ABSTRACT

With the development of rendering techniques, computer graphics generated images (CGIs) have been widely used in practical application scenarios such as architecture design, video games, simulators, movies, etc. Different from natural scene images (NSIs), the distortions of CGIs are usually caused by poor rendering settings and limited computation resources. What’s more, some CGIs may also suffer from compression distortions in transmission systems like cloud gaming and stream media. However, limited work has been put forward to tackle the problem of computer graphics generated images’ quality assessment (CG-IQA). Therefore, in this paper, we establish a large-scale subjective CG-IQA database to deal with the challenge of CG-IQA tasks. We collect 25,454 in-the-wild CGIs through previous databases and personal collection. After data cleaning, we carefully select 1,200 CGIs to conduct the subjective experiment. Several popular no-reference image quality assessment (NR-IQA) methods are tested on our database. The experimental results show that the handcrafted-based methods achieve low correlation with subjective judgment and deep learning based methods obtain relatively better performance, which demonstrates that the current NR-IQA models are not suitable for CG-IQA tasks and more effective models are urgently needed.

Index Terms— Computer graphic generated images (CGIs), image quality assessment (IQA), subjective experiment, no-reference (NR).

1. INTRODUCTION

Unlike natural scene images (NSIs), which are captured from the real world, computer graphic images (CGIs) are artificially rendered using computer graphics [1]. More specifically, rendering indicates the process of generating images from a 2D or 3D model described by means of a computer program, which has been widely used in architecture, video games, simulators, movies, etc. [2]. Note that we do not consider the images generated by the neural network based generative models such as GAN [3] and NERF [4] since the quality of these images are largely dependent on training samples and well-designed networks, which is out of our research purposes. Details of the quality assessment for generative images can be obtained from [5-7]. According to the rendering tools and purposes, CGIs can be further categorized into photorealistic images and non-photorealistic images. Photorealistic images are rendered by modeling the real world to achieve photorealism [8], while non-photorealistic images focus on enabling a wide variety of expressive styles for digital art, such as painting, drawing, and animated cartoons [9]. Despite of the different rendering purposes and techniques, both photorealistic and non-photorealistic images share similar distortions, such as texture loss caused by the limited computation resources, poor visibility caused by wrong exposure setting, and blur caused by low rendering accuracy. What’s more, accompanied by the rapid development of network service and entertainment consumption, people can perceive large numbers of CGIs through live broadcast and cloud gaming [10]. CGIs in such situations are also affected by the inevitable compression distortions in transmission systems, which damage the quality of CGIs and greatly influence user’s Quality of Experience (QoE).

In the last decade, image quality assessment (IQA) has been developed to facilitate the progress of image processing and analysis. Large numbers of IQA models [11-14, 15, 16, 17, 18, 19, 20, 21] have been proposed to predict the human perception of NSIs. However, CGIs and NSIs have huge differences in content and distortions, which indicates that it is difficult to transfer previous NSI-specific models to the CGI field. What’s more, little work has been dedicated to specifically assessing the quality of CGIs. A summarization of the gap in CGIs quality assessment (CG-IQA) is given here: 1) Nearly all existing CG-IQA databases are constructed in former times. The CGIs are selected from limited types of sources. Such CGIs are outdated and not able to cover the range of current rendering techniques. 2) The existing CG-IQA databases are relatively small in scale, which are not sufficient to support deep learning methods. 3) Most of the developed methods are full-reference (FR) and focus on limited types of distortions. Such methods focus on the quality of CGIs whose distortions are manually introduced to the reference images. However, in most situations, the reference CGIs are not available and the types of distortions are vari-
3D movies. In which 600 CGIs are from 3D games and 600 CGIs are from the process described above, a total of 1,200 CGIs are obtained, manually introduce new compression distortions. After the videos except screenshots from local game demos, we do not move the life bars, mini maps, and subtitles. Considering specifically eliminate the CGIs with similar contents and re-diversity and restrict the distractions of irrelevant things, we by extracting the frames of the movies. To ensure the scene solutions. We also personally collect 4,000 3D movie images ing to increase content diversity and cover more range of res- images from screenshots of local game demos and cloud gam- ages sourced from 18 popular 3D games and 26 recent 3D we collect 9,212 3D game images and 8,818 3D movie im- database designed for computer-generated images forensic), Thanks to the contributions of the LSCGB database [22] (a database designed for computer-generated images forensic), we collect 9,212 3D game images and 8,818 3D movie images sourced from 18 popular 3D games and 26 recent 3D movies. Additionally, we personally collect 3,424 3D games images with an interface designed by Python Tkinter on an iMac monitor which supports the resolution up to 4096 × 2304. We invite 12 male subjects and 8 female subjects to participate in the subjective experiment. The viewers are seated at a distance of around 1.5 times the screen height (45cm) in a laboratory environment that has normal indoor illumination levels. The quality scale scores from 0 to 5, with a minimum interval of 0.1. The whole experiment is split into four sessions and each session includes 300 CGIs for quality evaluation to ensure that each session lasts no more than half an hour. Therefore, each CGI is evaluated by 20 subjects, which generates a total of 20 × 1,200 = 24,000 quality scores. After the subjective experiment, we obtain all the quality scores from the subjects. Let $r_{ij}$ denote the raw score provided by the $i$-th subject on the $j$-th image, the z-scores are computed from the raw scores as follows:

