No-Reference Image Quality Assessment by Hallucinating Pristine Features

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Abstract—In this paper, we propose a no-reference (NR) image quality assessment (IQA) method via feature level pseudo-reference (PR) hallucination. The proposed quality assessment framework is rooted in the view that the perceptually meaningful features could be well exploited to characterize the visual quality, and the natural image statistical behaviors are exploited in an effort to deliver the accurate predictions. Herein, the PR features from the distorted images are learned by a mutual learning scheme with the pristine reference as the supervision, and the discriminative characteristics of PR features are further ensured with the triplet constraints. Given a distorted image for quality inference, the feature level disentanglement is performed with an invertible neural layer for final quality prediction, leading to the PR and the corresponding distortion features for comparison. The effectiveness of our proposed method is demonstrated on four popular IQA databases, and superior performance on cross-database evaluation also reveals the high generalization capability of our method. The implementation of our method is publicly available on https://github.com/Baoliang93/FPR.

Index Terms—Image quality assessment, no-reference, mutual learning, pseudo-reference feature.

I. INTRODUCTION

IMAGE quality assessment (IQA), which aims to establish the quantitative connection between the input image and the corresponding perceptual quality, serves as a key component in a wide range of computer vision applications [1], [2], [3]. The typical full-reference (FR) IQA models resort to fidelity measurement in predicting image quality via measuring the deviation from its pristine-quality counterpart (reference). The pioneering studies date back to 1970’s and a series of visual fidelity measures have been investigated [4]. Recently, there has been a demonstrated success for developing the FR quality measures, including the Peak Signal-to-Noise Ratio (PSNR), Structural Similarity Index (SSIM) [5], Multiscale SSIM (MS-SSIM) [6], Visual Salience-Induced Index (VSI) [7], Median Absolute Deviation (MAD) [8] and Visual Information Fidelity (VIF) [9]. Unfortunately, in the vast majority of practical applications, the reference images are usually absent or difficult to obtain, leading to the exponential increase in the demand for no-reference (NR) IQA methods. Compared with FR-IQA, NR-IQA is a more challenging task due to the lack of pristine reference information.

In the literature, numerous NR-IQA methods have been proposed based on the hypothesis that natural scenes possess certain statistical properties. Thus, the quality can be assessed by measuring the deviation of the statistics between distorted and pristine images [10], [11], [12]. With the development of deep learning technologies, the image quality can be inferred by learning from the labeled image data [13], [14], [15], [16], [17], [18], [19]. However, such data-driven based methods highly rely on the large-scale training samples. Recently, the free-energy based brain theory [20], [21], [22], [23] provides a novel solution for NR-IQA from the Bayesian view. In particular, the free energy theory reveals that human visual system (HVS) may attempt to infer the reference signals to reduce the uncertainty of perceived visual signals by an internal inference model. Rooted in the widely accepted view that the intrinsic, perceptually-meaningful and learnable features could govern the image quality, in this work, we focus on the feature level reference information estimation for IQA. This method avoids the modeling of the image signal space of which the understanding is still quite limited. Herein, we propose to learn a new NR-IQA measure named FPR, by inferring the quality through Feature-level Pseudo-Reference information. The underlying design philosophy of our method is learning the quality-specific PR feature instead of the restoration-specific PR feature. Along this vein, we can get rid of the design of a specific network for PR image generation, which is still a very challenging task. Besides, a gated recurrent units (GRU) [24] aggregation strategy is proposed to aggregate the quality of each patch in the test image. The GRU network processes the image patches in order, and the long-term memory enjoyed by GRU can construct the long-dependency between each patch. To verify the performance of our method, we conduct both intra-database and cross-database experiments on four databases, including TID2013 [25], LIVE [26], CSIQ [8] and KADID-10k [27]. Experimental results have demonstrated
the superior performance of our method over existing state-of-the-art models. The main contributions of this paper are summarized as follows,

- We introduce the free-energy theory for the NR-IQA task based on deep learning. To capture the image distortion, the pristine feature is estimated by the supervision of an FR-IQA model, mimicking the internal inference mechanism in HVS.
- We learn the PR feature by a mutual learning strategy, leveraging the reference information. To improve the discrimination capability between the estimated PR feature and the distortion feature, a triplet loss is further adopted.
- We develop the aggregation strategy for the predicted scores of different patches in an image. The strategy benefits from the GRU, and generates the attention maps of the testing images for quality aggregation.

II. RELATED WORKS

Due to the lack of reference information, the existing NR-IQA measures can be classified into two categories: quality-aware feature extraction based NR-IQA and discrepancy estimation based NR-IQA. In the first category, the quality-aware features are extracted based on a natural scene statistics (NSS) model or a data-driven model, and the quality is finally predicted by a regression module. In the second category, the PR images are first constructed, then the discrepancy between the input images and its PR images is measured. The philosophy is that the larger the discrepancy, the worse quality the image possesses. Herein, we provide an overview of the two categories of NR-IQA models as well as the mutual learning methods.

