Deep Feature Statistics Mapping for Generalized Screen Content Image Quality Assessment

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Abstract—The statistical regularities of natural images, referred to as natural scene statistics, play an important role in no-reference image quality assessment. However, it has been widely acknowledged that screen content images (SCIs), which are typically computer generated, do not hold such statistics. Here we make the first attempt to learn the statistics of SCIs, based upon which the quality of SCIs can be effectively determined. The underlying mechanism of the proposed approach is based upon the mild assumption that the SCIs, which are not physically acquired, still obey certain statistics that could be understood in a learning fashion. We empirically show that the statistics deviation could be effectively leveraged in quality assessment, and the proposed method is superior when evaluated in different settings. Extensive experimental results demonstrate the Deep Feature Statistics based SCI Quality Assessment (DFSS-IQA) model delivers promising performance compared with existing NR-IQA models and shows a high generalization capability in the cross-dataset settings. The implementation of our method is publicly available at https://github.com/Baoliang93/DFSS-IQA.

Index Terms—Image quality assessment, screen content image, no-reference, scene statistics, distribution deviation.

I. INTRODUCTION

SCREEN content images (SCIs) have attracted dramatic attention in recent years with the rapid development of digital devices and online communication [1], [2], [3]. The SCI appears in various media, such as electronic books, online news, and screen sharing. Serving as the fundamental technology in SCI compression, exhibition, and processing, assessing the quality of SCI automatically becomes a highly demanding task. In practice, due to the imperfect transmission condition and limited storage space, the quality of SCIs can be degraded by several distortion types.

To assess the image quality, the most reliable way is to collect subjective opinions by crowdsourcing [4], [5], [6], [7], [8]. However, the subjective study is usually laborious and expensive. To count for this, numerous objective methods have been proposed for SCI quality assessment (SCIQA) [9]. According to the availability of reference images, the SCIQA methods fall into two categories: full-reference (FR) SCIQA and no-reference (NR) SCIQA. For FR-SCIQA, the hand-crafted features such as structural features, luminance features, and Gabor features are exploited in [10], [11], and [12]. With the popularisation of deep learning, the convolutional neural network (CNN) based models have been widely investigated in [13] and [14]. For example, Yang et al. adopted a fully convolutional network to separate the image into structural regions and texture regions and extracted the structural features and perceptual features from the two regions for SCIQA [14]. Compared with the FR-SCIQA, the NR-SCIQA is more practical in real-world applications. In [15] and [16], the quality-aware features including the picture complexity, brightness, sharpness, and textures are adopted. Driven by the hypothesis that the human visual system (HVS) is highly sensitive to sharp edges, Zheng et al. divided the SCI into sharp edge regions and non-sharp edge regions [17]. Recently, the deep-learning based NR-SCIQA models have shown superior performance by learning the quality-aware features from the data [18], [19], [20], [21], [22]. In particular, Chen et al. incorporated a naturalization module in stacked CNNs for quality-aware feature learning [20]. Yang et al. proposed a multi-task learning framework which both the distortion types and distortion degrees were analyzed in [22]. However, despite the success of those methods, they usually suffered from the over-fitting problem, presenting an inferior generalization capability, especially in cross-dataset settings.

We believe that the statistics-based methods, which have been proven to be effective for the quality assessment of natural images (NIs), become pivotal for SCIs as well. Typically, natural scene statistics (NSS) which have been explored with the assumption that natural images usually hold specific

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synthesize the image semantics and distortion to mimic the process of human quality rating.

II. RELATED WORKS

A. No-Reference Image Quality Assessment Methods

Getting rid of the requirement of reference images in evaluation, the NR-IQA takes an increasingly important role in real-world applications. The traditional NR-IQA methods can be mainly classified into two categories: NSS-based methods [25], [26], [31], [32], and free-energy based methods [33], [34], [35], [36], [37]. For the NSS construction, Tang et al. explored the NSS descriptor based on the magnitudes and phases of the pyramid wavelet coefficients [31]. A spatial NSS model was constructed by exploring the distribution of locally normalized luminance [25]. Xue et al. exploited the joint statistics of gradient magnitude map and Laplacian of Gaussian response for NR-IQA [38]. In [39] and [40], the visual codebooks were constructed from local image patches, aiming for the NSS encoding. Inspired by the free-energy-based brain theory [33], [34], [35], [36], [37] that HVS always attempts to reduce the uncertainty and explains the perceived scene by an internal generative model, Zhai et al. proposed a psychovisual quality model in [37]. Analogously, Gu et al. incorporated the free-energy inspired features and the “naturalness” related features for quality regression [35]. In [41], the salience map was introduced to guide the quality aggregation due to its high relevance with the semantic obviousness.

