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Task-Specific Normalization for Continual Learning of Blind Image Quality Models

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Abstract—In this paper, we present a simple yet effective continual learning method for blind image quality assessment (BIQA) with improved quality prediction accuracy, plasticity-stability trade-off, and task-order/-length robustness. The key step in our approach is to freeze all convolution filters of a pre-trained deep neural network (DNN) for an explicit promise of stability, and learn task-specific normalization parameters for plasticity. We assign each new IQA dataset (i.e., task) a prediction head, and load the corresponding normalization parameters to produce a quality score. The final quality estimate is computed by a weighted summation of predictions from all heads with a plasticity-stability trade-off, and task-order/-length robustness.

We start with a pre-trained DNN as the feature extractor. We append all convolution filters, and share them along with all parameters of the task sequence [2], [14]. In this paper, we describe a simple yet effective continual learning method of training BIQA models based on a technique called learning with forgetting (LwF) [12]. Like many continual learning methods (for classification), LwF adds a form of regularization [13] to mildly adjust model parameters for new tasks while respecting old tasks. Nevertheless, this type of regularization-based methods have two limitations. First, it is practically difficult to set the trade-off parameter for stability (i.e., the ability to consolidate acquired knowledge from old tasks) and plasticity (i.e., the ability to learn new knowledge from the current task). Second, the performance is usually sensitive to the order and the length of the task sequence [2], [14].

In this paper, we describe a simple yet effective continual learning method for BIQA based on parameter decomposition. We start with a pre-trained DNN as the feature extractor. We freeze all convolution filters, and share them along with all parameter-free nonlinear activation and pooling layers across tasks during the entire continual learning process. We append a prediction head, implemented by a fully connected (FC) layer, when learning a new task. We allow the parameters of batch normalization (BN) [15] following each convolution to be specifically learned for each task. Through this task-specific normalization, a better plasticity-stability trade-off can be made with a negligible increase in model size. During training set}

Index Terms—Blind image quality assessment, continual learning, task-specific normalization.

I. INTRODUCTION

There is an emerging trend to develop image quality assessment (IQA) models [1] and image processing methods in alternation: Better IQA models provide more reliable guidance to the design and optimization of the latter, while new image processing algorithms call for the former to handle novel visual artifacts. This suggests a desirable IQA model to easily adapt to such distortions by continually learning from new data (see Fig. 1).

This paper focuses on continual learning of blind IQA (BIQA) models [2], [3], which predict the perceptual quality of a "distorted" image without reference to an original undistorted counterpart. Over the past 20 years, the research in BIQA has shifted from handling distortion-specific [4], single-stage [5], synthetic artifacts to general-purpose [6], multi-stage [7], authentic ones, and from relying on handcrafted features to purely data-driven approaches [8]. Existing BIQA models are generally developed and tested using human-rated images from the same dataset, i.e., within the same subpopulation [2].

As such, even the best-performing BIQA methods, e.g., those based on deep neural networks (DNNs) are bound to encounter subpopulation shift when deployed in the real world.

Direct fine-tuning model parameters with new data may result in catastrophic forgetting [9], [10] of previously seen data. The dataset combination trick in [11] has been proven effective in handling subpopulation shift, but is limited by the computational scalability and the dataset accessibility. Recently, Zhang et al. [2] formulated continual learning for BIQA with five desiderata. They also described the first continual learning method of training BIQA models based on a technique called learning with forgetting (LwF) [12].

Like many continual learning methods (for classification), LwF adds a form of regularization [13] to mildly adjust model parameters for new tasks while respecting old tasks. Nevertheless, this type of regularization-based methods have two limitations. First, it is practically difficult to set the trade-off parameter for stability (i.e., the ability to consolidate acquired knowledge from old tasks) and plasticity (i.e., the ability to learn new knowledge from the current task). Second, the performance is usually sensitive to the order and the length of the task sequence [2], [14].

In this paper, we describe a simple yet effective continual learning method for BIQA based on parameter decomposition. We start with a pre-trained DNN as the feature extractor. We freeze all convolution filters, and share them along with all parameter-free nonlinear activation and pooling layers across tasks during the entire continual learning process. We append a prediction head, implemented by a fully connected (FC) layer, when learning a new task. We allow the parameters of batch normalization (BN) [15] following each convolution to be specifically learned for each task. Through this task-specific normalization, a better plasticity-stability trade-off can be made with a negligible increase in model size. During
inference, we load each group of BN parameters to produce a quality estimate using the corresponding prediction head. The final quality score is computed by a weighted summation of predictions from all heads with a lightweight $K$-means gating (KG) mechanism.

In summary, our contributions are threefold.

