Deep Single-Exposure HDR Imaging Approaches

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Abstract. The purpose of single-exposure HDR image reconstruction is to recover the missing information in the saturated region of the LDR image, and use neural network to reconstruct the HDR image. In recent years, single-exposure HDR imaging using deep learning (DL) has made significant progress. In this study, the latest development of deep single-exposure HDR imaging method was comprehensively and deeply investigated and analyzed. At present, there are five main methods for deep single-exposure HDR imaging: direct learning from a single LDR image, generating bracketed LDR image stacks, computationally efficient learning, learning camera imaging pipeline, and learning neural sensors. Importantly, this study reviewed the limitations and future work of each category. In addition, this study also discussed the potential and future trends of each category constructively.

Keywords: Deep Learning; Deep Single-exposure HDR; Neural Network; Neural Sensors.

1. Introduction

Ordinary digital cameras cannot capture a wide range of light intensity levels in natural scenes. This will result in the loss of pixel information in the under-exposed and over-exposed areas of the image, resulting in a low dynamic range (LDR) image. In order to recover the lost information and represent the wide range illumination in the image, it is necessary to generate a high dynamic range (HDR) image [2]. The purpose of single-exposure HDR image reconstruction is to restore the missing information in the saturated region of the LDR image, and use neural network to reconstruct the HDR image.

Although the deep HDR image is successfully reconstructed by combining a group of LDR images with different exposures, this mode still has limitations, it must deal with the misalignment with the reference image caused by the scene movement, or it needs a special optical system. Single exposure HDR image reconstruction avoids these limitations. The unique advantage of single-exposure HDR reconstruction is that it can use images taken by standard cameras, and even restore the full dynamic range of traditional LDR content [1]. Therefore, single-exposure HDR reconstruction has attracted the attention of the research community.

In this study, the latest development of deep single-exposure HDR imaging method was comprehensively and deeply investigated and analyzed. This study divides the existing deep single-exposure HDR imaging methods into five categories: direct learning from a single LDR image, generating bracketed LDR image stacks, computationally efficient learning, learning camera imaging pipeline, and learning neural sensors. Importantly, this study reviewed the limitations and future work of each category. In addition, this study also discussed the potential and future trends of each category constructively. Finally, this paper summarizes the full text.

2. Approaches

2.1. Direct Learning from a Single LDR Image

It is a challenging task to reconstruct HDR from any single exposure LDR image [3]. The most direct method is to use the encoder-decoder network structure to learn directly from a single LDR image. Zhang et al. proposed a complete end-to-end learning method to estimate the extremely high dynamic range of outdoor lighting from a single LDR 360 ° panoramic view. Their main idea is to use a large synthetic data set composed of a realistic virtual city model, and use the HDR skylight detector in the real world for illumination to train the deep convolution automatic encoder. The main contribution of 3D panorama autoencoder and regression can be summarized as a complete end-to-end learning method, which can directly return HDR from the LDR information in the outdoor panorama. Of course, this is a challenging task: the sun can be 17 f-stops brighter than the rest of the sky. In order to learn this relationship, they rely on a large set of HDR sky environment maps. They use them as light sources to render high-quality composite city models, thus forming a large composite panorama. From this data set, they trained a deep convolution automatic encoder from LDR to HDR, and through a large number of experiments on synthetic and real data, it successfully and accurately predicted the extreme dynamic range of outdoor lighting[20].

HDRCNN, proposed by Eilertsen et al, is a representative method for reconstructing HDR images from a single LDR image by estimating the missing information in bright image parts (such as highlights) lost due to camera sensor saturation. HDRCNN is based on the design of fully convolutional neural network (CNN) in the form of hybrid dynamic range automatic encoder. In order to improve the generalization of complex saturated scenes, HDR images from existing data sets are used to simulate various LDR exposures. The main contribution of HDRCNN can be summarized as hybrid dynamic range automatic encoder, which is customized to operate on LDR input data and output HDR images. It uses HDR specific transfer learning to skip links, color space and loss functions. In addition, a deep learning system[3] is proposed, which can reconstruct high-quality HDR images from any single exposure LDR images, provided that the saturation region is relatively small.

