SCID: A DATABASE FOR SCREEN CONTENT IMAGES QUALITY ASSESSMENT

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ABSTRACT

Perceptual quality assessment of screen content images (SCIs) has become a new challenging topic in the recent research of image quality assessment (IQA). In this work, we construct a new SCI database (called as SCID) for subjective quality evaluate of SCIs and investigate whether existing IQA models can effectively assess the perceptual quality of distorted SCIs. The proposed SCID, which is currently the largest one, containing 1,800 distorted SCIs generated from 40 reference SCIs with 9 types of distortions and 5 degradation levels for each distortion type. The double-stimulus impairment scale (DSIS) method is then employed to rate the perceptual quality, in which each image is evaluated by at least 40 assessors. After processing, each distorted SCI is accompanied with one mean opinion score (MOS) value to indicate its perceptual quality as ground truth. Based on the constructed SCID, we evaluate the performances of 14 state-of-the-art IQA metrics. Experimental results show that the existing IQA metrics do not be able to evaluate the perceptual quality of SCIs well and an IQA metric specifically for SCIs is thus desirable. The proposed SCID will be made publicly available to the research community for further investigation on the perceptual processing of SCIs.

Index Terms— image quality assessment, screen content images, mean opinion score

1. INTRODUCTION

Recent developments in cloud computing, multi-device communication and the Internet of Things make screen content images (SCIs) get more and more attentions [1]. One inherent problem with these multimedia services is the perceptual quality degradation during various image processing stages (e.g., compression, transmission), which could lead to bad multimedia quality of experience. For that, image quality assessment (IQA) has been regarded as an effective performance index to guide and facilitate various image processing tasks [2]. A typical SCI consists of discontinuous-tone content, e.g., graphics, text, and icon rendered by electronic devices, and continuous-tone content, e.g., natural image scene captured by cameras, which is quite different from the natural image. Therefore, developing an IQA metric that can automatically, accurately, and efficiently predict perceptual quality of SCIs consistently with the human visual system (HVS) perception is in demand.

In order to address the problem of IQA, many research efforts are devoted to incorporate HVS's features into the IQA models and have achieved many important successes. A milestone in the IQA area is the structural similarity (SSIM) [2], which consider the structural information degradation in the IQA instead of the traditional pixel difference based on the observation that people is more sensitive in the structure information. Even though, lots of objective IQA models have shown their effectiveness on the quality evaluation of natural image [3], it remains an open-ended question whether these methods can deliver good performance on quality assessment of SCIs [4]. This is mainly due to the fact that the image structure and SCIs exhibits different statistic properties in textual and pictorial regions from the natural image.

To the best of our knowledge, the research of SCI subjective quality assessment is limited. There is only one publicly available SCI database, namely, SIQAD [5], which is the currently largest SCI database. The defects of this SIQAD database is obvious: small amount of reference and distorted SCIs and the content of the reference SCIs and type of distortion is not enough. In this paper, a new and large-scale SCI database (denoted as SCID) is established, which includes 1,800 distorted SCIs and 40 reference SCIs. The distorted SCIs are generated by 9 different types of distortions and 5 degradation levels for each type of distortion. The refer-

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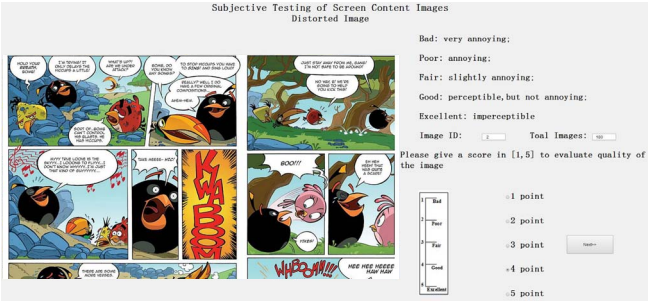

Fig. 1. Screenshot of the subjective study graphical user interface.

ence SCIs are selected from the Internet and screen content video sequences provided by the joint collaborative team on video coding group, which covers popular and typical screen content application scenarios. The considered 9 distortion type are Gaussian noising (GN), Gaussian blurring (GB), Motion blurring (MB), Contrast change (CC), JPEG, JPEG2000 (J2K), color saturation change (CSC), color quantization with dither (CQD), and screen content coding using HEVC-SCC [6].