A. Quality-Aware Feature Extraction Based NR-IQA

Typically, conventional NR-IQA methods extract the quality-aware features based on the natural scene statistics (NSS) and predict the image quality by evaluating the destruction of naturalness. In [28] and [29], based on the Mean-Subtracted Contrast-Normalized (MSCN) coefficients, the NSS are modeled with a generalized Gaussian distribution and the quality can be estimated by the distribution discrepancy. The NSS features have also been exploited in the wavelet domain, [12], [30], [31], [32]. In [31], to discriminate degraded and undegraded images, the complex pyramid wavelet transform is performed and the magnitudes and phases of the wavelet coefficients are characterized as the NSS descriptor. Analogously, in [11], the discrete cosine transform (DCT) is introduced for NSS model construction, leading to a Bayesian inference-based NR-IQA model. Considering the structural information is highly quality-relevant, the joint statistics of gradient magnitude and Laplacian of Gaussian response are utilized in [33] to model the statistical naturalness. In [34], the hybrid features consisting of texture components, structural information and intra-predicted modes are extracted and unified for adaptive bitrate estimation. Recently, there has been a surging interest in deep-feature extraction for NR-IQA. In [13], a shallow ConvNet is first utilized for patch-based NR-IQA learning. This work is extended by DeepBIQ [16], where a pre-trained convolutional neural network (CNN) is fine-tuned for the generic image description. Instead of learning only from the quality score, the multi-task CNN was proposed in [35], in which both the quality estimation and distortion identification are learned simultaneously for a better quality degradation measure. However, although those deep-learning based methods have achieved high-performance improvement, insufficient training data usually create the over-fitting problem. To alleviate this issue, extra synthetic databases e.g. [36], [37], [38] have been proposed for more generalized model learning. The training data can also be enriched by ranking learning. In [39], [40], [41], and [38], the quality scores of an image pair are regressed and ranked, leading to the more quality-sensitive feature extraction. In [42] and [43], to accelerate the model convergence, “Norm-in-Norm” loss was proposed. The embedded normalization has been proved to be able to improve the smoothness of the loss landscape. It is generally acknowledged that combining different databases for IQA can highly enrich the training samples. However, the annotation shift usually causes unreliable data fusion. In [44], Zhang et al. adopted rank-based learning to account for this problem, and the MOS uncertainty is also explored during optimization. The distortion type identification and quality regression are learned successively in [45], aiming to capture more accurate distortion.

B. Discrepancy Estimation Based NR-IQA

The NR-IQA problem can be feasibly converted to the FR-IQA problem when the reference image can be inferred through generative models. In [46], the PR image is generated by a quality-aware generative network, then the discrepancy between the distorted image and PR image is measured for quality regression. In contrary to constructing the PR image with perfect quality, the reference information provided by the PR image that suffered from the severest distortion was explored in [47], then an NR-IQA metric was developed by measuring the similarity between the structures of distorted and the PR images. In [48], both a pristine reference image (generated via a restoration model) and a severely distorted image (generated via a degradation model) are utilized for quality prediction. Analogously, by comparing the distorted images and their two bidirectional PRs, the bilateral distance (error) maps are extracted in [49].

C. Mutual Learning

The assumption of mutual learning is highly relevant with the dual learning and collaborative learning, as their assumptions all lie in the encouragement of the models to teach each other during training. For example, the dual learning was adopted in [50], where two cross-lingual translation models are forced to learn from each other through the reinforcement learning. Comparing with dual learning, the same task is learned in the collaborative learning. In [51], multiple student models are expected to learn the same classification task while their inputs are sampled from different domains. Different from the dual learning and collaborative learning, both the tasks and inputs of the models in mutual learning are identical.
For example, the deep mutual learning was utilized in [52], where two student models are forced to learn the classification collaboratively by a Kullback Leibler (KL) loss. This work was further extended in [53], with the KL loss replaced by a generative adversarial network. In our method, the mutual learning strategy was adopted to improve the learnability of the PR feature and we further impose the triplet constraint to the output features, significantly enhancing their discriminability.

III. THE PROPOSED SCHEME

We aim to learn an NR-IQA measure by hallucinating the PR features. In the training stage, given the pristine reference, we attempt to build a FR-IQA model with the distorted and corresponding pristine reference images. The PR feature is subsequently learned in a mutual way. Finally, the GRU-based quality aggregation is performed to obtain the final quality score.

A. PR Feature Learning

As shown in Fig. 1, in the training phase, we learn to hallucinate the PR feature $F^{PR}$ from a single distorted image by the guidance of the pristine reference feature $F^R$. In particular, the $F^R$ is constructed from an FR model based on the quality-embedding feature extractor, and the $F^{PR}$ is decomposed from the feature $F^{NR}$ which is regarded as a fusion feature that contains the entire information of the PR feature $F^{PR}$ and the distortion feature $F^D$.

In general, there are two properties a desired PR feature for quality prediction should possess. First, the PR feature should be learnable. Constructing the pristine image from the distorted one is usually a challenging task due to the corruption of content caused by different distortion types. For example, the texture regions could be difficult to be recovered when it is corrupted by blur distortion. Such challenges also bring the difficulties to learn pristine (PR) features. To account for this, self-supervised based methods can be adopted, such as the generative adversarial network (GAN) based models [54], [55] or natural images prior based methods [56], [57]. As indicated in [58], the self-supervised learning methods greatly depend on the difficulty level of the task and the amount of training data. In this paper, we learn the PR feature in a supervised manner based on the reference as it is possible to obtain abundant pristine images. In particular, the features extracted from the reference images are used as guidance to provide a clear picture for the PR feature learning. Though in the training process the reference image could be taken advantage of, the PR feature may not be able to be feasibly learned by only forcing the inferred PR feature to be close to a pre-defined reference feature. As such, the learning capability of the NR-IQA network should be carefully considered during the reference feature estimation. In other words, when we learn the PR feature, the reference feature extraction should be learned mutually. Second, the PR feature should be discriminative enough when comparing with the distortion feature. Enhancing the discriminability could improve the quality sensitivity.
of the PR feature and subsequently promote the prediction performance.