Recently, deep learning technologies have achieved great success for NR-IQA. In [42], the patch-based NR-IQA model was learned by several CNN layers. This work was extended by DeepBIQ [43], where a pre-trained network is fine-tuned for the generic image description. In [44], the multi-tasks including the quality prediction and distortion type identification were explored, aiming for the distortion discrimination capability enhancement. However, the deep-learning based methods are usually suffered from the over-fitting problem, due to the limited size of training data. In [45], [46], [47], and [21], the rank information of image pairs was explored which was able to enrich the training samples and mitigate the over-fitting problem to some extent. The generalization performance could also be enhanced by the knowledge transferred from the distortion type identification networks learned from synthesis image databases [21], [48], [49]. In particular, a deep bilinear model was proposed by Zhang et al. [48], combining both the pre-trained image distortion classification network and image category classification network for quality regression. Fang et al. [50] proposed an IQA model for smartphone photography, in which the interactions between image attributes and high-level semantics were explored in a multi-task learning manner. To enhance the model generalization capability on cross-tasks, the incremental learning frameworks were proposed in [51] and [52]. Chen et al. proposed a self-supervised pre-training strategy for quality-aware feature extraction [53]. Yue et al. exploited both labeled data and unlabeled data for a semi-supervised IQA model learning [54]. Inspired by the free-energy theory, the pseudo-reference information was restored in image-level [55].
Fig. 2. Illustration of the framework of our proposed method. In the training phase, the images are grouped with a triplet including a reference image ($I^r$), a distorted image ($I^d$), and an auxiliary image ($I^a$). In particular, $I^d$ shares the same content with $I^r$ while its quality is degraded by the distortion. $I^a$ is sampled from pristine images but its content is different from $I^r$. Then the quality-aware feature of each image is extracted via a multi-scale feature generator and further disentangled into a semantic-aware feature ($F_{rs}$, $F_{ds}$, $F_{as}$) and a distortion-aware feature ($F_{rd}$, $F_{dd}$, $F_{ad}$). We force the normalized distortion-aware feature to obey a unified distribution ($F_{gaus}$) and treat the unified distribution as the feature statistics shared by the SCIs. As a consequence, the distortion of the $I^d$ can be measured by the feature distribution divergence estimation. Finally, the quality of $I^d$ can be regressed by incorporating both its semantic information ($F_{ds}$) and distortion information ($F_{dd}$). In the testing phase, only the testing image (without reference) is needed for quality prediction.

and feature-level [56], leading to more discriminative feature extraction.

B. No-Reference SCI Quality Assessment Models

Compared with the NIs, SCIs present distinct statistical differences, leading to a dramatic performance drop when the natural IQA models are tested on SCIs. This phenomenon brings a high demand for IQA models designed specifically for SCIs. In the literature, the NR SCIQA models can be roughly classified into three categories: distortion-aware feature extraction based methods, multi-task learning based methods, and transfer-learning based methods. For the distortion-aware feature extraction, Fang et al. combined the local-global luminance features and texture features with the assumption that HVS was more sensitive to luminance or texture degradation [16]. In [15], the features that represent picture complexity, screen content statistics, global brightness, and sharpness of details were extracted and regressed for SCI quality prediction. The CNNs were utilized for more powerful feature extraction in [20] and [57]. For example, Yue et al. decomposed the input SCI into predicted and unpredicted portions and learned the quality prediction in an end-to-end manner [57]. For the multi-task learning based methods, Jiang et al. learned a noise classification task auxiliarily for the SCI quality prediction in [58]. In [22], the identification tasks of both distortion types and distortion levels were incorporated into the quality prediction model. For the transfer-learning based methods, Chen et al. firstly explored the quality assessment transferred from NIs to SCIs with unsupervised domain adaptation [21]. The unified IQA models that are able to assess the quality of both NIs and SCIs also attracted much attention [59], [60]. For example, Min et al. proposed a unified NR-IQA model with a content-adaptive weighting module [60]. Though those methods have achieved promising performance on SCIQA, the generalization capability of those models is still not well studied. In this paper, we make the first attempt to learn the statistics of SCIs and by which, the generalization capability of the SCIQA can be improved significantly.

III. THE PROPOSED SCHEME

The goal of the proposed method is to determine the quality of the SCIs without reference. The philosophy behind it is comparing the statistics of the input image against the assumed distribution which is regarded to reflect the “naturalness” of pristine SCIs. As such, the perceptual quality of SCIs can be estimated by measuring the destruction of the learned distribution. With those mild assumptions, we propose an NR-SCIQA model by constructing the expected distribution in the deep feature space, thus the quality of test images can be regressed from the distribution deviation. As shown in Fig. 2, our proposed framework consists of image patch sampling, quality-aware feature extractor, and quality regression. More specifically, the image patch sampling aims to obtain fixed-size image patches from the original SCI, thus the model can be trained and tested when SCIs are of different resolutions. Subsequently, we extract the quality-aware features of each patch based on a multi-stage feature extractor, from which
the distortion at different scales can be effectively captured. Herein, the quality-aware feature is expected to contain both the semantic information and distortion information of the input SCI. This is reasonable and its evidence can be exemplified in Fig. 3. From the figure, we can observe that even though the image pairs share the same distortion level, their quality scores can be extremely different, revealing that the image quality is governed by both distortion and content. This phenomenon is also consistent with previous natural IQA works such as [48] and [61]. Along this vein, we disentangle the quality-aware feature into a semantic-specific feature and a distortion-aware feature. For the distortion-aware feature, we impose a unified distribution on it and treat the predefined distribution as the feature statistics of SCIs. Regarding the semantic-specific feature, a triplet constraint is adopted based on the underlying principle that the semantic information of the distorted image is similar to the reference image while possessing a large difference from the auxiliary image. Finally, the quality of the distorted SCI can be regressed by synthesizing both the distortion information and semantic information. Before diving into the details of the proposed model, we first provide the definitions of the symbols in Fig. 2 as follows,