- We propose a new continual learning method for BIQA. The resulting method, which we name TSN-IQA, integrates new knowledge into BN parameters without catastrophic forgetting of acquired knowledge.
- We design a lightweight KG module that only requires learning a set of distortion-aware BN parameters (instead of relying on an extra DNN [2]) to compute the weightings of prediction heads during inference.
- We perform extensive experiments to demonstrate the advantages of our method in terms of quality prediction accuracy, plasticity-stability trade-off, and task-order/length robustness.

II. RELATED WORK

In this section, we give an overview of recent progress in BIQA. We then review representative continual learning methods for classification, and discuss normalization techniques in the broader context of deep learning.

A. BIQA MODELS

Many early BIQA methods are based on hand-engineered natural scene statistics (NSS) in spatial [6], [16], transformed [17], or both domains [18]. In recent years, deep learning began to show its promise in the field of BIQA. Patchwise training [8], [19], transfer learning [20], and quality-aware pre-training [21]–[23] were proposed to compensate for the lack of human-rated data. Of particular interest is the introduction of IQA datasets with realistic distortions [24]–[26], which excite a series of BIQA models to address the synthetic-to-real generalization. Zhang et al. [27] assembled two network branches to account for synthetic and realistic distortions separately. Su et al. [28] investigated content-aware convolution for robust BIQA, while Zhu et al. [29] aimed to learn more transferable quality-aware representations by meta-learning. Zhang et al. [11] proposed a dataset combination strategy to train BIQA models on multiple IQA datasets. They later formulated the continual learning setting for BIQA, and introduced a method that combines LwF [12] with a $K$-means gating (KG) module [2]. Concurrently, Liu et al. [3] proposed a continual learning method for BIQA based on a replay strategy. Ma et al. [30] relied on model pruning techniques to enable continual learning of BIQA methods.

In this paper, we follow the setting in [2], and propose a new continual learning method for BIQA with significantly improved performance in several aspects.

B. CONTINUAL LEARNING FOR CLASSIFICATION

While humans rarely forget previously learned knowledge catastrophically, machine learning models such as DNNs tend to do so when learning new concepts [10], [31]. Enforcing regularization is a common practice to mitigate the catastrophic forgetting problem in continual learning. For example, Li and Hoiem [12] proposed LwF, which leverages model predictions of previous tasks as pseudo labels. Elastic weight consolidation (EWC) [32], variational continual learning (VCL) [33], synaptic intelligence (SI) [34], and memory-aware synapses (MAS) [35] work similarly by identifying and penalizing changes to important parameters of previous tasks. From this perspective, parameter decomposition [13] can be seen as a form of hard regularization, disentangling model parameters into task-agnostic and task-specific groups. This may be done by either masking learned parameters of previous tasks [36]–[38] or growing new branches to accommodate new tasks [39]. For example, Yoon et al. [14] proposed additive parameter decomposition to achieve task-order robustness. Singh et al. [40] calibrated the convolution responses of a continually trained DNN with a few parameters for new tasks. In this paper, we take a similar but much simpler parameter decomposition approach to achieve accurate and robust continual learning for BIQA.

C. NORMALIZATION IN DEEP LEARNING

There is increasing evidence that normalization is a canonical neural computation throughout the visual system, and in many other sensory modalities and brain regions [41]. As biologically inspired, deep learning also incorporates different instantiations of normalization for various purposes, such as accelerating model training [15] and improving model generalization [42]. BN is a popular technique to improve the training efficiency of DNNs, in which the convolution responses are divided by the standard deviation (std) of a pool of responses along the batch (and spatial) dimensions. Xie et al. [43] learned separate BN layers to harness adversarial examples, which improves image recognition models. Li et al. [44] proposed adaptive BN for domain adaptation, assuming that domain-invariant and domain-specific computations are learned by the convolution filters and the BN layers, respectively. Chang et al. [45] specialized BN layers using a two-stage algorithm for unsupervised domain adaptation. Dumoulin et al. [46] relied on conditional instance normalization [47] to synthesize the artistic styles of diverse paintings. Zhang et al. [48] presented a passport normalization for deep model intellectual property protection. In this paper, we introduce task-specific BN to accomplish continual learning of DNN-based BIQA models.

III. PROPOSED METHOD

In this section, we first revisit the formulation of continual learning for BIQA in [2], and then elaborate the training and inference procedures of the proposed TSN-IQA. To facilitate mathematical comprehension, we summarize a list of variables in Table III-A.