The remaining of this paper is organized as follows. Introduction of subjective testing processing for building the S-CID is considered in Section 2.Some existing objective image quality models are introduced and evaluated on the built SCID database in Section 3. Finally, we draw some concluding in Section 4.

2. SUBJECTIVE QUALITY ASSESSMENT OF SCREEN CONTENT IMAGES

In order to adequately evaluate the performances of existing IQA models and analyze their advantage and disadvantage in a fair setting, we firstly construct a new and large-scale SCI database, which includes 40 reference and 1800 distorted S-CIs, followed by conducting a subjective quality test.

2.1. Introduction of SCID

The SCIs distinguished as a compound image consists of discontinuous-tone and continuous-tone contents. In order to build a reasonable SCI database, extensive efforts on searching representative SCIs over the Internet have been conducted through large manpower. With thoughtful evaluations, 40 images were selected from several hundreds of collected SCIs as the reference SCIs, as they cover various combination of image contents, including texts, lines, and natural images. All of them are cropped to a fixed size, with the resolution of 1280×720.

In our constructed SCID, we deployed 9 types of distortions, with 5 levels of degradations (approximately distributed from the degree of imperceptibility to the very annoying level) generated for each type, which are detailed in the following.

- Gaussian Noise (GN): the corresponding distorted SCIs with GN are obtained by performing MATLAB function "*imnoise*". The mean is zero, and the values of standard deviation used were between 0.001 and 0.1.
- Gaussian Blur (GB): the corresponding distorted SCIs with GB are obtained by performing MATLAB function "*imfilter*" with Gaussian kernel. The standard deviation is ranging from 0.58 to 2.1.
- Motion Blur (MB): the corresponding distorted SCIs with MB are obtained by performing MATLAB function "*imfilter*" with motion kernel, which stimulates the linear motion of a camera. The blurring level is controlled by the following two parameters len and theta. In our experiments, theta is zero and len is between 2 and 6.4.
- Contrast Change (CC): image contrast is also a usual image distortion that has a significant effect on the HVS, the corresponding distorted SCIs with CC are obtained by performing MATLAB function "*imadjust*".
- JPEG compression (JPEG): the MATLAB function "*imwrite*" is used to implement JPEG algorithm. The corresponding distorted SCIs with JPEG compression are obtained by compressing the reference SCIs via JPEG with a quality factor in the range of 5 to 75.
- JPEG2000 compression (J2K): the corresponding distorted SCIs with JPEG2000 compression are genered by performing JasPer software [7] at compression ratio ranging from 0.08 to 0.01.
- Color Saturation Change (CSC): the corresponding distorted SCIs with CSC are obtained by keeping the luminance component unchanged while changing the chrominance components.
- HEVC Screen Content Compression (HEVC-SCC): the compression of SCIs is a hot topic in multimedia processing applications and HEVC-SCC [6] is able to achieve high compression ratio, HEVC-SCC is also employed to generate the distorted SCIs. The corresponding distorted SCIs with HEVC-SCC compression are obtained by performing HEVC-SCC encoder with standard configurationłAll Intra Main setting. The quantization parameters are set between 16 and 48.
- Color quantization with dithering (CQD): the corresponding distorted SCIs with CQD are obtained by performing MATLAB function *rgb2ind*. This function is used to convert RGB image to indexed image using dithering minimum variance quantization, where the parameter N is to control the number of color and is set between 5 and 30.

