

# AIGCOIQA2024: PERCEPTUAL QUALITY ASSESSMENT OF AI GENERATED OMNIDIRECTIONAL IMAGES

Liu Yang<sup>1</sup>, Huiyu Duan<sup>1</sup>, Long Teng<sup>1</sup>, Yucheng Zhu<sup>1</sup>, Xiaohong Liu<sup>1</sup>, Menghan Hu<sup>2</sup>, Xiongkuo Min<sup>1</sup>, Guangtao Zhai<sup>1</sup>, Patrick Le Callet<sup>3</sup>

<sup>1</sup> Shanghai Jiao Tong University, Shanghai, China      <sup>2</sup> East China Normal University, Shanghai, China

<sup>3</sup> Université de Nantes, Nantes, France

Email: {ylyl.yl, huiyuduan, tenglong, zyc420, xiaohongliu, minxiongkuo, zhaiguangtao}@sjtu.edu.cn,  
mhhu@ce.ecnu.edu.cn, patrick.lecallet@univ-nantes.fr

## ABSTRACT

In recent years, the rapid advancement of Artificial Intelligence Generated Content (AIGC) has attracted widespread attention. Among the AIGC, AI generated omnidirectional images hold significant potential for Virtual Reality (VR) and Augmented Reality (AR) applications, hence omnidirectional AIGC techniques have also been widely studied. AI-generated omnidirectional images exhibit unique distortions compared to natural omnidirectional images, however, there is no dedicated Image Quality Assessment (IQA) criteria for assessing them. This study addresses this gap by establishing a large-scale AI generated omnidirectional image IQA database named AIGCOIQA2024 and constructing a comprehensive benchmark. We first generate 300 omnidirectional images based on 5 AIGC models utilizing 25 text prompts. A subjective IQA experiment is conducted subsequently to assess human visual preferences from three perspectives including quality, comfortability, and correspondence. Finally, we conduct a benchmark experiment to evaluate the performance of state-of-the-art IQA models on our database. The database will be released to facilitate future research.

**Index Terms**— AI generated content (AIGC), text-to-image generation, omnidirectional images, image quality assessment

## 1. INTRODUCTION

AI Generated Content (AIGC) refers to generate various forms of content such as texts, images, musics, videos, and 3D interactive contents, *etc*, using AI. Thanks to the rapid advancement of generative models such as Generative Adversarial Network (GAN) [1], Variational Auto Encoders (VAE) [2] and Diffusion Models (DMs) [3], *etc.*, as well as language-vision models such as BLIP2 [4] and CLIP [5], *etc.*, recent AI Generated Images (AIGIs) [6, 7] have shown excellent performance, and have been extended to omnidirectional image generation. Omnidirectional images can provide 360-degree free viewing experience, which are widely used in Virtual Reality (VR), Augmented Reality (AR), game development, cultural heritage protection and other fields, which are generally shown in the Equirectangular Projection



**Fig. 1.** An overview of the AIGCOIQA2024 database.

(ERP) format to warp the image and adapt to omnidirectional characteristics. The recent emergence of AI based omnidirectional image generation models [8, 9] have shown their potential of fast and creative omnidirectional content generation.

However, many omnidirectional images generated by AI are of low quality and cannot meet the visual expectations of the users. Compared with natural omnidirectional images, AI generated omnidirectional images may not only exhibit the issues such as blurriness, noise, distortion, and lighting problems, but also exist some unique degradations caused by the AI generation, such as unrealism, unreasonable composition, and low relevance between text and image. These quality degradation issues can significantly affect the immersive experience of the users in real-world applications. Therefore, it is significant and necessary to identify and evaluate the generated omnidirectional images that do not meet the user preferences, and either discard or modify them accordingly.

Existing Image Quality Assessment (IQA) models primarily focus on low-level aspects of image quality, such as lighting, color, and clarity. As aforementioned, AI generated omnidirectional images may not only show degradations in low-level visual aspects but also in high-level preference aspects. While there are quantitative metrics such as Fréchet Inception Distance (FID) [10] proposed to evaluate the performance of generation models, these algorithms can only assess the authenticity dimension of an image set, which lack the capability to evaluate a single image and perform text-image correspondence measure. Other algorithms, like CLIPScore [11], mainly consider the text-image correspondence dimension of AI-generated images, while ignoring the comprehensive assessment of authenticity and overall qual-

ity of omnidirectional images. Recently, some studies have established IQA databases for classical AI-generated images and performed benchmark experiments [12] [13]. However, IQA studies for AI-generated omnidirectional images are still lacking, which have significant difference compared with classical image in terms of formats, characteristics, and applications.