A. PROBLEM FORMULATION

When training on the $t$-th dataset $D_t$, i.e., the $t$-th task, a BIQA model $f_w$, parameterized by a vector $w$, has no direct
access to previous training images in \( \{ \mathcal{D}_k \}_{k=1}^{t-1} \), leading to the following objective:

\[
\mathcal{L}(\mathcal{D}_t; w) = \frac{1}{|\mathcal{D}_t|} \sum_{(x, \mu_x) \in \mathcal{D}_t} \ell(f_w(x), \mu_x) + \lambda \Omega(w),
\]

where \( x \) and \( \mu_x \) denote the “distorted” image and the corresponding mean opinion score (MOS), respectively. \( \ell(\cdot) \) is a quantitative measure of quality prediction performance, and \( \Omega(\cdot) \) is an optional regularizer. A good BIQA model under this setting should adapt well to new tasks, and meanwhile endeavor to mitigate catastrophic forgetting of old tasks as measured by

\[
\sum_{k=1}^{t} \mathcal{L}(\mathcal{V}_k; w) = \sum_{k=1}^{t} \left( \frac{1}{|\mathcal{V}_k|} \sum_{(x, \mu_x) \in \mathcal{V}_k} \ell(f_w(x), \mu_x) \right),
\]

where \( \mathcal{V}_k \) denotes the test set for the \( k \)-th task. Five desiderata are suggested in [2] to make continual learning for BIQA feasible and nontrivial: 1) common perceptual scale, 2) robust to subpopulation shift, 3) limited access to previous data, 4) no test-time oracle, and 5) bounded memory footprint.

### B. Model Estimation

Inspired by UNIQUE [11], we exploit relative quality information to learn a common perceptual scale for all tasks. Specifically, given an image pair \((x, y)\), we compute a binary label:

\[
r(x, y) = \begin{cases} 
1 & \text{if } \mu_x \geq \mu_y \\
0 & \text{otherwise}
\end{cases}
\]

Careful readers may find that we do not infer a continuous value \( p(x, y) \), which denotes the probability of \( x \) perceived better than \( y \) based on the Thurstone’s model [49] or the Bradley-Terry model [50] as typically done in previous work [11, 23]. This is because the computed probability may vary with the precision of the subjective testing methodology. For example, if \( x \) is marginally better than \( y \) and a precise subjective method such as the two-alternative forced choice (2AFC) is adopted, \( p(x, y) \) can be close to one. By contrast, if a less precise subjective method such as the single stimulus continuous quality rating is used, \( p(x, y) \) may only be slightly larger than 0.5. Compared to \( p(x, y) \), we also empirically observe that \( r(x, y) \) leads to faster convergence and improved accuracy results. When learning the \( t \)-th task, we transform \( \mathcal{D}_t = \{x_t^{(i)}, \mu_t^{(i)}\}_{i=1}^{N_t} \) to \( \mathcal{P}_t = \{x_t^{(i)}, y_t^{(i)}, r_t^{(i)}\}_{i=1}^{N_t} \), where \( N_t \leq (\frac{N}{2^t}) \).

Our BIQA model consists of a feature extractor implemented by a DNN, \( f_\phi(\cdot) \), producing a fixed-length image representation independent of input resolution. For the \( t \)-th task, we append a prediction head implemented by an FC layer, \( h_\psi_t(\cdot) \), outputting a corresponding quality score. Under the Thurstone’s Case V model [49], we estimate the probability that \( x \) is of higher quality than \( y \) by

\[
\hat{p}_t(x, y) = \Phi \left( \frac{h_\psi_t(f_\phi(x)) - h_\psi_t(f_\phi(y))}{\sqrt{2}} \right),
\]

where the quality prediction variance is fixed to one. We measure the statistical distance between the ground-truth labels and predicted probabilities using the fidelity loss [51] due to its favorable optimization behaviors [11]:

\[
\ell(x, y; \phi, \psi_t) = 1 - \sqrt{r(x, y)p_t(x, y)} - \sqrt{1 - r(x, y)(1 - \hat{p}_t(x, y))}.
\]

To make a better trade-off between plasticity and stability while keeping a bounded model size, our BIQA method chooses to maximally share computation across tasks, and customize a tiny fraction of parameters to account for the incremental difference introduced by new tasks. In particular, our feature extractor is composed of several stages of convolution, BN, halfwave-rectification (i.e., ReLU nonlinearity), and max-pooling. We freeze all pre-trained convolution parameters during model development, and learn a group of 4-tuple BN parameters for the \( t \)-th task

\[
z_{BN} = \gamma_t \left( \frac{z - \mu_t}{\sigma_t} \right) + \beta_t,
\]

where \( \mu_t \) and \( \sigma_t \) are the mean and the std estimated by the exponentially decaying moving average over mini-batches. \( \gamma_t \) and \( \beta_t \) are the learnable scaling and shift parameters (see also Fig. 2). After training on a \( T \)-length task sequence, we obtain \( T \) groups of task-specific BN parameters.

