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Blind Images Quality Assessment of Distorted Screen Content Images

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Abstract. *:Studies on screen content images (SCIs) has emerged recently. Methods of acquiring accurate and reliable image quality evaluation as well as multimedia technology have advanced and they recently have become highly instrumental in multi-device communication applications. Screen content images generally contain text generated by computer and image graphics. High quality screen content images (SCIs) generation has been observed to be a challenge because they may not always have similar properties to that of natural scenes. Therefore, blind image quality assessment approach is made difficult by fact that SCIs do not present any reliable statistical models. This paper proposes a no-reference/blind image quality assessment of distorted screen content images in order to attend to the problem mentioned above by extracting 22 perceptual-inspired features with free energy, structural degradation, log-energy, and contrast. After features extraction, our metric employs support vector machine based on regression module to convert all features into a single with an overall quality score. Finally, we can observe that our experimental model in SIQAD and QACS databases delivers computational effectiveness and a good correlation performance with regard to the quality standards perceived by humans. This method also provides a greater score compared to other state-of-the-art on no-reference quality assessment metric.*
Keywords: Blind; Image quality assessment; Log-energy; Contrast.

1. **Introduction.** With the rapid development of internet technology and cloud computing, there have been aspiration to enable clients with mobile devices find interest in the computationally intensive and graphically rich services by transmitting the remote screen to the clients. In these scenarios, the time variant interface can be regarded as a screen content images (SCIs), which are a mixture of pictorial regions and computer generated textual contents [1].

Various distortions such as blurring, contrast change, and compression artifacts may occur during SCIs processing. For instance, when SCIs are captured by smart phones, distortions like blurring may appear due to hand-shakes or out-of-focus of the camera. Moreover, different brightness or contrast settings with respect to screen contents can also affect the contrast variation of captured SCIs [2]. Nowadays, many research studies have increased emphasis on image quality assessment (IQA), because of its demand in modern image processing and the idea that it is not limited to natural scenes. Currently, the digital images can have a combination of computer generated sources, such as graphics, texts, charts and maps that can be imposed and rendered on an electronic device or a photo editing software. Such kind of images can be denoted as the screen content images

a) b)

FIGURE 1. Screen content images, selected from SIQAD and QACS database for demonstrations. a) 12 images from SIQAD database, and b) 12 images from QACS database.

(SCIs) [2]. Screen content images (SCIs) are observed in various multimedia applications and services. An observation was made that the SCIs can yield fairly different image characteristics compared to that of natural images (Figure 1). For some SCIs, radical changes due to sharp region transitions and texts is extremely evident.

Ways of developing consistent models that meet the judgment made by the human vision system (HVS) is one of the biggest challenges. In effort made to solve this problem, previous researchers used the PSNR to assess the visual quality of the processed SCI. On the contrary, PSNR has proved itself to be inconsistent with the human vision perception [35]. Even though, there are numerous IQA techniques that have been proposed for quality assessment of natural pictures [36], whether these IQA techniques can be applicable to SCIs is still an open question. Hence, it is meaningful to investigation both subjective and objective metrics for the quality evaluation of SCIs [2].

This paper proposes an objective model to evaluate the visual quality of distorted SCIs. This model consists of an objective technique with the same strategy using in BQMS [21]. A SCS model has been established to enable addition of more components that are related to the quality of objective techniques in order to evaluate the visual quality of images, namely free energy measure, structural degradation, log-energy, and contrast. Dedicate on Screen Content Images research is relatively new when we focus on visual quality assessment. We considered using the free energy feature due to good correlation with human rankings of noisy and blurred images [26]. The log-energy of wavelet subbands is calculated to obtain the scalar guide of the global sharpness of variation in SCIs to human visual perception. Due to the important characteristics and effects that the contrast presents on perception in digital images, we decided to incorporate it as the basis for the improvement the quality of the image. Also, we incorporate the structural degradation model due to the good performance that the images corrupted by various types of distortion such as blur and noise have present the consistent changes with visual quality.

