Computers and Electrical Engineering 91 (2021) 107057

Contents lists available at ScienceDirect

Computers and Electrical Engineering

journal homepage: www.elsevier.com/locate/compeleceng

Learning HDR illumination from LDR panorama images☆,☆☆

Xin Jin [a,b,c], Xingfan Zhu [c], Xinxin Li [d], Kejun Zhang [c], Xiaodong Li [c,*], Xiaokun Zhang [c], Quan Zhou [e], Shujiang Xie [f], Xi Fang [c]

[a] State Key Laboratory of Shale Oil and Gas Enrichment Mechanisms and Effective Development, China
[b] Sinopec Key Laboratory of Shale Oil/Gas Exploration and Production Technology, China
[c] Beijing Electronic Science and Technology Institute, China
[d] Xidian University, China
[e] Nanjing University of Posts and Telecommunications, China
[f] School of Economics, Minzu University of China, China

ARTICLE INFO

Keywords:
Spherical harmonic lighting
All convolutional neural network
Augmented reality

ABSTRACT

For indoor scenes, the fourth-order spherical harmonic function is used to model the illumination, resulting in that 48 spherical harmonic coefficients are used to represent the whole scene. The illumination contained in the low dynamic range image is insufficient, so high dynamic range environment maps are adopted in this part, and the aim is to predict spherical harmonic coefficients of the corresponding high dynamic range image from the low dynamic range image. For this problem, the MSE loss function is used in this paper. Experiments verify the effectiveness of our method. The final visual results show that our method can predict accurate spherical harmonic coefficients, and the recovered luminance is realistic.

1. Introduction

The illumination determines the appearance of indoor scenes, such as color, brightness, and shadows on the ground. The illumination of indoor scenes has been widely used in many fields such as post-production of films, virtual military exercises, graphic design, and video game design. All of these applications involve inserting virtual objects into physical scenarios. To realize the realistic combinations of virtual objects and real scenes, illumination estimation becomes a critical work.

However, estimating the illumination from a single indoor image is difficult. In real scenes, the image formation process is affected by many factors, such as material properties, camera parameters, scene lighting, etc. In addition, multiple combinations of these factors will also have the same effect on the formation of the image, resulting in the uncertainty of the estimated illumination.

A simple and direct way to capture scene illumination is to place light probes such as mirror spheres and integrating spheres in the scene. However, this approach is not feasible because most of the images we use were not taken with a light probe in such a scene, and it is often impossible to place a probe in the scene.

Recently, deep learning has developed rapidly and successfully to solve many problems in computer vision. The application of deep learning to illumination estimation has become a hot topic in the field of computer vision. Many studies have used deep neural networks to estimate the illumination of a single indoor image [1,2], and achieved good results. However, how to obtain high quality and high precision illumination estimation from a single image is still a problem worth exploring.

☆ This paper was recommended for publication by associate editor Manu Malek.
☆☆ This paper is for CAEE special section VSI-aicv4. Reviews processed and recommended for publication to the Editor-in-Chief by Guest Editor Dr. Yujie Li.
* Corresponding author.
E-mail address: lxd@besti.edu.cn (X. Li).

https://doi.org/10.1016/j.compeleceng.2021.107057
Received 23 April 2020; Received in revised form 9 February 2021; Accepted 24 February 2021
Available online 16 March 2021
0045-7906/

Compared with the outdoor scene, the indoor scene environment is more complex and more difficult to recover due to the number and types of light sources affecting objects in the indoor scene. Different from the method of outdoor illumination, this paper adopts spherical harmonic function to solve the problem of indoor illumination. The spherical harmonic coefficient calculated by this function can represent the illumination distribution in all directions in the scene. Thus, the illumination analysis of indoor images is transformed into the prediction of these coefficients.

The main contributions of this paper are as follows:

(1) We proposed a method to recover high dynamic range illumination from low dynamic range image.
(2) We build an indoor dataset with various illumination conditions.