To better understand human visual preferences for AI generated omnidirectional images and facilitate the development of IQA algorithms for such images, we construct a database termed AIGCOIQA2024, which contains 300 omnidirectional images and collected corresponding human preference ratings from three perspectives. Specifically, we first generate 300 omnidirectional images based on 5 different models with 25 text prompts describing diverse indoor and outdoor scenes. Different from general AIGC IQA databases, such as AIGCIQA2023 [12], in the subsequent subjective preference assessment experiment, subjects are instructed to score the images from the perspectives of quality, comfortability, and correspondence based on human visual preferences on account of the AIGC degradations and the applications of the omnidirectional images. Our contributions can be summarized as follows:

- We propose to assess AI generated omnidirectional images from the perspectives of quality, comfortability, and correspondence to quantify human visual preferences.
- A human preference assessment database for omnidirectional images, termed AIGCOIQA2024, is established, which is the first AIGC IQA database for omnidirectional images to the best of our knowledge.
- We analyze the human preference characteristics for AI generated omnidirectional images based on the constructed database.
- We conduct a benchmark experiment, evaluating performance of some state-of-the-art (SOTA) models on our AIGCOIQA2024 database in terms of quality, comfortability, and correspondence.

The remaining content of this paper is outlined as follows. In section 2, we describe the construction procedure of our AIGCOIQA2024 database in detail, including the process of image generation and the execution of subjective experiments. In section 3, we conduct statistics analysis for images in AIGCOIQA2024 along with the analysis of the subjective data. Section 4 introduces the benchmark experiment, showing the performance of state-of-the-art (SOTA) models on AIGCOIQA2024 database. In Section 5 we conclude the paper and highlight future research directions.

## 2. AIGCOIQA2024 DATABASE CONSTRUCTION

### 2.1. Omnidirectional Image Generation

In order to better understand human visual preferences for AI-generated omnidirectional images, we establish an IQA



**Fig. 2.** An example of the subjective experiment interface in unity, participants can use the cursor to click on the score box to select the “quality” score.

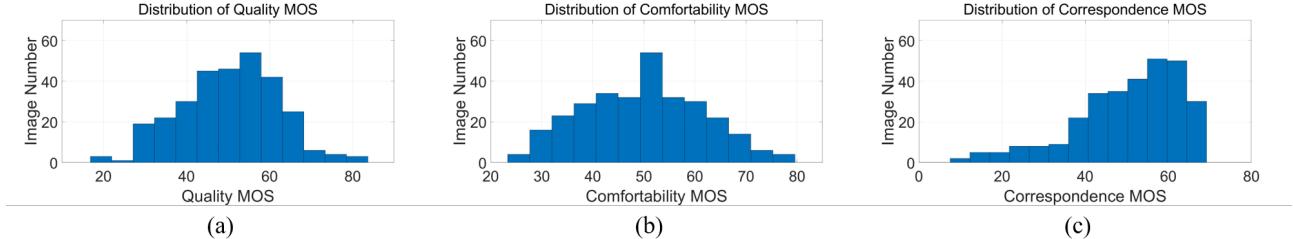
database containing 300 omnidirectional images. We first collect 25 omnidirectional images from the MVDiffusion [8] [14] training dataset and SUN360 [15] as natural instances. Then we use BLIP2 [4] to annotate the images to form preliminary prompts, and use GPT4 to add details and polish them. The generated prompts describe 12 indoor and 13 outdoor scenes, respectively, which are diverse and cover a wide range of scenarios. The descriptions of the prompts contain abundant scene details, making the generated images more distinguishable in terms of text-image correspondence.

For each prompt, we adopt 5 AIGC models, including MVDiffusion [8], Text2Light [9], DALLE [6], omni-inpainting [8] [16] and a fine-tuned Stable Diffusion model [7] to generate omnidirectional images. When fine-tuning Stable Diffusion model [7], we use 2000 and 4000 BLIP2-labeled [4] indoor/outdoor ERP omnidirectional images to fine-tune the Unet module only to achieve indoor/outdoor omnidirectional generation. We generate two omnidirectional images for each of the first four generation models mentioned above, respectively, and one for fine-tuned Stable Diffusion model [7]. For MVDiffusion [8] generation, we adjust the denoising time to generate distinguishable images. Overall, taking natural omnidirectional images into account, we have a total of 12 omnidirectional images for each prompt, and a total of  $(12 + 13) \times 12 = 300$  omnidirectional images in the database. Fig. 1 gives an overview of the images in our AIGCOIQA2024.