Santos et al. in identified the disadvantage of applying the same convolution filter to well-exposed and saturated pixels, which would cause ambiguity in the training process and lead to checkerboard and halo artifacts in HDR images. To solve this problem, they proposed a novel learning-based method using CNN, which has masking characteristics and perceptual loss. The main contribution of feature masking CNN can be summarized as a feature masking mechanism to avoid relying on invalid information in saturated regions. This masking method greatly reduces artifacts and improves the quality of the final result. In addition, they adapt the VGG-based perceptual loss function to the HDR reconstruction task. Compared with the loss function of pixel direction, their loss [1] can better reconstruct sharp texture in saturated region.

In contrast, Marnerides et al. proposed a novel multi-scale CNN architecture called ExpandNet. In the local range, one branch of the network learns how to maintain and expand high-frequency details, while the extended branch learns the information of the larger pixel neighborhood. The last third branch provides the overall information by learning the global context of the input. The main contribution of ExpandNet can be summarized as multi-branch CNN, which provides a dedicated solution [4] for extending single-exposure LDR content to HDR, because each branch involves different aspects of expansion. Deep bilateral learning is a novel neural network architecture inspired by bilateral grid processing and local affine color transformation, as proposed by Gharbi et al. Their architecture learns to make local, global and content-related decisions to approximate the required image conversion. The main contribution of this method can be summarized as a model, which is trained offline from data, so it is not necessary to access the original operator at runtime. This enables their models to learn complex, scene-related transformations [5], which have no available reference implementation, such as the photo editing of human mappers.

These pioneering methods have inspired many attempts to improve the exposure diversity of LDR images. Moriwaki et al. found that the use of reconstruction loss, such as mean square error (MSE) loss, usually leads to the loss of blurring effect and semantic details in HDR images. In order to solve these problems, in addition to HDR reconstruction loss, a mixed loss composed of perceptual loss and adversarial loss is also proposed. The reconstruction loss is designed so that the intensity gradient in saturated and dark regions can be reconstructed. All losses are defined in the logarithmic space of image strength, which is crucial for making learning easy to handle. The main contributions of this method can be summarized as follows: this is the first study to introduce the perceptual loss of HDR reconstruction. The method [7] also proposes a novel inverse tone mapping network called "iTM-Net". In order to obtain the relative brightness by using iTM-Net linearization, a novel loss function considering the nonlinear relationship between LDR and HDR images is proposed. In the novel loss function, the hue of the target HDR image is mapped to the LDR image by using the reversible hue mapping operator, and then the distance between the hue mapping image and the predicted image is calculated. The main contribution of this method can be summarized as the proposed loss function, which can not only normalize HDR images, but also widely distribute the pixel values of HDR images, such as LDR images.

2.2. Generating Bracketed LDR Image Stacks

The technology of generating bracketed LDR image stacks, in short, is a technology that takes some method to generate bracketed LDR image stacks from an HDR image, and then reconstructs an HDR image from the bracketed LDR images.

In fact, the lack of high-quality training data for single-exposure HDR reconstruction is an uncomfortable problem. For this reason, Endo et al. proposed a data-driven method of inverse tone mapping based on CNNs. The key idea of this method is to synthesize LDR images shot at different exposures (i.e., bracketed images) based on supervised learning, and then reconstruct HDR images by combining them. The training dataset consists of various bracketed images, which are created using HDR images and CRF databases. In addition, this method also proposes a neural network structure based on 2D convolution and 3D deconvolution, which has a skip connection for generating overexposed and under-exposed images. This method can not only reproduce the natural color without introducing visible noise, but also reproduce the color of saturated pixels[8].

A novel ITM method was apposed, which uses a deep neural network with chain structure to generate multiple exposure image stacks from a single LDR image. The proposed neural network is composed of six sub-networks, which can generate images with the first three exposures and the last three exposures from the input LDR images with intermediate exposures. As a result, the proposed network can solve the problems of ghost and tear in conventional HDRI. In addition, the proposed network is scalable because it can be further expanded to obtain a wider dynamic range. In addition, since patch-based learning has been carried out, there is less restriction[9] on the image resolution of the restored HDR image.