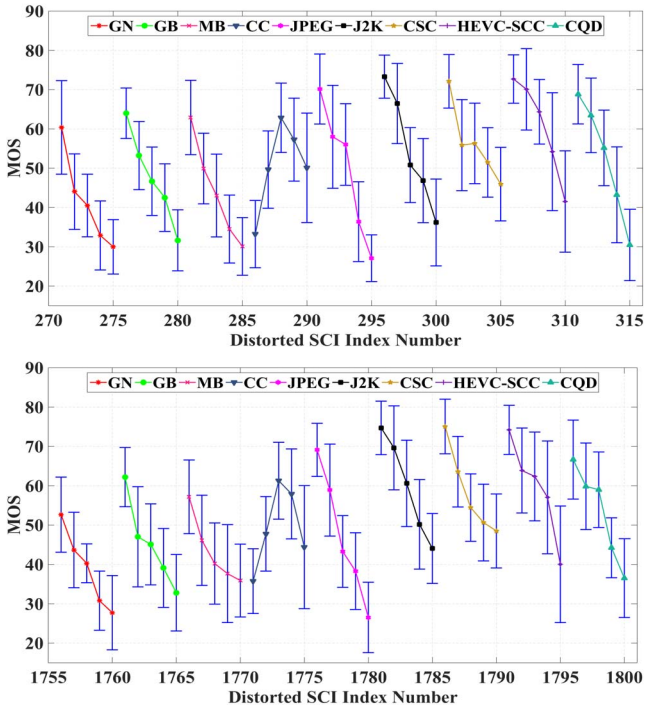

Fig. 2. The obtained MOS values of two reference SCIs and corresponding confidence intervals (the blue error bars indicate the standard deviation of the subjective scores).

2.2. Methodology on Subjective Testing

Several subjective testings, as specified in ITU-R BT.500-13 [8], aims at assessing the quality of images. According to the availability of different stimulus, these methods can be classified as single stimulus and double stimulus. The double stimulus approach asks the subjective viewers to evaluate the quality between reference and distorted images, while the single stimulus only a single image is presented to assessor, and asks them to give a opinion score by themselves. As illustrated in [3], the single stimulus approach is of high efficiency on subjective testing. On the contrary, the methodology of double stimulus is known to be of better reliability [8]. In our study, the double stimulus impairment scale (DSIS) method is employed. Additionally, for the convenience of scoring, we employ the 5-category discrete scale to obtain the subjective opinions. The reference SCI is presented to the subjective viewers about 10 seconds, followed by mid-grey presentation. Then the distorted SCI is presented to the subjective viewers. The subjects are asked to provide their judgements based on the overall impression given by the image, and express these judgements in terms of the score used to define the subjective scale (from 1 to 5). Note that the higher the score the better the perceptual quality is. The test desktops is equipped with 23-inch LED monitors (the resolution is 1920×1080), 16 GB RAM and 64-bit Windows operating system, are placed in a laboratory with normal indoor light.

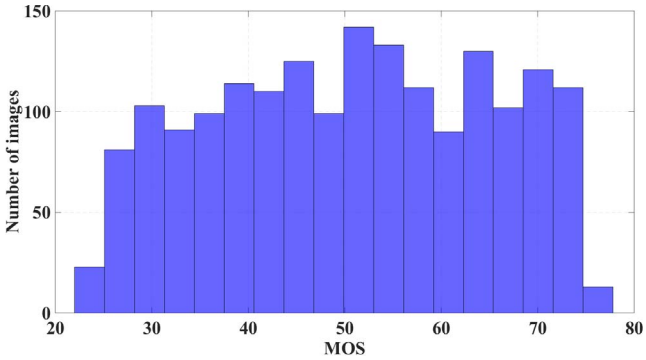

Fig. 3. Histogram of the MOS values of distorted SCIs in SCID.