The proposed method is conceptually appealing in the sense of learnability and discriminability. Regarding the learnability, a mutual learning strategy is adopted. As shown in Fig. 1, in the training process, the paired images including the distorted image and its corresponding reference are fed into the quality-embedding feature extractor, generating the reference feature \( F^R \) and distortion feature \( F^D \). The integrity feature extractor, which accepts the distorted image only, is encouraged to generate the feature \( F^{NR} \) with high quality-awareness. To this end, we force the \( F^{NR} \) to be derived from both the information of the pseudo reference feature \( F^{PR} \) and the distortion feature \( F^D \). As shown in Fig. 1, we adopt the invertible neural networks (INNs) [59], [60] to disentangle the \( F^{NR} \) into a pseudo reference feature \( F^{PR} \) and a distortion feature \( F^D \), without losing any information. Instead of using the concatenation of \( F^{PR} \) and \( F^D \) for quality regression, the \( F^{NR} \) utilized enjoys higher quality-awareness, generalization capability, and less inference time. In Fig. 2, we plot the structure of an INN block, which consists of transmission functions including \( F \), \( \mathcal{H} \), and \( G \). For the \( l \)-th block, the \( F^{NR} \) is split into \( F^{NR}_{1,l} \) and \( F^{NR}_{2,l} \) along the channel axis, and they undergo the invertible transformations [59], [60] as follows,

\[
F^{NR}_{1,l+1} = F^{NR}_{1,l} + F \left( F^{NR}_{2,l} \right),
\]

\[
F^{NR}_{2,l+1} = F^{NR}_{2,l} \odot \exp \left( \mathcal{H} \left( F^{NR}_{1,l+1} \right) \right) + G \left( F^{NR}_{1,l+1} \right). \tag{1}
\]

The inverse transformation is computed as follows,

\[
F^{NR}_{2,l} = F^{NR}_{2,l+1} - G \left( F^{NR}_{1,l+1} \right) \odot \exp \left( -\mathcal{H} \left( F^{NR}_{1,l+1} \right) \right),
\]

\[
F^{NR}_{1,l} = F^{NR}_{1,l+1} - F \left( F^{NR}_{2,l} \right). \tag{2}
\]

The outputs \( F^{NR}_{1,l+1} \) and \( F^{NR}_{2,l+1} \) are fed to the following INN blocks, and three blocks are finally utilized. We denote the output two features at the third block as \( F^{PR} \) and \( F^D \) which are constrained by the triplet loss \( \mathcal{L}_{trip} \) for the discriminative reference feature learning.

The mutual learning strategy enables the integrity feature extractor and quality-embedding feature extractor to be learned simultaneously with the feature distance constraint. Thus, more learnable reference feature can be generated by the GR model. The connection among the features \( F^{NR} \), \( F^{PR} \) and \( F^D \) are constructed by an invertible layer, consisting of three invertible neural networks (INNs) [61]. Through the INNs, the integrity feature \( F^{NR} \) can be disentangled to a pseudo reference feature \( F^{PR} \) and a distortion feature \( F^D \), without losing any information due to the invertibility of INNs.

To equip the discriminative capability, a triplet loss is further utilized [62] as the distance measure between the reference features \( (F^R, F^{PR}) \) and the corresponding measure between the distortion features \( (F^D, F^D) \), which is expressed as follows,

\[
\mathcal{L}_{trip} = \sum_{i=1}^{N} \left[ \left\| F^R_i - F^{PR}_i \right\|_2^2 - \left\| F^R_i - F^D_i \right\|_2^2 + \delta \right]_+ \tag{3}
\]

\[
+ \sum_{i=1}^{N} \left[ \left\| F^D_i - F^D_i \right\|_2^2 - \left\| F^D_i - F^{PR}_i \right\|_2^2 + \delta \right]_+, \tag{3}
\]

where \( i \) is input patch index in a batch, \( N \) is the batch size and \( \delta \) is a margin that is enforced between positive and negative pairs. With this loss, on the one hand, the distance between the reference feature and PR feature can be reduced. On the other hand, the discrepancies between the reference/PR feature and two distortion features can be enlarged.

As illustrated in Fig. 1, to maintain the relationship of \( F^{PR} \) and \( F^D \) to be consistent with \( F^R \) and \( F^D \), we concatenate \( F^R \) with \( F^D \) (denoted as \( \text{Concat}(F^R, F^D) \)) and \( F^{PR} \) with \( F^D \) (denoted as \( \text{Concat}(F^{PR}, F^D) \)) for quality prediction through a shared quality aggregation module.

### B. GRU-Based Quality Aggregation

To aggregate the predicted quality score of each patch in an image, the aggregation module should be invariant of the patch numbers. In this paper, we propose a GRU-based quality score aggregation module as shown in Fig. 1. More specifically, regarding the concatenated features \( \text{Concat}(F^R, F^D) \) and \( \text{Concat}(F^{PR}, F^D) \), two sub-branches are adopted for quality prediction. The first branch is a fully-connected (FC) layer that is responsible for patch-wise quality prediction with the patch-wise concatenated feature as input. Another sub-branch consists of one GRU layer and one FC layer. Different from [15], the inputs of the GRU layer are the features of all the patches in an image. With GRU, the long-term dependencies between different patches can be modeled and synthesized, then we normalize the output weights from the last FC layer for final attention map generation,

\[
w_i = \frac{\alpha_i}{\sum_j N_p \alpha_j}, \tag{4}
\]

where \( i \) is the patch index in an image, and \( N_p \) is the number of patches. \( \alpha_i \) and \( w_i \) are the predicted and normalized attention weights of \( i \)-th patch, respectively. Finally, the global image quality \( Q \) can be estimated as

\[
Q = \sum_{i=1}^{N_p} w_i q_i = \frac{\sum_{i=1}^{N_p} \alpha_i q_i}{\sum_{i=1}^{N_p} \alpha_i}, \tag{5}
\]

where \( q_i \) is the predicted quality of \( i \)-th patch. As shown in Fig. 1, we also adopt the same strategy (network) for the quality aggregation of the patch-wise integrity feature \( F^{NR} \). Due to the distinct representations of the fused feature and concatenated features, the parameters of the two aggregation modules are not shared during the model training.
C. Objective Function