A deep neural network architecture was proposed by Lee et al., based on GAN architecture to solve the inverse tone mapping problem and reconstruct missing signals from a single LDR image. In addition, they trained a CNN based neural network to infer the relationship between the relative exposure values using the conditional GAN structure. Therefore, the proposed method generates an HDR image recovered in the saturated (or dark) region of a given LDR image. The main contribution of this method can be summarized as follows: it converts LDR images into nonlinear LDR images corresponding to +1 or - 1 exposure stops. This feature enables the architecture to generate images with different exposure levels without additional network and training process. In addition, they built a relatively simple network structure by changing the deep structure effect of deep-chain HDRI [10] into a recursive structure. Kim et al. proposed a distinguishable HDR synthesis process, which realizes the end-to-end training process and reduces the generation of local inversion artifacts. They also combine the image decomposition method to separate the exposure transmission task and the cyclic network to gradually increase or decrease the exposure level, so as to reconstruct the multi-exposure stack from a single exposure image. The main contribution of this method can be summarized as a recursive method that effectively utilizes the recursive process in multi-exposure stack generation. Their network learning generates sequential images with multiple exposures in the recursive structure [11], because the recursive process needs to maintain the gradient until the entire multi-exposure stack is generated.

In order to build a training data, set of low-contrast and high-contrast image pairs for end-to-end CNN learning, Cai et al. built a large-scale multi-exposure image data set, including 589 carefully selected high-resolution multi-exposure sequences with 4413 images. Thirteen representative multi-exposure image fusion and stack-based high dynamic range imaging algorithms are used to generate contrast enhanced images for each sequence, and subjective experiments are conducted to screen the best quality image as the reference image for each scene. Using the constructed dataset, CNN can be easily trained as a SICE intensifier to improve the contrast of underexposed or overexposed images [12]. Instead of generating multiple exposures, An et al. proposed a single-lens high dynamic range (HDR) imaging algorithm using deep convolution neural network (CNN) with line-by-line exposure changes in a single image. They first convert the input original Bayer image into the irradiance value by calibrating the lines with different exposures. Then, they developed a new CNN model to recover the lost information caused by underexposure or overexposure and reconstruct the original radiation map. Finally, they obtained the HDR image by applying the de-mamosaic algorithm to the original radiation map. Compared with traditional algorithms, the proposed algorithm provides higher quality HDR images with more details and fewer artifacts[13].

2.3. Computationally Efficient Learning

Although HDR image quality can be improved by increasing network depth or adding more losses, it involves considerable computational cost. A novel feedback network FHDR to reconstruct HDR images from individual exposure LDR images was presented by Khan et al. Intensive connections in forward passing enable feature reuse to learning a robust representation with minimal parameters. Local and global feedback connectivity enhances learning ability to guide initial lower-level functionality from advanced functions. Iterative learning forces the network to create from coarse to fine representations, thus leading to early reconstructions. The FHDR network was able to successfully recover both under-and overexposed areas [2]. Yang et al. formulated the image correction task into an HDR transformation process and proposed a novel method called deep reciprocating HDR transformation (DRHT). Given the input LDR image, they first reconstruct the lost details in the HDR domain. Then, they perform tone mapping on the predicted HDR data to generate an output LDR image with restored details. To this end, they proposed a unified framework consisting of two cnns for HDR reconstruction and tone mapping. They are end-to-end integrated for joint training and prediction [14]. Since the correction network can be removed after training, there is no additional reasoning cost. Zeng et al. found that in the camera imaging pipeline, 3D lookup tables (3D LUTs) are important for manipulating the color and hue of photos. Therefore, they learn adaptive 3D lookup tables (3D LUTs) of images to achieve fast and powerful photo enhancement. They learn multiple basic 3D luts and a small CNN in an end-to-end way. Small CNN works on the down-sampling version of the input image to predict the weight related to the content, so as to fuse multiple basic 3D luts into image-adaptive LUTs for effectively converting the color and hue of the source image. Their model contains less than 600K parameters, and it takes less than 2 ms to process 4k resolution images using a Titan RTX GPU. The main contributions of Image-adaptive 3D LUT CNN can be summarized as follows: they are the first method to learn 3D LUTs using paired or unmatched data sets for automatic photo enhancement. More importantly, their proposed learning architecture can learn image adaptive 3D LUTs to achieve intelligent and high-performance photo enhancement, which is impossible for the current 3D LUT model. This method produces satisfactory results with less calculation cost [15].

