Related Work on Image Quality Assessment

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***Abstract*—Due to the existence of quality degradations introduced in various stages of visual signal acquisition, compression, transmission and display, image quality assessment (IQA) plays a vital role in image-based applications. According to whether the reference image is complete and available, image quality evaluation can be divided into three categories: Full-Reference(FR), Reduced- Reference(RR), and Non- Reference(NR). This article will review the state-of-the-art image quality assessment algorithms.**

I. Traditional FR-IQA

For traditional FR-IQA, an Image Quality Assessment Based on A Degradation Model (NQM) was proposed by Damera-Venkata N et al. in 2000 [1]. Then Wang Z et al . [2] put forward a multi-scale structural similarity method, which supplied more flexibility than previous single-scale methods in incorporating the variations of viewing conditions. In 2004 , they introduced an alternative framework for quality assessment [3]. Different from the traditional attemption to quantify the visibility of errors between a distorted image and a reference image, they developed a Structural Similarity Index and demonstrated its promise through a set of intuitive examples. Quality assessment (QA) research is to design algorithms that can automatically assess the quality of images or videos in a perceptually consistent manner. Traditionally, QA systems are invariably involved with judging the visual quality of images and videos that are meant for "human consumption."By using statistical models in an information-theoretic setting, Sheikh H R et al. [4] derove a novel QA algorithm that provided clear advantages over the traditional approaches.

The well-known structural similarity index brings IQA from pixel- to structure-based stage. Zhang L et al. [5] brought a novel feature similarity (FSIM) index for full reference IQA based on the fact that human visual system (HVS) understood an image mainly according to its low-level features.It could achieve much higher consistency with the subjective evaluations than state-of-the-art IQA metrics. Many state-of-the-art perceptual image quality assessment (IQA) algorithms share a common two-stage structure: local quality/distortion measurement followed by pooling. While the pooling stage is often done in ad-hoc ways, lacking theoretical principles and reliable computational models. Aimed at testing the hypothesis that when viewing natural images, the optimal perceptual weights for pooling should be proportional to local information content, Wang Z et al. [6] concluded with much useful findings based upon six publicly-available subject-rated image databases. Chandler D M et al. [7] presented an efficient metric for quantifying the visual fidelity of natural images based on near-threshold and suprathreshold properties of human vision. The proposed VSNR metric was generally competitive with current metrics of visual fidelity.

II. Traditional RR-IQA

With the strong neurobiological support for sparse representation, Liu Y et al. [8] approximated the internal generative model with sparse representation and proposed an image quality metric accordingly, which was (free-energy principle and sparse representation-based index for image quality assessment). Their experiment showed the effectiveness of the FSI and its superiority over representative image quality assessment methods.

Fairly comparing the performance becomes a major challenge due to the enormous size of the image space and the limited resource for subjective testing. Most IQA models involve machine learning or manual parameter tuning steps to boost their performance on these databases, K Ma et al. [9] proposed a substantially different methodology to compare IQA models, which provided the strongest test to let the IQA models compete with each other. To more accurately compare different IQA algorithms, Q Wu et al. [10] explored a perceptually weighted rank correlation indicator, which rewarded the capability of correctly ranking high-quality images and suppressed the attention toward insensitive rank mistakes. They focused on activating a "valid" pairwise comparison of images whose quality difference exceeded a given sensory threshold (ST). Each image pair was assigned a unique weight that was determined by both the quality level and rank deviation. The proposed indicator offered new insight into interpreting visual perception behavior.