The arrangement of this paper is as follows: Section 2 describes related work; Section 3 introduces the approach employed in this paper; Section 4 shows the experiments; Section 5 summaries the conclusion and discussion.

2. Related work

A lot of research work have explored this problem and many methods have been proposed.

The light probe is a simple and direct way to capture luminance. Some methods capture high dynamic range illumination of a scene based on mirrored spheres and several photographs taken at different exposures.

Some methods rely on priors on scene geometry, illumination, and reflectance [3] to recover the illumination from an image. However, these priors apply only to specific scenes and cannot be used in other scenes, which limit the application of this method.

Based on the Preetham model, Hosek et al. [4] improved and put forward a sky brightness model, which can more accurately represents the sky brightness distribution than the Preetham model, and in the subsequent work, the model was extended to include the solar radiation function [5].

Lalonde et al. [6] also extended the Preetham model. They added a new empirical solar model, which represented the outdoor environmental light as the sum of the Preetham sky model and the solar model.

Some methods recover illumination parameters by using prior knowledge [7–11] about scene layout, reflectivity and scene illumination, which is used to create optimization or Bayesian models. Since this prior knowledge applies only to specific scenes and cannot be applied to other scenes, the application of these methods in real scenes has great limitations.

Xing et al. [12] proposed a dynamic light estimation method based on online video sequence, which is suitable for outdoor scenes with no shadow region and uneven sky brightness distribution.

Ma et al. [13] proposed a deep learning method to predict the sun's orientation directly from a picture, which adopted Alexnet network structure and compared the prediction results with different loss functions. The experimental results showed that the model trained by cosine distance had the highest prediction accuracy.

Jin et al. [14] proposed that short-cuts structure was added to the deep neural network structure to realize the fusion of low-level and high-level features, enhancing the image features extracted by the network.

Hold-geoffroy et al. [15] proposed a method based on CNN to estimate the high dynamic range illumination information corresponding to the low dynamic range image of a single outdoor. In this method, the physic-based Ho ek-Wilkie [4,5] sky model is first applied to the sky region in the panorama to obtain solar orientation, atmospheric turbidity, camera parameters and other lighting parameters. Then the deep neural network is trained using part of the images (training images) and acquired lighting parameters (label data) from the panoramic image.

Yi et al. [16] proposed to recover scene illumination represented as an environment map from human faces in an image. Highlights were extracted from faces by inputting a single image into the Highlight-Net. Then, this highlights were employed to generate an environment map.

Zhang et al. [17] proposed an end-to-end method for predicting illumination information in a high dynamic range from outdoor panoramic images with low dynamic range. This method uses the operation of convolution and deconvolution to realize the inverse tonal mapping process from low dynamic range to high dynamic range [18]. To train the network, the author synthesizes a large number of images with high dynamic range and corresponds images with low dynamic range. Meanwhile, this dataset also convenience future research work.

Gardner et al. [1] proposed an indoor light analysis method based on deep learning. The method uses a light source first classifier for light source location in low dynamic range images for automatic labeling, this tagging information as the tag data used for training a light source location prediction network, reuse after a small high dynamic range image to fine-tune trained network data sets to realize the image intensity information of the forecast.

Weber et al. [2] proposed a method for recovering an environment map from a single object image. The method first trains a depth encoder to learn how to represent the indoor lighting environment as a low-dimensional hidden vector, then trains a depth neural network to learn the mapping relationship between the image of a single object and the hidden vector space, where the geometry and reflectivity of the object in the image are known information. Finally, these hidden vectors generate the environment map representing the indoor lighting through the decoder.

Lan et al. [19] proposed a dual residual-path block (DRPB) that uses hierarchical features from the original low-resolution images. Li et al. [20] presented an innovative mobile learning platform QFK (quest for knowledge) , which follows the game-based learning paradigm. Xu et al. [21] proposed a novel model called ternary adversarial networks with self-supervision (TANSS) in this paper, to overcome the limitations of existing methods on this challenging task.

