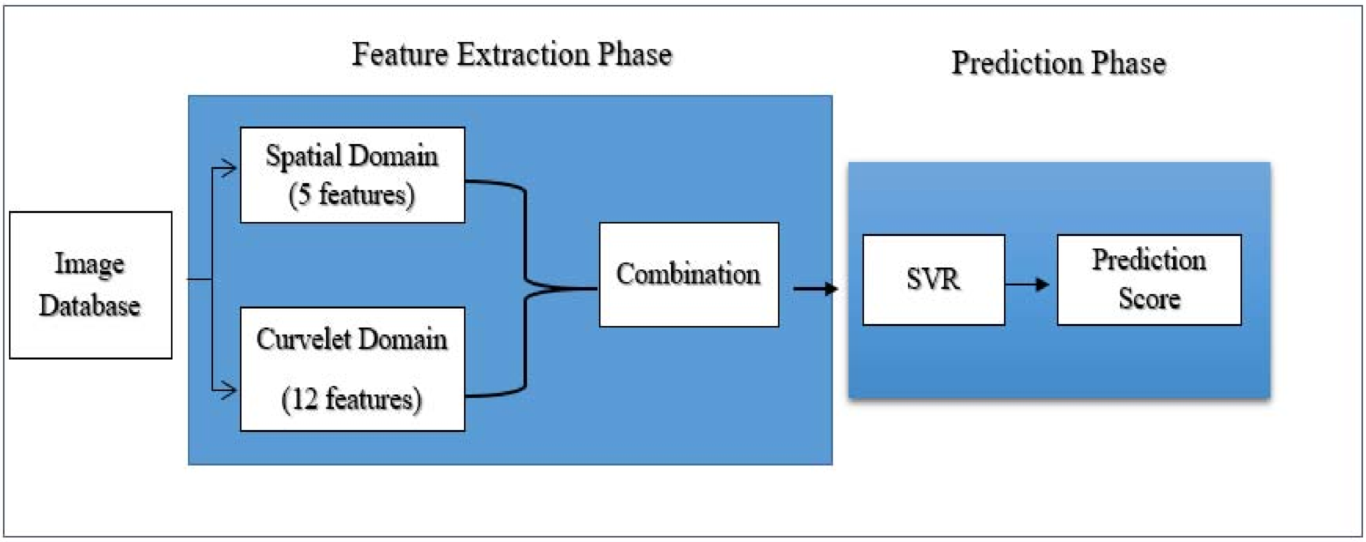

Fig. 3: Enhanced Proposed Block Diagram.

B. Image Quality Prediction phase

After the feature vector of a given image is calculated, we adopt Support Vector Regression (SVR) (via LIBSVM-3.12 package [17]) to determine the mapping function between the feature set and the subjective quality score. Then, a mapping is trained to predict the quality scores by using SVR. SVR is preferred because this machine learning algorithm has been successfully adopted in other NR-IQA approaches.

IV. EXPERIMENTAL RESULTS AND DISCUSSIONS

Our experiments have been designed to assess the effect of adding NSS features in Curvelet domain on performance of NRIQACDI. The details of experiments described in the next sections.

A. IQA Databases

For the experiments, we select the test images from the three publicly available databases, namely CSIQ database [18], TID2013 database [19] and CID2013 database [5]. We use only the contrast distorted images in the three databases (that is, reference images are excluded). A total of 116, 250, and 400 distorted images are selected from CSIQ [18], TID2013 [19], and CID2013 [5], respectively. The distorted image sizes for CSIQ, TID2013, and CID2013 were 512 x 512 pixels, 384 x 512 pixels, and 768 x 512 pixels, respectively. The difference Mean Opinion Scores (DMOS) associated with distorted images, which is ranging from 0 to 1, is reported, where a lower DMOS signifies a higher quality. We performed experiments on a laptop with an Intel (R) Core (TM) 2 Duo CPU, 2G RAM memory with a MATLAB R2013a platform.