III. Traditional NR-IQA

Mittal A et al. [11] proposed a natural scene statistic-based distortion-generic blind/no-reference (NR) image quality assessment (IQA) model that operated in the spatial domain. The new model used scene statistics of locally normalized luminance coefficients to quantify possible losses of "naturalness" in the image due to the presence of distortions, thereby leading to a holistic measure of quality. Q Wu et al. [12] proposed a no reference image quality assessment (NR-IQA) algorithm based on distortion identification (DI) and multi-channel label transfer (LT). The experimental results show that the proposed method outperforms representative NR-IQA approaches and some full-reference metrics. Existing blind image quality assessment (BIQA) methods are mostly opinion-aware. However, the BIQA models learned by opinion-aware methods often have weak generalization capability, hereby limiting their usability in practice. Zhang L et al. [13] developed an opinion-unaware BIQA method that did not need any distorted sample images nor subjective quality scores for training, and experiments demonstrated its superior quality-prediction performance to the state-of-the-art opinion-aware BIQA methods. Ghadiyaram D et al. [14] proposed a "bag of feature maps" approach that avoid assumptions about the type of distortion(s) contained in an image. They trained a regressor to conduct image quality prediction and showed it was able to achieve good-quality prediction power better than other leading models. Most existing Natural scene statistics (NSS)-based IQA methods extract features either from spatial domain or from transform domain. There is little work to simultaneously consider the features from these two domains. So novel blind IQA method (NBIQA) based on refined NSS is proposed by Ou F Z et al. [15]. Experimental results tested on both LIVE IQA and LIVE-C databases showed that the proposed NBIQA performs better in terms of synthetic and authentic image distortion than current mainstream IQA methods. The general purpose no reference image quality assessment (NR-IQA) is a challenging task. Under this situation, Q Wu et al. [16] proposed a novel NR-IQA method that addressed these problems by introducing the multi-domain structural information and piecewise regression. Experimental results on three benchmark IQA databases (i.e., LIVE II, TID2008 and CSIQ) showed that the proposed method outperforms many representative NR-IQA algorithms. Q Wu et al. [17] proposed an efficient blind image quality assessment (BIQA) algorithm, which based on multichannel feature fusion and label transfer. This method got highly consistency with human perception. To bridge the gap between academic research accomplishment and industrial needs, a novel BIQA method was proposed by selecting statistical features extracted from binary patterns of local image structures in 2015. This method allowed us to largely reduce the feature space to eventually one dimension.

Block-based compression causes severe pseudo structures, but pseudo structures of images compressed by different levels show some degree of similarity. So Min X et al. [18] proposed to evaluate the quality of compressed images via the similarity between pseudo structures of two images. Their proposed pseudo structural similarity (PSS) model calculated the similarity between pseudo structures of the distorted image and MDI. Via comparative tests, the proposed PSS model, on one hand, was comparable to state-of-the-art competitors, and on the other hand, it performed the best in the hotly-researched screen content image (SCI) database. Aiming to correct quality rank-orders between the test images, which was a highly desirable property of image quality models, Q Wu et al. [19] proposed a novel rank-order regularized regression model to address this problem. By combing with a new local spatial structure feature, they had achieved highly consistent quality prediction with human perception and better preserved the correct perceptual preference. Motivated by the fact that it was difficult to approximate a complex and large data set via a global parametric model, Q Wu et al. [19] proposed a novel local learning method for BIQA to improve quality prediction performance, which leading to consistent quality prediction improvements over many state-of-the-art BIQA algorithms. Limited by fluctuating bandwidth and various network impairments, the streaming video inevitably suffered kinds of stalling events, which significantly distorted its temporal structures and results in annoying jerky playback. So Q Wu et al. [20] proposed an efficient quality metric to blindly evaluate the user experience for stalled streaming video without using its original sequence. Traditional blind image quality assessment (IQA) measures generally predict quality from a sole distorted image directly. Min X et al. [21] first introduced multiple pseudo reference images (MPRIs) by further degrading the distorted image in several ways and to certain degrees, and then compared the similarities between the distorted image and the MPRIs. Via such distortion aggravation, validation was conducted on four mainstream natural scene image and screen content image quality assessment databases, and their proposed method was comparable to or outperforms the state-of-the-art blind IQA measures.