Lu et al. [22] plan to develop an intelligent learning model called Brain Intelligence (BI) that generates new ideas about events without having experienced them by using artificial life with an imagined function. They will also conduct demonstrations of the developed BI intelligence learning model on automatic driving, precision medical care, and industrial robots.

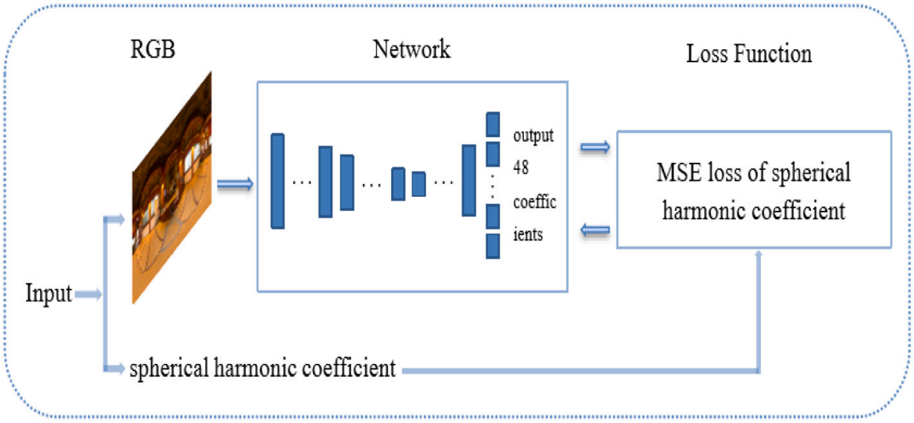

Fig. 1. The method of indoor illumination analysis based on image.

3. Approach

Due to the more commonly used JPG, PNG images belong to low dynamic range images, they contain less information on illumination. However, high dynamic range images such as HDR and ERX contain more illumination information. Therefore, in this paper, the high dynamic range indoor environment map is mainly used, and the corresponding high dynamic range spherical harmonic coefficient is predicted from the low dynamic range panoramic image. For this problem, the method proposed in this paper is shown in Fig. 1.

3.1. Spherical harmonic illumination

The method of using the spherical harmonic function to represent the illumination is called spherical harmonic illumination. The spherical harmonic illumination is a simplified representation of illumination, which uses a small number of coefficients to represent the surrounding complex ambient light, and these coefficients are used to reconstruct the illumination environment when rendering. It is a real-time rendering technology, which belongs to the category of precomputed radiative transfer (PRT). It is widely used in the field of game graphics rendering, and is used to simulate complex scene lighting quickly and in real time. It can simulate not only indoor scene lighting, but also outdoor scene lighting.

Most of the formulas involved in illumination calculation are complex spherical formulas. Because these formulas are tedious and time-consuming to calculate, it is difficult to use them to calculate the illumination of a certain point in the space in real time. To achieve real-time illumination computation and improve rendering speed, the spherical harmonic function is proposed to replace the complex spherical function to simplify the computation.

The idea of fitting spherical function with spherical harmonic function is based on the Fourier transform in the field of mathematics. This theory holds that for any function, it can be expressed as the sum of multiple trigonometric functions multiplied by the coefficients:

$$f(x) = \sum_{i=1}^{n} c_i * g_i(x)$$

where, c_i is the coefficient, $g_i(x)$ is a set of mutually orthogonal basis functions. Any complex function can be represented by any combination of any number of basic functions. Therefore, a complex spherical function can also be expressed by a simple spherical harmonic basic function and the corresponding coefficients. The basic function used in the spherical harmonic function is derived from Legendre polynomials. The number of orthogonal basis functions in the polynomial is expressed by the number of orders. The higher the order, the greater the number of basic functions, the better the fitting effect of the original function, and the higher the illumination quality of the reconstruction, but the corresponding coefficients will also increase. In practice, only the first few orders are used to construct the spherical harmonic function, while in this paper, 16 basis functions in the first four orders are used.