Before the test officially started, several training sessions were held to instruct all participating evaluator about evaluation rules and procedures. Fig. 1 shows the user interface. Each distorted SCI is presented to the assessor for rating after its corresponding reference SCI and each distorted SCI is presented only once. The quality scales, in the bottom right of the window, are labeled to help the human subjects to perform the quality evaluation as shown in Fig. 1. All assessors are students with normal vision function (with age between 18 to 27) and did not have any image processing background and experience to avoid bias as much as possible. As suggest in [8], in order to avoid fatigue that may affect the accuracy of subjective assessment, the execution time of each test session should not exceed 30 minutes. Hence, we randomly and non-overlappingly divided the entire 1800 distorted SCIs into 10 sessions (the distorted SCIs which are generated by same reference SCI will not be continuously presented) and assign one session to a subject at a time. Each assessor randomly evaluates two or three sessions of SCIs, and each distorted SCI is rated by at least 40 different assessors. During the test, the assessors were mandated to take a break for every 30 minutes of evaluation work to avoid fatigue. At last, a total of 430 assessment sessions are obtained.

3. EXPERIMENTAL RESULTS

The experiments consist of two parts: reliability analysis of the constructed database SCID and performances evaluation of the existing IQA models on SCID, which will be reported in the following two subsections.

3.1. Reliability Analysis of the Constructed SCID

Before we process the raw subjective scores to obtain the final MOS values, which can be further used as the ground truth for the performance evaluation of the quality models, we first need to detect and reject the unreliable subjects as suggested by [8]. For that, the raw subjective ratings are firstly converted

Table 1. Performance comparisons of 14 classical and state-of-the-art IQA models on the *SCID* database.

