Exploring Contrast Multi-Attribute Representation With Deep Network for No-Reference Perceptual Quality Assessment

Xiaodong Yang, Zhenqi Han, Yedong Wang, Lizhuang Liu, and Dan Zhao

***Abstract*—Aiming at the effectiveness of contrast feature design, we proposed a promising novel non-reference quality assessment approach in exploring Attribute-Based representation. The method generates three perceptual attribute categories tailored to contrast. The first is semantic attribute derived from deep convolutional neural network, which implements adaptive contrast prediction relevant to scenario content. Second, for perceiving Spatial channel attribute, the global and local features generated by dark channel map through the designed dual convolution structures. Third, for statistical attribute, we assume the enhanced image as "reference" and calculate the structural similarity with pristine image, and the entropy and histogram metrics are also employed to assist learning. After that, for maximizing utilization, the features are embedded and integrated hierarchically to translate into objective score. In addition, a medium-scale contrast distortion database is established to support further research, which is more challenging than existing datasets because of the sufficient content and sophisticated changes. We demonstrate the availability of structures quantitatively and verify the rationality of hypothesis. Extensive experiments reveal that the proposed method outperforms advanced methods and achieves the state-of-the-art on the created database and CSIQ, TID2013, CCID2014.**

***Index Terms*—Image quality assessment, contrast-changed images, perceptual attributes, deep network.**

I. Introduction

DUE to the rapid development of imaging and processing technology, high-quality images in smartphones and televisions have become people's daily requirements. Among the numerous factors affecting image quality, contrast plays a crucial role in human perception. Therefore, building an automatic and reliable quality assessment approach for contrast-changed image is inherently imperative, which can not merely facilitate contrast enhancement, but also guide parameters tuning to achieve optimal quality for both displays and cameras.

In general research, subjective assessment methods [1] based on human visual system (HVS) are most accurate, but time-consuming and cost ineffective. Meanwhile, objective assessment methods are practical in scenarios due to their repeatability and scalability. According to the utilization of reference information, objective image quality assessment (IQA) methods can be divided into three categories: full reference (FR), reduce-reference (RR) and no-reference (NR). Since reference images are always unavailable in practice, NR methods are gradually brought to the forefront. Following is a brief review of IQA works.

Existing works mainly concentrate on the synthetic and authentic distortions, which mix multifarious factors including Gaussian blur, noise and compression, artifacts, exposure errors etc.. In earlier studies, feature design and natural statistical models were primary IQA thoughts, such as popular metrics SSIM [2] and NIQE [3]. Most recently, many deep convolutional neural network (CNN) structures of IQA have emerged in succession. DCNN [4], DeepSim [5] and DeepQA [6] performed well in FR, and models [7]–[12] greatly improve the accuracy of NR task. However, we notice that the general methods cannot pay sufficient attention to contrast features.

Several researches concerning contrast-change IQA have been done. In FR metrics, C-PCQI [13] have achieved good performance by decomposing patch into mean intensity, signal strength and structure components. Gu *et al.* [14]–[16] devoted to RR works. They presented RIQMC and LAGSI using mutual information and sequence statistics while building CID2013 and CCID2014 contrast-changed databases. Worth noting, the improved phase consistency method benefits automatic contrast enhancement to a large extent. Differently, Liu *et al.* proposed RCIQM [17] to integrate bottom-up and top-down strategies using free energy theory. NRIQA studies of contrast, have also recently been conducted more actively. Interestingly, a natural scence statistics (NSS) model [18] is proposed by exploring the relationship between image naturalness and perceptual quality. Gu *et al.* also contributed by devising NIQMC [19], where

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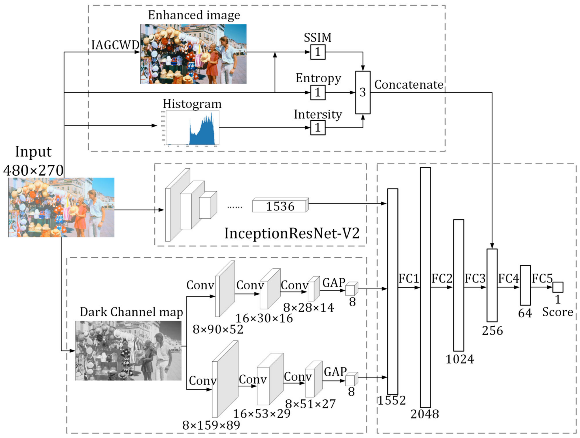