With the basic function, the conversion from spherical function to spherical harmonic function can be realized only by calculating the corresponding coefficient. The calculation of the spherical harmonic coefficient is based on the idea of probability theory, that is, the use of “finite” to estimate “infinite”. When calculating the coefficient of a spherical harmonic basis function, it is necessary to sample evenly on the sphere, the number of sampling points is determined by the specific situation, then calculate the spherical function value and the spherical harmonic based on function value of each sampling point, respectively, and calculate the product of the two, and finally calculate the sum of the results of all sampling points.

With the spherical harmonic coefficient, the reconstruction process of scene illumination is relatively simple. The illumination of any position on the sphere can be obtained by multiplying and summing each spherical harmonic basis function and its corresponding coefficients.

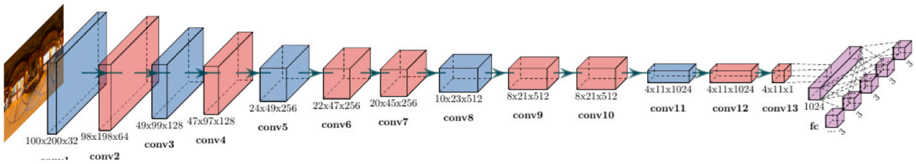

Fig. 2. Network structure.

Table 1
A detailed description of the network structure.

Input	200 × 400 × 3 (200: height, 400: width)			
1	conv: kernel = (3, 3)	stride = 2	filter = 32	output: 100 × 200 × 32
2	conv: kernel = (3, 3)	stride = 1	filter = 64	output: 98 × 198 × 64
3	conv: kernel = (3, 3)	stride = 2	filter = 128	output: 49 × 99 × 128
4	conv: kernel = (3, 3)	stride = 1	filter = 128	output: 47 × 97 × 128
5	conv: kernel = (3, 3)	stride = 2	filter = 256	output: 24 × 49 × 256
6	conv: kernel = (3, 3)	stride = 1	filter = 256	output: 22 × 47 × 256
7	conv: kernel = (3, 3)	stride = 1	filter = 256	output: 20 × 45 × 256
8	conv: kernel = (3, 3)	stride = 2	filter = 512	output: 10 × 23 × 512
9	conv: kernel = (3, 3)	stride = 1	filter = 512	output: 8 × 21 × 512
10	conv: kernel = (3, 3)	stride = 1	filter = 512	output: 8 × 21 × 512
11	conv: kernel = (3, 3)	stride = 2	filter = 1024	output: 4 × 11 × 1024
12	conv: kernel = (3, 3)	stride = 1	filter = 1024	output: 4 × 11 × 1024
13	conv: kernel = (1, 1)	stride = 1	filter = 1	output: 4 × 11 × 1
14	fc: output:1024			
15	16 (fc: output:3)			

3.2. Dataset preparation

Since this part should predict the corresponding high-dynamic range illumination from the low-dynamic range indoor image, this paper should use both low-dynamic range image and high-dynamic range images. Available in the field of computer vision. However, the existing high dynamic range of the indoor environment map dataset is small and difficult to obtain, so this article uses the images from multiple data sources, the first part of 130 images for download from the Internet, the second part is from the HDRI [23] Haven dataset of 103 indoor pictures, the third part is the Laval [24] HDR dataset of 2331 indoor pictures, these three parts constitute several 2564 data sets. To obtain the label data of these images, the fourth order spherical harmonic function is used to calculate them, and 48 spherical harmonic coefficients are obtained for each image. Where, 3 indicates that the number of channels in the RGB color space is 3.

In the training process of neural networks, the input image data are required to be of low dynamic range, so this study uses some image software to convert all the 2564 environmental maps of high dynamic range into JPG images. All images were then resized to 200*400 pixels. Finally, in this paper, it was randomly divided into training set, verification set and test set according to the ratio of 8:1:1, and 2054 training set pictures, 255 verification set pictures and 255 test set pictures were finally obtained. Tag data are also split into the same way.