$$z_{ij} = \frac{r_{ij} - \mu_i}{\sigma_i},$$

where $\mu_i = \frac{1}{N_i} \sum_{j=1}^{N_i} r_{ij}$, $\sigma_i = \sqrt{\frac{1}{N_i-1} \sum_{j=1}^{N_i} (r_{ij} - \mu_i)^2}$, and $N_i$ is the number of images seen by subject $i$. After that, we remove scores from unreliable subjects by using the recommended subject rejection procedure in the ITU-R BT.500-13 [23]. The z-scores are then linearly rescaled to $[0, 100]$. Finally, the MOS of the image $j$ is calculated by averaging the rescaled z-scores:

$$MOS_j = \frac{1}{M} \sum_{i=1}^{M} z'_{ij},$$

where $MOS_j$ indicates the MOS for the $j$-th CGI, $M$ is the number of the valid subjects, and $z'_{ij}$ are the rescaled z-scores. Some CGI samples and their corresponding MOSs are shown in Fig. 1. It can be seen that invisibility caused by wrong exposure and blur tend to result in poor MOS while CGIs containing exquisite details and fine illumination settings are more preferred by the viewers.

The distribution of the obtained MOS is illustrated in Fig. 2 and the respective distributions of MOS for movies images and games images are exhibited in Fig. 3, from which we can

| Database | Scale | Source | Scope | Resolution Range |
|----------|-------|--------|-------|------------------|
| CCT [11] | 528   | PC game images | Compression distortion | 720P 1080P |
| TGQA [11] | 1091 | Mobile game images | Aesthetic evaluation | 1080P |
| KUGVD [12] | 90 | PC game videos | Downsampling & Bitrates control | 480P 720P 1080P |
| TGV [13] | 1293 | Mobile game videos | Stull & Bitrates control | 480P 720P 1080P |
| Ours | 1200 | 3D movie & 3D game images | Rendering effect & Compression distortion | 480P ~ 4K |

2. SUBJECTIVE QUALITY ASSESSMENT

2.1. CGIs Collection

Thanks to the contributions of the LSCGB database [22] (a database designed for computer-generated images forensic), we collect 9,212 3D game images and 8,818 3D movie images sourced from 18 popular 3D games and 26 recent 3D movies. Additionally, we personally collect 3,424 3D games images from screenshots of local game demos and cloud gaming to increase content diversity and cover more range of resolutions. We also personally collect 4,000 3D movie images by extracting the frames of the movies. To ensure the scene diversity and restrict the distractions of irrelevant things, we specifically eliminate the CGIs with similar contents and remove the life bars, mini maps, and subtitles. Considering that most CGIs are obtained through compressed streams or videos except screenshots from local game demos, we do not manually introduce new compression distortions. After the process described above, a total of 1,200 CGIs are obtained, in which 600 CGIs are from 3D games and 600 CGIs are from 3D movies.
make several observations. First, the MOS of most images are located in the range [20, 80], showing a Gaussian-like distribution. Second, the score of images from 3D movies is slightly higher than that of images from 3D games in general, which is in line with common sense that movie content is carefully rendered through many complex processes, while game content is generated in real-time with limited sources.