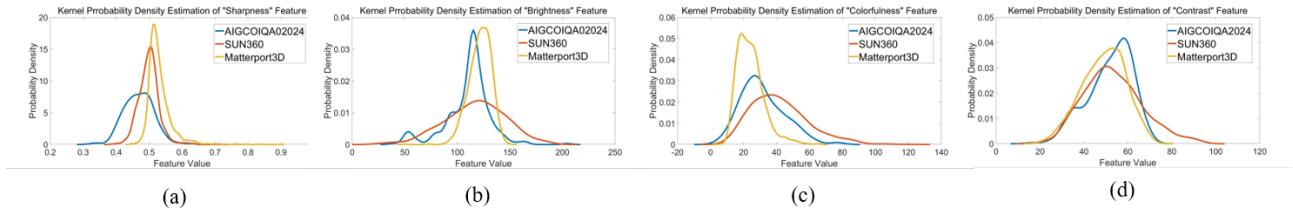
### 2.2. Subjective Experiment Setup

To measure human visual preferences for generated omnidirectional images, we further conduct a subjective evaluation experiment. Due to the inherent characteristics of omnidirectional images generated by AI, we cannot measure human visual preferences only from the dimension of “quality”, as discussed in AIGCIQA2023 [12]. However, different from the general AIGC IQA problem [12], AI generated omnidirectional images are mainly produced for VR and AR applications, in which users generally have particular visual characteristics [17–24]. Therefore, in this paper, we propose to evaluate human visual preferences for generated omnidirectional images from three perspectives, including quality, comfortability and correspondence.

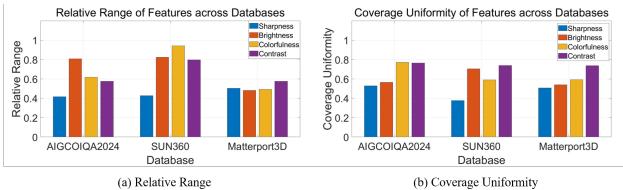
The first evaluative dimension is “quality”, *i.e.* a com-



**Fig. 3.** (a) MOS distribution of quality score.(b) MOS distribution of comfortability score.(c) MOS distribution of correspondence score.



**Fig. 4.** Kernel distribution of four selected features of three databases: AIGCOIQA2024, SUN360 [15], Matterport3D [14].



**Fig. 5.** Relative range and Coverage uniformity of the four selected features on the three databases.

hensive score of low-level visual qualities such as color, lighting and clarity, *etc*. Since generated omnidirectional images are mainly viewed in VR environments, We further present the second evaluation perspective, *i.e.*, “**comfortability**”, which is defined as the user experience preference for AI-generated omnidirectional images. Specifically, subjects are asked to give an overall score for the authenticity level, structure deformation level, as well as the comfort level. Since the generated omnidirectional images are mainly produced via the control of the text prompts, the correspondence between text and image is also a critical criteria for evaluating the quality of AI-generated omnidirectional images, *i.e.* “text-image correspondence”.

Then we conduct a subjective experiment under the guidance of ITU-R BT.500-14 [25], with a total of 20 subjects participating (10 males and 10 females). All subjects have normal or corrected-to-normal vision. After browsing 13 training samples, the participants are asked to view 300 omnidirectional images and score them from the perspectives of quality, comfortability and correspondence ranging from 1 to 10 with an interval of 1 based on the subject’s perception. The images are randomly sorted and displayed sequentially in head-mounted displays (HMDs) based on the software designed using the Unity, as shown in Fig. 2.