3.3. Network architecture

The neural network structure used to predict the 48 spherical harmonic coefficients in this section is shown in Fig. 2, and its detailed description is shown in Table 1. It uses a fully convolutional neural network structure, which is composed of only 13 convolutional layers used for extracting image features and 2 fully connected layers used for outputting results, but without max-pooling layers. Due to the deeper number of network layers, it is easier to cause gradient dispersion problems during training. As a result, network performance is degraded. To effectively alleviate this problem, and this article adds a short-cut structure to the network. This structure contains 4 convolutional layers. Each layer has a larger convolution step for convolution operations on the image. The convolution results of each layer are stitched in the channel direction with a certain layer in the main network. Because the number of network layers in the short-cut structure is small and the convolution step is large, it can achieve high-level feature extraction. The main network has many network layers and the convolution step is small so that it can achieve low-level features. extract. Therefore, short-cut structure can better achieve the fusion of high-level and low-level features.

To obtain the tag of images, the network finally needs a total of 48 sphere harmonic coefficients, the number of 48 can be divided into 16 groups. Each group contains three data, respectively, on the R, G, and B channel components. There is a certain relationship with each other. Therefore, in the last layer of the network, 16 full connection layers of length 3 are adopted to output all the coefficients in the form of grouping.

Also, the network needs to output 48 spherical harmonic coefficients, with a large number of coefficients, and these 48 numbers can be divided into 16 groups, each group contains 3 data, which are, respectively, represented on the R channel, G channel, and

Table 2
The quantitative experimental results.

Loss	SH	Environment map
Our method	0.1563	0.2344

Fig. 3. Render the resulting image.

B channel. The three components have a certain relationship with each other and affect each other. Therefore, this study uses 16 fully-connected layers of length 3 to output all the coefficients in packets at the last layer of the network. Except for the last two layers, all convolutional layers are followed by a BatchNormation operation [25] and a Relu activation function.

3.4. Loss function

In this part, the loss function used to train the above-mentioned neural network structure is the mean square error (MSE) loss function of 48 spherical harmonic coefficients.

Spherical harmonic loss is used to measure the numerical error between the predicted spherical harmonic coefficient and the real value. Since the spherical harmonic coefficient of the first four orders is used in this paper, mean square error loss of spherical harmonic coefficient of each order is defined as follows:

$$loss_{SH} = \frac{1}{16}\sum_{i=0}^{l-1}\left(\sum_{j=0}^{N_i}\left(\frac{1}{3}\sum_{k=0}^{3}\left(\widehat{SH}_{i,j,k} - \widetilde{SH}_{i,j,k}\right)^2\right)\right)$$

where, l represents the order, in this paper, $l = 4$, $N_i = 2 \times i + 1$, represents the number of groups of spherical harmonic coefficients contained in the first order, k represents the first component of each group of spherical harmonic coefficients, with a total of 3 values, respectively represent three channels in the RGB color space.

4. Experiments

For the loss function defined in this paper, and we first perform some preprocessing operation to the label data. Some parameters are unevenly distributed, with large differences between values, and contain a few extreme data values. For example, values for smaller data range between [0, 1], while values for larger data range between [40, 50]. If such original data are directly used for network training, it will cause loss value to produce a large shock, so that the network is difficult to converge, and poor results will finally be generated. To solve this problem, this study uses the mean value and variance of each parameter to normalize all data into the distribution with mean value of 0 and variance of 1. First, a quantitative experiment is performed to verify the effectiveness of our method. The experiment is mainly focused on the prediction error of spherical harmonic coefficients and the reconstruction error of the original environment map. The experimental results are shown in Table 2. Then, a qualitative experiment is used to show the rendering results and the reconstruction results, which are shown in Figs. 3 and 4.

It shows from Table 2 that our method can get to small error estimated value of spherical harmonic coefficients.