3. PERFORMANCE AND ANALYSIS

Many IQA methods have been proposed to accurately predict the quality levels of distorted images in the last decade. Considering that the CGIs in our database do not have pristine sources, only no-reference image quality assessment (NR-IQA) models are qualified for evaluating their quality. Hence we select several representative NR-IQA models to test their effectiveness on our database.

3.1. Comparing Algorithms and Evaluation Criteria

On the proposed database, we list the performance of multiple state-of-the-art (SOTA) NR-IQA algorithms, which can be categorized into two types:

- **Handcrafted-based methods:** BRISQUE [14], BMPRI [15], BLIINDS-II [16], NFERM [17] and UCA [11]. These methods operate by extracting handcrafted features from images and regress the features to quality scores. Besides, UCA is an opinion-unware method and do not need training.
- **Deep learning based methods:** DBCNN [18], HyperIQA [19], MUSIQ [20], MGQA [24] and StairIQA [25]. Additionally, MUSIQ is a transformer-based model.

To quantitatively show the assessment ability of different methods, four mainstream evaluation criteria are utilized to compare the performance between the predicted scores and MOS, which include Spearman Rank Correlation Coefficient (SRCC), Kendall’s Rank Correlation Coefficient (KRCC), Pearson Linear Correlation Coefficient (PLCC), Root Mean Squared Error (RMSE). An excellent model should obtain values of SRCC, KRCC, and PLCC close to 1, and the value of RMSE near 0. Before calculating the criteria, we first apply a five-parameter logistic function to map the predicted scores according to the practices in [26]:

\[
\hat{y} = \beta_1 \left(0.5 - \frac{1}{1 + e^{\beta_2(y - \beta_3)}} \right) + \beta_4 y + \beta_5 \tag{3}
\]

where \( \{\beta_i \mid i = 1, 2, \ldots, 5\} \) are parameters to be fitted, \( y \) and \( \hat{y} \) are the predicted scores and mapped scores respectively.

3.2. Experiment Setup

Normally speaking, most NR-IQA methods are training based, which needs a training set to learn a mapping function between the feature/image domain and the quality domain. Thus we split the database with a ratio of 8:2 for the training set and testing set respectively. For deep learning based methods, we retrained all the models on the new database with default hyperparameter settings for validation.

To reduce the effect of randomness, we repeat the above process 1,00 times for handcraft-based methods and 10 times for deep learning based methods, and record the average values of SRCC, KRCC, PLCC, and RMSE as the final experimental results.
Table 2: Performance comparison of state-of-the-art NR-IQA methods on the proposed database. The best-performing method in each row is highlighted.

| Type          | Handcrafted-based | Deep learning based |
|---------------|-------------------|---------------------|
| Methods       | BRISQUE | BMPRI | BLINDS | NFERM | UCA  | DBCNN | HyperIQA | MUSIQ | MGQA | StairIQA |
| SRCC ↑        | 0.2669  | 0.1870 | 0.1644 | 0.1502 | 0.1824 | 0.5868 | 0.6966  | 0.6907 | 0.7013 | 0.7199 |
| PLCC ↑        | 0.2640  | 0.1926 | 0.1700 | 0.1330 | 0.2021 | 0.5893 | 0.6989  | 0.6883 | 0.7194 | 0.7276 |
| KRCC ↑        | 0.1804  | 0.1255 | 0.1117 | 0.1010 | 0.1224 | 0.4186 | 0.5103  | 0.5010 | 0.5154 | 0.5300 |
| RMSE ↓        | 11.8700 | 11.9551 | 11.8996 | 12.0222 | 11.9603 | 10.8278 | 8.8676  | 10.0001 | 8.9580 | 8.5841 |

3.3. Experiment Performance

3.3.1. Handcrafted-based Methods

The experimental results are clearly shown in Table 2. With closer inspection, we can find that all the mainstream handcrafted-based NR-IQA methods designed for NSIs are not effective for predicting the quality value of CGIs. BRISQUE [14] is a classic NR-IQA model based on natural scene statistics (NSS) and obtains the best performance among handcrafted-based methods. However, its SRCC and PLCC results are still lower than 0.3. We attempt to give the reasons for the poor performance of the above handcrafted-based NR-IQA methods.

1) The mentioned handcrafted-based methods are specially designed for NSIs and NSIs are quite different from CGIs in content. The majority of them usually utilize many NSS distributions to estimate quality-aware parameters and these parameters do not work for CGIs, since the attribute distributions of CGIs do not meet the prior knowledge of NSIs. In all, the knowledge learned from NSIs by such NR-IQA methods is not suitable for qualifying the quality of CGIs.

