# A Survey of Deep Learning Methods in High Dynamic Range Technology

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## Abstract

High dynamic range (HDR) imaging provides the capability of handling real world lighting as opposed to the traditional low dynamic range (LDR) which struggles to accurately represent images with higher dynamic range. However, most imaging content is still available only in LDR, making it a hot research topic of generating HDR images and videos. Since the deep learning methods plays a more and more important role in computer vision and many other areas, this survey will mainly focus on the brilliant deep learning based methods. Classification and overview of HDR reconstruction methods together with the sorting and comparison of various methods will be introduced, followed by discussion of several classic or state-of-art methods in detail. At last, this survey gives conclusion and prediction for HDR technology evolution trend, which may be helpful for future research.

## 1. Introduction

Dynamic range is a physical parameter to describe the ratio of maximum to minimum value of variable signal. In the real world, the dynamic range of light is much larger than ordinary camera can capture.

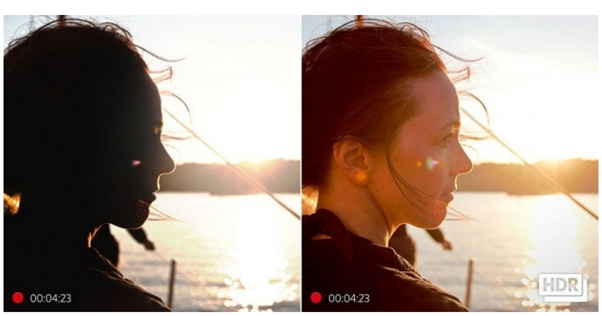


Figure 1. An example of HDR image. HDR image largely enriches the effects of light and shadow, providing a more realistic and pretty result to human's eyes.

To provide a more realist and pleasant visual experience, high dynamic range technology came into being. In 1997, Special Interest Group for Computer GRAPHICS conference, Paul Debevec et al. proposed a method to generate an HDR image by combining a set of low dynamic range images of the scene at different exposures [3]. After that paper, a large number of approaches are proposed using the same or original ideas to generate HDR image.

HDR brings excellent visual experience, and therefore being widely used in all kinds of media. HDR image has a higher dynamic range of light than other images, making it has greater difference of light and shade and is closer to the real world. Figure 1 shows us a comparasion of an HDR image and a LDR image. Owing to its wonderful feature, in photography HDR is usually used to capture sunrise, sunset, scenery, giviing them rich effects of light and shadow. HDR is widely used in not only photography, but also videos and games. At the same time, technology corporation invent advanced camera to shoot and displayer to display HDR images, videos and games.

Next parts in this survey will introduce existing research about HDR, as well as several classic and state-of-art methods in detail. This survey will mainly focus on HDR reconstruction by deep learning methods, following awesome-deep-hdr by vinthony on github, since the deep learning methods plays a more and more important role in computer vision,

## 2. Related Work

### 2.1. Overview of existing research about HDR

Nowadays HDR research is focused on two areas, which is HDR image and HDR video. Classifying by the input image number to reconstruct HDR image, we can divide HDR image into single-image HDR and multi-image HDR.

We will introduce them in detail respectively.

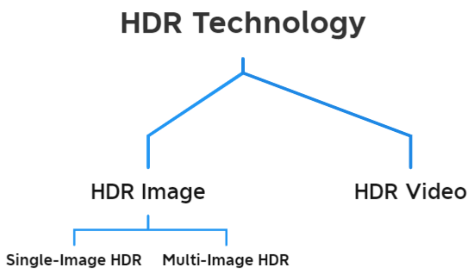


Figure 2. Classification of HDR technique

## 2.2. Single-Image HDR

Single-Image HDR technology requires the model to reconstruct an HDR image with the input of only one LDR image. It become a hot research topic because of its widespread application in smart phones and cameras, which make it possible to acquire a high-quality HDR image without updating user's devices and costing money. Recent days a large number of deep learning methods are proposed to solve this problem.