IV. Deep Learning Based Approaches

Bosse S et al. [22] presented a deep neural network-based approach to image quality assessment (IQA). The network was trained end-to-end and comprised ten convolutional layers and five pooling layers for feature extraction, and two fully connected layers for regression, which maked it significantly deeper than related IQA models. A number of full-reference image quality assessment (FR-IQA) methods adopted various computational models of the human visual system (HVS) from psychological vision science research. Kim J et al. [23] proposed a novel convolutional neural networks (CNN) based FR-IQA model, named Deep Image Quality Assessment (DeepQA), where the behavior of the HVS was learned from the underlying data distribution of IQA databases. Different from previous studies, their model seeked the optimal visual weight based on understanding of database information itself without any prior knowledge of the HVS. Through experiments, they showed that the predicted visual sensitivity maps agree with the human subjective opinions. Currently existing methods can't robustly predict visual differences like humans. Then Prashnani E et al. [24] presented a new learning-based method that was the first to predict perceptual image error like human observers. Their key observation was that the trained network could then be used separately with only one distorted image and a reference to predict its perceptual error, without ever being trained on explicit human perceptual-error labels. Kang L et al. [25] described a Convolutional Neural Network (CNN) to accurately predict image quality without a reference image. Taking image patches as input, the CNN worked in the spatial domain without using hand-crafted features that are employed by most previous methods. This approach achieved state of the art performance on the LIVE dataset and shows excellent generalization ability in cross dataset experiments. To tackle the problem of no-reference image quality assessment (IQA). Guan J et al. [26] proposed a learning-based IQA framework ”VIDGIQA”, which extracted quality features from the input image and regressed the visual quality on these features. Bosse S et al. [27] presented a no reference image (NR) quality assessment (IQA) method based on a deep convolutional neural network (CNN). They evaluated the network on the LIVE database and achieved a linear Pearson correlation superior to state-of-the-art NR IQA methods. They also applied the network to the image forensics task of decoder-sided quantization parameter estimation and also achieved correlations of r = 0.989. Yang S et al. [28] proposed an end-to-end saliency-guided deep neural network (SGDNet) for no-reference image quality assessment (NR-IQA). Their SGDNet was built on an end-to-end multi-task learning framework, while their saliency prediction sub-task was more universal.

The crucial challenge of image quality assessment (NR-IQA) is how to accurately measure the naturalness of an image. So Q Wu et al. [29] proposed a novel parametric image representation which was derived from the generic image prior (GIP). More specifically, they utilized the classic fields of experts model to capture the prior distribution of an image. Then, they used the parameters in modeling this prior distribution. They showed their method achieved competitive quality prediction accuracy. To alleviate the accuracy discrepancy between FR-IQA and NR-IQA methods, Kim J et al. proposed [30] a blind image evaluator based on a convolutional neural network (BIECON). Jia S et al. proposed [31] a novel method for No-Reference Image Quality Assessment (NR-IQA) by combining deep Convolutional Neural Network (CNN) with saliency map. Comparing the proposed ten-layer Deep CNN (DCNN) for NR-IQA with the state-of-the-art CNN architecture, DCNN architecture delivered a higher accuracy on the LIVE dataset. To mimic human vision, they introduced saliency maps combining with CNN to propose a Saliency-based DCNN (SDCNN) framework for NR-IQA. The results indicated their proposed SDCNN generalised well on other datasets. Various feature extraction mechanisms have been leveraged from natural scene statistics to deep neural networks in previous methods, the performance bottleneck still exists. Lin K Y et al. [32] proposed a hallucination-guided quality regression network to address the issue. They firstly generated a hallucinated reference constrained on the distorted image. Then paired the information of hallucinated reference with the distorted image. comprehensive experiments demonstrated the effectiveness of this approach. Kang L et al. [33] described a compact multi-task Convolutional Neural Network (CNN) for simultaneously estimating image quality and identifying distortions. They designed a compact structure, and demonstrated its learning power.

Recently, the studies towards blind assessment of enhanced images are still very lacking. In this paper, Q Wu et al. [34] proposed a data-driven blind image quality assessment (BIQA) method based on the quality-aware deep neural network (Q-DNN), in which a supervised learning model is utilized in the Q-DNN. K Ma et al. [35] threw light on new challenges for image quality assessment models. To test the generalization capability and to facilitate the wide usage of IQA techniques in real-world applications, they established a large-scale database named the Waterloo Exploration Database and presented three alternative test criteria to evaluate the performance of IQA models. Their study provided insights on how to improve the models, and shed light on how the next-generation IQA models may be developed.