Objective image quality assessment (IQA) can be classified into Full reference (FR) which refers to the assessment of the distorted image quality by comparing with the original image and Reduce Reference (RR) which uses some limited features from reference image instead of complete image to evaluate the quality of distorted image and No-reference; referring to the quality of an image without the need of any reference image or features.

The remaining of this paper is organized as follows. In Section II, the related work is described. Section III has described the screen content images database. Section IV we described the methodology we used in this research. Section V performance comparisons with other state-of-the-art IQA metrics are documented and discussed, and finally, section VI draws the conclusion.

2. **Related Work.** Numerous image quality databases have been created [37], [38] by adopting subjective testing strategies [39]. Currently, many Full reference IQA methods have been projected to objectively assess the quality of distorted natural images. Yang et al. [2], proposed to finds perceptual differences of textual and pictorial areas between distorted and undistorted images. Gu et al. [3], showed a performance comparison of mainstream Full-Reference (FR) image quality assessment (IQA) methods on screen content image databases. Niranjan et al. [4], they proposed to quantify the impact on the human visual system (HVS) of frequency distortion and noise injection in image restoration, adopting a distortion measure (DM) and noise quality measure (NQM). Wang et al. [5], used the small kernel for textual regions while a large kernel is also used to pictorial areas. Wang et al. [6] proposed to use multi-scale structural similarity techniques, which provisions further flexibility than single-scale techniques in incorporating the variations viewing conditions. An image synthesis-based approach is used to calibrate the parameters that define the relative importance across scales. proposed to use a two-stage approach that functions on the basis of both low-level and mid-level properties of human vision.

The first stage involves the visual detectability of the distortions is determined via wavelet-based models of visual masking and visual summation. The second stage is applied when the low-level property of perceived contrast and the mid-level property of global precedence are considered. Zhang et al. [8] proposed a novel low-level feature based on IQA metric, that the HVS can perceive an image mainly based on its salient low-level features. Two kinds of the feature are used, the phase congruency (PC) and gradient magnitude (GM). PC and GM play an important role in characterizing local image quality. Liu et al. [9] due to structural/constant changes, image quality is affected by luminance changes. They have proposed to use the gradient similarity to measure the change in contrast and structure in images to alleviate the shortcoming of the existing relevant schemes in this regard. Xue et al. [10] the image gradient is sensitive to image distortions, while different local structures in a distorted image suffer different degrees of degradations, due to these characteristics they proposed to create IQA model called gradient magnitude similarity deviation (GMSD). Their results implied that existing FR metrics, despite attaining superior performance when evaluating the quality of natural scene images, fails on the screen content in relation to IQA problem.

Similar problems are encountered using Blind/No-reference (NR) IQA models. Stirred by well-known Natural Scene Statistics (NSS) models [13], a variety of blind images quality models [14], including Gu at al. [15] have proposed a new blind sharpness measure via parameter analysis of classical autoregressive (AR) image model. This method is established upon the assumption that higher resemblance of the locally estimated (AR) model coefficients means lower sharpness. Mittal at al. [16] proposed a natural scene statistic-based distortion-generic blind/no-reference images quality assessment (IQA) model that operates in the spatial domain. Moorthy at al. [17] proposed blind image quality assessment (IQA) based on the hypothesis processes inherent to natural scenes possess certain statistical properties which are altered in the presence of distortion, rendering them un-natural and that by characterizing this un-naturalness using scene statistics one can identify the distortion afflicting the image and perform no-reference (NR) IQA. Gu at al. [18] likewise proposed a new no-reference (NR) IQA metric using the recently revealed free energy based theory and classical human visual system (HVS) inspired features. Mittal at al. [19] also proposed new IQA model based on the construction of a quality aware collection of statistical features based on a simple and successful space domain natural scene statistic (NSS) model. Zhang at al. [20] develop an opinion-unaware BIQA method that can compete with, and perhaps outperform, the existing opinion-aware methods. They integrate the feature of natural image statistic derived from multiple cues, and also learn a multivariate Gaussian model of image patches from the collection of pristine natural images. Gu et al. [21] have proposed the Blind efficient metric to evaluate quality measure for screen content images (BQMS). Through, it is also not effectively operative for natural scene images (NSIs), have been developed. Hence, the BQMS metrics may not be applicable to evaluate the quality of distorted SCIs due to the screen content statistics model. In this paper, we will study no-reference image quality assessment of distorted SCIs, and then further investigate the applicability of several state-of-the-art SCS methods to distorted SCIs problem encounter in the blind image.