### TABLE I

| Notation | Description |
|----------|-------------|
| (x, y) | an image pair |
| (\mu_x, \mu_y) | MOSs of \( x \) and \( y \) |
| \( D_t \) | the \( t \)-th dataset |
| \( \mathcal{P}_t \) | the \( t \)-th paired dataset |
| \( N_t \) | # of image pairs in the \( t \)-th paired dataset |
| \( f_\phi \) | a DNN parameterized by a vector \( \phi \) |
| \( h_\psi \) | the \( t \)-th prediction head parameterized by \( \psi_t \) |
| \( r(x, y) \) | the binary quality label of \((x, y)\) |
| \( \hat{p}_t(x, y) \) | the predicted probability of \((x, y)\) for the \( t \)-th task |
| \( \hat{p}_t(x) \) | the k-th centroid at the s-th stage for the \( t \)-th task |
| \( a_{st} \) | the weighting of \( x \) for the \( t \)-th prediction head |
| \( \hat{q}(x) \) | the predicted quality score of \( x \) |
C. Model Inference

During inference, we successively load each of $T$ groups of BN parameters along with the corresponding FC layer to compute $T$ quality scores. Due to the unavailability of the task oracle, we rely on an improved KG module [2] with a lightweight design goal, which is made possible by the proposed parameter decomposition scheme. Unlike [2], we only train a set of task-agnostic BN parameters on a large-scale image set with various synthetic distortions [27] for distortion-aware weighting computation, while keeping all convolution filters intact. Since the original BN parameters of the pre-trained feature extractor are not necessary, our gating mechanism introduces essentially no extra parameters, and adheres to the desideratum of bounded memory footprint.

We present the overview of the inference process in Fig. 3. During loading the $t$-th task, we load the distortion-aware BN parameters to the pre-trained $f_\phi$ to compute globally pooled convolution responses of image $x$ at the $s$-th stage, $f_\phi_s(x)$. Given $S$-stage convolutions, we obtain a feature summary of $D_t$: $\{f_\phi_s(x^{(i)}_1), \ldots, f_\phi_s(x^{(i)}_4)\}_{i=1}^{D_t}$. We then apply $K$-means [52] (for each stage of convolution responses) to compute $S$ groups of $K$ centroids $\{c_{kst}\}_{k=1}^K$. We measure the perceptual relevance of $x$ to $D_t$ by computing the minimal Euclidean distances between $f_\phi_s(x)$ and $c_{kst}$:

$$d_{st}(x) = \min_k \|f_\phi_s(x) - c_{kst}\|_2.$$  \hspace{1cm} (7)

We pass $\{d_{st}(x)\}_{t=1}^T$ to a softmax function to compute the weightings at the $s$-th stage for the $t$-th prediction head:

$$a_{st}(x) = \frac{\exp(-\tau d_{st}(x))}{\sum_{t'=1}^T \exp(-\tau d_{st}(x))},$$  \hspace{1cm} (8)

where $\tau \geq 0$ is a parameter to control the smoothness of the softmin function. We further average the weightings across stages to obtain

$$a_t(x) = \frac{1}{S} \sum_s a_{st}(x).$$  \hspace{1cm} (9)

We last compute the overall quality score by the inner product between the weighting and quality prediction vectors:

$$\hat{q}(x) = \sum_{t=1}^T a_t(x) h_{\psi_t}(f_\phi(x)).$$  \hspace{1cm} (10)

IV. EXPERIMENTS

In this section, we first describe the experimental setups for continual learning of BIQA models, and then compare the proposed TSN-IQA against previous training techniques, supplemented by abundant ablation studies. The source code is made publicly available at https://github.com/zwx8981/TSN-IQA for reproducible research.

A. Experimental Setups

We select six widely used IQA datasets: LIVE [5], CSIQ [56], BID [24], LIVE Challenge [25], KonIQ-10K [26], and KADID-10K [57]. We summarize the details of the six datasets in Table II. In general, the number of training pairs is proportional to the number of images in the training set of each dataset.

Following [2], we organize these datasets in chronological order for the main experiments. We randomly sample 70% and 10% images from each dataset for training and validation, respectively, and leave the remaining for testing. To ensure content independence in LIVE, CSIQ, and KADID-10K, we divide the training and test sets according to the reference images.