	Distortions	PSNR	SSIM [2]	MSSIM [9]	IWSSIM [10]	VIF [11]	GSIM [12]	GMSD [13]	FSIM [14]	FSIMc [14]	VSI [15]	MAD [16]	IFC [17]	SCDM [18]	SCQI [18]
PLCC	GN	0.9482	0.9354	0.9448	0.9431	0.9699	0.9170	0.9273	0.9516	0.9541	0.9556	0.9315	0.8897	0.8441	0.9319
	GB	0.7274	0.8711	0.8991	0.9174	0.8999	0.8449	0.7348	0.8493	0.8489	0.8307	0.8559	0.8406	0.6467	0.8244
	MB	0.7149	0.8794	0.9018	0.9055	0.8421	0.8383	0.7954	0.8523	0.8504	0.8177	0.8362	0.3372	0.6470	0.8147
	CC	0.7451	0.6903	0.8881	0.8989	0.8092	0.8675	0.8041	0.8947	0.9008	0.8093	0.4987	0.1198	0.7223	0.8353
	JPEG	0.8231	0.8581	0.9227	0.9308	0.9418	0.9373	0.9351	0.9419	0.9411	0.9140	0.9251	0.8762	0.8156	0.9036
	J2K	0.9177	0.8586	0.9185	0.9195	0.9489	0.9441	0.9422	0.9607	0.9594	0.9441	0.9381	0.8570	0.9391	0.9312
	CSC	0.0622	0.0890	0.0977	0.0527	0.0898	0.0560	0.0952	0.0966	0.9223	0.9119	0.1296	0.0764	0.5546	0.8393
	HEVC-SCC	0.7935	0.7914	0.8635	0.8883	0.8656	0.8835	0.9043	0.9228	0.9257	0.9035	0.8953	0.7918	0.8736	0.8708
	CQD	0.9210	0.7810	0.8668	0.8930	0.9085	0.8974	0.9177	0.9202	0.9296	0.8873	0.9014	0.7655	0.8859	0.8823
	Overall	0.7622	0.7343	0.7579	0.7877	**0.8179**	0.7042	**0.8337**	0.7719	**0.8054**	0.7694	0.7736	0.6285	0.4540	0.7596
SROCC	GN	0.9424	0.9171	0.9309	0.9305	0.9616	0.9112	0.9341	0.9378	0.9411	0.9455	0.9262	0.8877	0.9566	0.9556
	GB	0.7702	0.8698	0.8949	0.9165	0.8954	0.8420	0.7931	0.8476	0.8474	0.8221	0.8603	0.8351	0.8638	0.8638
	MB	0.7433	0.8588	0.8890	0.8918	0.8259	0.8194	0.8148	0.8370	0.8359	0.8013	0.8296	0.4477	0.8589	0.8587
	CC	0.7265	0.6564	0.8368	0.8475	0.6115	0.8304	0.5672	0.8473	0.8560	0.8158	0.4784	0.1198	0.7440	0.7465
	JPEG	0.8321	0.8490	0.9219	0.9275	0.9349	0.9366	0.9344	0.9403	0.9375	0.9142	0.9242	0.8770	0.9172	0.9171
	J2K	0.9072	0.8439	0.9097	0.9067	0.9369	0.9349	0.9279	0.9484	0.9462	0.9307	0.9330	0.8457	0.9271	0.9270
	CSC	0.0908	0.0963	0.1274	0.1336	0.1221	0.1214	0.1165	0.1182	0.9312	0.9141	0.1440	0.0521	0.8520	0.8970
	HEVC-SCC	0.8050	0.8263	0.8688	0.8867	0.8580	0.8730	0.8958	0.9098	0.9106	0.8929	0.8771	0.7869	0.8708	0.8721
	CQD	0.9080	0.7766	0.8626	0.8846	0.8918	0.8707	0.9047	0.9077	0.9137	0.8820	0.9024	0.7368	0.9058	0.9099
	Overall	0.7511	0.7146	0.7407	0.7714	**0.7969**	0.6945	**0.8138**	0.7550	**0.8066**	0.7621	0.7576	0.5799	0.7716	0.7814
RMSE	GN	3.9924	4.4458	4.1180	4.1780	3.0629	5.0127	4.7044	3.8613	3.7653	3.7138	4.5714	5.7380	6.7392	4.5600
	GB	7.2665	5.1998	4.6360	4.2163	4.6179	5.6648	7.1821	5.5903	5.5971	5.8956	5.4775	5.7354	8.0764	5.9943
	MB	7.6430	5.2044	4.7233	4.6376	5.8960	5.9607	6.6249	5.7180	5.7518	6.2922	5.9947	10.2905	8.3341	6.3394
	CC	5.9702	6.4767	4.1151	3.9218	5.2594	4.4524	5.3211	3.9979	3.8867	5.2583	7.7590	8.8876	6.1908	4.9217
	JPEG	8.5364	7.7179	5.7955	5.4930	5.0536	5.2369	5.3275	5.0471	5.0844	6.0971	5.7076	7.2431	8.6966	6.4390
	J2K	6.3221	8.1562	6.2890	6.2555	5.0207	5.2462	5.3283	4.4180	4.4891	5.2451	5.5103	8.1986	5.4692	5.8002
	CSC	9.8203	9.8003	9.7923	9.8257	9.7996	9.8239	9.7947	9.7933	3.8025	4.0392	9.7564	9.8106	8.1872	5.3503
	HEVC-SCC	8.4671	8.5037	7.0166	6.3904	6.9657	6.5176	5.9393	5.3583	5.2615	5.9628	6.1988	8.4969	6.7688	6.8407
	CQD	4.9813	7.9855	6.3768	5.7530	5.3440	5.6406	5.0796	5.0054	4.7125	5.8964	5.5354	8.2269	5.9379	6.0188
	Overall	9.1679	9.6133	9.2400	8.7243	**8.1479**	10.0552	**7.8210**	9.0040	**8.3947**	9.0456	8.9739	11.0157	12.6185	9.2113

into Z-scores per session. After then the methodology specified in the ITU-R BT 500-11 [8] is adopted to remove outliers. We compute the 95% confidence intervals which are derived from the standard deviation and the remaining are valid. By performing the aforementioned outlier rejection procedures for each session, 54 out of 430 assessment sessions were rejected in total. After outlier rejection, Z-scores are then linearly mapping to the range of [0, 100]. Finally, the mean of the rescaled Z-scores for each distorted SCI is calculated regard as the MOS value of each distorted SCI, which is considered as the ground truth representing the distorted SCIs perceptual quality, and their corresponding standard deviation take as confidence intervals.