2) The CGIs in our database are more diverse in distortion types and resolutions. The selected handcrafted-based methods are designed on traditional databases where only one or several distortions are manually added to the reference images and the range of resolutions is limited. Therefore, it is not surprising that these methods achieve poor performance on our database.

3.3.2. Deep Learning Based Methods

The selected deep learning based NR-IQA methods are significantly superior to handcrafted-based NR-IQA methods and StairIQA [25] achieves first place in all criteria. However, the SRCC and PLCC results of StairIQA are lower than 0.75, which are not satisfactory enough. We also try to analyze the reasons for deep learning based methods’ performance.

1) Deep learning based methods have a better ability to extract features that meet the training scope, which enables them to gain better performance. However, the backbones employed in such models are all pre-trained on databases consisting of mostly NSIs (e.g. ImageNet), which may limit the effectiveness of deep learning based models.

2) We think the scale of our database is still not enough to reach the performance bottleneck of deep learning based methods and they may suffer from the effect of over-fitting. Therefore, we will push forward our work and enlarge the scale of our database for further research.

4. CONCLUSION

Computer graphics generated images (CGIs) are becoming more and more common in people’s entertainment life, which makes the quality assessment of CGIs a hot topic in the multimedia area. In this paper, we conduct a large-scale subjective study for the quality assessment of CGIs and create a new CG-IQA database. 1200 images are selected from dozens of different genres of 3D games and 3D movies for the construction of our database. In subjective experiments, a total of 24,000 subjective scoring data are collected from 20 observers. Several popular SOTA NR-IQA methods also test on the new database, which include both handcrafted-based and deep learning based methods. The experimental results show that the handcrafted-based methods achieve low correlation with human perception and deep learning based methods achieve relatively better performance, but are far from satisfactory. Our proposed database fills a gap in the research field for CG-IQA. In future work, we would further enlarge the scale of the database and carry out specific IQA models for CG-IQA problems.

5. REFERENCES

[1] Xiongkuo Min, Kede Ma, Ke Gu, Guangtao Zhai, Zhou Wang, and Weisi Lin, “Unified blind quality assessment of compressed natural, graphic, and screen content images,” IEEE Transactions on Image Processing, vol. 26, no. 11, pp. 5462–5474, 2017.

[2] Matt Pharr, Wenzel Jakob, and Greg Humphreys, Physically based rendering: From theory to implementation, Morgan Kaufmann, 2016.

[3] Ian Goodfellow, Jean Pouget-Abadie, Mehdi Mirza, Bing Xu, David Warde-Farley, Sherjil Ozair, Aaron Courville, and Yoshua Bengio, “Generative adversarial nets,” Advances in neural information processing systems, vol. 27, 2014.