In summary, the objective function in our proposed method includes two triplet losses and three quality regression losses. In particular, for quality regression, compared with mean squared error (MSE), optimization with mean absolute error (MAE) is less sensitive to the outliers, leading to a more stable training process. Consequently, the objective function is given by,

$$\mathcal{L} = \mathcal{L}_{\text{mae}} + \lambda \mathcal{L}_{\text{trip}}$$

$$= \sum_{j=1}^{N_I} \left[ |\hat{Q}_j - Q^R | + |\hat{Q}_j - Q^{PR} | + |\hat{Q}_j - Q^{NR} | \right] + \lambda \left( \sum_{i=1}^{N_P} \left[ \left| \sum_{j=1}^{N_I} (F_i^R - F_i^{PR}) \right|_2^2 + \delta \right] \right) + \lambda \left( \sum_{i=1}^{N_P} \left[ \left| \sum_{j=1}^{N_I} (F_i^D - F_i^{PR}) \right|_2^2 + \delta \right] \right),$$

where $i$ and $j$ are the patch index and image index, respectively. $N_I$ is the number of images in a batch and $\hat{Q}_j$ is the Mean Opinion Score (MOS) provided by the training set. $Q^R$, $Q^{PR}$, $Q^{NR}$ are the quality scores predicted from the features $\text{Concat}(F^R, F^D)$, $\text{Concat}(F^{PR}, \hat{F}^D)$ and $F^{NR}$, respectively. In addition, we adopt $\lambda$ as the weight of the regularization term $\mathcal{L}_{\text{trip}}$ for quality regression. It is also worth noting that the extractions of $F^R$, $F^D$, $F^{PR}$, $\hat{F}^D$ are not
necessary in the testing phase, and we only adopt the $Q^{NR}$ for the final quality prediction, thus the computational complexity in testing phase can be highly reduced comparing with the network used in the training phase.

IV. EXPERIMENTAL RESULTS

IQA Databases: Since our model is trained in a paired manner, the reference image should be available during the training phase. As such, to validate the proposed method, we evaluate our model on four synthetic natural databases including: TID2013 [25], LIVE [63], CSIQ [8] and KADID-10k [27]. More details are provided in Table I.

TID2013. The TID2013 database consists of 3,000 images obtained in the range [0, 9], where larger MOS indicates better visual quality.

LIVE. The LIVE IQA database includes 982 distorted natural images and 29 reference images. Five different distortion types are included: JPEG and JPEG2000 compression, additive white Gaussian noise (WN), Gaussian blur (BLUR), and Rayleigh fast-fading channel distortion (FF). Different from the construction of TID2013, a single-stimulus rating procedure is adopted for quality rating, producing a range of different mean opinion scores (DMOS) from 0 to 100 and a lower DMOS value represents better image quality.

CSIQ. The CSIQ database contains 30 reference images and 866 distorted images. This database involves six distortion types: JPEG compression, JP2K compression, Gaussian blur, Gaussian white noise, Gaussian pink noise and contrast change. The images are rated by 35 different observers and the DMOS results are normalized into the range [0, 1].

KADID-10k. In this database, 81 pristine images are included and each pristine image is degraded by 25 distortion types in 5 levels. All the images are resized into the same resolution (512 × 384). For each distorted image, 30 reliable degradation category ratings have been obtained by crowd-sourcing.

Implementation Details: We implement our model by PyTorch [64]. In Fig. 3, we show the layer-wise network design of our proposed method. We crop the image patches without overlapping and the size is set by 64 × 64. The number of image pairs in a batch is set by 32. We adopt Adam optimizer [65] for optimization. The learning rate is fixed to 1e-4 with a weight decay set as 1e-4. The weighting parameters $\lambda$, $\delta$ are set as 20.0 and 0.5, respectively. We duplicate the samples by 16 times in a batch to augment the data. The maximum epoch is set by 1,000.

It should be mentioned that all the experimental pre-settings are fixed both in intra-database and cross-database training. For the intra-database evaluation, we randomly split the dataset into the training set, validation set and testing set by reference image to guarantee there is no content overlap among the three sets. In particular, 60%, 20%, 20% images are used for training, validation and testing, respectively. We discard the 25th reference image and the distorted versions in TID2013, as they are not natural image. 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 other three databases (TID2013, CSIQ, KADID-10k) to the DMOS range [0, 100] which is the same as LIVE database. Three evaluation metrics are reported for each experimental setting, including Spearman rank correlation coefficient (SRCC), Pearson linear correlation coefficient (PLCC) and perceptually weighted rank correlation (PWRC) [66]. The PLCC evaluates the prediction accuracy and the SRCC indicates the prediction monotonicity. Regarding the PWRC, the perceptual importance variation and subjective uncertainty are considered, which is confirmed to be reliable in recommending the perceptually preferred IQA model.