Fig. 2 illustrates two examples of MOS distributions, where the error bar indicates the corresponding confidence intervals of related scores. The horizontal axes are the distorted indices, and the vertical axes are MOS values. It is obvious that the distorted SCIs with different types of distortions and levels have different MOS values and similar confidence intervals values. This imply that the assessors have similar opinion about the perceptual quality of SCIs. It is worth noting that similar observations can be found for other distorted SCIs. In addition, Fig. 3 illustrates the histogram of the MOS values of all distorted SCIs in the constructed SCID. It can be found that the MOS values of all distorted SCIs exhibit a good separation ranging from low to high values. It means that the established SCID database agree with that the perceptual qualities of the distorted SCIs in a database should span the entire range of visual quality with a good separation (from imperceptible to high-annoying level) [19]. Therefore, we can draw the conclusion that the obtained MOS values are reliable and can be further organized as the ground truth for evaluate IQA models.

3.2. Performance Evaluation of the State-of-the-art IQA Metrics on the SCID

In order to investigate the effectiveness of the state-of-the-art IQA metrics for perceptual quality evaluation of SCIs, 14 objective IQA metrics are applied on the *SCID*. They are PSNR, SSIM [2], MSSIM [9], IWSSIM [10], VIF [11], GSIM [12], GMSD [13], FSIM and FSIMc [14], VSI [15], MAD [16], IFC [17], SCDM and SCQI [18]. As usual, we first map the objective scores evaluate by each quality model into a common space using a five-parameter logistic function to reduce the nonlinearity of the evaluated score. After that, three commonly-used criteria are adopt to evaluate the performance