3. **Screen Content Image Quality Database.** To investigate quality evaluation of SCIs, we have chosen the two types of database that fit best for this kind of research. First is Screen Image Quality Assessment Database (SIQAD) [29], contains 20 reference images and 980 distorted SCIs, including 7 types of distortion with 7 different levels of degradations generated for each type of distortion: Gaussian Blur (GB) and Motion Blur (MB) are also considered due to their commonly existing in practical applications. For example, when SCIs are captured by digital cameras, hand-shaking, out-of-focus or object moving would bring blur into images. Contrast Change (CC) is also an important factor affecting particularities of the HVS.

Dissimilar settings of brightness and contrast of screens will result in different visual experiences of spectators. Gaussian Noise (GN) is often involved in image acquisition and included in the most existing image quality database. JPEG Compression (JC) and JPEG2000 Compression (J2C) are two widely used methods for image compression and have been introduced into many quality assessment databases. Layer segmentation-backed Coding (LC) is another codec due to its efficient compression of SCIs.

The LC initially separates SCIs into textual and pictorial blocks with a segmentation index map in which textual blocks are marked by one and pictorial blocks by zero. We also use Quality Assessment of Compressed Screen Content Images (QACS) [30], which is composed of a total of 492 compressed images, generated by 24 undistorted SCIs, using two methods of types coding: High-Efficiency Video Coding (HEVC) are developed to specify the basic processing unit of coding, prediction and transform, and the Screen Compression (SCC) algorithm, which claims to improve the coding performance on screen contents by employing advanced techniques, such as intra block copy, transform skipping and base colour representation. The inclusion of HEVC and SCC compression artifacts, the inclusion of higher resolution SCIs, and the inclusion of more SCI content types and application scenarios [40].

4. **Methodology.** It is known that the HVS is relevant to image luminance, contrast, and sharpness. They change along with various image distortions, such as noise corruption, blur, compression artifacts and etc. Any natural image can be a test image whose features are first extracted in the form of numeric values. Next, a set of natural images are trained