### 2.3. Subjective Data Processing

We follow the instructions of ITU [26] to conduct the outlier detection and subject rejection. As a result, no subjects are

rejected and the rejection ratio is 3% for all ratings. For the remaining valid subjective scores, we convert the raw ratings into Z-scores, then linearly scale them to the [0,100] range. The final Mean Opinion Score (MOS) is calculated as follows:

$$z_{ij} = \frac{m_{ij} - \mu_i}{\sigma_i}, \quad z'_{ij} = \frac{100z_{ij} + 3}{6} \quad (1)$$

$$MOS_j = \frac{1}{N} \sum_{i=1}^N z'_{ij} \quad (2)$$

where  $m_{ij}$  is the subjective score given by the  $i$ -th subject to the  $j$ -th image,  $\mu$  is the mean score given by the  $i$ -th subject,  $\sigma$  is the standard deviation and  $N$  is the total number of subjects.

Fig. 3 illustrates histograms of the MOSs of quality, comfortability, and correspondence perspectives. The MOSs distribution shows that our database encompasses a broad range of scores, indicating its diversity. Moreover, different perspectives have different distributions, which also illustrates the differences between the three evaluation perspectives.

## 3. DATABASE ANALYSIS

### 3.1. Statistics Analysis for Generated Omnidirectional Images

We conduct statistical analysis for our AIGCOIQA2024 database in terms of four low-level vision feature dimensions including: “sharpness”, “brightness”, “colorfulness” and “contrast”. Some images from real-world omnidirectional databases, *i.e.*, Matterport3D [14] and SUN360 [15] for comparison. For simplicity, we refer to these four features as  $C_i$ , ( $i = 1, 2, 3, 4$ ), respectively. Fig. 4 shows the kernel distribution of each feature for these three databases. It can be observed that the generated omnidirectional images have a wide distribution in “sharpness” and “colorfulness” features, showing their diversity. For the “contrast” feature, generated omnidirectional images show similar characteristics



**Fig. 6.** Comparison of the differences between three evaluation perspectives. (a) The left two omnidirectional images have better quality, but worse comfortability and correspondence. (b) The left two omnidirectional images have better comfortability, but worse quality and correspondence. (c) The left two omnidirectional images have better correspondence, but worse quality and comfortability.

compared with other two natural omnidirectional databases. However, for the “brightness” feature, our database shows narrow distribution range compared to SUN360 [15].

To evaluate the distribution and uniformity of the databases over the four features, we further compute and compare the relative range and uniformity of coverage. The relative range is calculate as:

$$R_i^d = \frac{\max(C_i^d) - \min(C_i^d)}{\max_d(C_i^d)} \quad (3)$$

where  $C_i^d$  refers to the data distribution of database  $d$  on feature  $i$ , and  $\max_d(C_i^d)$  refers to the maximum value on feature  $i$  across all databases. Uniformity of coverage is calculated as the entropy of the B-bin histogram of  $C_i^d$  over all sources for each database  $d$ :

$$U_i^d = - \sum_{b=1}^B p_b \log_B p_b \quad (4)$$

where  $p_b$  is the normalized number of souces in bin  $b$  for each feature in each database.

The relative range and uniformity of coverage are plotted in Fig. 5, quantifying intra- and inter-database differences. It can be concluded from the figures that the images in our AIGCOIQA2024 dataset cover diverse ranges regarding the four selected features.

### 3.2. Preferences Analysis from Three Perspectives for Generated Omnidirectional Images

In order to further emphasize the different focus of our three evaluation dimensions and to verify the necessity of evaluating these three dimensions separately for a single AI generated omnidirectional image, three sets of examples are given

in Fig. 6. The four images in each set are generated based on the same prompt. For the left two images in each set, one dimension score is significantly higher than other two scores, while for the right two images, that score is significantly lower than other two scores. In Fig. 6 (a), Fig. 6 (b), Fig. 6 (c), the left two images have higher quality scores, comfortability scores, correspondence scores, respectively, while the right two images have lower scores in these corresponding dimensions. We conclude that different rating perspectives can reflect different human preferences, which are related but distinct. Therefore, the assessment for a generated omnidirectional image must be performed from multiple dimensions.

Summarizing from the above, IQA of AI-generated omnidirectional images from any of these three dimensions alone is one-sided, and these three evaluation dimensions are independent. Therefore, when evaluating IQA of AI-generated omnidirectional images, we must evaluate an image comprehensively from all the three dimensions of quality, comfortability, and correspondence proposed above.