[4] Ben Mildenhall, Pratul P Srinivasan, Matthew Tancik, Jonathan T Barron, Ravi Ramamoorthi, and Ren Ng, “Nerf: Representing scenes as neural radiance fields for
view synthesis,” in European conference on computer vision. Springer, 2020, pp. 405–421.
[5] Ali Borji, “Pros and cons of gan evaluation measures,” Computer Vision and Image Understanding, vol. 179, pp. 41–65, 2019.
[6] Shuyang Gu, Jianmin Bao, Dong Chen, and Fang Wen, “Giga: Generated image quality assessment,” in European Conference on Computer Vision. Springer, 2020, pp. 369–385.
[7] Gu Jinjin, Cai Haoming, Chen Haoyu, Ye Xiaoxing, Jimmy S Ren, and Dong Chao, “Pipal: a large-scale image quality assessment dataset for perceptual image restoration,” in European Conference on Computer Vision. Springer, 2020, pp. 633–651.
[8] Donald P Greenberg, Kenneth E Torrance, Peter Shirley, James Arvo, Eric Lafortune, James A Ferwerda, Bruce Walter, Ben Trumbore, Sumanta Pattanaik, and Sing-Choo Foo, “A framework for realistic image synthesis,” in Proceedings of the 24th annual conference on Computer graphics and interactive techniques, 1997, pp. 477–494.
[9] Drew Card and Jason L Mitchell, “Non-photorealistic rendering with pixel and vertex shaders,” Direct3D ShaderX: vertex and pixel shader tips and tricks, pp. 319–333, 2002.
[10] Asif Ali Laghari, Hui He, Kamran Ali Memon, Rashid Ali Laghari, Imitiaz Ali Halepoto, and Asiya Khan, “Quality of experience (qoe) in cloud gaming models: A review,” multiagent and grid systems, vol. 15, no. 3, pp. 289–304, 2019.
[11] Suiyi Ling, Junle Wang, Wenming Huang, Yundi Guo, Like Zhang, Yanqing Jing, and Patrick Le Callet, “A subjective study of multi-dimensional aesthetic assessment for mobile game image,” in Proceedings of the 1st Workshop on Quality of Experience (QoE) in Visual Multimedia Applications, 2020, pp. 47–53.
[12] Nabajeet Barman, Emmanuel Jammeh, Seyed Ali Ghorashi, and Maria G Martini, “No-reference video quality estimation based on machine learning for passive gaming video streaming applications,” IEEE Access, vol. 7, pp. 74511–74527, 2019.
[13] Shaoguo Wen, Suiyi Ling, Junle Wang, Ximing Chen, Lizhi Fang, Yanqing Jing, and Patrick Le Callet, “Subjective and objective quality assessment of mobile gaming video,” arXiv preprint arXiv:2103.05099, 2021.
[14] Anish Mittal, Anush Krishna Moorthy, and Alan Conrad Bovik, “No-reference image quality assessment in the spatial domain,” IEEE Transactions on image processing, vol. 21, no. 12, pp. 4695–4708, 2012.
[15] 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.
[16] Michele A Saad, Alan C Bovik, and Christophe Charrier, “Blind image quality assessment: A natural scene statistics approach in the dct domain,” IEEE transactions on Image Processing, vol. 21, no. 8, pp. 3339–3352, 2012.
[17] Ke Gu, Guangtao Zhai, Xiaokang Yang, and Wenjun Zhang, “Using free energy principle for blind image quality assessment,” IEEE Transactions on Multimedia, vol. 17, no. 1, pp. 50–63, 2014.
[18] Wei Xia Zhang, Kede Ma, Jia Yan, Dexiong Deng, and Zhou Wang, “Blind image quality assessment using a deep bilinear convolutional neural network,” IEEE Transactions on Circuits and Systems for Video Technology, vol. 30, no. 1, pp. 36–47, 2018.
[19] 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 Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition, 2020, pp. 3667–3676.
[20] Junjie Ke, Qifei Wang, Yilin Wang, Peyman Milanfar, and Feng Yang, “Musiq: Multi-scale image quality transformer,” in Proceedings of the IEEE/CVF International Conference on Computer Vision, 2021, pp. 5148–5157.
[21] Zicheng Zhang, Wei Sun, Xiongkuo Min, Wenhan Zhu, Tao Wang, Wei Lu, and Guangtao Zhai, “A no-reference evaluation metric for low-light image enhancement,” in 2021 IEEE International Conference on Multimedia and Expo (ICME). IEEE, 2021, pp. 1–6.
[22] Weiming Bai, Zhipeng Zhang, Bing Li, Pei Wang, Yangxi Li, Congxuan Zhang, and Weiming Hu, “Robust texture-aware computer-generated image forensic: Benchmark and algorithm,” IEEE Transactions on Image Processing, vol. 30, pp. 8439–8453, 2021.
[23] RECOMMENDATION ITU-R BT, “Methodology for the subjective assessment of the quality of television pictures,” International Telecommunication Union, 2002.
[24] Tao Wang, Wei Sun, Xiongkuo Min, Wei Lu, Zicheng Zhang, and Guangtao Zhai, “A multi-dimensional aesthetic quality assessment model for mobile game images,” in 2021 International Conference on Visual Communications and Image Processing (VCIP). IEEE, 2021, pp. 1–5.
[25] Wei Sun, Xiongkuo Min, Guangtao Zhai, and Siwei Ma, “Blind quality assessment for in-the-wild images via hierarchical feature fusion and iterative mixed database training,” arXiv preprint arXiv:2105.14550, 2021.
[26] Hamid R Sheikh, Muhammad F Sabir, and Alan C Bovik, “A statistical evaluation of recent full reference image quality assessment algorithms,” IEEE Transactions on image processing, vol. 15, no. 11, pp. 3440–3451, 2006.