A. Quality Prediction on Intra-Database

1) Overall Performance on Individual Database: In this sub-section, we compare our method with other state-of-the-art NR-IQA methods, including BRISQUE [28], M3 [33],
TABLE V
SRCC COMPARISON IN THREE DATABASES ON FOUR COMMON DISTORTION TYPES. THE TOP TWO RESULTS ARE HIGHLIGHTED IN BOLDFACE

| Dataset | Dist.Type | Method                  | SRCC   |
|---------|-----------|-------------------------|--------|
|         |           | DIIVIN [10]             |        |
|         |           | BLINDS-II [11]          |        |
|         |           | BRISQUE [28]            |        |
|         |           | CORNIA [68]             |        |
|         |           | HOSA [69]               |        |
|         |           | WaDiQaM-NR [15]         |        |
|         |           | DiQA [75]               |        |
|         |           | BIPI [67]               |        |
|         |           | BIPI [67]               |        |
|         |           | TSPR [49]               |        |
| LIVI    | WN        | 0.988                   | 0.947  |
|         | GB        | 0.923                   | 0.951  |
|         | JPEG      | 0.921                   | 0.958  |
|         | PRIK      | 0.922                   | 0.950  |
| TID2013 | WN        | 0.866                   | 0.800  |
|         | GB        | 0.872                   | 0.808  |
|         | JPEG      | 0.810                   | 0.846  |
|         | PRIK      | 0.831                   | 0.847  |
|         |           | CIIV                 |        |
|         |           | CORNIA [68]             |        |
|         |           | HOSA [69]               |        |
|         |           | WaDiQaM-NR [15]         |        |
|         |           | DiQA [75]               |        |
|         |           | BIPI [67]               |        |
|         |           | BIPI [67]               |        |
|         |           | TSPR [49]               |        |
| TID2013 | WN        | 0.835                   | 0.664  |
|         | GB        | 0.834                   | 0.814  |
|         | JPEG      | 0.628                   | 0.845  |
|         | PRIK      | 0.833                   | 0.888  |

TABLE VI
SRCC RESULTS OF INDIVIDUAL DISTORTION TYPES ON TID2013 DATABASE. THE TOP TWO RESULTS ARE HIGHLIGHTED IN BOLDFACE

| SRCR | BRISQUE [28] | M3 [33] | FRIQUEE [67] | CORNIA [68] | HOSA [69] | MEON [37] | DB-CNN [70] | FPR (Ours) |
|------|-------------|---------|--------------|-------------|-----------|------------|-------------|------------|
| Additive Gaussian noise | 0.711   | 0.766   | 0.730   | 0.692   | 0.933   | 0.813   | 0.790   | 0.953   |
| Additive noise in color components | 0.432   | 0.56   | 0.573   | 0.137   | 0.551   | 0.722   | 0.700   | 0.897   |
| Spatially correlated noise | 0.746   | 0.782   | 0.866   | 0.741   | 0.842   | 0.926   | 0.826   | 0.967   |
| Masked noise | 0.252   | 0.577   | 0.345   | 0.451   | 0.468   | 0.728   | 0.666   | 0.876   |
| High frequency noise | 0.842   | 0.900   | 0.847   | 0.815   | 0.931   | 0.948   | 0.911   | 0.934   |
| Impulse noise | 0.765   | 0.738   | 0.730   | 0.616   | 0.809   | 0.901   | 0.798   | 0.771   |
| Quantization noise | 0.662   | 0.832   | 0.764   | 0.661   | 0.815   | 0.888   | 0.825   | 0.920   |
| Gaussian blur | 0.871   | 0.896   | 0.881   | 0.850   | 0.883   | 0.887   | 0.859   | 0.833   |
| Image denoising | 0.612   | 0.709   | 0.839   | 0.764   | 0.854   | 0.797   | 0.865   | 0.944   |
| JPEG compression | 0.761   | 0.844   | 0.813   | 0.797   | 0.891   | 0.850   | 0.894   | 0.925   |
| JPEG 2000 compression | 0.745   | 0.885   | 0.831   | 0.846   | 0.919   | 0.941   | 0.916   | 0.923   |
| JPEG transmission errors | 0.748   | 0.718   | 0.660   | 0.686   | 0.710   | 0.716   | 0.772   | 0.752   |
| Non-rectangularity pattern noise | 0.269   | 0.173   | 0.076   | 0.200   | 0.242   | 0.116   | 0.270   | 0.559   |
| Local look-wise distortions | 0.207   | 0.379   | 0.032   | 0.027   | 0.268   | 0.500   | 0.444   | 0.265   |
| Mean shift | 0.219   | 0.119   | 0.254   | 0.232   | 0.211   | 0.177   | -0.009   | 0.009   |
| Contrast change | -0.003   | 0.155   | 0.585   | 0.254   | 0.362   | 0.252   | 0.548   | 0.929   |
| Change of color saturation | 0.003   | -0.199   | 0.589   | 0.169   | 0.045   | 0.684   | 0.631   | 0.409   |
| Multiplicative Gaussian noise | 0.717   | 0.738   | 0.704   | 0.593   | 0.768   | 0.849   | 0.711   | 0.887   |
| Comfort noise | 0.196   | 0.353   | 0.318   | 0.617   | 0.622   | 0.406   | 0.752   | 0.830   |
| Lossy compression of noisy images | 0.609   | 0.692   | 0.641   | 0.712   | 0.838   | 0.772   | 0.860   | 0.982   |
| Color quantization with depth | 0.831   | 0.908   | 0.768   | 0.683   | 0.896   | 0.857   | 0.833   | 0.901   |
| Chromatic aberrations | 0.615   | 0.570   | 0.737   | 0.696   | 0.753   | 0.779   | 0.732   | 0.768   |
| Sparse sampling and reconstruction | 0.807   | 0.893   | 0.891   | 0.865   | 0.909   | 0.855   | 0.902   | 0.887   |

As we train our model in a paired manner, the FR results can also be acquired during the testing by involving the reference image. Herein, we also provide the FR results denoted as FPR (FR) in Tables II and III. From the tables, we can observe that our FR model can achieve higher performance when compared with our NR model, as the pristine image provide more accurate reference information for quality evaluation. We also observe that the performance of our FR model is not as good as some other FR models e.g., WaDiQaM-FR [15]. We believe this is reasonable, as the learning capability of our NR model must be considered simultaneously during the extraction of reference feature. In Table IV, we further report the performance comparison in terms of PWRC. For a fair comparison, the same data splittings are performed for each method, and the average results of 10 repeated experiments are reported. From the Table IV, we can observe that our method achieves the best performance on each dataset. A significant performance gain can be acquired by our method on the TID2013 dataset, revealing our method is also effective for ranking image pairs with higher quality levels.