2.4. Learning Camera Imaging Pipeline

The main challenge of reconstructing an HDR image from a single image is to recover the missing details in the underexposed or overexposed areas of the LDR image. Learning camera imaging pipeline technology, in short, is a technology to solve the problems of camera sensor quantization and saturation, and detail loss through imaging pipeline modeling, and then effectively reconstruct HDR images.

The SingleHDR proposed by Liu et al is a representative framework for modeling the formation process from HDR to LDR into three sub-steps: dynamic range limiting, nonlinear mapping with CRF and quantization. Their core idea is to decompose the single-image HDR reconstruction problem into three sub-tasks, instead of using the general network to learn the direct LDR to HDR mapping: i) de-quantization, ii) linearization and iii) hallucination, and develop three deep networks to deal with each task. First, given the input LDR image, they apply the de-quantization net to recover the missing details caused by quantization and reduce the visual artifacts (e.g., strip artifacts) in the underexposed area. Secondly, they use a linearized network to estimate the inverse CRF and convert the nonlinear LDR image into a linear image (i.e., scene irradiance). Based on the empirical model of crf, their linearized network leverage estimates additional hints of more accurate crf from the edge, strength histogram and monotonically increasing constraints. Third, they use hallucination network to predict the missing content in the overexposed area. In order to deal with other complex operations that are not modeled in the modern camera pipeline (such as lens shadow correction, sharpening), they use refined mesh and fine-tune the entire model end-to-end to reduce error accumulation and improve the generalization ability of the real input image. SingleHDR has been proved to have good performance for generating bracketed LDR image stacks[16].

2.5. Learning Neural Sensors

In the single-exposure HDR imaging pipeline, the biggest challenge is to correctly recover the saturated regions of the LDR images. The above methods solve this problem by generating LDR images from the CRF database, directly modeling reverse CRF or designing effective networks. However, these methods do not take into account the problems within the sensor. Learning neural sensors technology, in short, is a technology that uses deep neural network to model sensor processing to reconstruct HDR images. This technology is a promising direction of HDR imaging.

In particular, the method proposed by Metzler et al. is to jointly train the optical encoder and the electronic decoder. The encoder is parameterized by the point spread function (PSF) of the lens, the bottleneck is the sensor with limited dynamic range, and the decoder is the CNN. Then optimize the lens surface with CNN in the training stage; They manufactured this optimized optical element and attached it to the conventional camera as a hardware accessory in the reasoning process. In a wide range of simulations and physical prototypes, they have proved that this end-to-end deep optical imaging method for single-shot HDR imaging is superior to the purely CNN based method and other PSF engineering methods. The main contributions of this method can be summarized as follows: they introduced optical encoder for single HDR imaging and CNN-based decoder pipeline[17]. A similar method is proposed in [18]. AlghamdiIn et al. proposed a joint design for snapshot HDR imaging by designing a spatially variable modulation mask in the hardware and constructing an initial network to reconstruct the HDR image. They have realized the reconfigurable HDR camera design, which does not require customized sensors, but can be reconfigured between HDR and normal mode through very simple calibration steps. They proved that the proposed hardware-software solution provides a flexible and powerful way to modulate the exposure of each pixel, and the network requires little hardware knowledge to faithfully reconstruct HDR images [18]. However, the overall framework is an end-to-end learning method.