We choose a variant of ResNet-18 [58] as the feature extractor. We keep the front convolution and four residual blocks, which are indexed by Stage 1 to Stage 4, respectively. We append an FC layer as the prediction head on top of the convolution response from Stage 4, and compute the weightings using the convolution responses from later two stages. As such, 10,112 learnable parameters are introduced by BN and FC layers for each new task, accounting for less than 0.18% of the total network parameters. During inference, the number of centroids used in $K$-means is set to $K = 128$ for each new task, which introduces 98,304 parameters for additional memory budget, accounting for about 0.88% of the backbone network parameters. Putting together, the current configuration ensures that TSN-IQA conforms to the bounded memory footprint desideratum.

For each task, stochastic optimization is carried out by Adam [59] with an initial learning rate of $1 \times 10^{-3}$. We decay the learning rate by a factor of 10 at the 8-th epoch, and train our method for a maximum of twelve epochs. We set the temperature to $\tau = 32$ in Eq. (8). We test on images of the original size.

We use Spearman’s rank correlation coefficient (SRCC) to measure the prediction performance. When continually learning a BIQA model on a $T$-length task sequence, we

1Empirically, we find that TSN-IQA is insensitive to the choice of $K$. 
compute the mean SRCC between model predictions and MOSs of each dataset as a measure of prediction accuracy:

\[
mSRCC = \frac{1}{T} \sum_{k=1}^{T} SRCC_{Tk},
\]

(11)

where \(SRCC_{Tk}\) is the SRCC result of the \(t\)-th model on the \(k\)-th dataset. We then compute a mean plasticity index (mPI):

\[
mPI = \frac{1}{T} \sum_{t=1}^{T} PI_t = \frac{1}{T} \sum_{t=1}^{T} SRCC_{tt},
\]

(12)

\(i.e.,\) the average result of the model on the current dataset along the task sequence, and a mean stability index (mSI) by measuring the variability of model performance on old data when learning on a new task:

\[
mSI = \frac{1}{T} \sum_{t=1}^{T} SI_t,
\]

(13)

\(\text{mPSI} = \frac{1}{T} \sum_{t=1}^{T} PSI_t = \frac{1}{2T} \sum_{t=1}^{T} (PI_t + SI_t).\)  (15)

\(B.\) \textit{Competing Methods}

We describe several competing methods for training. For a fair comparison, we rely on the same backbone network \(i.e.,\) ResNet-18 as TSN-IQA for implementation. We further instantiate TSN-IQA using a two-stream DNN, composed of a variant of ResNet-18 and a VGG-like network, which allows for a direct performance comparison with other methods that share the setup in [2].

- \textbf{Separate Learning (SL)} is the standard in BIQA, which trains the model using a single prediction head on one of the six training sets.
- \textbf{Joint Learning (JL)} refers to the dataset combination trick [11] to address the cross-distortion-scenario challenge in BIQA. As an upper bound of all continual learning methods, JL trains the model with a single head on the combination of all six training sets.
- \textbf{LwF} [12] in BIQA is based on a multi-head architecture, which introduces a stability regularizer that uses the previous model outputs as soft labels to preserve the performance of previously seen data. LwF relies on the...
newest head for quality prediction. We also leverage the task oracle to select the corresponding head for quality prediction, denoted by LwF-O.

- **LwF-KG** [2] uses a modified LwF [12] for training and the KG mechanism for inference.
- **SI** [34] is also a regularization-based continual learning method, which estimates important parameters for previous tasks. Similar to LwF, we implement a multi-head architecture for SI, and rely on the newest head to predict image quality. We try to improve the performance with the KG mechanism, denoted by SI-KG, and leverage the task oracle as well, denoted by SI-O.
- **MAS** [34] shares a similar philosophy with SI to penalize the changes to important weights. The difference lies only in the calculation of the cumulative importance measure. Similarly, MAS uses the latest head for quality prediction, and has two variants that include the KG module and the task oracle, denoted by MAS-KG and MAS-O, respectively.
- **TSN-IQA** makes use of task-specific BN to handle new tasks, and enhances the KG module in [2] using rich feature hierarchies with less memory footprint. We also replace the KG module with the task oracle for quality prediction, denoted by TSN-IQA-O.
C. Main Results

Table III lists mSRCC, mPI, mSI, and mPSI results on the six IQA test sets. Several interesting observations have been made. First, without any remedy for catastrophic forgetting, the performance of SL is far from satisfactory, consistent with previous findings [2]. Particularly, we identify a significant performance drop when SL transits from CSIQ to BID (see Table IV), where an apparent subpopulation shift from synthetic to realistic distortions is introduced. Second, direct application of LwF, SI, and MAS from image classification to BIQA achieves significantly better performance over SL in terms of mSI and similar performance in terms of mPI.