## 4. EXPERIMENT

### 4.1. Benchmark Models

To evaluate the performance of various existing models on the prediction of human visual preferences for AI generated omnidirectional images, we employ 19 state-of-the-art no-reference (NR) IQA models for comparison. The selected models can be categorized into three groups:

- **Handcrafted-based** models, which include QAC [27], BMPRI [28], NIQE [29], ILNIQE [30], HOSA [31],

**Table 1.** Performance comparision of the state-of-the-art NR-IQA models on the evaluation of human preferences for AI generated omnidirectional images from the perspectives of quality, comfortability and correspondence. The best performances are marked in **RED** and the second-best performances are marked in **BLUE**.

Dimension	Quality			Comfortability			Correspondence		
	Model	SRCC	KRCC	PLCC	SRCC	KRCC	PLCC	SRCC	KRCC
QAC [27]	0.1802	0.1197	0.0933	0.2665	0.1823	0.2483	0.1756	0.1175	0.0023
BMPRI [28]	0.4285	0.3010	0.5612	0.2652	0.1776	0.3728	0.2705	0.1780	0.3092
NIQE [29]	0.6858	0.4814	0.6236	0.5741	0.4128	0.6072	0.6672	0.4786	0.5776
ILNIQE [30]	0.0434	0.0293	0.0617	0.0298	0.0186	0.0902	0.2959	0.1964	0.3055
HOSA [31]	0.7114	0.5154	0.7175	0.4793	0.3282	0.5020	<b>0.7200</b>	<b>0.5262</b>	0.6738
BPRI-PSS [32]	0.3673	0.2465	0.4299	0.2153	0.1427	0.2216	0.5782	0.4101	0.6491
BPRI-LSSs [32]	0.3018	0.2094	0.4398	0.2435	0.1668	0.3516	0.1004	0.0672	0.1536
BPRI-LSSn [32]	0.3604	0.2300	0.5095	0.1506	0.0825	0.3268	<b>0.5532</b>	0.3878	0.5433
BPRI [32]	0.3553	0.2503	0.4849	0.2866	0.1986	0.4092	0.1863	0.1269	0.2319
FISBLIM [33]	0.6472	0.4588	0.6124	0.4425	0.3015	0.3492	0.6836	0.4929	0.5493
CLIPScore [11]	0.3308	0.2241	0.3320	0.1752	0.1192	0.1666	0.3809	0.2641	0.4915
CNNIQA [34]	0.7066	0.5127	0.6345	0.5715	0.4068	0.5709	0.5935	0.4222	0.5291
Resnet18 [35]	0.7722	<b>0.5852</b>	0.7286	0.6537	0.4728	0.6047	<b>0.6709</b>	0.4801	0.6829
Resnet34 [35]	0.6343	0.4632	0.6478	0.6551	0.4747	0.6177	0.5414	0.3848	0.6407
VGG16 [36]	0.7956	0.6047	0.7351	0.7074	0.5309	0.6616	0.6598	0.4747	0.6936
VGG19 [36]	0.7628	0.5731	0.7105	0.7310	0.5439	0.6893	0.6773	0.4927	<b>0.7054</b>
HyperIQA [37]	<b>0.8354</b>	<b>0.6405</b>	<b>0.7769</b>	0.7477	0.5564	0.7516	0.6506	0.4701	0.7052
MANIQA [38]	0.8038	0.6160	0.7682	<b>0.7837</b>	<b>0.5906</b>	<b>0.7796</b>	<b>0.7198</b>	<b>0.5303</b>	<b>0.7598</b>
TReS [39]	<b>0.8355</b>	<b>0.6378</b>	<b>0.7803</b>	<b>0.7768</b>	<b>0.5857</b>	<b>0.7763</b>	0.7036	0.5174	0.6996

FISBLIM [33], BPRI-PSS [32], BPRI-LSSs [32], BPRI-LSSn [32] and BPRI [32].

- **Vision-language pretrained** models, which include CLIPScore [11].
- **Deep learning-based** models, including CNNIQA [34], Resnet18 [35], Resnet34 [35], VGG16 [36], VGG19 [36], HyperIQA [37], MANIQA [38] and TReS [39].

For traditional hand-crafted models, we directly employ them to predict the preference scores for the omnidirectional images in our database. For CLIPScores [11], we simply calculate the score using the cosine similarity between text and image embeddings. For deep learning-based IQA models, we partition the database into training and testing sets with a ratio of 3:2, without scene or text-prompt repeat. based on different scenes. The training parameters are setthe same as the officially released code.

