Learning to Blindly Assess Image Quality in the Laboratory and Wild

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Abstract—Previous models for blind image quality assessment (BIQA) can only be trained (or fine-tuned) on one subject-rated database due to the difficulty of combining multiple databases with different perceptual scales. As a result, models trained in a well-controlled laboratory environment with synthetic distortions fail to generalize to realistic distortions, whose data distribution is different. Similarly, models optimized for images captured in the wild do not account for images simulated in the laboratory. Here we describe a simple technique of training BIQA models on multiple databases simultaneously without additional subjective testing for scale realignment. Specifically, we first create and combine image pairs within individual databases, whose ground-truth binary labels are computed from the corresponding mean opinion scores, indicating which of the two images is of higher quality. We then train a deep neural network for BIQA by learning-to-rank massive such image pairs. Extensive experiments on six databases demonstrate that our BIQA method based on the proposed learning technique works well for both synthetic and realistic distortions, outperforming existing BIQA models with a single set of model parameters. The generalizability of our method is further verified by group maximum differentiation (gMAD) competition.

Index Terms—Blind image quality assessment, deep neural networks, learning-to-rank, gMAD competition.

I. INTRODUCTION

Blind image quality assessment (BIQA) aims to predict the perceptual quality of a visual image without reference to its original counterpart. The majority of BIQA models [1]–[4] have been developed in well-controlled laboratory environments, whose feature representations are adapted to common synthetic distortions (e.g., Gaussian blur and JPEG compression). Only recently has BIQA of images captured in the wild with realistic distortions become an active research topic [5]. Poor lighting conditions, sensor limitations, lens imperfections, and amateur manipulations are the main sources of distortions in this scenario, which are generally more complex and difficult to simulate. As a result, models trained on databases of synthetic distortions (e.g., LIVE [6] and TID2013 [7]) are not capable of handling databases of realistic distortions (e.g., LIVE Challenge [5] and KonIQ-10k [8]). Similarly, models optimized for realistic distortions do not work well for synthetic distortions [9].

Very limited effort has been put to develop unified BIQA models for both synthetic and realistic distortions. Mittal et al. [12] based their NIQE method on a prior probability model of natural undistorted images, aiming for strong generalizability to unseen distortions. Unfortunately, NIQE is only able to handle a small set of synthetic distortions. Zhang et al. [13] extended NIQE [12] by extracting more powerful natural scene statistics for local quality prediction. Combining multiple IQA databases for training seems a simple and plausible solution. However, existing databases have different perceptual scales due to differences in subjective testing methodologies (see Table I). A separate subjective experiment on images sampled from each database is then required for scale realignment [9]. To verify this, we linearly re-scale the mean opinion scores (MOSs) of each of the six databases to [0, 100], and show sample images that have approximately the same re-scaled MOS in Fig. 1 which have dramatically different perceptual quality as expected. Using these noisy re-scaled MOSs for training results in sub-optimal performance (see Table II).
In addition to absolute MOSs, recent methods also exploit relative ranking information to learn BIQA models from three major sources: distortion specifications \cite{3, 14}, full-reference IQA models \cite{15-17}, and human data \cite{18}. Liu et al. and Ma et al. extracted ranking information from images with the same content and distortion type but different levels to pre-train deep neural networks (DNNs) for BIQA. Their methods can only be applied to synthetic distortions, whose degradation processes are exactly specified. Ye et al. \cite{15} and Ma et al. \cite{16, 17} supervised the learning of BIQA models with ranking information from full-reference IQA models. Their methods cannot be extended to realistic distortions either, because the reference images are not available or may not even exist for full-reference models to compute quality values. The closest work to ours is due to Gao et al. \cite{18}, who inferred pairwise rank information from MOSs. However, the model is not end-to-end optimized, which only delivers reasonable performance on a small set of synthetic distortions. Moreover, they didn’t explore the idea of combining multiple IQA databases via relative rankings.