Fig. 1. Proposed architecture: Input is contrast distortion image, and output is objective quality score. It consists of CNN backbone, dark channel characteristic abstraction module, statistical calculation module and FC transformations.

they introduced visual salience and Kullback-Leibler divergence to combine local and global factors, which trades off at the price of intensive computing. Moreover, for hand-crafted features design, Xu *et al.* [20] considered four measures such as skewness, and BIQME [21] extracted 17 features associated to contrast and sharpness, all of which were used for establishing evaluation mapping. What is unique is that Yan *et al.* suggested CEIQ [22] metric, which acquired an similarity through contrast enhancement and applied support vector regression (SVR). The above methods mostly select and assemble features for specific distortions or datasets, thereby it is desirable to investigate the contrast characteristics comprehensively to break the restrictions.

Under the great prosperity of feature mining, we sprout the idea of exploring multi-attribute representation of perceptual contrast in deep feature space. Therefore, a supervised NRIQA networks for contrast-changed images is proposed, which emerges three-fold attributes, namely semantic, channel and statistic, and then integrates them hierarchically. The primary contributions of this study are: 1) Automatic learning and mutual guidance are realized through attribute-driven model design, and the semantic features are obtained. 2) Reveal the relationship between dark channel and contrast, and devise the dual convolution module. 3) Inspired by the fact that contrast enhancement can promote quality, the metric relied on improved adaptive gamma correction with weighting distribution (IAGCWD) and Structural Similarity (SSIM) is put forward. 4) Constructs a practical database of contrast change from ultra-high definition display to support advanced research.

II. Proposed Approach

The overall framework of proposed approach (termed as CMIQ) is shown in Fig. 1. In this pipeline, the algorithm feeds contrast-distorted images into three parallel structures, CNN backbone, dark channel characteristic abstraction, and statistical calculations respectively, then derives corresponding features as results. Subsequently, the semantic and channel features pass through three fully connected (FC) layers, then concatenated with mature statistical features, and finally mapped to quality scores. Hierarchical integration enables the network to fully utilize the multi-attribute features of contrast, thereby improving the assessment performance.

Fig. 2. Enhancement comparison. The first row are original images, the second and third rows are the corresponding enhanced images of CLAHE and IAGCWD, respectively.

A. Semantic Attribute

Semantic attributes include the underlying characteristics, object state, and scene understanding, whereas for contrast this is content-related global information. For this purpose, the well-performing Inception-ResNet-v2 [23] is considered an ideal backbone, because the shortcut structure can facilitate training and the inception module increases multi-scale adaptability. We inherit the prior knowledge from recognition tasks, and fine-tune it on distortion datasets to automatically generate condensed content-related features of contrast.

B. Statistical Attribute

Statistical attribute of contrast are the intuitive reflection of image gray distribution, which is consistent with visual perception. In particular, the assumption that the enhanced image quality would be better than original image motivates us to construct a SSIM based metric, which adopt IAGCWD as enhancement technique. The statistical calculation structure is shown in Fig. 1, which are regarded as systematic priors for beneficial promotion and guidance.

1) Similarity Based on IAGCWD Enhancement: IAGCWD is a extraordinary image contrast enhancement method, and the gray transformation formula [24] is:

$$T(I) = round\left[I_{max}(\frac{I}{I_{max}})^{\gamma(I)}\right] \tag{1}$$

Where, I is the input image, $T(I)$ is the value after transformation, and $\gamma(I)$ is the cumulative distribution function (CDF). For bright images, IAGCWD [25] adopts negative image strategy to reduce local over-intensity and retain details. Through observation in Fig. 2, the brightness restoration of IAGCWD is more remarkable compared with the Contrast Limited Adaptive histogram equalization (CLAHE), which possesses high color naturalness and sharpness.