Researchers adopt and customize various deep learning network to reconstruct HDR image from one LDR image. Eilertsen et al. [2017] use deep CNNs to stimulate a set of images of different exposures and build a image stack [4]. Merging images of different exposures enables to merge different ranges therefore producing a high dynamic range image. Most deep learning methods for single-image HDR adopt similar strategy, and just do some optimization and adjustment in some specific implementation. Endo et al. [2017] attempt to use supervised learning in single-image HDR reconstruction [5]. While some researchers adopt other deep learning network, such as Siyeong et al. [2018] [14]and Moriwaki et al. [2018] [18] using generative adversarial networks(GAN) to stimulate more trustworthy image of other exposures in order to generate more vivid HDR image.

Researchers also put forward lots of innovative ideas in every aspect for better reconstruction. These innovations can be about the network structure. Marnerides et al. [2018] propose a three-branch CNN called ExpandNet, extracting multidimensional features for reconstruction [17]. Siyeong et al. [2018] propose a CNN of chain structure, as well as designing a new activation function called MPReLU [13]. Zeeshan et al. [2018] propose FHDR, which introduce feedback mechanisms to the network, largely enhancing the model's learning ability through local and global feedback [10]. Yu-Lun et al. [2020] design three independent networks, dequantization,linearization and hallucination network, for reversing image formation pipeline, which makes the model robust in situations never met [16].

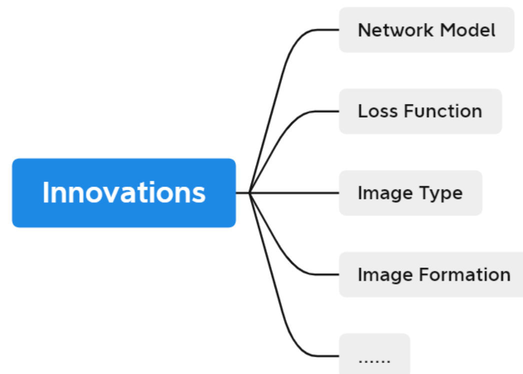


Figure 3. Innovation types of Single-Image HDR methods

The innovations are also reflectd in other respects such as loss function, image type or even fundamental principles. Moriwaki et al. [2018] use hybrid loss, which consisted of reconstruction loss, perceptual loss and adversarial loss, to optimize the model [18]. Wei et al. [2021] apply HDR technology in spherical panoramas, which also get great results [23]. Yu-Lun et al. [2020] even return to the process of image formation, reversing the image formation camera pipeline, to reconstruct realistic HDR image [16].

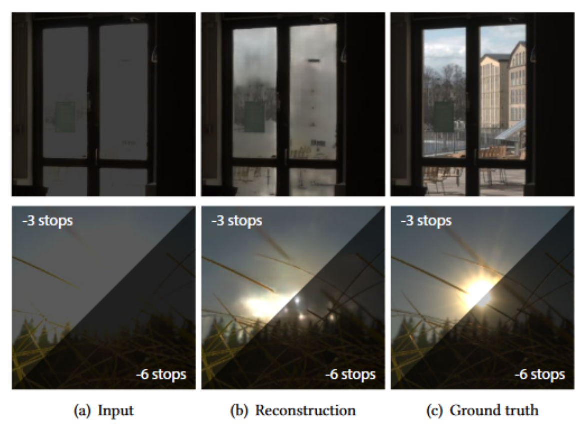


Figure 4. Single-Image HDR methods are unable to inpaint saturated or underexposed regions.

This survey sorts out the methods mentioned above and organizes them in to a table, describing each method's publishing time, model type, dataset, fea-