#### 4.2. Performance Analysis

Three evaluation metrics, including Spearman Rank Correlation Coefficient (SRCC), Pearson Linear Correlation Coefficient (PLCC), and Kendall’s Rank Correlation Coefficient (KRCC), are adopted to evaluate the performance of the models from the perspectives of quality, comfortability, and correspondence.

Table 1 demonstrates the performance of the aforementioned state-of-the-art models. It can be observed that, in general, hand-crafted models show poor performance for

evaluating the human preference of generated omnidirectional images, and these models perform almost worse for the dimension of comfortability compared to other two dimensions. Deep learning-based models generally outperform hand-crafted models, but their performance is still not entirely satisfactory. Particularly, they struggle to achieve good performance in quality, comfortability and correspondence simultaneously. These models generally perform better in the quality dimension but worse in the comfortablity and correspondence dimensions, due to the unawareness of the authenticity and comfortable texture of natural omnidirectional images, as well as the ignoring of utilizing the text information. These can be explored in future works.

#### 5. CONCLUSION AND FUTURE WORKS

It is important to study the human preferences for AI-generated omnidirectional images, which is rarely researched in the current literature. To this end, we first construct a database named AIGCOIQA2024, AI-generated omnidirection images and corresponding collected preference ratings from the perspectives of quality, comfortability and correspondence, respectively. Based on the database, we analyze the human visual preference characteristics for the generated omnidirectional images, and conduct a benchmark study. The current models cannot well handle this new task. It is worthwhile to explore the characteristic of natural omnidirectional images to improve the comfortability evaluation and exploit text information to improve the correspondence assessment in the future.