In this letter, we aim to develop a unified BIQA model for both synthetic and realistic distortions with a single set of model parameters. To achieve this, we describe a simple technique of training BIQA models on multiple databases without performing additional subjective experiments to bridge their perceptual gaps. Specifically, we are able to generate and combine image pairs within individual databases, whose ground-truth binary labels are inferred from the corresponding MOSs, indicating which of the two in each pair has better quality. We then learn a DNN for BIQA using a pairwise learning-to-rank algorithm \cite{19}. Through extensive experiments on six databases covering both synthetic and realistic distortions, we find that our BIQA model significantly outperforms existing ones by a large margin, especially in the cross-distortion-scenario setting. We further verify its generalizability by group maximum differentiation (gMAD) competition \cite{20}.



## II. Method

In this section, we detail the construction of the training set from multiple IQA databases, followed by pairwise learning procedure and network specification.

### A. Training Set Construction

Given \( J \) subject-rated IQA databases, we randomly sample from the \( j \)-th database \( N_j \) image pairs \( \{(x^j_i, y^j_i)\}_{i=1}^{N_j} \). For each pair \( (x^j_i, y^j_i) \), we infer its relative ranking from the corresponding absolute MOSs, and compute a binary label \( r^j_i \), where \( r^j_i = 1 \) indicates that \( x^j_i \) is of higher perceptual quality and \( r^j_i = 0 \) indicates the opposite. By doing so, we are able to combine an arbitrary number of IQA databases without performing any realignment experiment, and generate a training set \( \mathcal{D} = \{\{(x^j_i, y^j_i), r^j_i\}_{i=1}^{N_j}, \ldots, \{(x^J_i, y^J_i), r^J_i\}_{i=1}^{N_J}\} \).

### B. Learning-to-Rank for BIQA

Given the training set \( \mathcal{D} \), our goal is to learn a differentiable function \( f_w(x) \) parameterized by a vector \( w \), which takes image \( x \) as input and computes an overall quality value \( \mathcal{D} \). Specifically, we make use of the Bradley-Terry model \cite{24} and assume that the true perceptual quality \( q(x) \) follows a Gumbel distribution, whose location is determined by \( f_w(x) \). The quality difference \( q(x) - q(y) \) is then a logistic random variable, and \( \Pr(q(x) \geq q(y)) \) can then be computed from the logistic cumulative distribution function, which has a closed form

\[
\Pr(q(x) \geq q(y)|w) = \frac{\exp(o_w(x, y))}{1 + \exp(o_w(x, y))},
\]

where \( o_w(x, y) = f_w(x) - f_w(y) \). Combined with the true label \( r \), we formulate the binary cross entropy loss as

\[
\ell(x, y, r|w) = -r \log \Pr(r = 1|x, y, w) - (1-r) \log(1 - \Pr(r = 1|x, y, w))
\]

\[
= -r o_w(x, y) + \log(1 + \exp(o_w(x, y))).
\]

In practice, we sample a mini-batch \( B \) from \( \mathcal{D} \) in each iteration and use a variant of the stochastic gradient descent method to adjust the parameter vector \( w \) by minimizing the empirical loss

\[
\ell(B|w) = \frac{1}{|B|} \sum_{(x,y),r \in B} \ell(x, y, r|w),
\]

where \( |B| \) represents the cardinality of \( B \). During backpropagation, the gradient of \( \ell(B|w) \) with respect to \( w \) is derived as

\[
\frac{\partial \ell(B|w)}{\partial w} = \frac{1}{|B|} \sum_{(x,y),r \in B} \left( -r + \frac{\exp(o_w(x, y))}{1 + \exp(o_w(x, y))} \right) \times \left( \frac{\partial f_w(x)}{\partial w} - \frac{\partial f_w(y)}{\partial w} \right).
\]

### C. Network Specification

Due to the successes of DNNs in various computer vision and image processing applications, we adopt a ResNet \cite{25} as the backbone to construct our quality prediction function \( f_w(x) \). The two-stream learning framework is shown in Fig. 2. Each stream consists of a stage of convolution, batch normalization, ReLU nonlinearity, and maxpooling, followed by four groups of layers based on the bottleneck architecture \cite{25}. To better summarize the spatial statistics and generate a fixed-length representation regardless of image size, we replace the first-order average pooling in the original ResNet with a second-order bilinear pooling \cite{9}, which has been proven to
TABLE II
MEDIAN SRCC RESULTS ACROSS TEN SESSIONS ON SIX IQA DATABASES COVERING BOTH SYNTHETIC AND REALISTIC DISTORTIONS. THE DATABASES FOR TRAINING MODELS THAT RELY ON HUMAN ANNOTATIONS ARE INCLUDED IN THE BRACKET.