SSIM [2] is a classical image similarity metric, which is defined as:

$$SSIM(x,y) = [l(x,y)]^{\alpha} \cdot [c(x,y)]^{\beta} \cdot [s(x,y)]^{\gamma} \tag{2}$$

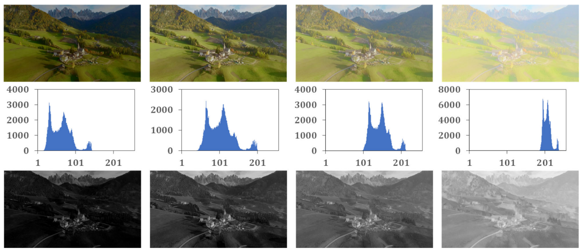

Fig. 3. Histogram distribution and dark channel maps. The original images in first row have different contrast distortion.

$l(x,y)$, $c(x,y)$ and $s(x,y)$ are luminance, contrast and structural components respectively, and their importance parameters are regulated to 1 in general.

2) Image Entropy: Image information entropy reflects the average amount of whole characteristics, calculated as:

$$H = -\sum_{i=0}^{255} p_i log p_i \tag{3}$$

P_i, obtained from the gray histogram, represents the proportion of pixels with gray value i in the image.

3) Histogram Intensity: Taking into account observation of Xu *et al.* [20], we notice that the image histogram distribution correlates well with subjective scores as Fig. 3. The higher the contrast, the wider the distribution. We modified the definition of histogram intensity indicator as:

$$R = \frac{1}{256}\sum_{i=0}^{255}(Y_i > h) \tag{4}$$

Where Y_i represents the count of the ith grayscale in the histogram, h is the threshold set to 50.

C. Channel Attribute

Inspired from dark channel prior [26], we design a characteristic abstraction module to acquire the spatial channel attribute of contrast. For image J, the dark channel J_{dark} is calculated as:

$$J^{dark}(x) = \min_{y\in\Omega(x)} \left(\min_{c\in\{r,g,b\}} J^c(y)\right) \tag{5}$$

Where J^c is the RGB color channel of J, and the intensity J_{dark} is an approximation to the thickness of mist visually. In Fig. 3, the contrast change is intuitively similar to that of fog. Brighter dark channel value results in worse contrast, and thus the remarkable consistency between them can be qualitatively concluded.

In the suggested module, the dark channel map is input into double convolution branches to extract contrast global and local features. They contain 3 convolutional layers and 1 global average pooling (GAP) layer with 8, 16 and 8 kernels, the padding is 0. Their essential difference lies in the kernel size. Branch 1 is 11*11, 7*7, 3*3, its receptive field is larger, and the features after multi-layer stacking are more global; branch 2 is 5*5, 3*3, 3*3, for capturing local details.

III. Results and Discussions

A. Datasets and Details

Among public databases tailored to contrast distortion, CID2013 [14], CCID2014 [15], CSIQ [25] and TID2013 [27] are benchmarks, and subjective annotations are Mean Opinion Score (MOS) or Difference Mean Opinion Score (DMOS). But they are mostly created from the degradation of limited, debased pristine images in oversimplified lab-setting. Considering the actual requirements, we constructed a meaningful database of high-definition display (HDCIQ) with abundant contents and sophisticated changes. The sources of HDCIQ covers 4 K display images of people, landscapes, and urban scenes. With the contrast change caused by the registers value of display system, we take screenshots to get 586 pictures, and then process them 480*270 resolution, as shown in Figs. 2 and 3. We invite two experienced professionals engaged in display IQA to carefully observe and annotate MOS in the range [0, 100]. Worth noting, HDCIQ is prominent for human visual perception rather than absolute contrast level. For all datasets, we use a ratio of 80% and 20% to divide disjoint training and test sets randomly. In the model training phase, Inception-ResNet-v2 is initialized with pre-trained weights from ImageNet, Adam optimizer and MSE loss function are selected, and the batch size is 16 to accelerate the convergence process. The learning rate is gradually decreased in three stages, 1e-3/2, 1e-3/5, and 1e-4/5, with 50 steps each. During test phases, Pearson linear correlation coefficient (PLCC), Spearman rank correlation coefficient (SROCC) and Kendall rank correlation coefficient (KROCC) work for measuring the consistency and monotonicity of objective evaluation with respect to ground truth.