## 6. REFERENCES

- [1] Ian Goodfellow, Jean Pouget-Abadie, Mehdi Mirza, Bing Xu, David Warde-Farley, Sherjil Ozair, Aaron Courville, and Yoshua Bengio, “Generative adversarial nets,” in *Proceedings of the Advances in Neural Information Processing Systems*, 2014, vol. 27.
- [2] Diederik P Kingma and Max Welling, “Auto-Encoding Variational Bayes,” *arXiv e-prints*, p. arXiv:1312.6114, Dec. 2013.
- [3] Robin Rombach, Andreas Blattmann, Dominik Lorenz, Patrick Esser, and Björn Ommer, “High-resolution image synthesis with latent diffusion models,” in *Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition (CVPR)*, pp. 10684–10695.
- [4] Junnan Li, Dongxu Li, Silvio Savarese, and Steven Hoi, “BLIP-2: Bootstrapping Language-Image Pre-training with Frozen Image Encoders and Large Language Models,” *arXiv e-prints*, p. arXiv:2301.12597, Jan. 2023.
- [5] Alec Radford, Jong Wook Kim, Chris Hallacy, Aditya Ramesh, Gabriel Goh, Sandhini Agarwal, Girish Sastry, Amanda Askell, Pamela Mishkin, Jack Clark, Gretchen Krueger, and Ilya Sutskever, “Learning transferable visual models from natural language supervision,” in *Proceedings of the International Conference on Machine Learning*. pp. 8748–8763, PMLR.
- [6] Aditya Ramesh, Prafulla Dhariwal, Alex Nichol, Casey Chu, and Mark Chen, “Hierarchical Text-Conditional Image Generation with CLIP Latents,” *arXiv e-prints*, p. arXiv:2204.06125, Apr. 2022.
- [7] Robin Rombach, Andreas Blattmann, Dominik Lorenz, Patrick Esser, and Björn Ommer, “High-resolution image synthesis with latent diffusion models,” in *Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition (CVPR)*, June 2022, pp. 10684–10695.
- [8] Shitao Tang, Fuyang Zhang, Jiacheng Chen, Peng Wang, and Yasutaka Furukawa, “MVDiffusion: Enabling holistic multi-view image generation with correspondence-aware diffusion,” in *Proceedings of the Neural Information Processing Systems (NeurIPS)*, 2023.
- [9] Zhaoxi Chen, Guangcong Wang, and Ziwei Liu, “Text2light: Zero-shot text-driven hdr panorama generation,” *ACM Trans. Graph.*, vol. 41, no. 6, nov 2022.
- [10] Martin Heusel, Hubert Ramsauer, Thomas Unterthiner, Bernhard Nessler, and Sepp Hochreiter, “GANs Trained by a Two Time-Scale Update Rule Converge to a Local Nash Equilibrium,” in *Proceedings of the Advances in Neural Information Processing Systems*, 2017, vol. 30.
- [11] Jack Hessel, Ari Holtzman, Maxwell Forbes, Ronan Le Bras, and Yejin Choi, “CLIPScore: A Reference-free Evaluation Metric for Image Captioning,” *arXiv e-prints*, p. arXiv:2104.08718, Apr. 2021.
- [12] Jiarui Wang, Huiyu Duan, Jing Liu, Shi Chen, Xiongkuo Min, and Guangtao Zhai, “Aigcqa2023: A large-scale image quality assessment database for ai generated images: from the perspectives of quality, authenticity and correspondence,” in *Proceedings of the CAAI International Conference on Artificial Intelligence (CICAI)*. Springer, 2023, pp. 46–57.
- [13] Chunyi Li, Zicheng Zhang, Haoning Wu, Wei Sun, Xiongkuo Min, Xiaohong Liu, Guangtao Zhai, and Weisi Lin, “Agicqa-3k: An open database for ai-generated image quality assessment,” *arXiv preprint arXiv:2306.04717*, 2023.
- [14] Angel Chang, Angela Dai, Thomas Funkhouser, Maciej Halber, Matthias Niessner, Manolis Savva, Shuran Song, Andy Zeng, and Yinda Zhang, “Matterport3d: Learning from rgb-d data in indoor environments,” *Proceedings of the International Conference on 3D Vision (3DV)*, 2017.
- [15] Jianxiong Xiao, Krista A. Ehinger, Aude Oliva, and Antonio Torralba, “Recognizing scene viewpoint using panoramic place representation,” in *Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition (CVPR)*, 2012, pp. 2695–2702.
- [16] Rafail Fridman, Amit Abecasis, Yoni Kasten, and Tali Dekel, “SceneScape: Text-Driven Consistent Scene Generation,” *arXiv e-prints*, p. arXiv:2302.01133, Feb. 2023.
- [17] Yuxin Zhu, Xilei Zhu, Huiyu Duan, Jie Li, Kaiwei Zhang, Yucheng Zhu, Li Chen, Xiongkuo Min, and Guangtao Zhai, “Audio-visual Saliency for Omnidirectional Videos,” *arXiv e-prints*, p. arXiv:2311.05190, Nov. 2023.
- [18] Xilei Zhu, Huiyu Duan, Yuqin Cao, Yuxin Zhu, Yucheng Zhu, Jing Liu, Li Chen, Xiongkuo Min, and Guangtao Zhai, “Perceptual Quality Assessment of Omnidirectional Audio-Visual Signals,” in *Proceedings of the CAAI International Conference on Artificial Intelligence (CICAI)*, Singapore, 2024, pp. 512–525.
- [19] Huiyu Duan, Xiongkuo Min, Wei Sun, Yucheng Zhu, Xiao-Ping Zhang, and Guangtao Zhai, “Attentive deep image quality assessment for omnidirectional stitching,” *IEEE Journal of Selected Topics in Signal Processing*, vol. 17, no. 6, pp. 1150–1164, 2023.