| Database          | LIVE [6] | CSIQ [10] | TID2013 [7] | BID [11] | LIVE Challenge [5] | KonIQ-10k [8] |
|-------------------|----------|-----------|-------------|----------|-------------------|---------------|
| MS-SSIM [21]      | 0.951    | 0.910     | 0.790       | –        | –                 | –             |
| NLFD [22]         | 0.942    | 0.937     | 0.798       | –        | –                 | –             |
| NIQE [14]         | 0.906    | 0.632     | 0.343       | 0.468    | 0.464             | 0.521         |
| ILNIQE [13]       | 0.907    | 0.832     | 0.658       | 0.516    | 0.469             | 0.507         |
| dipIQ [16]        | 0.940    | 0.511     | 0.453       | 0.099    | 0.187             | 0.228         |
| MEON (LIVE) [1]   | 0.634    | 0.559     | 0.343       | 0.468    | 0.464             | 0.521         |
| deepIQA (TID2013) [8] | 0.833 | 0.687     | 0.378       | 0.100    | 0.378             | 0.145         |
| PQR (BID) [23]    | 0.634    | 0.559     | 0.374       | –        | 0.120             | 0.133         |
| PQR (KonIQ-10k)   | 0.729    | 0.709     | 0.530       | 0.755    | 0.770             | 0.680         |
| DB-CNN (TID2013)  | 0.883    | 0.817     | 0.409       | 0.414    | 0.414             | 0.518         |
| DB-CNN (LIVE Challenge) [9] | 0.709 | 0.691     | 0.403       | 0.762    | –                 | 0.754         |
| Linear re-scaling | 0.924    | 0.807     | 0.746       | 0.842    | 0.824             | 0.880         |
| Ours (LIVE)       | 0.948    | 0.732     | 0.576       | 0.598    | 0.533             | 0.735         |
| Ours (LIVE Challenge) | 0.537 | 0.517     | 0.392       | 0.852    | 0.856             | 0.796         |
| Ours (LIVE+LIVE Challenge) | 0.955 | 0.785     | 0.593       | 0.838    | 0.840             | 0.826         |
| Ours              | 0.957    | 0.867     | 0.806       | 0.851    | 0.853             | 0.892         |

We flatten $\bar{z}$ and append a fully connected layer to compute a scalar that represents the perceptual quality of the input image. The weights of the two streams are shared during the entire optimization process.

III. EXPERIMENTS

In this section, we first describe training and testing procedures. We then compare the performance of the optimized method to a set of state-of-the-art BIQA models. Last, we report the gMAD competition results of our method against top performing models.

A. Model Training

We generate the training set and conduct comparison experiments on six IQA databases, including LIVE [6], CSIQ [10], TID2013 [7], LIVE Challenge [5], BID [11], and KonIQ-10k [8]. The first three are synthetic, while the last three are realistic. More information of these databases can be found in Table. We randomly sample 80% images in each database for training and leave the rest for evaluation. Regarding LIVE, CSIQ, and TID2013, we split training and test sets according to the reference images to guarantee the content independence between the two sets. From the six databases, we are able to generate more than 240,000 image pairs. During testing, we use Spearman rank-order correlation coefficient (SRCC) to quantify the performance on individual databases.

We adopt ResNet-34 [25] as the backbone of $f_w(x)$, and train it using the Adam optimizer [27] for eight epochs. The initial learning rate is set to $10^{-4}$ with a decay factor of 10 for every two epochs. A warm-up training strategy is adopted: only the last fully connected layer with random initialization is learned in the first two epochs with a mini-batch of 128; for the remaining epochs, we fine-tune the entire network with a mini-batch of 32. In all experiments, we test on images of original size. To reduce the bias caused by the randomness in the training and test set splitting, we repeat this process for ten times and report the median SRCC results.