- $I^d, I^r, I^a$: The input triplet images. In particular, $I^d$ is an image sampled from the distorted images with its corresponding reference image denoted as $I^r$. The $I^a$ is an image sampled from all the reference images while its content is different from the distorted image.
- $F^{qua}$: The quality-aware feature extracted by the multi-scale feature generator.
- $F^{rs}, F^{ds}, F^{as}$: The semantic-aware features disentangled from the $F^{qua}$. In particular, $F^{rs}, F^{ds}, F^{as}$ are the semantic-aware feature of $I^r, I^d, I^a$, respectively. Herein, the semantic-aware feature means the feature that is determined by the image content while not sensitive to the image distortion, i.e., images with different contents would lead the semantic-specific features to be dissimilar to each other.
- $F^{rd}, F^{dd}, F^{ad}$: The distortion-aware features disentangled from the $F^{qua}$. In particular, $F^{rd}, F^{dd}, F^{ad}$ are the distortion-aware feature of $I^r, I^d, I^a$, respectively. Herein, the distortion-aware feature means the feature that is sensitive to the image distortion (including the distortion type and distortion level) while not sensitive to the image content.
- $F^{gau}$: A feature that is sampled from the pre-defined multivariate normal distribution. It has the same dimension with $F^{rd}, F^{dd}$, and $F^{ad}$.
- $\Phi^{dd}$: The KL divergence between the distribution formed by the $F^{dd}$ of different patches in $I^d$ and the multivariate normal distribution.
- $F^{att}$: A feature generated by $F^{ds}$ which reflects the attention value of each dimension of $\Phi^{dd}$.
- $Q^p$: The predicted quality score of $I^d$.

A. Triplet Samples for Training

As shown in Fig. 2, we partition the training samples into triplets and each triplet includes a distorted image ($I^d$), its corresponding reference image ($I^r$), and an auxiliary image ($I^a$). In particular, the auxiliary image $I^a$ is randomly sampled from the pristine images while containing a different scene with the $I^r$. The triplet samples herein aim to disentangle the quality-aware feature into the semantic-specific feature and quality-aware feature which will be elaborated in Sec. III-B. In real-world applications, the spatial resolutions of SCIs can be variant, leading to difficulties in training CNN models at the image-level. As a consequence, we crop all the training images into several patches with identical sizes. It should be noted that the triplet images are only utilized in the training phase and only a single test image is needed during testing.

B. Quality-Aware Feature Extractor

The quality-aware feature extractor consists of two stages including the multi-scale feature generator as well as the feature disentanglement.

1) Multi-Scale Feature Generator: The multi-scale feature generator is constructed based upon the principle that quality-aware features can be well established by the statistics of deep representations at different scales [62], [63], [64], [65]. We provide the structural details of our multi-scale feature generator in Fig. 4. As shown in the figure, the input of the feature generator is the image patch cropped from the whole image and the feature generator contains five stages at different scales. Each stage of the generator consists of several convolutional layers and one max-pooling layer. The processing of stage $t$ can be formulated as follows,

$$F^{ms}_t = f_t(X),$$  

where $X$ represents the input patch. $F^{ms}_t$ and $f_t$ mean the output feature map and processing function at stage $t$ and $t \in \{1, 2, 3, 4, 5\}$. For each $F^{ms}_t$, we adopt the adaptive mean pooling and adaptive standard deviation (std) pooling [66] to reduce their spatial dimensions into a fixed scale ($3 \times 3$). Herein, the two spatial pooling strategies (mean and std) have been the widely-used aggregation strategies for IQA. In particular, the mean pooling is able to deliver the global information of learned features [42], [48], [64] and the feature
variation can be captured by the std pooling [61], [65], [67], [68], [69], as such, the two types of pooling strategies are jointly considered in our feature generator. Subsequently, we concatenate those pooled features along with the channel dimension and further process them by two convolutional layers, leading to the final quality-aware feature $F_{i,qua}^{qua}$,

$$
F_{i,qua}^{qua} = f_{mp}(F_{i,ms}^{mp}) \oplus f_{sp}(F_{i,sp}^{ms}), \quad t \in \{1, 2, 3, 4, 5\},
$$

(2)

$$
F_{i,qua}^{qua} = f_{c}(F_{i,ms}^{ms} \oplus F_{i,ps}^{ms} \oplus F_{i,ms}^{ms} \oplus F_{i,ms}^{ms} \oplus F_{i,ms}^{ms}),
$$

(3)

where $f_{mp}$ and $f_{sp}$ represent the adaptive mean pooling and std pooling operations, respectively. $\oplus$ means the concatenation operation. $f_{c}$ is the function of the last two convolutional layers.