B. Comparative Experiments

1) Public Datasets: The comparison of CMIQ against the state-of-the-art techniques has been conducted on the benchmark databases. In Table I, evidently, CMIQ outperforms NR methods on evaluation indices except the SRCC of XU [20], and is competitive with the FR and RR metrics, which substantiate the advantages of multi-attributes representation and deep network features. Furthermore, the distributions of CMIQ almost coincide with diagonal in Fig. 4, which vividly explains its high consistency.

2) HDCIQ Database: Firstly, CMIQ is compared on HDCIQ with excellent learning-based models for synthetic distortion. As shown in Table II, CMIQ ranks first for better expresses the contrast characteristics. Secondly, CMIQ is trained on CCID2014 and tested on HDCIQ for fair comparison with contrast distortion-oriented methods. NIQMC has the highest PLCC at 0.5713, followed by CMIQ at 0.5005 because of excessive attention in comprehensive features.

C. Ablation Study

Table III shows the correlation between statistical metrics and subjective assessment. It is relatively high on CCID2014 and CSIQ as their excessively regular and primitive distortion.

TABLE I
PERFORMANCE COMPARISON ON CSIQ, TID2013 AND CCID2014 DATASETS. THE HIGHEST VALUE AMONG NR METHODS IS SHOWN IN BOLD

Methods	CSIQ			TID2013			CCID2014		
	PLCC	SROCC	KROCC	PLCC	SROCC	KROCC	PLCC	SROCC	KROCC
CMIQ(Pro.)	**0.9782**	0.9526	**0.8419**	**0.9157**	**0.8888**	**0.734**	**0.8719**	**0.8666**	**0.6747**
CEIQ [22]	0.9532	0.9475	0.8182	0.8718	0.8193	0.6302	0.8675	0.8363	0.6362
XU [20]	0.9657	**0.9603**	0.8306	0.9128	0.8814	0.7045	—	—	—
NIQMC [19]	0.8747	0.8533	0.6689	0.7225	0.6458	0.4687	0.8438	0.8113	0.6052
BIQME [21]	0.8276	0.8202	0.6501	0.7479	0.6510	0.4783	0.8588	0.8309	0.6305
FANG [18]	0.6998	0.7232	0.5178	0.4113	0.3478	0.2291	0.7890	0.7822	0.5684
IL-NIQE [29]	0.5468	0.5005	0.3510	0.2275	0.1517	0.1030	0.5764	0.5121	0.3590
RIQMC [14] -RR	0.9652	0.9579	0.8279	0.8651	0.8044	0.6178	0.8726	0.8465	0.6507
RRED [30] -RR	0.9415	0.9382	0.7838	0.5606	0.3068	0.2419	0.7064	0.6595	0.4677
PCQI [13] -FR	0.9454	0.9394	0.7820	0.9175	0.8805	0.7074	0.8885	0.8754	0.6858
FSIM [31] -FR	0.9378	0.9420	0.7883	0.6819	0.4413	0.3588	0.8201	0.7658	0.5707

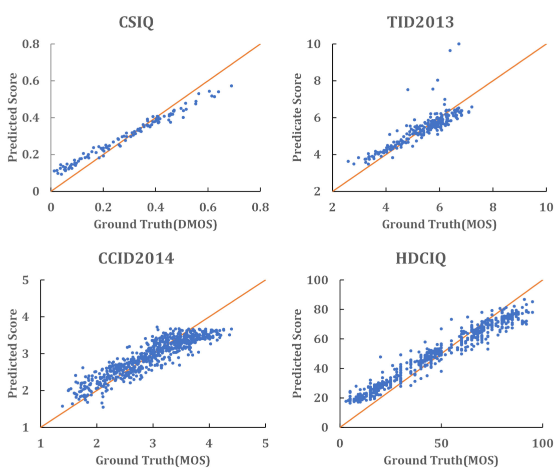

Fig. 4. Scatter diagrams of the predicted distribution of CMIQ on public datasets and HDCIQ, each pot corresponds to an image.