B. Model Performance

1) Main Results: We compare our method with three knowledge-driven BIQA models that do not require MOSs for training - NIQE [12], ILNIQE [13] and dipIQ [16], and four data-driven DNN-based models - MEON [3], deepIQA [4], PQR [23] and DB-CNN [9]. The implementations are obtained from the respective authors. The results are listed in Table I where we have several interesting observations. First, our method significantly outperforms the three knowledge-driven models. Although NIQE [12] and its feature-enriched version ILNIQE [13] are designed for arbitrary distortion types, they do not perform well on realistic distortions and challenging synthetic distortions in TID2013 [7]. dipIQ [16] is only able to handle distortion types that have been seen during training. As a result, the performance on all databases except LIVE is particularly weak, which suggests that it may be difficult for distortion-aware BIQA methods to handle unseen distortions.
We then compare our model with four recent DNN-based methods. Since previous data-driven models can only be trained on one IQA database, we highlight in the table the databases used to train the models. Despite pre-trained on a large number of synthetically distorted images, MEON fine-tuned on LIVE does not generalize to other databases with different distortion types and scenarios. Although trained with more synthetic distortion types in TID2013, deepIQA performs slightly worse on CSIQ and LIVE Challenge than MEON due to label noise in patch-based training. By bilinearly pooling two feature representations that are sensitive to synthetic and realistic distortions, respectively, DB-CNN trained on TID2013 achieves reasonable performance on databases built in the wild. Based on a probabilistic formulation, POR targets realistic distortions and trains two models on BID and KonIQ-10k separately. Benefiting from a larger number of training images with more diverse content and distortion variations, the model trained on KonIQ-10k generalizes much better to the rest databases than the one trained on BID. Our method performs significantly better than all competing models on all six databases, and is close to two full-reference models (MS-SSIM and NLPD). We believe this performance improvement arises because the proposed learning technique allows us to train our method on multiple databases simultaneously, adapting the feature representation to multiple distortion scenarios. In addition, the pre-trained weights on object recognition is helpful to prevent our method over-fitting to any single pattern within individual databases.

2) gMAD Competition Results: We further qualitatively examine the generality of our method using gMAD competition on the large-scale Waterloo Exploration Database. We first let our method compete with the best knowledge-driven BIQA model ILNIQE in Fig. 3. Our method successfully falsifies ILNIQE. Specifically, ILNIQE treats the clear image (c) and the extremely JPEG-compressed image (d) with the same visual quality, which is in strong disagreement with human perception. Meanwhile, our method survives from the attack by ILNIQE, where images (a) and (b) appear to have similar perceptual quality. We then compare our method with the top-performing DNN-based model DB-CNN in Fig. 4. We find that our method roughly matches DB-CNN on the Waterloo Exploration Database. DB-CNN finds a counterexample, indicating that our method fails to handle the extremely blurred image (b). Similarly, our method spots the weakness of DB-CNN when dealing with Gaussian noise (image (d)). Nevertheless, if we incorporate realistically distorted images into the competition, our method may find stronger failure cases of DB-CNN.

3) Ablation Study: We first investigate how our method behaves when we gradually add more databases into training. From Table II we observe that when trained on a single synthetic/realistic database, our method does not generalize to realistic/synthetic databases, which confirms previous empirical studies. When trained on the LIVE and LIVE Challenge databases, we observe improved performance on the three synthetic databases and the large-scale KonIQ-10k database, which verifies the effectiveness of the proposed training technique. The training image pairs from the two databases effectively provide mutual regularization, guiding the network to a better local optimum. When trained on all six databases, our method delivers the best performance across databases. We also train a baseline model using linearly re-scaled MOSs of the six databases. Compared to the proposed method, the performance of the baseline model drops significantly due to the inaccuracy of linear re-scaling (see Fig. 1).

IV. CONCLUSION

We have introduced a BIQA model and a method of training it on multiple IQA databases simultaneously. Our BIQA model is the first of its kind to handle both synthetic and realistic distortions with a single set of model parameters. The proposed learning technique is model agnostic, meaning that it can be combined with other data-driven BIQA models.
especially advanced ones (e.g., DB-CNN [9]) for improved performance. In addition, it is straightforward to incorporate more image pairs into training, when new IQA databases are available. We hope that the proposed learning technique would become a standard tool for existing and next-generation BIQA models to meet the cross-distortion-scenario challenge.

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