Third, equipped with the KG module, LwF-KG, SI-KG, and MAS-KG outperform their counterparts in terms of both mSRCC and mPSI. The performance is even comparable to their "upper bounds" (i.e., LwF-O, SI-O, and MAS-O) under all evaluation measures. Notably, compared to TSN-IQA which shares the majority of parameters between the feature extractor and the KG module, these models require twice more memory budget. Fourth, TSN-IQA-O achieves the best results, which outperforms LwF-O, SI-O, and MAS-O in terms of mSRCC and mPSI by large margins, and serves as the "upper bound" of TSN-IQA for further improvement. Fifth, both LwF-KG and TSN-IQA demonstrate improved performance regarding the plasticity/stability trade-off by switching ResNet-18 to a more advanced two-stream DNN. Sixth, when the task oracle is available, LwF-O is comparable to TSN-IQA-O for the two-stream backbone. But, this is not the case when ResNet-18 is the backbone, where TSN-IQA-O significantly surpasses LwF-O. This indicates that TSN-IQA is more resilient to changes in the backbone architecture. Lastly, TSN-IQA consistently outperforms LwF-KG [2] in terms of mPSI and mSRCC when using the same backbone network (ResNet-18 or the two-stream DNN), verifying the technical contribution of the proposed approach.

We plot PSI$_t$ as a function of the task index $t$ in Fig. 4, from which we find our method is more stable as the length of the task sequence grows for different backbone networks. We then look closely at the performance variations along the task sequence, and summarize the SRCC results continually in Table IV.

Several useful findings are worth mentioning. First, JL provides an effective but unscaleable solution to the subpopulation shift in BIQA, serving as the upper bound of all continual learning methods. Second, the plasticity of SL is reasonably good, but the results on previously learned tasks suffer from significant oscillations due to the subpopulation shift between synthetic and realistic distortions [11], [20], [27]. Third, the favorable performance of LwF-KG, SI-KG, and MAS-KG against LwF, SI, and MAS especially on old tasks validates the KG module for summarizing quality predictions.

We last conduct a qualitative analysis of our BIQA model by showing representative test images from the task sequence in Fig. 5. We find that for frequently-seen distortion appearances (e.g., global blurring in (a)), all heads tend to make reasonable predictions, and more weightings are given to the corresponding head. Meanwhile, if one distortion type occurs in multiple datasets (e.g., JPEG2000 compression in (b)), the heads that have seen the distortion work well, while others do not. Fortunately, the KG module is able to underweight inaccurate heads. Moreover, TSN-IQA successfully aligns images of synthetic and realistic distortions in a common perceptual scale, despite not being exposed to pairs of images from different distortion scenarios.

D. Results of Task-Order/-Length Robustness

In real-world applications, novel distortions may emerge in arbitrary order. As a result, a continual learning method for BIQA is expected to be robust to different task orders. In addition to (I) the default chronological order, we experiment with seven more task orders: (II) synthetic and realistic distortions in alternation: LIVE $\rightarrow$ BID $\rightarrow$ CSIQ $\rightarrow$ LIVE Challenge $\rightarrow$ KADID-10K $\rightarrow$ KonIQ-10K, (III) synthetic distortions followed by realistic distortions: LIVE $\rightarrow$ CSIQC $\rightarrow$ KADID-10K $\rightarrow$ BID $\rightarrow$ LIVE Challenge $\rightarrow$ KonIQ-10K, (IV) realistic distortions followed by synthetic distortions: BID $\rightarrow$ LIVE Challenge $\rightarrow$ KonIQ-10K $\rightarrow$ LIVE $\rightarrow$ CSIQC $\rightarrow$ KADID-10K, and (V)-(VIII) the reverses of Orders (I)-(IV).
We compare TSN-IQA to LwF-KG [2] in Table V. The main observation is that our method is more robust than LwF-KG for all task orders under all metrics. Furthermore, we note that the results of Orders V and VIII are slightly lower than those of other orders. We believe these arise because we begin with KADID-10K [57], a synthetic dataset that is considered visually much harder than LIVE [5] and CSIQ [56], therefore posing a challenge for performance stabilization. Given a specific task order, we also measure the task-length robustness by the mean $mPSI$ of different lengths, $\{mPSI_t\}_{t=1}^T$. We compare our method to LwF-KG [2] in Table VI. We find the task-length robustness to be dependent on the task order, and TSN-IQA performs better than LwF-KG across all task orders. A relatively inferior result is observed for Order V, where KADID-10K [57] is listed in the first place. Altogether, these promising results indicate that TSN-IQA has great potential for use in practical quality prediction scenarios.