2) Quality-Aware Feature Disentanglement: As we discussed before, human beings rate the image quality governed by both distortion level as well as the scene semantics. To fully exploit the quality feature of $F_{i,qua}^{qua}$, we disentangle it into a distortion-aware feature and a semantic-specific feature. The disentanglement layer consists of two convolutional layers with the ReLU activation function following each. To ensure the disentanglement of the quality-aware feature $F_{i,qua}^{qua}$, we first adopt the triplet loss as the objective function with the principle that the semantic features $F_{i,ras}^{ras}$ and $F_{i,ds}^{ras}$ should be similar to each other while both of them are different from the $F_{i,ras}$ due to the fact that the content shared by $I^{r}$ and $I^{d}$ are different from $I^{a}$,

$$
L_{trip} = \frac{1}{B} \sum_{i=1}^{B} \left[ \left\| F_{i,ras}^{ras} - F_{i,ras}^{d} \right\|_{2}^{2} - \left\| F_{i,ras}^{ras} - F_{i,ras}^{ras} \right\|_{2}^{2} + \alpha \right],
$$

(4)

where $i$ is the input image index in a batch $B$. $F_{i,ras}^{ras}$, $F_{i,ras}^{d}$, and $F_{i,ras}^{ras}$ are the features $F_{i,ras}$, $F_{i,ras}$, and $F_{i,ras}$ of $i$-th image. The $\alpha$ is a margin that is enforced between positive and negative pairs.

For the distortion-aware feature, we impose the Gaussian distribution regularization on the feature space. In particular, each dimension of the distortion-aware feature of the pristine SCIs is expected to obey the standard distribution ($\text{mean} = 0, \text{std} = 1$) and is independent of each other. In addition, we force the features of the distorted SCIs to share the same distribution except that the means and variances are determined by the distortion. To account for this, we first perform the distribution normalization to the distortion-aware feature $F_{i,ras}^{d}$ as follows,

$$
F_{i,ras}^{d,n} = \frac{F_{i,ras}^{d} - \mu}{\sigma + \epsilon},
$$

(5)

where $F_{i,ras}^{d,n}$ denotes the normalized results and $\epsilon = 1e - 9$ to avoid zero division error. The $\mu$ and $\sigma$ are the mean and std vectors of $F_{i,ras}^{d}$. In particular, supposing $N$ patches are sampled from a distorted image and we denote the $\mu_{j}$ and $\sigma_{j}$ as the mean and std values of the $j$-th dimension of $F_{i,ras}^{d}$. The $\mu_{j}$ and $\sigma_{j}$ can be formulated as follows,

$$
\mu_{j} = \frac{1}{N} \sum_{n=1}^{N} \left( F_{i,ras}^{d,n},j \right),
$$

(6)

and

$$
\sigma_{j} = \sqrt{\frac{1}{N-1} \sum_{n=1}^{N} (F_{i,ras}^{d,n},j - \mu_{j})^{2}},
$$

(7)

where the $F_{i,ras}^{d,n},j$ indicates the $j$-th dimension value of $F_{i,ras}^{d}$ of the $n$-th image patch. Through such normalization, the distribution divergence between different distorted SCIs can be mitigated, and the unified distribution regularization is performed by an MMD loss given by,

$$
L_{mmd} = \frac{1}{B} \sum_{i=1}^{B} \phi \left( F_{i,ras}^{d,n,i} \right) - \sum_{i=1}^{B} \phi \left( F_{i,ras}^{d,n,i} \right) \right\|_{2},
$$

(8)

where the $i$ indicates the $i$-th image in a batch $B$ and $F_{i,ras}^{d,n,i}$ is the feature sampled from an independent multivariate normal distribution that shares the same dimensions with $F_{i,ras}^{d,n,i}$. The $\phi$ is a function that maps the features into the Reproducing Kernel Hilbert Space (RKHS) [70]. We apply the Gaussian kernel [70] to compute $L_{mmd}$ such that the distribution discrepancy between $F_{i,ras}^{d,n}$ and $F_{i,ras}^{d,n,i}$ is expected to be minimized. Moreover, for the distortion features $F_{i,ras}^{d}$, a distortion type classification loss is further implemented,
effectively enhancing the distortion discrimination capability,

$$\mathcal{L}_{\text{cls}} = -\frac{1}{B} \sum_{i=1}^{B} \sum_{k=1}^{K} y_i^k \log \left( p_i^k \right),$$  \hspace{1cm} (9)

where \( i \) indicates the \( i \)-th input image in a batch. \( p_i^k \) and \( y_i^k \) indicate the prediction result and ground-truth label of the \( k \)-th distortion category, respectively. The \( K \) is the total number of distortion categories.

### C. Quality Regression

The quality of the distorted image is regressed by integrating both the semantic information and the distortion information. In particular, the image distortion is estimated by measuring the distribution deviation between the distribution generated by \( N \) sampled image patches and the pre-defined multivariate normal distribution. As both the generated distribution and the normal distribution are Gaussian distributions, their deviation can be efficiently measured by the KL divergence as follows,

$$\Phi^{F_{dd}} = -\frac{1}{2} \left( 1 + \log \sigma^2 - \sigma^2 - \mu^2 \right),$$  \hspace{1cm} (10)

where \( \mu \) and \( \sigma \) are mean and std vectors of \( F_{dd} \) acquired by Eqn. (6) and Eqn. (7), respectively. \( I \) is a vector with the same dimension as \( \sigma \) and the value of each dimension is 1. We denote the \( \Phi^{F_{dd}} \) as the distortion feature. To explore the relationship between the semantic feature and distortion feature for final quality regression, we use the semantic feature to generate the channel-wise attention for the distortion feature under the philosophy that the different dimensions of the distortion contribute to final quality with different weights and the weights are determined by the image semantic information. Such processing can be described as follows,

$$Q^p = r \left( \varphi(F_{ds}) \otimes \Phi^{F_{dd}} \right),$$  \hspace{1cm} (11)