B. Assessment of Enhanced IQA Performance

In order to evaluate the performance of IQA, the performance metrics such as (1) Spearman Rank-Order Correlation Coefficient (SROCC), (2) Pearson's (Linear) Correlation Coefficient (PLCC) and (3) Root Mean Square Error (RMSE) between the predicted objective scores and the subjective Mean Opinion Scores (MOS) were employed. Conditions such as SROCC~1, LCC~1 and RMSE~0 indicate good performance in terms of correlation with human perception. Parameters such as prediction monotonicity, prediction accuracy and prediction consistency can be measured by using these metrics.

Due to the fact that regression is essentially a learning algorithm that requires training, K-fold Cross Validation (CV) was employed for the assessment of the performance of IQA to assess how well the IQA could be generalized to independent groups of data while minimizing bias.

While conducting K-fold cross validation, three databases were randomly partitioned into 10 subsets. The method called 10-fold leave-one-out CV was employed to test the proposed metric. Here, 90 % of the database was treated as training set while the remaining were employed as testing set. Assessment was conducted K times and the results were then averaged. Multiple rounds of cross-validation (k = 2 to 10) were performed on different partitions to minimize variability. The above cross-validation was repeated 100 times (to avoid bias) and the averaged results are shown in Table I and Table II.

TABLE I. The average PLCC, SROCC and RMSE across 100 train-test rounds for three Databases using features in spatial domain

k	**CSIQ**			**TID2013**			**CID2013**		
	PLCC	***SROCC***	***RMSE***	***PLCC***	***SROCC***	***RMSE***	***PLCC***	***SROCC***	***RMSE***
2	0.62963	0.63170	0.13174	0.49409	0.465217	0.8602	0.8390	0.85109	0.3409
3	0.64576	0.62749	0.13133	0.51657	0.473423	0.8456	0.8432	0.85365	0.3381
4	0.64446	0.63106	0.13035	0.51502	0.477406	0.8561	0.8422	0.85083	0.3359
5	0.64052	0.61053	0.13079	0.51657	0.480021	0.8458	0.8443	0.85882	0.3345
6	0.63978	0.62976	0.13082	0.51303	0.47259	0.8461	0.8448	0.85429	0.3350
7	0.65770	0.61097	0.12872	0.51636	0.468608	0.8469	0.8469	0.85021	0.3326
8	0.66336	0.61755	0.12678	0.51798	0.476596	0.8506	0.8460	0.85277	0.3336
9	0.64454	0.60876	0.12865	0.52676	0.469455	0.8452	0.8478	0.85545	0.3333
10	0.65177	0.62936	0.12848	0.51630	0.482692	0.8437	0.8457	0.86009	0.3339

TABLE II. The average PLCC, SROCC and RMSE across 100 train-test rounds for three Databases using the adding NSS Curvelet features.

k	CSIQ			TID2013			CID2013		
	PLCC	*SROCC*	*RMSE*	*PLCC*	*SROCC*	*RMSE*	*PLCC*	*SROCC*	*RMSE*
2	0.76629	0.740842	0.1099	0.5271	0.482466	0.86362	0.8537	0.86485	0.3282
3	0.76797	0.745311	0.1124	0.5639	0.51389	0.84060	0.8546	0.86689	0.3280
4	0.77986	0.749115	0.1059	0.5382	0.490437	0.85235	0.8581	0.86841	0.3232
5	0.77999	0.78146	0.1077	0.5594	0.50509	0.83771	0.8561	0.86914	0.3232
6	0.78629	0.771987	0.1082	0.5682	0.513117	0.83177	0.8602	0.86562	0.3213
7	0.79063	0.774753	0.1038	0.5519	0.492892	0.83838	0.8617	0.86570	0.3197
8	0.78848	0.76533	0.1053	0.5630	0.510808	0.83483	0.8625	0.87099	0.3216
9	0.79020	0.76236	0.1069	0.5723	0.517177	0.82775	0.8614	0.86915	0.3223
10	0.78250	0.761439	0.1052	0.5696	0.51648	0.82874	0.8614	0.87163	0.3183

Table I shows the average result of assessment using the feature vector obtained from spatial domain (NRIQACDI). Table II shows the average result of assessment using adding NSS features Curvelet domain to NRIQACDI. The result in Table II are better than the result in Table I. The next section discusses and identifies whether the differences in the performances among NRIQACDI and by adding NSS features in curvelet domain are significant.