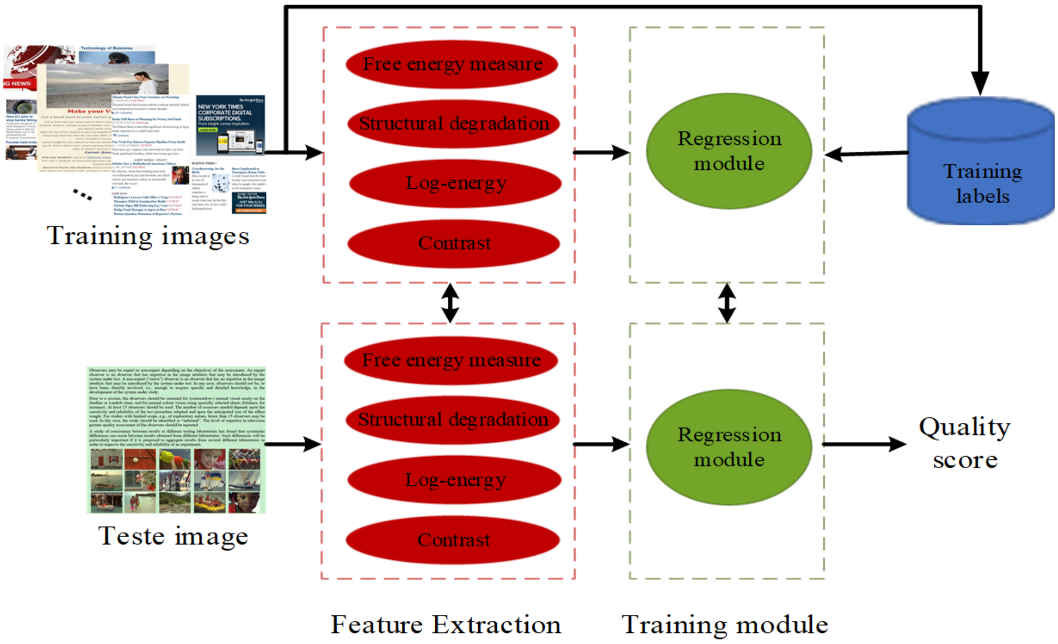

FIGURE 2. Flowchart of blind image metric in screen content images.

and features are extracted and stored in matrix form. Both features are then compared and accordingly ranking are done which predicts the quality of an image.

In this paper, we proposed to study no-reference/blind image quality assessment of distorted SCIs, and then further investigate the applicability of several state-of-the-art methods to distorted SCIs problem encounter in the blind image. Same in BQMS [21], we also have established the SCS model incorporates more sets of features of free energy measure, structural degradation, log-energy, and contrast. Our method differed from BQMS [21], in the number of incorporate the sets of features. We have proposed to use 22 features in our proposed metric, as shown in Table 1, below. The flowchart of no-reference/blind image method is shown in Figure 2.

We using the SVR to train some images and associated the MOS/DMOS values to acquire the model, also we predict objective quality scores of the rest images based on the model for testifying performance.

4.1. **Free energy theory.** The free energy theory is using the perspective of human action, perception, and learning, based on existing brain principles [22]. This method can predict the category of a visual signal and can assistance avoid redundant information. To facilitate the operation, it is assumed that the internal generation model for a parameter G is made. Give an input visual information I, spatial x model parameters of the joint distribution can be calculated by "coincidence" (gritty by entropy) of a given image by adjusting the parameter variable x to develop a given scene. The joint distribution model is computed as:

$$-\log p\left(I\right) = -\log \int p\left(I,\ x\right) dx, \tag{1}$$

where it introduces a helper term $q(x|I)$ together the denominator and numerator in equation (1) and rewrite it as

$$-\log p\left(I\right) = -\log \int q\left(x|I\right) \frac{p\left(I, x\right)}{q\left(x|I\right)}\, dx \tag{2}$$

Define $q(x|I)$ is a later distribution model given the input image signal parameters subsequently, we use Jensen variation formula get from equation (2).

$$-\log p\left(I\right) \leq\ -\log \int q\left(x|I\right) log\frac{p\left(I,x\right)}{q\left(x|I\right)}\ dx \tag{3}$$

the subsequent are free energy:

$$\mathrm{J}\left(x\right) =\ -\int q(x|I)log\frac{p\left(I,x\right)}{q(x|I)}\ dx, \tag{4}$$

The linear AR model is a simple and effective model to describe natural scene images [23], so we used and defined as:

$$l_n = L^k\left(\ l_n\right)\alpha + \gamma_n\ , \tag{5}$$

Where L_n Is a pixel image, $L^k(l_n)$ is a vector that consist of k nearest neighbors of $l_n, \alpha = (\alpha_1, \alpha_2, \ldots, \alpha_k)^T$ is AR coefficient variable, and γ_n is the error term. The input distorted image I to estimate predicted visual signals can be evaluated by $L^k(l_n)\alpha_{opt}$, where α_{opt} is l_n AR model parameters based on least square optimal estimation.