where \( Q^p \) is the predicted quality score and the \( \varphi(\cdot) \) means the attention generator consists of two fully connected layers with the ReLU and sigmoid as the activation functions, respectively. The \( \otimes \) means the point-wise multiplication. The \( r(\cdot) \) represents the regression layer, consisting of a fully connected layer and a ReLU layer. Finally, the regressed quality can be supervised by the mean absolute error (MAE) loss as follows,

$$\mathcal{L}_{\text{mae}} = \frac{1}{B} \sum_{i=1}^{B} \left\| Q_i^p - Q_i^g \right\|_1,$$  \hspace{1cm} (12)

where \( Q_i^g \) is the ground-truth quality score of the \( i \)-th input image in a batch. In summary, the final objective function of our model is as follows,

$$\mathcal{L}_{\text{all}} = \mathcal{L}_{\text{mae}} + \lambda_1 \mathcal{L}_{\text{trip}} + \lambda_2 \mathcal{L}_{\text{mmd}} + \lambda_3 \mathcal{L}_{\text{cls}} + \left( \left\| \Phi^{F_{dd}} \right\|_2^2 + \left\| \Phi^{F_{ad}} \right\|_2^2 + \left\| \Phi^{F_{rd}} - \Phi^{F_{ad}} \right\|_2^2 \right),$$  \hspace{1cm} (13)

where the \( \Phi^{F_{rd}} \) and \( \Phi^{F_{ad}} \) represent the distribution divergence of \( F_{rd} \) and \( F_{ad} \) measured by Eqn. (10). Herein, we minimize their values during training, aiming to persuade them towards a normal distribution. The \( \lambda_1, \lambda_2, \) and \( \lambda_3 \) are three trade-off parameters.

### IV. Experimental Results

In this section, we first present our experimental setup, including the implementation details of the proposed model and benchmarking datasets. Then we compare the proposed method with the state-of-the-art NR SCI-IQA models in both cross-dataset settings and intra-dataset settings. Next, the ablation study is performed for the functional verification of each module proposed in our method. Finally, we explain the learned distortion-aware and semantic-aware features with significant feature visualizations.

1) Implementation Details: We implement our model by PyTorch [71]. In the training phase, we crop the image into patches without overlapping with the patch size set by 32 × 32. The number of images in a batch is 96, including 32 distorted images, 32 reference images, and 32 auxiliary images (as shown in Fig. 2). We adopt Adam optimizer [72] for optimization. The learning rate is fixed to 1e-4 with a weight decay set as 1e-4. The parameters \( \lambda_1, \lambda_2, \) and \( \lambda_3 \) in Eqn. (13) are set by 1.0, 5e-3 and 1.0, respectively. We duplicate the samples 16 times in a batch to augment the data. The maximum epoch is set by 200. The \( \alpha \) in Eqn. (4) is a positive value that decides the margin between positive pairs and negative pairs. We empirically set its value to 1.0 during training.

It is worth mentioning that all the experimental pre-settings are fixed in both intra-database and cross-database training. For the intra-database evaluation, we randomly split the dataset into a training set, a validation set, and a testing set by reference images to guarantee there is no content overlap among the three subsets. In particular, 60%, 20%, and 20% images are used for training, validation, and testing, respectively. The experimental results on intra-database are reported based on 10 random splits. To make errors and gradients comparable for different databases, we linearly map the MOS/DMOS ranges of the SIQAD and SCID databases to the DMOS range [0, 100]. Three evaluation metrics are reported for each experimental setting, including Spearman Rank Correlation Coefficient (SRCC), Pearson Linear Correlation Coefficient (PLCC), and Root Mean Square Error (RMSE). The PLCC estimates the prediction linearity and consistency, SRCC measures the prediction monotonicity, and RMSE evaluates the prediction accuracy. Higher PLCC, SRCC, and lower RMSE indicate better performance of the quality model.

2) SCI Datasets: More details regarding the SIQAD dataset and SCID dataset can be found in Table I, which are briefly introduced as follows.

- SIQAD dataset [24] contains 20 reference SCIs and 980 distorted SCIs. The distorted images are derived from seven distortion types including Gaussian Noise (GN), Gaussian Blur (GB), Motion Blur (MB), Contrast Change (CC), JPEG, JPEG2000, and Layer Segmentation based Coding (LSC). For each distortion type, seven distortion levels are generated.

- SCID dataset [30] consists of 1800 distorted SCIs generated by 40 reference images. In this dataset, nine distortion types are involved including GN, GB, MB, CC, JPEG, JPEG2000, Color Saturation Change (CSC), High-Efficiency Video Coding Screen Content Compression.
A. Quality Prediction on Cross-Dataset Settings