Furthermore, we compare our method with two PR image based NR-IQA methods named BPRI [47] and TSPR [49].
As shown in the Table VI, we can easily observe that our method can achieve the highest accuracy on most distortion types (over 60% subsets). By contrast, lower SRCC values are obtained on some specific distortion types, e.g., mean shift. The reason may lie in the challenge of PR feature hallucination due to valuable information buried by the severe distortion. It is worth noting that our method achieves significant performance improvements on some noise-relevant distortion types (e.g., additive Gaussian noise, masked noise) and compression-relevant distortion types (e.g., JPEG compression, JPEG 2000 compression). The result is consistent with the performance on LIVE database, verifying the capacity that our model possesses in restoring the PR features from different distortion types.

### B. Cross-Database Evaluation

To verify the generalization capability of our FPR model, we further evaluate our model on cross-database settings. We compare our method with seven NR-IQA methods, including: BRISQUE, M3, FRIQUEE, CORNIA, HOSA and two CNN-based counterparts DIQam-NR and HyperIQA. The results of DIQam-NR are reported from the original paper, and we re-train the HyperIQA by the source codes provided by the authors. All experiments are conducted with one database as training set and the other two databases as testing sets. We present the experimental results in Table VIII, from which we can find the model trained on LIVE (CSIQ) is easier to generalize to CSIQ (LIVE) as similar distortion types introduced by the two databases. However, it is a much more difficult task to generalize the model trained on CSIQ or LIVE to the TID2013 database, due to these unseen distortion types involved in TID2013 database. Despite this, we can still achieve a high SRCC in the two settings, demonstrating the superior generalization capability of our method.

### C. Ablation Study

In this subsection, to reveal the functionalities of different modules in our proposed method, we perform the ablation study on TID2013 database. To be consistent with the experimental setting on intra-database, 60%, 20%, 20% images in TID2013 are grouped for training, validation and testing sets without content overlapping. Herein, we only report the ablation results by one fixed experimental splitting in Table IX. In particular, we first ablate the PR and INN modules from our model and retain the Integrity Feature Extractor and GRU-based Quality Aggregation modules. The performance drops dramatically due to the fact that no extra constraint be introduced to prevent the over-fitting problem. Then we replace the INN module by directly concatenating the learned pseudo reference feature and distortion feature for quality regression, resulting in the second ablation setting. The lower SRCC (0.86 v.s 0.89) reveals that more generalized model can be learned by our INN module. As described before, the triplet loss $L_{trip}$ is adopted to learn more discriminative features. In this sense, we ablate the $L_{trip}$ in our third experiment. Again, a significant performance drop can be observed. The reason may lie in the quality discriminative feature learning resulting from the constraint of $L_{trip}$. Through $L_{trip}$, we build

### Table VII: Average SRCC and PLCC Results of Individual Distortion Type on LIVE Database. The Top Two Results Are Highlighted in Boldface

| Distortion Type | SRCC | PLCC |
|-----------------|------|------|
| JPEG           | 0.967 | 0.965 |
| JP2K           | 0.955 | 0.949 |
| WN             | 0.962 | 0.944 |
| GB             | 0.967 | 0.949 |
| FF             | 0.980 | 0.964 |
| DB-CNN [70]    | 0.986 | 0.967 |

### Fig. 4: T-SNE visualization of the features extracted from TID2013 and LIVE databases.

Following the experimental setting in [49] that four shared distortion types, i.e., JPEG, GB, WN and JP2K in the TID2013, LIVE and CSIQ databases are used for performance comparison. The results are presented in Table V. We can observe that our method achieves the best performance in most settings and significantly outperforms the comparison methods in terms of the average SRCC values. These results reveal the effectiveness of our PR information constructed at the feature level. It also should be noted that compared with the generative adversarial networks (GAN) utilized in [46] and [49] for reference information restoration at pixel-level, the lighter network in our method can significantly reduce the inference time.

2) **Performance on Individual Distortion Type:** To further explore the behaviors of our proposed method, we present the performance on individual distortion type and compare it with several competing NR-IQA models. The results of experiments performed on TID2013 database and LIVE database are shown in Table VI and Table VII, respectively. For each database, the average SRCC values of above ten settings are reported. As shown in the Table VI, we can easily observe that our

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**TABLE VII**

**Average SRCC and PLCC Results of Individual Distortion Type on LIVE Database. The Top Two Results Are Highlighted in Boldface**

| Distortion Type | SRCC | PLCC |
|-----------------|------|------|
| JPEG           | 0.967 | 0.965 |
| JP2K           | 0.955 | 0.949 |
| WN             | 0.962 | 0.944 |
| GB             | 0.967 | 0.949 |
| FF             | 0.980 | 0.964 |
| DB-CNN [70]    | 0.986 | 0.967 |