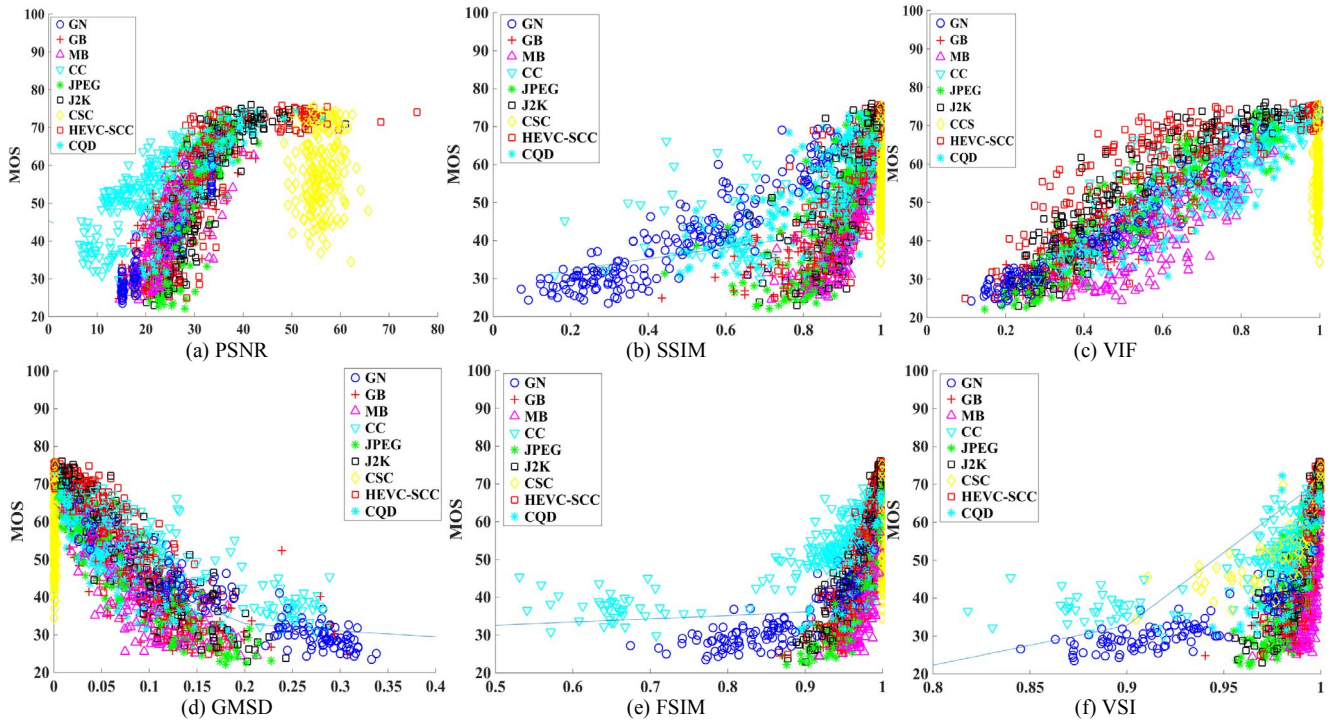

Fig. 4. Scatter plots of MOS versus classical (a) PSNR, (b) SSIM, (c) VIF, statef-of-the-art (d) GMSD, (e) FSIM, and (f) VSI on our created SCID database. The blue lines as shown in each sub-plot are curves fitted with a five-parameter non-linear function.

from different aspects. The first one Pearson linear correlation coefficient (PLCC), which is to evaluate the prediction accuracy. The Spearman rank order correlation coefficient (SROCC) measures the prediction monotonicity. The root mean squared error (RMSE) is introduced for evaluating the prediction consistency, respectively [12, 17]. Higher values of PLCC and SROCC mean a better perceptual image quality. On the contrary, the lower RMSE witnesses a good prediction consistency. The corresponding experimental results are reported in Table 1, where the top three performance figures are marked in boldface.

From the Table 1, it can be seen that GMSD achieves highest consistency with human visual perception. Note that this is quite different from the performance of these IQA metrics on natural images, where SCDM and SCQI have been demonstrated as the ones with much better performances than GMSD. This implies that the HVS is more sensitive to the local structure and edge information, which are very often encountered in SCIs and GMSD can well describe. It can be further observed that the above-mentioned IQA metrics are, overall, not able to achieve good performances on SCID. They are thus not suitable to be directly applied on perceptual quality assessment of SCIs. This is because that these IQA metrics are designed for natural images while SCIs have different image characteristic from natural images. This study implies that it is of great necessity to investigate the perceptual quality assessment specifically for SCIs. Fig. 4 provides the scatter plots of subjective scores (i.e., MOS) against objective scores predicted by several classical and state-of-the-art IQA models (i.e., PSNR, SSIM, VIF, GMSD, FSIM, and VSI) on our created database (SCID) for a demonstration. There is a fitted line (in blue) as presented in each sub-plot, which is obtained by exploiting a nonlinear curve fitting process. It can be observed that the scores as computed by the natural image IQA models are relative far away from the fitted line. This means that natural image IQA models can not effective evaluate perceptual quality of SCIs.

4. CONCLUSION

In this paper, a new and largest SCI database (i.e., SCID) is constructed for the study on perceptual quality assessment of SCIs, which contains 40 reference SCIs and 1,800 distorted SCIs. These distorted SCIs are generated by degraded reference SCIs under 9 different types of distortions, and each distortion type has five degradation levels. The double-stimulus impairment scale (DSIS) method is then employed to rate the perceptual quality to obtain the ground truth (i.e., MOS) for each distorted SCI, followed by analyzing its reliability and conducting performance evaluations of the traditional and state-of-the-art IQA metrics on the constructed SCID. It can be observed that these IQA models, which were originally designed for natural images, can not performance well on SCID in terms of correlation with the HVS perception on the SCI

quality. Hence, it is demanded to design novel objective IQA models specifically for SCIs. Furthermore, the constructed S-CID will be made publicly available for that upon acceptance in future.

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