4.2. **Structural degradation model.** The structural degradation model is using, after the low-pass filter, images besmirched in numerous alteration categories and intensities will appear as distinct degrees of spatial frequency decrease. The structural degradation was computed as:

$$H_\beta\left(w\right) = E\left(\frac{\sigma\left(\mu_w\overline{\mu_w} + C\right)}{\sigma\left(\mu_w\right)\sigma\left(\overline{\mu_w}\right) + C}\right) \tag{6}$$

$$H_\alpha\left(w\right) = E\left(\frac{\sigma\left(\sigma_w\overline{\sigma_w} + C\right)}{\sigma\left(\sigma_w\right)\sigma\left(\overline{\sigma_w}\right) + C}\right) \tag{7}$$

where the $\sigma\left(\mu_{\mathrm{w}}\overline{\mu_{\mathrm{w}}}\right)$ and $\sigma\left(\mu_{\mathrm{w}}\overline{\sigma_{\mathrm{w}}}\right)$, is local covariance, C is a small constant, to prevent the denominator is zero, and $E()$ is global average. Therefore, the BQMS model is not effective in the prediction of natural scene images (NSIs). First, we have also established the SCS model incorporates more sets of features that are more related to the quality of no-reference/blind natural scene images, i.e. log-energy, and contrast to improve performance.

4.3. **Log-energy.** We also use a three level of separable discrete wavelet transform (DWT) and measure the log-energy of the DWT sub-bands [24]. The image is decomposed into three level wavelet sub bands, including HH, HL, and LH. The measure log-energy of each sub band was computed as:

$$K_{a,\ b} = \log_{10}\left(1 + \ \frac{1}{A_b}\sum_c a_b^2\ \ (c)\right) \tag{8}$$

where a, b is either LH, HL or HH, A_b is the number of DWT coefficients of sub band and c is the pixel index. The total Log-energy at each decomposition level was measured via:

$$K_b = (1 - \beta)\,\frac{K_{LH_b} + K_{HL_b} +\ K_{HH_b}}{2} \tag{9}$$

where β was set 0.8 empirically to emphasize the high-frequency content.

TABLE 1. Different features used in our proposed metric

N° of Features	Features description
f_{01}	Free energy entropy based on AR model
$f_{02} - f_{13}$	Structural degradation model
f_{14}	Log-energy
$f_{15} - f_{22}$	Contrast

4.4. **Contrast.** As one of the most important characteristics of digital images, the contrast has the significant effects on the image quality. The Gradient Local Binary Pattern (GLBP) feature can be used to reflect the extent of the image contrast, and thus used as a basis for image quality [25].

$$L_{glbp}(\alpha) = \sum_{\beta=1} U\beta R\left(GLBP_{i,j}(\beta),\ \alpha\right) \tag{10}$$

$$R(x,y) = \begin{cases} 1, & x = y \\ 0, & otherwise \end{cases}, \tag{11}$$

Where M is the numeral of image pixels, $\alpha \in [0, K]$ is the possible GLBP patterns, and $U\beta$ is the weight assigned to the GLBP code. We use the gradient magnitude calculated by

$$G(i) = \sqrt{(D *\ V_x)^2\ (i) +\ (D *\ V_y)^2\ (i)} \tag{12}$$

where symbol * denotes the convolution operation; Vx and Vy are the Prewit filters; D and D denote the distorted image and its corresponding magnitude map with$i$ as the location index, as the GLBP weight of each pixel.

4.5. **Image quality evaluation.** Due to the characteristics presented by each feature, we decided to use 22 features extracted from free energy, structural degradation, log-energy, and contrast because we believe that this kind of features is closely related to the quality of human visual perceptions. We considered using the free energy feature due to good correlation with human rankings of noisy and blurred images [26]. The log-energy of wavelet sub-bands is calculated to obtain the scalar guide of the global sharpness of variation in SCIs to human visual perception, is also competitive with the currently best performing techniques both for sharp estimation and no-reference IQA.

Due to the important characteristics and effects that the contrast presents on perception in digital images, we decided to incorporate it as the basis for the improvement the quality of the image. Also, we incorporate the structural degradation model due to the good performance that the images corrupted by various types of distortion such as blur and noise have present the consistent changes with visual quality.