In this subsection, we first evaluate the performance of our method on the SIQAD and SCID datasets with the cross-dataset settings. Herein, there are two settings: training on the SIQAD dataset and testing on the SCID dataset, and training on the SCID dataset and testing on the SIQAD dataset. These settings are denoted as SIQAD $\rightarrow$ SCID and SCID $\rightarrow$ SIQAD, respectively. There exists a large domain gap caused by the unshared content, distortion types, and distortion levels between two different datasets, such that cross-dataset testing appears to be an effective way to evaluate the model generalization capability. We compare the proposed method with both handcrafted feature based methods including NIQE [25], IL-NIQE [73], BRISQUE [26], DIIVINE [28], CORNIA [39], HOSA [74], BQMS [75], SIQE [15], ASIQE [15], NRLT [16], and deep-learning based methods including DIQaM-NR [64], WaDIQaM-NR [64], PQSC [76], RIQA [58], MtDI [22], GraphIQA [77], and VCRNet [78]. As shown in Table II, most deep-learning based methods achieve inferior performance than the traditional ones (e.g., CORNIA), revealing the so-called over-fitting problem. However, our method achieves the best overall performance in both two settings, demonstrating superior generalization capability that can be learned by the scene statics construction. In Table III and Table IV, we further present the performance comparison on the individual distortion types. In Table III, the distortion types including CC, HEVC-SCC, and CQD in the SCID dataset are unseen when trained on the SIQAD dataset, leading to a significant performance drop compared with other distortion types. However, our method still achieves superior performance on those distortion types when compared with other deep-learning based models. A consistent phenomenon can be observed in the setting Table IV (SCID $\rightarrow$ SIQAD). Herein, it should be noted that our method can only alleviate but not completely...
eliminate the challenges posed by unseen data, motivating further exploration of high generalization models based upon the statistics learning.

B. Quality Prediction on Intra-Dataset Settings

In this sub-section, we first compare our method with several state-of-the-art NR-IQA methods on the SIQAD dataset. The competing models include NIQE [25], BRISQUE [26], QAC [79], IL-NIQE [73], BQMS [75], SIQE [15], ASIQE [15], NRLT [16], HRFF [17], CLGF [80], Li et al. [81], DIQaM-NR [64], WaDIQaM-NR [64], Yang et al. (Tcy20) [82], Yang et al. (TIP21) [83], GraphIQA [77], and VCRNet [78]. The intra-dataset experiment is conducted under ten times random splitting and the top two results are highlighted in boldface.

| Distortion Type | Shared | Unseen |
|-----------------|--------|--------|
| CORNIA Traditional | SRCC PLCC | GB GB CC JPEG J2K SC SCHEVIC SC CQD |
| HOA Traditional | SRCC PLCC | GB GB CC JPEG J2K SC SCHEVIC SC CQD |
| NREL Traditional | SRCC PLCC | GB GB CC JPEG J2K SC SCHEVIC SC CQD |
| PQSC Traditional | SRCC PLCC | GB GB CC JPEG J2K SC SCHEVIC SC CQD |
| WaDIQaM-NR Deep Learning | SRCC PLCC | GB GB CC JPEG J2K SC SCHEVIC SC CQD |
| DIQaM-NR Deep Learning | SRCC PLCC | GB GB CC JPEG J2K SC SCHEVIC SC CQD |
| GraphIQA Deep Learning | SRCC PLCC | GB GB CC JPEG J2K SC SCHEVIC SC CQD |
| VCRNet Deep Learning | SRCC PLCC | GB GB CC JPEG J2K SC SCHEVIC SC CQD |
| DFSS-IQA (Ours) Deep Learning | SRCC PLCC | GB GB CC JPEG J2K SC SCHEVIC SC CQD |

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TABLE V

| Criteria | Method | PLCC | SRCC | RMSE |
|----------|--------|------|------|------|
| NIQE [25] | 0.3415 | 0.3695 | 13.4670 |
| BRISQUE [26] | 0.7237 | 0.7708 | 8.2565 |
| QAC [79] | 0.3751 | 0.3009 | 13.2690 |
| IL-NIQE [73] | 0.3854 | 0.3575 | 13.9320 |
| BQMS [75] | 0.7575 | 0.7251 | 9.3456 |
| SIQE [15] | 0.7906 | 0.7625 | 8.7650 |
| ASIQE [15] | 0.7884 | 0.7570 | 8.8064 |
| NRTL [16] | 0.8442 | 0.8202 | 7.4156 |
| HKFF [17] | 0.8520 | 0.8320 | 7.5960 |
| CLGF [80] | 0.8331 | 0.8107 | 7.9172 |
| DIQM-NR [64] | 0.8799 | 0.8662 | 6.7894 |
| WaDIQM-NR [64] | 0.8890 | 0.8780 | 6.7552 |
| Yang et al. (TIP21) [33] | 0.8529 | 0.8336 | 7.2817 |
| Yang et al. (TVC20) [82] | 0.8738 | 0.8543 | 6.9335 |
| GraphIQA [77] | 0.8493 | 0.8535 | 7.5770 |
| VCRNet [78] | 0.8544 | 0.8357 | 7.7165 |
| DFSS-IQA (Ours) | 0.8818 | 0.8820 | 6.6684 |

We can observe the method achieves the best overall performance on the SIQAD dataset in terms of both PLCC and RMSE. The SRCC results are also comparable with the best method WaDIQM-NR (0.8818 v.s. 0.8890), revealing that the high generalization capability of our method could be achieved without sacrificing intra-dataset performance. In addition, our method presents an effective visual quality assessment for each individual distortion type as the distortion-aware features can be learned by measuring the KL-divergence.