Table 1. Comparasion of various Single-Image HDR methods

| Method | Info | Model | Dataset | Features | To be improved |
| --- | --- | --- | --- | --- | --- |
| [4] | SIGGRAPH 2017 | Deep CNNs | Shot from HDR video dataset(Amizi [1] and other papers) by virtual camera | Subjective judgement, CNNs stimulate different exposures | Removing artifacts, recovering saturated regions |
| [5] | SIGGRAPH 2017 | CNN | Collecting from EMPA HDR Database and other papers | First attempt at supervised learning, various data source | Better the behaviour with large under and overexposed regions |
| [17] | Eurographics 2018 | 3-branches CNN, called ExpandNet | Fairchild database [6] | Novel proposed 3-branches extracting multidimensional features | Data argmentation, better understanding branch's function |
| [13] | IEEE 2018 | CNN of chain structure | Generating new dataset of midddle exposed images | Building a image stack, new activation function MPReLU | Handling low exposure images |
| [14] | ECCV 2018 | GAN | VDS dataset and VDS dataset | Buiding a image stack, using GAN | |
| [18] | ArXiv 2018 | GAN | From [4] and web images crawled by author | Hybrid loss: reconstruction loss, perceptual loss and adversarial loss | Inpainting large saturated region |
| [10] | SIP 2019 | Feedback Network, FHDR | City Scene dataset and others [29] | Local and gobal feedback enhancing learning ability | |
| [20] | SIGGRAPH 2020 | CNN | Different datasets for each steps. MIT Places etc. | Feature-masking mechanism, VGG-based perceptual loss function | |
| [16] | CVPR 2020 | Dequantization, linearization and hallucination 3-network | Constructing two datasets: HDR-SYNTH and HDR-REAL | Reversing image formation pipeline therefore robust | |
| [23] | ArXiv 2021 | Spherical CNNs | Constructing HDRPano-I Dataset | For spherical panoramas, physical plausibility | Adaptation for various HDR image scopes |

tures of the method and ideas for the method's improvement in chronological order1. Through this table we found that most methods follow that generating images of different exposures then merging. We can also get the idea of the biggest challenge in Single-Image HDR technology: recovering the saturated and under-exposed regions. However, this challenge is an ill-posed problem, because the missing signals not appearing in the given image are extremely hard to recover, just like 4 shows.

### 2.3. Multi-Image HDR

Another way to reconstruct an HDR image is to input more than one image, which is called Multi-Image HDR. Using a set of images means that the model don't need to stimulate images of different exposures and brings convenience. However, the difficulty turns to how to deal with the motion of camera and objects since the images may not be shot at the same time, explaining why it has a broad application in dynamic scenes aiming to reconstruct an HDR image through multiply images with object motion.

Most state-of-art methods solve this problem in a similar way: align the images then merge them to an HDR image. However, the most effective and wide-used alignment algorithm, optical flow algorithm proposed by Liu et al. [2009] [15], will cause unpleasant artifacts that heavily affect the perceived naturalness of the result(showed in the Align High column in 5, from Kalantari et al. [2017] [9]). Then, many models focus on how to remove those annoying artifacts.

There are lots of attempts. Yan et al. [2019] [26] propose a three sub-networks on different scales to capture the high-level information, middle level features and local details for artifacts removing. Shi et al. [2019] [25] use an attention-guide network for ghost-free HDR imaging. Yan et al. [2020] [27] update their method to better utilize non-local feature and propose a NHDRRnet to remove artifacts for better result. Niu et al. [2021] [19] first introduce GAN to Multi-Image HDR methods, getting realistic results in missing regions, as well as proposing a deep HDR supervision scheme for eliminating artifacts of the reconstructed HDR images. Wu et al. [2018] [24] find a fundamental way to remove artifacts, which is to refuse optical flow algorithm, which will unavoidable cause artifacts.


Figure 5. Artifacts appear in the Align High column. Removing artifacts becomes a hot research topic in deep learning Multi-Image HDR.

### 2.4. HDR Video

Compared with HDR image, HDR video reconstruction is a more challenging problem, since the model has to recover the HDR image for every input frame, but not just for a single reference image. However, significant progress has been made in HDR image reconstruction, HDR video reconstruction is less explored. The common method to generate HDR video is to utilize video sequences captured with alternating exposure, which is a promising direction for low-cost HDR video re- construction.

Here are some recent deep learning methods to reconstruct HDR video. Kalantari et al. [2019] [8] propose the first deep learning approach to produce an HDR video from a sequence of alternating exposures. Kim et al. [2019] [11] introduce a novel deep network with modulation blocks that focus on enhancing local contrast for the joint super-resolution and inverse tone-mapping problem. They use another deep learning model, GAN, to restudy the joint ST-ITM problem in 2020 [12]. The same year, Chen et al. [2] propose a coarse-to-fine network which first performs image alignment and HDR fusion in the image space and then in feature space, for HDR video reconstruction from sequences with alternating exposures. They create a real-world video dataset captured with alternating exposures as a benchmark to enable quantitative evaluation for this problem, inspiring and making it convenient for future research on HDR video.