All features present characteristics that go against the types of distortion in the screen content. Based on the above-mentioned arguments, we believe that the features extracted may contribute to the result of the visual quality being able to be, close to the real vision. With the above-mentioned quality-aware perceptual features, we employed the support vector regression (SVR) [27], to convert the features to an overall quality score. For an inquiry image, the quality can be predicted using the trained SVR model. In our implementation, we use the LibSVM package to implement the SVR using the Radial Basis Function (RBF) kernel [28].

Table 2. Performance comparison with the popular state-of-the-art NR blind image quality models

Databases	SIQAD (980images) [29]			QACS (492 images) [30]		
Metric	PLCC	SRCC	RMSE	PLCC	SRCC	RMSE
BRISQUE [16]	0.7792	0.7304	8.8794	0.4622	0.4342	1.9363
NFERM [18]	0.7986	0.7683	8.6137	0.4485	0.4034	1.9459
GMLF [32]	0.7493	0.7112	9.4603	0.5484	0.5194	1.8344
ARISMC [15]	0.5824	0.5286	11.5484	0.4183	0.3441	1.9632
NRSL [33]	0.6452	0.5993	10.8918	0.6206	0.5890	1.7179
Proposed	**0.8337**	**0.8162**	**7.8600**	**0.5006**	**0.4847**	**1.8797**

5. **Experimental Results and Discussions.** To the best of our knowledge, we have measured and equated the performance of the model compared to 10 modern IQA models on the SIQAD and QACS databases.

5.1. **Evaluation Protocol.** Only two existent databases can be used to screen content images quality evaluation, us: SIQAD [29] database, which includes 980 distorted SCIs generated by corrupting with distortion types, like noise, blur, and contrast. Also, QACS [30] Database is used which contains 492 distorted SCIs generated by two distortion types, like HEVC and SCC compression technologies. In most of the cases, the performance of IQA metrics can be evaluated by computing the correlation between the objective and subjective ratings via a five parameter of logistic function as suggested by VQEG [31]:

$$Q\ (y) = \ \sigma_1 \left(\frac{1}{2} - \ \frac{1}{1 + \ exp\,(\ \sigma_2 \times (y - \sigma_3\ ))} \ + \sigma_4 \times y + \sigma_5 \right) \tag{13}$$

withy and Q(y) being the input objective score and the mapped score, respectively. $\sigma_i (i = 1, 2, 3, 4, 5)$ are free parameters to be determined during the curve fitting process respectively. The IQA metrics are evaluated by three criteria: 1) Spearman rank-order correlation coefficient (SRCC) for predicting monotonicity; 2) Pearson linear correlation coefficient (PLCC); and 3) root-mean-squared error (RMSE) for predicting accuracy. It is worth noting that a higher value of PLCC and SRCC means a better accuracy and monotonicity and a low value in RMSE indicates a better performance.

5.2. **Result and Comparisons.** We use the images in the SIQAD and QACS to behavior the comparison experiments by using the proposed with some popular the state-of-the-art bling image quality, like BRISQUE [16], NFERM [18], GMLF [32], ARISMC [15], and NRSL [33]. We apply all the metrics to the grayscale version of images and compute the correlations between the predicted scores MOS/DMOS values in terms of the PLCC, RMSE, and SRCC. We can observe the conducted in the determination of the proposed methods have good success. Table 1 summarizes the experimental results.

We can observe from the Table 2, that the proposed method can produce the optimum grades in all SCI's databases (SIQAD and QACS). In the SIQAD database, NFERM crops the second optimum and the NRSL also give the second optimum result in QACS database. Our method performance a good result than other blind image quality assessment. Therefore, it can be, deduced that our method is very promising. We also compared the performance of the proposed model with 10 state of the art NR IQA metrics, including BRISQUE [16], NFERM [18], GMLF [32], GWH-GLBP [26], DIVIINE [17], ARISMC

Table 3. Performance comparison of 10 modern NR-IQA models in related databases and average results. We bold the three top models