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**Fig. 4:** T-SNE visualization of the features extracted from TID2013 and LIVE databases.
TABLE VIII
SRCC COMPARISON ON DIFFERENT CROSS-DATABASE SETTINGS. THE NUMBERS IN BOLD ARE THE BEST RESULTS

| Training | LIVE | CSIQ | TID2013 |
|----------|------|------|---------|
|          | CSIQ | TID2013 | LIVE | TID2013 | LIVE | CSIQ |
| BRISQUE [28] | 0.562 | 0.358 | 0.847 | 0.454 | 0.790 | 0.590 |
| M3 [33]     | 0.621 | 0.344 | 0.797 | 0.328 | 0.873 | 0.605 |
| FRIQUEE [67] | 0.722 | 0.461 | 0.879 | 0.463 | 0.755 | 0.635 |
| CORNIA [68]  | 0.649 | 0.360 | 0.853 | 0.312 | 0.846 | 0.672 |
| HOA [69]     | 0.594 | 0.361 | 0.773 | 0.329 | 0.846 | 0.612 |
| DIQA-NR [15] | 0.681 | 0.392 | -     | -     | -    | 0.717 |
| HyperIQA [71]| 0.697 | 0.538 | 0.905 | 0.554 | 0.839 | 0.543 |
| FPR (Ours)  | 0.620 | 0.433 | 0.895 | 0.522 | 0.884 | 0.732 |

TABLE IX
SRCC PERFORMANCE WITH ABLATION STUDIES PERFORMED ON THE TID2013 DATABASE

| Exp ID | PR | INN | $L_{trip}$ | Patch Aggregation | SRCC |
|--------|----|-----|------------|-------------------|------|
|        |    |     |            | Mean | Weighted | GRU |       |
| 1      | ✗  | ✗   | ✗          | ✓    | ✓        | ✓   | 0.670 |
| 2      | ✓  | ✗   | ✓          | ✓    | ✓        | ✓   | 0.859 |
| 3      | ✓  | ✓    | ✗          | ✓    | ✓        | ✓   | 0.772 |
| 4      | ✓  | ✓    | ✓          | ✓    | ✓        | ✓   | 0.869 |
| 5      | ✓  | ✓    | ✓          | ✓    | ✓        | ✓   | 0.848 |
| 6      | ✓  | ✓    | ✓          | ✓    | ✓        | ✓   | 0.887 |

D. Feature Visualization

To better understand the performance of our proposed method, we visualize the quality relevant features $F^R$, $F^{PR}$, $F^D$ and $\hat{F}^D$. More specifically, we first learn two models by our method on TID2013 database and LIVE database, respectively. Then 900 image pairs of each database are randomly sampled from the two databases for testing. For each database, we reduce the feature dimensions of $F^R$, $F^{PR}$, $F^D$ and $\hat{F}^D$ to three by T-SNE [78] and the results are visualized in Fig. 4. As shown in Fig. 4, we can observe that the discrepancy of the reference feature $F^R$ and the pseudo reference feature $F^{PR}$ is small due to the mutual learning strategy. By contrast, the large discrepancy can be acquired between the pseudo reference feature $F^{PR}$ and distortion feature $F^D$ as the triplet loss performed, leading to the better performance.

In Fig. 5, we further visualize the feature maps of $F^R$, $F^D$, $F^{PR}$, $\hat{F}^D$ and $F^{NR}$ of several sampled distorted images. In particular, we reduce the channel dimension of $F^D$, $F^R$, $F^{PR}$, $F^D$, and $\hat{F}^D$ to three by T-SNE [78] and the results are visualized in Fig. 4. As shown in Fig. 4, we can observe that the discrepancy of the reference feature $F^R$ and the pseudo reference feature $F^{PR}$ is small due to the mutual learning strategy. By contrast, the large discrepancy can be acquired between the pseudo reference feature $F^{PR}$ and distortion feature $F^D$ as the triplet loss performed, leading to the better performance.

In Fig. 5, we further visualize the feature maps of $F^R$, $F^D$, $F^{PR}$, $\hat{F}^D$, and $F^{NR}$ of several sampled distorted images. In particular, we reduce the channel dimension of $F^D$, $F^R$, $F^{PR}$, $F^D$, and $\hat{F}^D$ to one by average pooling for visualization. As shown in Fig. 5, we can observe that the distortion feature maps ($F^D$ and $\hat{F}^D$) present a high activation on the distortion. For example, in the sub-figure (e), the local block distortion causes the high values at the distorted block regions in $F^D$ and $\hat{F}^D$. The inferred $F^{PR}$ and $\hat{F}^D$ are consistent with $F^R$ and $F^D$ even for different distortion types. Meanwhile, a significant difference can be observed between $F^{PR}$ and $\hat{F}^D$ due to the proposed triplet loss as a constraint.

TABLE X
PERFORMANCE COMPARISON ON THE DEHAZING DATASET SHRQ [82]. THE TOP TWO RESULTS ARE HIGHLIGHTED IN BOLDFACE

| Method         | SHRQ-Aerial | SHRQ-Regular |
|----------------|-------------|-------------|
|                | SRCC | PLCC | PLCC | SRCC | PLCC |
| NIQE [73]      | 0.401 | 0.579 | 0.414 | 0.579 |       |
| BRISQUE [28]   | 0.370 | 0.510 | 0.414 | 0.744 |       |
| FRIQUEE [67]   | 0.655 | 0.723 | 0.571 | 0.761 |       |
| ILNIQE [74]    | 0.421 | 0.543 | 0.354 | 0.589 |       |
| DIQA-NR [15]   | 0.783 | 0.778 | 0.296 | 0.418 |       |
| WaDIQA-NR [15] | 0.864 | 0.869 | 0.636 | 0.833 |       |
| HyperIQA [71]  | 0.880 | 0.881 | 0.533 | 0.767 |       |
| LeanIQA [42]   | 0.914 | 0.921 | 0.720 | 0.880 |       |
| FPR (Ours)     | 0.901 | 0.898 | 0.692 | 0.846 |       |
Fig. 5. Visualizations of the extracted feature maps. In each sub-figure, from up to down, are the sampled distorted image patches $I^R$, the reference image patches $I^D$, the corresponding $F^D$, $F^P$, $F^P^R$, and $F^N^R$ presented, respectively. The images are distorted by: (a) JPEG compression, (b) JPEG transmission errors, (c) Chromatic aberrations, (d) JPEG2000 compression, (e) Local block-wise distortions of different intensity, and (f) Gaussian blur.