Martel et al. introduced neural sensor as a method to optimize the shutter function of each pixel in an end-to-end manner together with differentiable image processing methods such as neural network. This method can be interpreted as an optical encoder and digital decoder system, in which the sensor implements the physical coding layer, and the differential algorithm represents the digital decoder. Modeling the exposure function enables the sensor to capture the blurred LDR image and then use it to reconstruct the HDR image. The main contribution of this method can be summarized as follows: they introduced the idea of learning camera "perception" strategy in an end-to-end way. Specifically, they proposed a distinguishable neural sensor model to jointly optimize the spatially varying pixel exposure and image processing network [19].

3. Limitations and Future Work

With the rapid development of deep single-exposure HDR imaging, it also has its limitations. 3D panorama autoencoder and regression has three limitations. First of all, Zhang et al. noticed that they were sensitive to the tone mapping function of the input LDR. The second limitation is that their methods are limited to outdoor scenes, and when visible, the sun needs to be centered in the panoramic view. Finally, the output resolution is limited to 64 × 128, which is sufficient for re-illumination applications, but HDR information cannot be inferred from the full-resolution LDR background image[20].

HDRCNN has three limitations. First of all, how much missing information the network can handle depends on the content, which is usually difficult to quantify. However, underestimating highlights is also an inherent problem of training data. Some HDR images used to create training data show saturated pixels in high-intensity areas. There are also restrictions on how many compressed artifacts can exist in the input image. If there are occlusion artifacts around the highlight, these will damage the reconstruction performance to a certain extent[3].

Feature masking CNN has four limitations. First, although their methods can restore brightness and illusion texture, Santos et al. can not always reconstruct all details. In addition, when the input lacks sufficient information about the underlying texture, their methods may potentially introduce patterns that do not exist in the real image of the ground. In addition, in some cases, their method reconstructs saturated regions with incorrect colors. Finally, although their networks can be used to reconstruct HDR video from LDR video, their results are not stable in time[1]. ExpandNet has two limitations. First of all, to completely delete the artifacts, further investigation is needed, such as in the field of network acceptance. Secondly, dynamic methods may need further careful design to maintain time consistency[4]. The method proposed by Moriwaki et al., is that when the saturation region is too large, it is difficult for the generator to repair these regions[6].

The method proposed by Endo et al. has three limitations. First of all, their current methods are not enough to deal with scenes with very high dynamic range, because their models are trained with fixed exposure range. Secondly, if a given LDR image has a wide clipping area (especially in the case of a high-resolution image), the newly synthesized content (for example, cloud) shows tiled artifacts. Finally, although they have proved the effectiveness of their method compared with the existing rTMOs, their expression ability is still limited due to the relatively small data sets containing small changes compared with traditional tasks (such as image classification)[8]. The method proposed by Lee et al. has a limitation. The proposed network has limitations in recovering lost information according to context[9].

The proposed DRHT method is still limited to restoring details when there is obvious illumination contrast on the input image[14]. Image-adaptive 3D LUT CNN inherits two limitations from 3D LUT. First, Zeng et al.'s 3D LUT can adapt to different images according to their content; However, once the 3D LUT is determined for the input image, it is the same for different local areas in the image. Therefore, in some areas that need local enhancement, 3D LUT may produce unsatisfactory results. Secondly, as a compact and efficient operator, 3D LUT independently converts each input RGB value, but this limits its ability in detail enhancement[15].

The method proposed by Metzler et al. has four limitations. First of all, their methods have changed the formation of optical images, so post-processing becomes an essential part of the imaging pipeline. Second, careful management of the training set is crucial because it needs to include HDR images, whose values fully represent the values observed in the inference process. A network may not produce high-quality results without training. In addition, under dark imaging conditions, it may require a long time of exposure, which may lead to motion blur. Finally, optical blurring makes deconvolution more difficult, and glare causes PSF to shift, which limits the effective field of view of the captured data (the depth of field is not affected)[17].

The method proposed by AlghamdiIn et al. has two limitations. First of all, their method does not allow arbitrary encoding masks. Secondly, although simplified, the calibration procedure still exists in the pipeline[18]. The current limitation of the framework proposed by Martel et al. is adaptability. Even if you have learned the exposure procedure in the example, it will not change in a scenario-dependent manner. Because processing and sensing are juxtaposed, they may interact with each other based on the captured content[19].