TABLE II
COMPARISON BETWEEN CMIQ AND NRIQA METHODS ON HDCIQ

Methods	PLCC	SROCC
MetaIQA [9]	0.771	0.821
DBCNN [8]	0.835	0.852
Koncept512 [11]	0.824	0.874
HyperIQA [10]	0.920	0.926
CMIQ(Pro.)	**0.955**	**0.943**

TABLE III
CORRELATION BETWEEN CONTRAST METRICS AND SUBJECTIVE SCORES

Datasets	Metrics	PLCC	SROCC	KROCC
HDCIQ (MOS)	Entropy	0.4428	0.4860	0.3436
	Histogram	0.5317	0.5301	0.3800
TID2013 (MOS)	Entropy	0.5369	0.5189	0.3613
	Histogram	0.6290	0.5707	0.4079
CCID2014 (MOS)	Entropy	0.7888	0.8087	0.6069
	Histogram	0.7184	0.6946	0.4993
CSIQ (DMOS)	Entropy	-0.7080	-0.6765	-0.5007
	Histogram	-0.9109	-0.9028	-0.7430

Meanwhile, because of the sophisticated contrast changes, HDCIQ has the lowest consistency, hence the statistical metrics are not capable of predicting quality solely.

To demonstrate the contributions of network components, ablation experiments are reported in Table IV. All the attribute features are effective, and the combinated performance enables CMIQ to achieve the best prediction accuracy. Furthermore, 95% confidence intervals for PLCC, SROCC and KROCC were calculated through 10 repeated experiments, which are [0.944, 0.957], [9.936, 0.950] and [0.787, 0.811], so the effects of random initialization are acceptable.

TABLE IV
ABLATION EXPERIMENTS ON HDCIQ. SA REPRESENTS STATISTIC ATTRIBUTE, AND CA REPRESENTS CHANNEL ATTRIBUTE

Methods	PLCC	SROCC	KROCC
AlexNet	0.793	0.773	0.582
AlexNet+SA+CA	0.918	0.926	0.776
InceptionResNet-V2	0.929	0.936	0.785
InceptionResNet-V2+SA	0.942	0.938	0.790
InceptionResNet-V2+SA+CA	**0.955**	**0.943**	**0.799**

TABLE V
COMPARISON OF THE AVERAGE RUNTIME, THE UNIT IS (SECOND/IMAGE)

Methods	CEIQ	BIQME	CMIQ	NIQMC
HDCIQ(480*720)	0.0134	0.4752	0.3839	1.5588
TID2013(512*384)	0.0200	0.4250	0.5079	1.4010
CSIQ(512*512)	0.0289	0.4691	0.5451	1.2659
CCID2014(512*768)	0.0404	0.5108	0.6239	1.7734

D. *Runtime Measure*

For comprehensive comparisons, the average runtime of NR contrast methods are measured using test codes. As shown in Table V, for each resolution image, CEIQ consumes much less time than other methods, while NIQMC is the longest. The proposed CMIQ is unsatisfactory and lacks applicability for real-time scenarios, because its network structure is large-scale and involves a trade-off between accuracy and complexity.

IV. CONCLUSION

In this letter, the multi-attribute representations of contrast are studied, and a novel approach is presented to provide a DNN framework template for NRIQA of contrast-changed images. The structure incorporating Inception-ResNet-v2, dark channel characteristic abstraction module, statistical calculations and transformation is designed carefully to derive attribute features. For facilitating research, a sophisticated database of ultra-high definition images contrast is constructed elaborately. Comprehensive experiments confirme the superiority of CMIQ, which delivering influential performance among advanced techniques. In future, we will dedicate to implement multi-attributes through a concentrative network to reduce complexity and promote generalization.

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