Databases	SIQAD (980images) [29]			QACS (492 images) [30]			Weighted average (1472 images)		
Metric	PLCC	SRCC	RMSE	PLCC	SRCC	RMSE	PLCC	SRCC	RMSE
BRISQUE [16]	0.7792	0.7304	8.8794	0.4622	0.4342	1.9363	0.6732	0.6314	6.5587
NFERM [18]	0.7986	0.7683	8.6137	0.4485	0.4034	1.9459	0.6816	0.6463	6.3851
GMLF [32]	0.7493	0.7112	9.4603	0.5484	0.5194	1.8344	0.6822	0.6471	6.9114
GWH-GLBP [26]	0.5585	0.5355	11.825	0.4947	0.4331	1.8969	0.5372	0.5013	8.5066
DIVIINE [17]	0.6434	0.6109	10.782	0.4240	0.3782	1.9669	0.5701	0.5331	7.8356
ARISMC [15]	0.5824	0.5286	11.5484	0.4183	0.3441	1.9632	0.5276	0.4670	8.3447
NRSL [33]	0.6452	0.5993	10.8918	0.6206	0.5890	1.7179	0.6370	0.5959	7.8255
IL_NIQE [20]	0.3881	0.3574	13.1918	0.2325	0.2558	2.1577	0.3361	0.3234	9.5038
NIQE [19]	0.3790	0.3693	13.2462	0.4389	0.3805	1.9934	0.3990	0.3730	9.4851
NIQMC [34]	0.2149	0.1968	13.9798	0.4640	0.4188	1.9654	0.2981	0.2710	9.9641
Proposed	**0.8337**	**0.8162**	**7.8600**	**0.5006**	**0.4847**	**1.8797**	**0.7223**	**0.7053**	**5.8611**

Table 4. Performance comparison with the impact of training images.

Databases	SIQAD (980 images) [29]		QACS (492 images) [30]	
Train Test	Metric		Metric	
80% - 20%	PLCC	0.8337	PLCC	0.5006
	SRCC	0.8162	SRCC	0.4847
	RMSE	7.8600	RMSE	1.8797
60% - 40%	PLCC	0.8083	PLCC	0.3880
	SRCC	0.7887	SRCC	0.3810
	RMSE	8.4173	RMSE	2.0274
50% - 50%	PLCC	0.7904	PLCC	0.3699
	SRCC	0.7797	SRCC	0.3587
	RMSE	8.77931	RMSE	2.0582

[15], NRSL [33], IL_NIQE [20], NIQE [19], and NIQMIC [34]. Also, we have applied all the metrics to the grayscale type of images and compute the correlations between the predicted scores MOS/DMOS values in terms of the PLCC, RMSE, and SRCC.

We report the correlation results in Table 3, using the linearly weights average performance comparison, where the relative weights were assigned in proportion to the number of images in the testing databases. The best performance is marked with the bold font. It is shown that the proposed achieve the highest overall correlation values. We also computed the proposed method when different settings are utilized such as, 80%, 60% and 50% of the images are selected for training, and the remaining 20%, 40%, and 50% images are used for the test. We also computed the median performance across 1,000 times and the median values are used as the performance results.

In Table 4, we can observe that the performance of the model proposed degrades as the number of training images decrease. Though, it is also noticed that even after adopting only 50% of the images for training, the performance of the proposed method is still very hopeful. This is an indication of the proposed methods insensitivity towards a number of the training image.

6. **Conclusion.** In this paper, we have addressed the quality assessment of distorted screen content images. First, we have established the SCS model incorporates more sets of features of free energy measure, structural degradation, log-energy, and contrast. Due to the characteristics presented by each feature, we decided to use 22 features to evaluate our performance method on two screen content images databases (SIQAD and QACS). We use support vector regression (SVR) [27], to convert all features into the single quality score. The experimental results and comparisons have confirmed the effectiveness and advantages of the proposed quality model. As future work, we will use the proposed model for benchmarking and perceptual optimization of screen content image algorithms.

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