## 3. Analysis and Discussion

In this part, we will talk several models in detail by refering to some classic or state-of-art methods, seeking better understanding of HDR technology and some enlightening and heuristic thoughts in this research area.

### 3.1. ExpandNet for Single-Image HDR

'ExpandNet: A deep convolutional neural network for high dynamic range expansion from low dynamic range content' is a paper written by Marnerides, Bashford-Rogers, Hatchett and Debattista proposed in Eurographics 2018. This paper proposes a fully automatic, end-to-end, parameter free method for the expansion of LDR content based on a novel CNN architecture which improves image quality for HDR expansion.

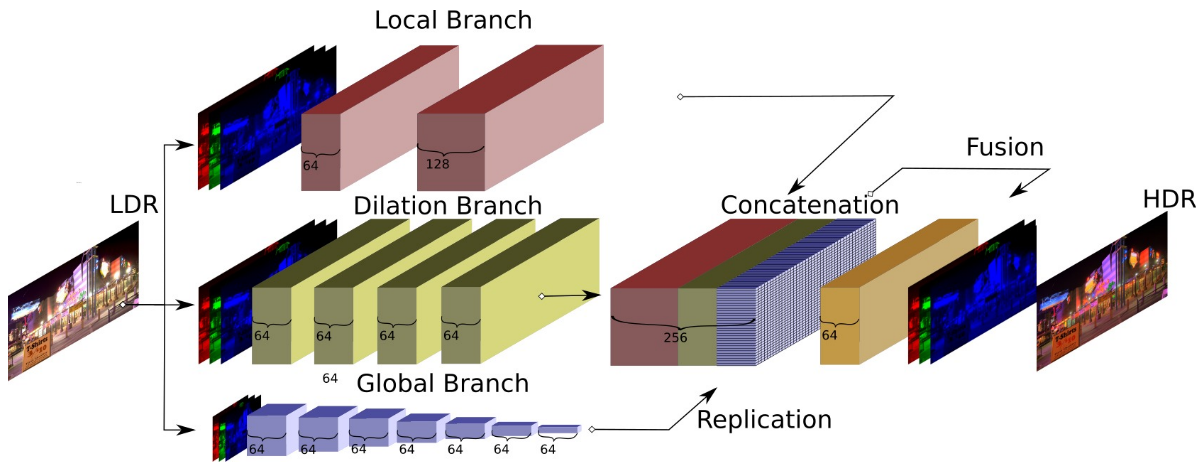


Figure 6. The architecture overview of ExpandNet.

### 3.1.1 Model

As the picture shows 6, ExpandNet is consist of three branches and each branch is itself a CNN that accepts an RGB LDR image as input, with the local branch handling local detail, the dilation branch for medium level detail, and a global branch accounting for higher level image-wide features.

The LDR input is propagated through the the local and dilation branches, while a resized input is propagated through the global branch. The output of the global branch is superposed over each pixel of the outputs of the other two branches. The resulting features are fused using convolutions to form the last feature layer which then gives an RGB HDR prediction. The size of branches are well-designed to best fit the image processing.

All branches refuse to use upsampling and two of them refuse to use downsampling, which is a common approach in the design of CNNs, in order to reduce artifacts and improve the quality of the predicted HDR images.