There are many ways to improve these limitations in the future. Zhang et al. proposed that the future work includes adapting to the network and learning high-resolution HDR texture from limited field of view LDR images[20]. Eilertsen and others believe that bit depth expansion can also be achieved through deep learning. In addition, future work includes restoring the dark areas of the image. Another direction of future work is to study how to improve the reconstruction of images degraded by compression artifacts. Finally, although the recent development of the Generation Countermeasures Network (GAN) has shown promising results in many imaging missions, they have several limitations. An important challenge for future work is to overcome these challenges in order to achieve high resolution and robust estimation [3]. Santos et al. believed that in the future, it would be interesting to solve the final limit through time regularization. In addition, they want to try the architecture of the network to improve the efficiency of their methods and reduce the memory footprint[1]. Marnerides et al. proposed that Long Short-Term Memory networks may provide a solution for the second limitation [4]. Moriwaki et al. proposed that deepening the network, collecting larger data sets and conducting user research are their future work[6].

Endo et al. proposed that the first limitation can be alleviated by increasing the number of inferred bracketed images, but the cost is greater memory footprint. In addition, it may be helpful to consider the logarithm of pixel values. As for the second limitation, one solution is to use a larger kernel and a larger training image, which again leads to larger memory consumption and longer training time. A better way is to integrate new content on the basis of local patches while considering the global environment of the scene. In order to enrich their training data set, it is a promising way to synthesize HDR images using 3D computer graphics. They also want to combine random factors, such as the generation of a confrontation network (GAN), to synthesize reasonable images, even in large underexposed/overexposed areas [8]. Lee et al. proposed that they will further study the network structure by using conditional generation antagonism network (c-gan), which can impose additional constraints on HDR reconstruction. It will eliminate unexpected artifacts and enhance image quality by generating images that cannot be distinguished from the ground truth by the discriminator [9].

Yang et al. proposed that in the future, they would expand their training data set to include such extreme cases to improve performance [14]. Zeng et al. proposed that a possible solution to solve the first limitation is to combine some local contrast enhancement methods (such as local tone mapping algorithm) with their 3D LUT. However, it should be noted that for high-resolution images, the local tone mapping method is still time-consuming, and how to effectively embed the local enhancement operation into 3D LUT will be their future work. In practice, a possible solution to solve the second limitation is to combine 3D LUT transform with some denoising modules, as is usually done in the camera imaging pipeline. They also left this to their future work [15].

Metzler et al. proposed that the end-to-end method can be used to design optical devices tailored for specific tasks, rather than just capture the clearest images. Evaluating the benefits of end-to-end optimization of optics and image processing for other applications, including multispectral, optical field and lens less imaging or computational microscopy, is an interesting way to work in the future [17]. AlghamdiIn et al. proposed that a network will be developed in the future work. This network can learn mask and decoded HDR images from a single encoded LDR image to completely eliminate the calibration step [18]. Martel and others believe that hardware is an important research direction in the future [19].

4. Discussion

Based on the above analysis, various aspects of depth single-exposure HDR imaging method are studied. Deep single-exposure HDR imaging has several advantages:

a. Single-exposure HDR imaging eliminates the alignment problem of LDR images and is affected to a lesser extent by the ghost effect.
b. It is more flexible in applications and simplifies data collection.
c. It has computational efficiency.

There is no unsupervised method for single-exposure HDR imaging. In view of the fact that unsupervised methods can overcome the difficulty of tagged data sets and that unsupervised methods are relatively mature in the direction of super-resolution, future research may explore more effective learning in this direction. Applied comparative learning and domain adaptation to unsupervised HDR imaging may be beneficial.

5. Conclusion

In this study, the latest development of deep single-exposure HDR imaging method was comprehensively and deeply investigated and analyzed. This study divides the existing deep single-exposure HDR imaging methods into five categories. Importantly, this study reviewed the limitations and future work of each category. Deep single-exposure HDR imaging has both advantages and challenges. Future research may lead to more developments in the direction of unsupervised.

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