- [20] Huiyu Duan, Wei Shen, Xiongkuo Min, Danyang Tu, Jing Li, and Guangtao Zhai, “Saliency in augmented reality,” in *Proceedings of the 30th ACM International Conference on Multimedia*, 2022.
- [21] Huiyu Duan, Guangtao Zhai, Xiongkuo Min, Yucheng Zhu, Yi Fang, and Xiaokang Yang, “Perceptual quality assessment of omnidirectional images,” in *Proceedings of the IEEE International Symposium on Circuits and Systems (ISCAS)*, 2018, pp. 1–5.
- [22] Huiyu Duan, Lantu Guo, Wei Sun, Xiongkuo Min, Li Chen, and Guangtao Zhai, “Augmented reality image quality assessment based on visual confusion theory,” in *Proceedings of the IEEE International Symposium on Broadband Multimedia Systems and Broadcasting (BMSB)*, 2022, pp. 1–6.
- [23] Yucheng Zhu, Guangtao Zhai, Yiwei Yang, Huiyu Duan, Xiongkuo Min, and Xiaokang Yang, “Viewing behavior supported visual saliency predictor for 360 degree videos,” *IEEE Transactions on Circuits and Systems for Video Technology*, vol. 32, no. 7, pp. 4188–4201, 2022.
- [24] Huiyu Duan, Guangtao Zhai, Xiaokang Yang, Duo Li, and Wenhan Zhu, “Ivqad 2017: An immersive video quality assessment database,” in *Proceedings of the International Conference on Systems, Signals and Image Processing (IWSSIP)*, 2017, pp. 1–5.
- [25] Huiyu Duan, Xiongkuo Min, Yucheng Zhu, Guangtao Zhai, Xiaokang Yang, and Patrick Le Callet, “Confusing image quality assessment: Toward better augmented reality experience,” *IEEE Transactions on Image Processing*, vol. 31, pp. 7206–7221, 2022.
- [26] B. Series, “Methodology for the subjective assessment of the quality of television pictures,” Tech. Rep. ITU-R BT, ITU-R, 2012.
- [27] Wufeng Xue, Lei Zhang, and Xuanqin Mou, “Learning without human scores for blind image quality assessment,” *Proceedings of the IEEE Computer Society Conference on Computer Vision and Pattern Recognition*.
- [28] Xiongkuo Min, Guangtao Zhai, Ke Gu, Yutao Liu, and Xiaokang Yang, “Blind image quality estimation via distortion aggravation,” *IEEE Transactions on Broadcasting*, vol. 64, no. 2, pp. 508–517, 2018.
- [29] Anish Mittal, Rajiv Soundararajan, and Alan C. Bovik, “Making a “completely blind” image quality analyzer,” *IEEE Signal Processing Letters*, vol. 20, no. 3, pp. 209–212, 2013.
- [30] Lin Zhang, Lei Zhang, and Alan C. Bovik, “A feature-enriched completely blind image quality evaluator,” *IEEE Transactions on Image Processing*, vol. 24, no. 8, pp. 2579–2591, 2015.
- [31] Jingtao Xu, Peng Ye, Qiaohong Li, Haiqing Du, Yong Liu, and David S. Doermann, “Blind image quality assessment based on high order statistics aggregation,” *IEEE Transactions on Image Processing*, vol. 25, pp. 4444–4457, 2016.
- [32] Xiongkuo Min, Ke Gu, Guangtao Zhai, Jing Liu, Xiaokang Yang, and Chang Wen Chen, “Blind quality assessment based on pseudo-reference image,” *IEEE Transactions on Multimedia*, vol. 20, no. 8, pp. 2049–2062, 2018.
- [33] Ke Gu, Guangtao Zhai, Min Liu, Xiaokang Yang, Wenjun Zhang, Xianghui Sun, WanHong Chen, and Ying Zuo, “Fisblim: A five-step blind metric for quality assessment of multiply distorted images,” in *Proceedings of the SiPS*, 2013, pp. 241–246.
- [34] Le Kang, Peng Ye, Yi Li, and David Doermann, “Convolutional neural networks for no-reference image quality assessment,” in *Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition (CVPR)*, June 2014.
- [35] Kaiming He, Xiangyu Zhang, Shaoqing Ren, and Jian Sun, “Deep residual learning for image recognition,” in *2016 IEEE Conference on Computer Vision and Pattern Recognition (CVPR)*, 2016, pp. 770–778.
- [36] Karen Simonyan and Andrew Zisserman, “Very Deep Convolutional Networks for Large-Scale Image Recognition,” *arXiv e-prints*, p. arXiv:1409.1556, Sept. 2014.
- [37] Shaolin Su, Qingsen Yan, Yu Zhu, Cheng Zhang, Xin Ge, JinQiu Sun, and Yanning Zhang, “Blindly assess image quality in the wild guided by a self-adaptive hyper network,” in *2020 IEEE/CVF Conference on Computer Vision and Pattern Recognition (CVPR)*, 2020, pp. 3664–3673.
- [38] Sidi Yang, Tianhe Wu, Shuai Shi, Shanshan Lao, Yuan Gong, Mingdeng Cao, Jiahao Wang, and Yujiu Yang, “MANIQA: Multi-dimension Attention Network for No-Reference Image Quality Assessment,” *arXiv e-prints*, p. arXiv:2204.08958, Apr. 2022.
- [39] S. Alireza Golestaneh, Saba Dadsetan, and Kris M. Kitani, “No-reference image quality assessment via transformers, relative ranking, and self-consistency,” in *Proceedings of the IEEE/CVF Winter Conference on Applications of Computer Vision (WACV)*, January 2022, pp. 1220–1230.