C. Ablation Study

In this subsection, we reveal the functionalities of different modules in our method, we perform the ablation studies on both SIQAD and SCID databases with the cross-dataset settings. More specifically, three main modules are designed in our method including the Gaussian distribution regularization module, the semantic attention module, and the distortion type classification module. As shown in Table VIII, we denote the above three modules as “Gaus.”, “Atten.”, and “CLS”,
Fig. 6. T-SNE [87] visualization of the disentangled features. (a) Distortion-aware features ($\mathbf{F}_d$ and $\mathbf{F}_dd$). (b) Semantic-aware features ($\mathbf{F}_{ds}$). The “Ref.” and “Dis.” mean the features extracted from reference images and distorted images, respectively. The distortion-aware features of the reference images are clustered into one group due to their similar quality and the features of distorted images are distributed in different spaces by their distortion types and levels. In comparison, the semantic-specific features are clustered into 20 groups as different content types those images contain.

### TABLE VII

PERFORMANCE ON SCID DATASET UNDER THE INTRA-DATASET SETTING. THE TOP TWO RESULTS ARE HIGHLIGHTED IN BOLDFACE.

| Method          | PLCC  | SRCC  | RMSE  |
|-----------------|-------|-------|-------|
| BLINDS-II [88]  | 0.5851| 0.5569| 12.6253|
| NIQE [25]       | 0.2931| 0.2508| 13.5401|
| BRISQUE [26]    | 0.6004| 0.5687| 11.6976|
| NFERM [36]      | 0.5928| 0.5803| 11.7647|
| IL-NIQE [73]    | 0.2573| 0.2436| 13.6852|
| BQMS [75]       | 0.6188| 0.6125| 11.1251|
| SIQE [15]       | 0.6343| 0.6009| 10.9483|
| ASIQE [15]      | 0.6381| 0.6046| 10.5873|
| NRTL [16]       | 0.6216| 0.6092| 10.9042|
| CLGP [80]       | 0.6978| 0.6870| 10.1439|
| DfQAM-NR [64]   | 0.7086| 0.6965| 10.3085|
| WaDfQAM-NR [64] | 0.7885| 0.7654| 8.8139|
| Yang et al. (TIP21) [83] | 0.7147| 0.6920| 10.3988|
| Yang et al. (Tey20) [82] | 0.7867| 0.7562| 8.5949|
| GraphiQA [77]   | $0.8342$ | $0.8309$ | $7.5717$ |
| VCRNet [78]     | $0.8370$ | $0.8332$ | $9.1558$ |
| **DFSS-IQA (Ours)** | **0.8138** | **0.8146** | **8.0125** |

### TABLE VIII

ABLATION STUDIES UNDER TWO CROSS-DATASET SETTINGS.

| Setting | SIQAD $\rightarrow$ SCID | SCID $\rightarrow$ SIQAD |
|---------|--------------------------|--------------------------|
| Gauss. | Atten. | CLS | SRCC | PLCC | SRCC | PLCC | SRCC | PLCC |
| X      | X       | ✓  | 0.7570 | 0.7697 | 0.7966 | 0.8174 |
| ✓      | X       | ✓  | 0.7159 | 0.7217 | 0.7446 | 0.7732 |
| ✓      | ✓       | ✓  | 0.7210 | 0.7275 | 0.7483 | 0.7841 |
| ✓      | ✓       | ✓  | 0.7669 | 0.7815 | 0.7969 | 0.8344 |

respectively. From the table, we can observe the worst performance is obtained when we ablate the attention module as the semantic-specific feature can adaptively adjust the relationship between the distribution divergence and the quality degradation. In addition, the performance drops again when we ablate the distortion type classification. This phenomenon demonstrates that distortion discrimination capability plays an important role in quality prediction. The Gaussian distribution regularization performed based on the MMD loss is ablated in the last experiment. In particular, we directly use the quality feature of $F_{qua}$ for quality regression and distortion type classification. The ablation results on both the SIQAD and SCID datasets reveal the inferiority of the feature-based model when compared with the distribution-based one. The best performance is achieved when all the modules are adopted, demonstrating the three modules contribute to the final performance.

In Fig. 5, to explore the optimal hyperparameter $\lambda_2$, we set its value to be $5e^{-1}$, $5e^{-2}$, $5e^{-3}$, $5e^{-4}$. We can observe the best performance is achieved when we set the parameter to $5e^{-3}$, and a large value or a smaller one will cause the performance to drop to some extent. The reason may lie in the trade-off between the strong distribution regularization and the variation in image quality.