In Fig. 3, (A) is the original high dynamic range indoor environment map, (B) is an image of a certain field of view, (C) is the rendering result of our method, (D) is the ground truth. It can be seen from Fig. 3 that the rendering result of our method is realistic and close to the ground truth.

In Fig. 4, (A) is the original high dynamic range indoor environment map, (B) is the reconstructed environment map of our method, (C) is the ground truth. It can be seen from Fig. 4 that the reconstructed result of our method is realistic and close to the ground truth.

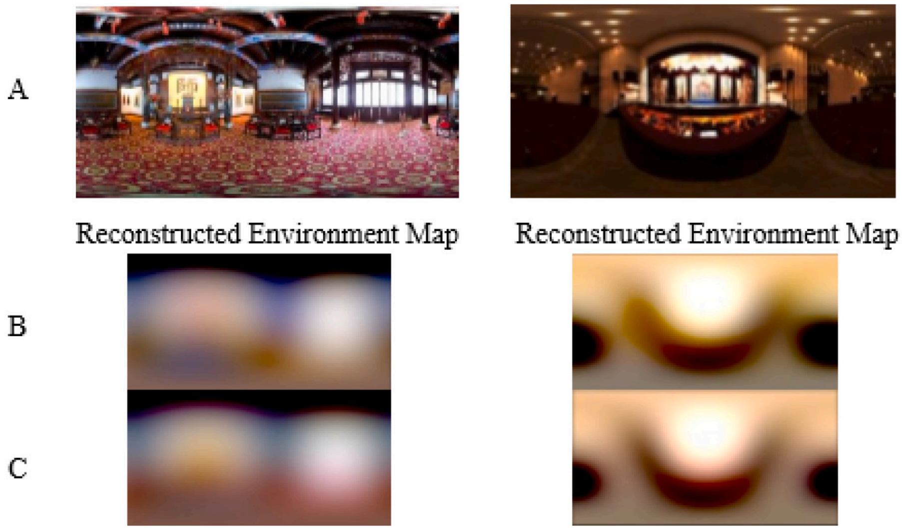

Fig. 4. Reconstruction of two different loss functions.

5. Conclusion and discussion

For more complex indoor ambient lighting, we use the 48 spherical harmonic coefficients generated by the sampling of the 4th order spherical harmonic function to simplify their representation. Therefore, the original illumination analysis problem of indoor images is simplified to the prediction problem of spherical harmonic coefficients. Simultaneously, to obtain an increasing amount of accurate illumination information from the image, we adopt the high dynamic range indoor environment map. The spherical harmonic coefficient label information corresponding to these high dynamic range environment maps is first generated. Then, these images are converted from high dynamic range to low dynamic range by using image tools. Finally, the corresponding illumination information of high dynamic range is predicted from these low dynamic range images. A series of experiments verify our method from both quantitative and qualitative aspects.

For the problem of indoor illumination analysis based on image, the spherical harmonic function is used to simplify the representation of illumination. However, the restoration result of this method is relatively rough, which can only reconstruct the low-frequency signal, and the high-frequency information is lost a lot, which limits the generation of partial illumination effect, such as object shadow projection. To better capture the high-frequency signal, the wavelet function or other basis functions can be used to simulate illumination in the future.

CRediT authorship contribution statement

Xin Jin: Algorithm design, Network structure design. **Xingfan Zhu:** Algorithm design, Writing and reviewing. **Xinxin Li:** Algorithm design, Network structure design, Algorithm implementation, Writing and reviewing. **Kejun Zhang:** Data preprocessing, Algorithm implementation. **Xiaodong Li:** Data preprocessing. **Xiaokun Zhang:** System design. **Quan Zhou:** Visualization. **Shujiang Xie:** Visualization. **Xi Fang:** Algorithm implementation.

Declaration of competing interest

No author associated with this paper has disclosed any potential or pertinent conflicts which may be perceived to have impending conflict with this work. For full disclosure statements refer to https://doi.org/10.1016/j.compeleceng.2021.107057.