### E. Ablation Studies

In this subsection, we conduct ablation experiments to probe the performance variations of TSN-IQA. Note that all experiments are conducted using the default chronological order.
First, to verify the necessity of the core design of our method - task-specific BN, we train a single group of task-agnostic BN parameters along the task sequence. During inference, we use the converged BN parameters to make predictions for all tasks. As shown in Table VII, this variant achieves an mPSI of 0.822 and an mSRCC of 0.624, which are far below the results by TSN-IQA. We next compare the performance using the ImageNet pre-trained BN with the proposed distortion-aware BN for the KG module. Being exposed to various types of distortions, the distortion-aware BN parameters help the KG module assign weightings to predictions heads more reasonably, leading to higher mPSI and mSRCC results. We then evaluate the influence of the feature hierarchy on the KG module by incorporating different stages of convolution responses. The results in Table VII show that multi-stage features are more beneficial, and the combination of Stage-3 and Stage-4 features delivers the most perceptual gains.

Lastly, we experiment with three different DNNs as the backbone networks, i.e., VGG-16 [61], ResNet-50 [58], and the two-stream DNN [2]. From Table VII, we observe that the proposed parameter decomposition scheme is generic for continual learning of BIQA models, which can be enhanced by working with more powerful backbone networks.

### Further Analysis

1) **IQA Dataset Analysis:** During continual learning on a task sequence, TSN-IQA is trained to capture the informative and discriminative information of each task using a group of task-specific BN parameters. It remains to be seen 1) whether the learned BN parameters reflect distinctive aspects of different datasets, and 2) whether they can explain the performance variations. To answer these questions, we first retrieve the exponentially decaying moving averages of the mean and std parameters from the last BN layer learned for each task, which are assumed to follow a multivariate Gaussian distribution. With such T Gaussian distributions at hand, we compute the pairwise Kullback–Leibler (KL) divergence \(\{KL_{ij}\}_{i,j=1}^T\).
From Table VIII, we identify a clear trend that datasets with similar distortion scenarios have relatively smaller divergence values. We then load each group of task-specific BN parameters (together with the corresponding prediction head), and test it on all datasets, by which we obtain pairwise SRCC results among all datasets \( \{ \text{SRCC} \}^{T}_{i,j=1} \) (Table IX). Finally, we are able to measure the correlation between the learned BN parameters and the performance variations with an SRCC of 0.776 between \( \{ \text{SRCC} \}^{T}_{i,j=1} \) and \( \{ \text{KL}\}^{T}_{i,j=1} \). This provides empirical evidence that the more similar the datasets are in distortion scenarios, the better the inter-dataset prediction accuracy.

2) Generalizability Analysis: To empirically verify that TSN-IQA can be used to predict the perceptual quality of images beyond all seen datasets, we test the model learned in chronological order of the six tasks on three additional datasets, including TID2013 [53], SPAQ [54], and AGIQA-3K [55]. We report the SRCC results and the average weightings computed by the KG module over all images in Table X, from which we have two useful observations. First, the proposed TSN-IQA presents reasonable generalizability to the tasks it is not exposed to. Second, the KG module assigns perceptually meaningful weightings to the prediction heads. Specifically, the prediction heads learned on LIVE, CSIQ, and KADID-10K are assigned higher weightings when handling TID2013, containing multiple synthetic distortions. Similarly, the prediction heads for BID, LIVE Challenge, and KoniQ-10K are assigned higher weightings for SPAQ, which is dominated by realistic camera distortions. The situation becomes a little intricate on AGIQA-3K, a new dataset comprising artificially generated images. All prediction heads are assigned non-trivial weightings, exposing the uncertainty of TSN-IQA in handling this novel image type. We also compare TSN-IQA with three recent BIQA methods, i.e., PQR [20], HyperIQA [28], and CONTRIQUE [60], following the same cross-dataset evaluation setup. As shown in Table XI, TSN-IQA outperforms other BIQA models on all three datasets, especially on TID2013 [53] that contains synthetic distortions. Nevertheless, there remains considerable room for improvement in quality prediction of artificially-generated images that exhibit substantial subpopulation shift.

3) Computational Complexity Analysis: We compare the computational complexity of TSN-IQA with LwF-KG [2]. The computation of a single forward pass for the two methods are identical. Specifically, given an image with a size of \( 224 \times 224 \times 3 \), the number of multiply–accumulate operations (MACs) of TSN-IQA is about 18.2 G. After continually learned on \( T \) tasks, TSN-IQA computes \( T \) quality estimates with \( T \) groups of task-specific BN parameters during inference. As such, the computational complexity is linear with respect to the number of training tasks, which can be straightforwardly accelerated by parallel computing.