C. Statistical Performance Analysis

C.1 Percentage of difference of two performance metrics

we calculate the difference between the two-performance metrics for each k in each of the databases by following

$$d_i = cvtc_i - c_i \tag{2}$$

Where *ci* is performance metric values before adding Curvelet features and *cvtci* is performance metric values after adding Curvelet features. Then the average of the percentage of differences of all the k values and databases are computed. The percentage is measured by dividing the difference in performance by the absolute value of performance metric of *ci*

$$dp = \frac{1}{n}\left(\sum_{i=1}^{n} d_i / abs(c_i)\right) \tag{3}$$

where n is the number of all k in all databases. The absolute value is used to preserve the sign of difference of performance in the percentage (increment or decrement). Table III shows the percentage of difference in each of the performance metrics.

TABLE III. Percentage of difference between before and after adding Curvelet features.

DB	PLCC	SROCC	RMSE
TID2013	8.21%	6.48%	-1.11%
CID2013	1.71%	1.63%	-3.71%
CSIQ	20.89%	22.48%	-17.34%
Overall Databases	10.27%	10.20%	-7.39%

C.2 Statistical Significance and hypothesis testing

To ascertain which differences in the performances are statistically significant, we applied a hypothesis testing based on the Paired T-tests is applied on the performance metric value obtained before and after adding Curvelet features in order to produce the p-value (see Table IV). In general, p-value of < 0.05 shows that there is a significant difference within the values. Table IV shows the P-values of the Paired T-tests for adding Curvelet feature.

TABLE IV. P-Values of differences between before and after adding Curvelet features.

DB	PLCC	SROCC	RMSE
TID2013	Significant	Significant	Significant
CID2013	Significant	Significant	Significant
CSIQ	Significant	Significant	Significant
Overall Databases	Significant	Significant	Significant

D. Discussion

Our aim from experiments to measure the difference in the performance of NRIQACDI before and after adding NSS features in Curvelet domain for each k in each of the databases. And identifies whether the differences are statistically significant. Based on the experiments results in Table III and Table IV, we can clarify the following:

1. Table III shows that there is an improvement in the experimental result using TID2013 database. The PLCC and SROCC increase by 8.21% and 6.48%, respectively. The RMSE decreases by 1.11%. All the p-values for TID2013 in Table IV are less than 0.05, indicating that the differences in all performance matrices are significant.

2. As for CID2013, there are marginal increments in PLCC and SROCC of 1.71% and 1.63%, respectively. The RMSE decreases by 3.71%. Nevertheless, all the p-values for CID2013 in Table IV are less than 0.05, indicating that the differences in all performance matrices are significant statistically.

3. For the CSIQ database which is our secondary target for improvement, we have observed remarkable increments of 20.89% and 22.48% in PLCC and SROCC, respectively. However, RMSE decreases significantly by 17.34%. The statistical test results also indicate that the differences in all performance matrices are significant.

4. Regarding the averaged results of the three databases, it is evident that the increments in PLCC and SROCC are significant (i.e. 10.27% and 10.20%, respectively). Nevertheless, RMSE decreases by 7.39%. All the p-values for Overall Databases in Table IV are less than 0.05, indicating that the differences in all performance matrices across all databases are statistically significant.

From the statistical test, the p-values are less than 0.05, indicating that there are significant improvements in PLCC, Spearman and RMSE. Therefore, by adding the Curvelet features, the performance of NRIQACDI can be improved.

V. Conclusion

The accuracy can be enhanced by the effective use of available features in different domains and the selection of a suitable feature selection method. In the current study, we have improved the performance of NRIQACDI by using features available in curvelet domain. The experiment results based on K-fold cross validation (with K ranging from 2 to 10) and statistical test showed that the performance of NRIQACDI could be enhanced. In future, improvements of NRIQACDI, exploration of feature fusion methods and using a suitable feature selection method.

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