Acknowledgments

This work is partially supported by the National Natural Science Foundation of China (grant numbers 62072014, 61772047, 61876093), the Beijing Natural Science Foundation, China (grant number L192040), the Open Project Program of Sinopec Key Laboratory of Shale Oil/Gas Exploration and Production Technology, China (grant number: G5800-20-ZS-KFZY003), the Natural Science Foundation of Jiangsu Province, China under Grant BK20181393.

References

[1] Gardner, Marc-André, Sunkavalli K, Yumer E, et al. Learning to predict indoor illumination from a single image. ACM Trans Graph 2017;36(6):1–14.
[2] Weber H, Prevost D, Lalonde J-F. Learning to estimate indoor lighting from 3d objects. 2018, arXiv:1806.03994.
[3] Lombardi S, Nishino K. Reflectance and illumination recovery in the wild. IEEE Trans Pattern Anal Mach Intell 2016;38(1):129–41.
[4] Hosek Lukas, Wilkie Alexander. An analytic model for full spectral sky-dome radiance. ACM Trans Graph 2012;31(4):1–9.
[5] HošekHošek Lukáš, Wilkie Alexander. Adding a solar-radiance function to the Hošek-Wilkie skylight model. IEEE Comput Graph Appl 2013;33(3):44–52.
[6] Lalonde Jean-François, Matthews Iain. Lighting estimation in outdoor image collections. In: 2014 2nd International conference on 3D vision, vol. 1. IEEE; 2014, p. 131–8.
[7] Barron Jonathan T, Malik Jitendra. Shape, illumination, and reflectance from shading. IEEE Trans Pattern Anal Mach Intell 2014;37(8):1670–87.
[8] Lombardi Stephen, Nishino Ko. Reflectance and illumination recovery in the wild. IEEE Trans Pattern Anal Mach Intell 2015;38(1):129–41.
[9] Liu Ruijun, Shi Yuqian, Yi Bu, Xu Yang, Lu Huimin, Wang Xiangshang, Lu Weihua, Ji Changjiang. Humanized computing for mass customization application in curriculum management. Mob Netw Appl 2019;1–12.
[10] Liu Ruijun, Yang Rui, Li Shanxi, Shi Yuqian, Jin Xin. Painting completion with generative translation models. Multimedia Tools Appl 2020;79(21):14375–88.
[11] Liu Ruijun, Zhuang Chu, Yang Rui, Ma Liang. Effect of economically friendly acustimulation approach against cybersickness in video-watching tasks using consumer virtual reality devices. Appl Ergon 2020;82:102946.
[12] Xing GuanYu, Zhou Xuehong, Liu YanLi, Qin XueYing, Peng QunSheng. Online illumination estimation of outdoor scenes based on videos containing no shadow area. Sci China Inf Sci 2013;56(3):1–11.
[13] Ma Wei-Chiu, Wang Shenlong, Brubaker Marcus A, Fidler Sanja, Urtasun Raquel. Find your way by observing the sun and other semantic cues. In: 2017 IEEE international conference on robotics and automation. IEEE; 2017, p. 6292–9.
[14] Jin Xin, Sun Xing, Zhang Xiaokun, Sun Hongbo, Xu Ri, Zhou Xinghui, Li Xiaodong, Liu Ruijun. Sun orientation estimation from a single image using short-cuts in DCNN. Opt Laser Technol 2019;110:191–5.
[15] Hold-Geoffroy Yannick, Sunkavalli Kalyan, Hadap Sunil, Gambaretto Emiliano, Lalonde Jean-François. Deep outdoor illumination estimation. In: Proceedings of the IEEE conference on computer vision and pattern recognition, 2017. p. 7312–21.
[16] Yi R, Zhu C, Tan P, et al. Faces as lighting probes via unsupervised deep highlight extraction. In: ECCV, 2018.
[17] J. Zhang, F. Lalonde J. Learning high dynamic range from outdoor panoramas. In: 2017 IEEE international conference on computer vision, 2017. p. 4529–38.
[18] Springenberg, Riedmiller. Striving for simplicity: The all convolutional net. 2014, arXiv:1412.6806.
[19] Lan Rushi, Sun Long, Liu Zhenbing, Lu Huimin, Pang Cheng, Luo Xiaonan. MADNet: A fast and lightweight network for single image super-resolution. IEEE Trans Cybern 2019.
[20] Li Y, Lu H, Kihara K, et al. Motor anomaly detection for aerial unmanned vehicles using temperature sensor. Artif Intell Robot 2018.
[21] Xu Xing, Lu Huimin, Song Jingkuan, Yang Yang, Shen Heng Tao, Li Xuelong. Ternary adversarial networks with self-supervision for zero-shot cross-modal retrieval. IEEE Trans Cybern 2019.
[22] H. Lu, Y. Li, M. Chen, et al. Brain intelligence: Go beyond artificial intelligence. Mob Netw Appl 2017.
[23] Zaal G. HDRI haven. 2018, https://hdrihaven.com.
[24] Lalonde J-F, Asselin L-P, Becirovski J, Hold-Geoffroy Y, Garon M, Gardner M-A, Zhang J. The laval HDR sky database. 2016, http://www.hdrdb.com.
[25] Rempel AG, Trentacoste M, Seetzen H, Young HD, Heidrich W, Whitehead L, Ward G. LDR2HDR: On-the-fly reverse tone mapping of legacy video and photographs. ACM Trans Graph 2017;26(3):39.