Zhang W et al. [36] proposed a deep bilinear model for blind image quality assessment (BIQA), which handled both synthetic and authentic distortions. Their model consisted of two convolutional neural networks (CNN), each of which specialized in one distortion scenario. Experiments demonstrate that the proposed model achieves superior performance on both synthetic and authentic databases. Ma K et al. [37] proposed a multi-task end-to-end optimized deep neural network (MEON) for blind image quality assessment (BIQA). Different from most deep neural networks, biologically inspired generalized divisive normalization (GDN) was chosen instead of rectified linear unit as the activation function. And experients demonstrated GDN was effective at reducing model parameters/layers while achieving similar quality prediction performance. Ma K et al. [38] focused on learning blind image quality assessment (BIQA) models, which predicted the quality of a digital image with no access to its original pristine-quality counterpart as reference. Q Wu et al. [39] proposed an unified deep auxiliary learning network to train the blind image sharpness assessment (BISA) metric and enhancer simultaneously. The proposed method aimed to exploit the complementary information between two tasks and boost both of their performance. Experimental results showed that the proposed method outperforms many state-of-the-art algorithms in both the BISA and sharpness enhancement tasks. Deraining quality assessment (DQA) plays an important role in evaluating and guiding the design of the image deraining algorithm. Existing deraining algorithms are far from sufficient to measure the practicability of a deraining algorithm. By building a subjective DQA database that collected diverse authentic rain images and their derained versions, and developing a blind quality metric is to predict the deraining quality, Q Wu et al. [40] proposed a bi-directional gated fusion network (B-GFN). For image quality assessment(IQA), much rearsch tended to use the deep learning based approaches. Various blind image quality assessment models have been developed to quantity the distortion degrees across different HDR images. However, blind image quality assessment models exclude visual content information and fail to conduct an end-to-end image enhancement towards a desired quality score. L Wang et al. [41] proposed to jointly conduct blind tone-mapped image quality assessment and enhancement via disentangled representation learning. Limited by the static model and once-for-all learning strategy, existing blind image quality assessment (BIQA) methods failed to perform the cross-task evaluations in many practical applications. To address this issue, R Ma et al.

[42] proposed a dynamic Remember and Reuse network. Their network sequentially updated the parameters for every task one by one, and part of task-specific parameters was settled with each update step. Extensive experiments showed this method efficiently achieved the cross-task BIQA without catastrophic forgetting.

In addition, C Huang et al. [43] proposed a deep convolutional network for quality evaluation of object segmentation, which could help obtain better segmentation result based on the predicted segmentation quality score. To assess a saliency map's quality, the only way is to compute it with the ground-truth reference map. However, the ground-truth reference map for the saliency region is unavailable. Facing this fact, L Tang et al. [44] proposed a deep saliency quality assessment network (DSQAN) to predict the saliency quality scores directly from saliency maps, which could not only lead better quality prediction accuracy, but also brought out more robust results. In order to predict the quality score of saliency map by only looking over the saliency map itself. L Tang et al. [44] proposed deep saliency quality assessment network (DSQAN). Their experimental results on the MSRA10K dataset demonstrated that our proposed method has the ability to precisely predict the quality of a given saliency map. Due to the absence of manually annotated bounding-box in practice, the quality metric towards blind assessment of object proposal is highly desirable for singling out the optimal proposals. Q Wu et al. [19] proposed a blind proposal quality assessment algorithm based on the Deep Objectness Representation and Local Linear Regression (DORLLR). Their method outperformed the state-of-the-art blind proposal evaluation metrics. Blind image quality assessment (BIQA) of distorted stereoscopic pairs without referring to the undistorted source is a challenging problem. J Wang et al. [45] proposed a binocular rivalry inspired multi-scale model to predict the quality of stereoscopic images. Experimental results showed that the proposed 3D-BIQA model could lead to significantly improved quality prediction performance. In image segmentation, W Shi et al. [46] proposed two types of CNN structures such as double-net and multi-scale network for segmentation quality evaluation. To train and verify the proposed networks, they constructed a novel objective segmentation quality evaluation dataset with large amount of data by combining several proposal generation methods. In capturing quality cues in blind segmentation quality assessment (SQA) is a challenging task, F Meng et al. [47] proposes a new blind SQA method that captured a variety of quality cues using two considerations. An end-to-end segmentation quality assessment network was proposed to capture these different types of quality cues by the above-mentioned two considerations. Existing detection or recognition systems typically select one state-of-the-art proposal algorithm to produce massive object-covered candidate windows, while Q Wu et al. [48] proposed a lazy learning strategy to train the GPE. They tried to build query-specific training subset for each given proposal, and showed the proposed method delivers a higher quality prediction accuracy even with respect to the deep neural network learned by end-to-end method. Images acquired by outdoor vision systems easily suffer poor visibility and annoying interference due to the rainy weather. Q Wu et al. [49] first created a de-raining quality assessment (DQA) database that collected 206 authentic rain images and their de-rained versions produced by 6 representative single image rain removal algorithms. Then, a subjective study was conducted on our DQA database, which collected the subject-rated scores of all de-rained images. Experiments confirmed that the proposed method significantly outperforms many existing universal blind image quality assessment models.

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