### TABLE XI
Performance Comparison on SIQAD [84] and SCID [85] Datasets. The Top Two Results Are Highlighted in Boldface

| Method | NIQE [73] | IL-NIQE [74] | BRISQUE [28] | DIIVINE [10] | QAC [86] | CORNIA [68] | HOFA [69] | BQMS [87] | SIQR [88] |
|--------|-------------|--------------|--------------|--------------|-----------|--------------|-----------|-----------|-----------|
| SRCCL  | 0.399       | 0.320        | 0.775        | 0.659        | 0.301     | 0.788        | 0.718     | 0.725     | 0.763     |
| PLCC   | 0.381       | 0.386        | 0.811        | 0.691        | 0.375     | 0.815        | 0.766     | 0.758     | 0.791     |
| Method | ASIQE [88]  | CLGF [89]    | NRLT [90]    | DIQA-NR [15] | WdDIQA-NR [15] | HRFP [91] | Yang et al. [TIP21] | Yang et al. [TCS20] | FPR (Ours) |
| SRCCL  | 0.787       | 0.811        | 0.822        | 0.860        | 0.862     | 0.832        | 0.834     | 0.854     | 0.873     |
| PLCC   | 0.788       | 0.833        | 0.844        | 0.871        | 0.877     | 0.852        | 0.853     | 0.874     | 0.886     |

| Method | NIQE [73] | IL-NIQE [74] | BRISQUE [28] | DIIVINE [10] | QAC [86] | CORNIA [68] | HOFA [69] | BQMS [87] | SIQR [88] |
|--------|-------------|--------------|--------------|--------------|-----------|--------------|-----------|-----------|-----------|
| SRCCL  | 0.280       | 0.102        | 0.471        | 0.436        | 0.557     | 0.672        | 0.690     | 0.613     | 0.601     |
| PLCC   | 0.322       | 0.260        | 0.520        | 0.462        | 0.585     | 0.694        | 0.711     | 0.619     | 0.634     |
| Method | ASIQE [88]  | CLGF [89]    | NRLT [90]    | DIQA-NR [15] | WdDIQA-NR [15] | HRFP [91] | Yang et al. [TIP21] | Yang et al. [TCS20] | FPR (Ours) |
| SRCCL  | 0.605       | 0.687        | 0.609        | 0.721        | 0.758     | -            | 0.692     | 0.756     | 0.652     |
| PLCC   | 0.638       | 0.698        | 0.622        | 0.740        | 0.766     | -            | 0.715     | 0.767     | 0.856     |

### E. Performance on Images From Other Scenarios

The quality evaluation of images from other scenarios such as image enhancement datasets [79], [80], [81], [82], [83] and screen content image (SCI) datasets [84], [85] are also important tasks. To verify our model on those tasks, we further conduct experiments on one image enhancement dataset and two screen content image (SCI) datasets. In particular, the quality of the dehazing images is studied in the SHRQ dataset [82] and the quality of the distorted SCIs is studied in both SIQAD dataset [84] and SCID dataset [85]. Herein, we first provide a brief overview of the above datasets as follows,

- SHRQ dataset [82] consists of two subsets including the SHRQ-Regular and SHRQ-Aerial. The SHRQ-Regular includes 360 dehazed images created from 45 synthetic hazy images while the SHRQ-Aerial includes 240...
dehazed images created from 30 synthetic hazy images. In subjective testing, subjects need to rate the quality of the dehazed images using a five-grade continuous quality scale. Besides the dehazed image, the hazy image and the reference haze-free image are also provided.

- SIQAD dataset [84] 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 [85] consists of 1800 distorted SCIs generated by 40 reference images. In this dataset, nine distortion types are involved including GN, GB, MB, CC, JPEG compression, J2K, color saturation change (CSC), high-efficiency video coding screen content compression (HEVC-SCC), and Color quantization with differencing (CQD). Each distortion type contains five degradation levels. All the SCIs in SIQAD are with a resolution of $1280 \times 720$.

We compare our method with the existing methods on those datasets and present the comparison results in Table X and Table XI. For the SHRQ dataset, our method achieves comparable performance with the latest method LiteartytQA [42]. For SCIs, our method is able to achieve the best performance on both the SIQAD dataset and SCID dataset, revealing the high generalization capability of our method on SCIs.

V. CONCLUSION

In this paper, we propose a novel NR-IQA method named FPR by restoring the reference information at feature-level. The image quality is evaluated by measuring the discrepancy at the feature-level and the PR feature is inferred based upon the INNs. The mutual learning strategy and triplet loss ensure the learnability and discriminability of PR features. To aggregate the patch-wise quality scores in an image, a GRU-based quality aggregation module is further proposed. The superior performance on the natural IQA databases, dehazing IQA databases, and screen content IQA databases demonstrates the effectiveness of our model. Moreover, our method also achieves promising performance on the cross-dataset settings, demonstrating the high generalization capability of our model.

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