Xin Jin was born in Anhui province, China. He received the Ph.D. degree from Beihang University, China. Now, he is an associate professor at department of cyber security, Beijing Electronic Science and Technology Institute, China. His research is focused on visual computing and visual media security.

Xingfan Zhu was born in Jiangsu province, China. He received the Bachelor's degree from Xidian University, China. Now, he is a graduate student in Beijing Electronic Science and Technology Institute, China. His research is focused on visual computing.

Xinxin Li was born in Hebei province, China. She received the B.S. degree from Hebei Normal University Of Science and Technology, China. She is currently pursuing the M.S. degree in computer science and technology at Xidian University, China. Her research interest is focused on image illumination estimation.

Kejun Zhang was born in Jilin province, China. He received the Ph.D. degree from University of Science and Technology Beijing, China. Now, he is a professor at Beijing Electronic Science and Technology Institute, China. His research is focused on intelligent computing, natural language processing, content security and cloud computing security.

Xiaodong Li was born in Henan province, China. He received the Ph.D. degree from Northwestern Polytechnic University, China. Now, he is an associate professor at department of cyber security, Beijing Electronic Science and Technology Institute, China. His research is focused on information security and visual media security.

Xiaokun Zhang was born in Gansu province, China. He is now a professor and leader of the Department of Computer Science and Technology, Beijing Electronic Science and Technology Institute, China. His research interests include computer science and technology.

Quan Zhou received Ph.D. degree in electronics and information engineering from Huazhong University of Science and Technology(HUST), Wuhan, China in 2013. Now he is an assistant professor in the college of Telecommunications and Information engineering at Nanjing University of Posts and Telecommunications. His research interests include computer vision and pattern recognition. He is member of IEEE.

Shujiang Xie received the Ph.D. degree from Nankai University, China. He was a postdoc at Renmin University of China. He was a visit scholar at Brock University, Canada. Now, he is a professor at School of Economics, Minzu University of China. His research is focused on smart city and economics.

Xi Fang received the Ph.D. degree from Peking University, Beijing, China, in 2016. He is currently an Assistant Professor with Beijing Electronic Science and Technology Institute, Beijing, China. He has published over 40 academic articles in peer-reviewed journals and prestigious conferences. His research interests include coherent optical communication, orthogonal frequency division multiplexing systems, channel estimation, phase noise suppression, etc.