We have also tried a variant of the KG module that implements hard assignment by setting \( \tau = +\infty \). With such a modification, only one forward pass is needed to compute the final quality score, which reduces the computational complexity by a factor of \( T \). As shown in Table XII, although this computationally efficient variant delivers slightly inferior performance than the default TSN-IQA, it outperforms LwF-KG with the same computational complexity.

4) Performance Stability: We test the performance stability of TSN-IQA with respect to five different random initializations. As shown in Table XIII, TSN-IQA consistently demonstrates superior performance over other methods irrespective of the chosen backbone network.

V. CONCLUSION AND DISCUSSION

We have introduced a simple yet effective method of continually learning BIQA models. The key to the success of the proposed TSN-IQA is to train task-specific BN parameters for each task while holding all pre-trained convolution filters fixed. On the one hand, TSN-IQA encourages more effective feature representation learning for different tasks. This is because BN participates all network stages of feature processing, which is better suited in the continual learning scenario for noticeably improved quality prediction accuracy, plasticity-stability trade-off, and task-length/order robustness. On the other hand, it permits a significant reduction in the number of parameters
used for the KG mechanism, which only needs to replace a set of BN parameters.

TSN-IQA relies on five desiderata as specified in [2], among which the assumption of a common perceptual scale is foremost. It is well-known that the perceived quality of a visual image depends not only on the image content itself, but also on the subjective testing protocols as well as viewing conditions. For example, switching from single-stimulus methods to 2AFC approaches generally improves the accuracy of fine-grained quality annotations. We take this into consideration by pursuing binary labels as ground-truths. Moreover, the visibility of some distortions (e.g., JPEG compression) varies with the effective viewing distance. Although it would be ideal to give a complete treatment of viewing conditions (e.g., as part of the model input), our computational study shows the possibility to learn a common perceptual scale for different IQA datasets with MOSs collected under similar viewing conditions and having overlapping quality ranges. With the explosive growth of user-generated and computer-generated images, it is also desirable to perform online continual learning for BIQA, where there is no distinct boundaries between tasks (or datasets) during training.

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| Backbone | Method | mSRCC | mPI | mSI | mPSI |
|----------|--------|-------|-----|-----|------|
| ResNet-18 | SL     | 0.695 (± 0.018) | 0.852 (± 0.005) | 0.753 (± 0.004) | 0.802 (± 0.003) |
|          | SI     | 0.677 (± 0.116) | 0.856 (± 0.007) | 0.868 (± 0.010) | 0.862 (± 0.008) |
|          | SI-KG  | 0.712 (± 0.086) | 0.854 (± 0.008) | 0.866 (± 0.019) | 0.860 (± 0.013) |
|          | MAS    | 0.717 (± 0.018) | 0.854 (± 0.007) | 0.865 (± 0.006) | 0.859 (± 0.006) |
|          | MAS-KG | 0.747 (± 0.022) | 0.862 (± 0.006) | 0.871 (± 0.007) | 0.862 (± 0.006) |
|          | LwF    | 0.697 (± 0.026) | 0.846 (± 0.004) | 0.880 (± 0.011) | 0.863 (± 0.007) |
|          | LwF-KG | 0.801 (± 0.003) | 0.840 (± 0.003) | 0.964 (± 0.003) | 0.902 (± 0.002) |
|          | TSN-IQA | 0.839 (± 0.004) | 0.851 (± 0.003) | 0.983 (± 0.003) | 0.917 (± 0.001) |

| Two-Stream DNN | Method | mSRCC | mPI | mSI | mPSI |
|----------------|--------|-------|-----|-----|------|
| SL             | 0.672 (± 0.016) | 0.875 (± 0.005) | 0.802 (± 0.008) | 0.839 (± 0.004) |
| SI             | 0.705 (± 0.021) | 0.875 (± 0.005) | 0.833 (± 0.008) | 0.854 (± 0.005) |
| SI-KG          | 0.799 (± 0.008) | 0.862 (± 0.009) | 0.948 (± 0.011) | 0.905 (± 0.005) |
| MAS            | 0.687 (± 0.043) | 0.877 (± 0.003) | 0.826 (± 0.020) | 0.851 (± 0.111) |
| MAS-KG         | 0.806 (± 0.015) | 0.865 (± 0.003) | 0.950 (± 0.006) | 0.908 (± 0.004) |
| LwF            | 0.688 (± 0.019) | 0.873 (± 0.011) | 0.841 (± 0.008) | 0.857 (± 0.009) |
| LwF-KG         | 0.810 (± 0.009) | 0.850 (± 0.008) | 0.979 (± 0.001) | 0.914 (± 0.004) |
| TSN-IQA        | 0.839 (± 0.009) | 0.858 (± 0.005) | 0.981 (± 0.004) | 0.920 (± 0.004) |
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