To explore an optimal output dimension of our multi-scale feature generator, we further conduct a study of the feature dimension setting in Table IX. As shown in the table, a noticeable performance drop could be observed on the two cross-dataset settings (SCID $\rightarrow$ SIQAD and SIQAD $\rightarrow$ SCID) when the output dimension is reduced to 256. The reason may lie in the limited feature dimension which leads to the disentangled features cannot fully capture the distortion-aware and semantic-aware information from the input image. Subsequently, we increase the feature dimension from 512 to 1792, and the performance improvement is only evidenced in the SCID $\rightarrow$ SIQAD setting, accompanied by an increase in model complexity. A significant performance drop can be observed when the dimension is increased to 2048, revealing a larger feature dimension could result in a negative effect on the model generalization capability. Based upon the above observations, we set the final output dimension to 512, by which, the best trade-off between model accuracy and efficiency can be achieved.
Fig. 7. Feature distribution visualization results. Sub-images in odd rows are the reference images and distorted images. Sub-images in even rows are their corresponding feature distributions. In each row, the same dimension of the feature is selected for better comparison. From up to down, the distortion types are Gaussian Noise, Contrast Change, Gaussian Blur, JPEG2000, and Layer Segmentation based Coding. “µ” and “σ” represent the mean and std of each feature distribution. “kld” means the KL-divergence between the feature distribution and the standard Gaussian distribution. The “↓” means the lower the value the better the quality.
that the quality prediction should be an aggregation of the different dimensions of the distortion-aware features, revealing In addition, we can observe that distortion-awareness exists in divergence is able to reflect the distortion levels effectively. as the distortion becomes severe, revealing that the distribution imposed distortion. In particular, the KL divergence increases values due to the standard distribution being corrupted by the distributions of $F$. we randomly select one dimension of $F$ dataset is adopted for feature extraction, and for each row, Fig. 7. More specifically, the model learned on the SIQAD dataset. This phenomenon reveals that the disentangled features are of high awareness of image semantics. To better understand the performance of our method, we disentangle the quality-aware feature into a semantic-specific feature and a distortion-aware feature. To verify the disentanglement, a t-SNE visualization is adopted in Fig. 6. In particular, the two types of features extracted from images of the SIQAD dataset are visualized. From the figure, we can observe: 1) The distortion-aware features of the reference images are clustered into one group as their distortions are the same though the images contain different contents. In comparison, the features of distorted images are distributed in different spaces by their distortion levels, revealing the features are of high awareness of image distortions. 2) Regarding the semantic-specific feature, the images are clustered into one group when they are with the same content and the total number of content clusters is 20 which corresponds to the number of contents in the SIQAD dataset. This phenomenon reveals that the disentangled features are of high awareness of image semantics.

To better understand the performance of our method, we visualize the quality relevant features $F^{rd}$ and $F^{dd}$ in Fig. 7. More specifically, the model learned on the SIQAD dataset is adopted for feature extraction, and for each row, we randomly select one dimension of $F^{rd}$ and $F^{dd}$ for their distribution visualization. As shown in Fig. 7, the distributions of $F^{rd}$ and $F^{dd}$ present different mean and std values due to the standard distribution being corrupted by the imposed distortion. In particular, the KL divergence increases as the distortion becomes severe, revealing that the distribution divergence is able to reflect the distortion levels effectively. In addition, we can observe that distortion-awareness exists in different dimensions of the distortion-aware features, revealing that the quality prediction should be an aggregation of the distributions at different dimensions. In Fig. 8, we further present the histograms of the mean values, std values, and KL divergences of the distortion-aware features, from which, we can observe the mean values of the feature distributions of the pristine images are close to 0, std values are close to 1, and the KL divergences are significantly small, demonstrating a unified distribution that the pristine SCIs obey. In comparison, the mean values, std values, and KL divergences of the distorted images are dispersed, revealing the feature statistics would be destructed due to the distortions.

D. Feature Visualization

In our method, we disentangle the quality-aware feature into a semantic-specific feature and a distortion-aware feature. To verify the disentanglement, a t-SNE visualization is adopted in Fig. 6. In particular, the two types of features extracted from images of the SIQAD dataset are visualized. From the figure, we can observe: 1) The distortion-aware features of the reference images are clustered into one group as their distortions are the same though the images contain different contents. In comparison, the features of distorted images are distributed in different spaces by their distortion levels, revealing the features are of high awareness of image distortions. 2) Regarding the semantic-specific feature, the images are clustered into one group when they are with the same content and the total number of content clusters is 20 which corresponds to the number of contents in the SIQAD dataset. This phenomenon reveals that the disentangled features are of high awareness of image semantics.

To better understand the performance of our method, we visualize the quality relevant features $F^{rd}$ and $F^{dd}$ in Fig. 7. More specifically, the model learned on the SIQAD dataset is adopted for feature extraction, and for each row, we randomly select one dimension of $F^{rd}$ and $F^{dd}$ for their distribution visualization. As shown in Fig. 7, the distributions of $F^{rd}$ and $F^{dd}$ present different mean and std values due to the standard distribution being corrupted by the imposed distortion. In particular, the KL divergence increases as the distortion becomes severe, revealing that the distribution divergence is able to reflect the distortion levels effectively. In addition, we can observe that distortion-awareness exists in different dimensions of the distortion-aware features, revealing that the quality prediction should be an aggregation of the distributions at different dimensions. In Fig. 8, we further present the histograms of the mean values, std values, and KL divergences of the distortion-aware features, from which, we can observe the mean values of the feature distributions of the pristine images are close to 0, std values are close to 1, and the KL divergences are significantly small, demonstrating a unified distribution that the pristine SCIs obey. In comparison, the mean values, std values, and KL divergences of the distorted images are dispersed, revealing the feature statistics would be destructed due to the distortions.

V. CONCLUSION

In this paper, we propose a novel NR-SCIQA method by constructing the specific statistics of SCIs in the deep feature space. In particular, we first extract the quality-aware feature at multi-scales and disentangle it into the distortion-aware feature and semantic-specific feature. The unified distribution constraint is imposed on the distortion-aware feature, aiming for the construction of the statistics of SCI. Finally, the image quality can be estimated by combining both the distribution information and semantic information. Experimental results have demonstrated the superior generalization capability of our scene statistic-based model, especially in cross-dataset settings. The proposed method sheds light on the exploration of the intrinsic statistics of SCIs and provides potential guidance for high-quality image generation with computers.

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