### 3.1.2 Activations, Loss Function and Dataset

All the layers use the Scaled Exponential Linear Unit (SELU) activation function, a variation of ELU, which ensures that the distributions of the activations at each layer have a mean of zero and unit variance, providing a lower memory cost and preserving all the properties of ELU. The final layer of the network uses a Sigmoid activation, mapping the output to [0,1].

$$\mathrm{SELU}(z) = \beta \begin{cases} z & \text{if } z > 0 \\ \alpha e^{z} - \alpha & \text{if } z \leq 0 \end{cases}$$

In terms of loss function, $L_1$ distance rather than $L_2$ distance is chosen because more frequently used $L_2$ distance is found to cause blurry results for images. Cosine is used because it measures the angle between vectors while ignoring magnitude, which is helpful to detect color shift.

$$\mathcal{L}_i = \left\| \tilde{I}_i - I_i \right\|_1 + \lambda \left( 1 - \frac{1}{K} \sum_{j=i}^{K} \frac{\tilde{I}_i^j \cdot I_i^j}{\left\| \tilde{I}_i^j \right\|_2 \left\| I_i^j \right\|_2} \right)$$

The dataset is consisted of $1,013$ training images and 50 test images, with resolutions ranging from $800 \times 800$ up to $4916 \times 3273$, collected from HDR videos, web and Fairchild database.

### 3.1.3 Discussion

For a quantitative evaluation of the work, four metrics are considered, Peak Signal to Noise Ratio (PSNR), Structural Similarity (SSIM), Multi-Scale Structural Similarity (MS-SSIM), and HDR-VDP-2.2. ExpandNet performs reasonably well in these four metrics compared with 10 state-of-art deep learning based or non deep learning based methods, particularly getting best HDR results when a significant number of pixels in the input image are over or under-exposed.

## 3.2. Feedback Network for Single-Image HDR

'FHDR: HDR Image Reconstruction from a Single LDR Image using Feedback Network' is written by Zeeshan Khan, Mukul and Shanmuganathan, proposed in 2019 IEEE Global Conference on Signal and Information Processing. Feedback network is inspired by Zamir's work [28], for overcoming the shortcoming that deep networks consume a lot of computational resources and tend to over-fit the training data.


Figure 7. FHDR performs well in recovering the underexposed and overexposed regions.

#### 3.2.1 Model

The FHDR architecture consists of three blocks, the first of which is the Feature Extraction block(FEB), followed by the Feedback block (FBB) and an HDR reconstruction block (HRB). FHDR adopt a global residual skip connection for bypassing low level LDR features at every iteration to guide the HDR reconstruction block in the final layers.

The basic unit of the feedback block is a Dilated Dense Block (DDB), a modification of the Dense block proposed in [7], helping in utilisin all the hierarchical features from the input. There are two level feedback. The global feedback block is considered as an RNN with a global hidden state for transferring high-level features, while local feedback capturing low-level features.

#### 3.2.2 Dataset and Evaluation

For the dataset, FHDR chooses standard City Scene dataset(created by Zhang et al. [29]) and another HDR dataset curated from various sources shared in [4], which contains about $40,000$ pairs of low resolution LDR and ground truth HDR images and 1010 HDR images of high resolution respectively.

In three evaluation metrics, PSNR, SSIM and Q-score, FHDR performs best in both City Scene Dataset and Curated HDR Dataset compared to many state-of-art methods.

#### 3.2.3 Discussion

FHDR have many advantages over other methods, such as dense connections in the forward-pass enabling feature-reuse resulting using minimum parameters, local and global feedback connections enhancing the learning ability by transferring low-level and high-level features. Moreover, it has a strong ability to recover the underexposed and overexposed regions, making it beyond compare7.

### 3.3. Attention-Guided Net for Multi-Iamge HDR

'Attention-guided Network for Ghost-free High Dynamic Range Imaging' is written by Yan1, Gong, Shi, Hengel, Shen, Reid and Zhang, proposed in CVPR 2019. They introduce attention modules to generate soft attention maps to evaluate the importance of different image regions for obtaining the required HDR image, expecting to highlight the features complementary to the reference image and excluding regions with motion and severe saturation, thus obtaining ghost-free HDR results.

#### 3.3.1 Model

The model working for multi-image HDR reconstruction contains attention mechanism, thus is called AHDRNet. It consists of two major subnetworks, while the attention network generating the attention map to identify the misaligned components before merging the features for alleviating the ghosting artifacts, and the merging network takes the features extracted with the attention guidance and merges them to hallucinates the details in the regions contaminated by the saturation and misaligned moving objects.

#### 3.3.2 Dataset and Discussion

Researchers use Kalantari's dataset [9] and the datasets without ground truth such as Sen's datasets

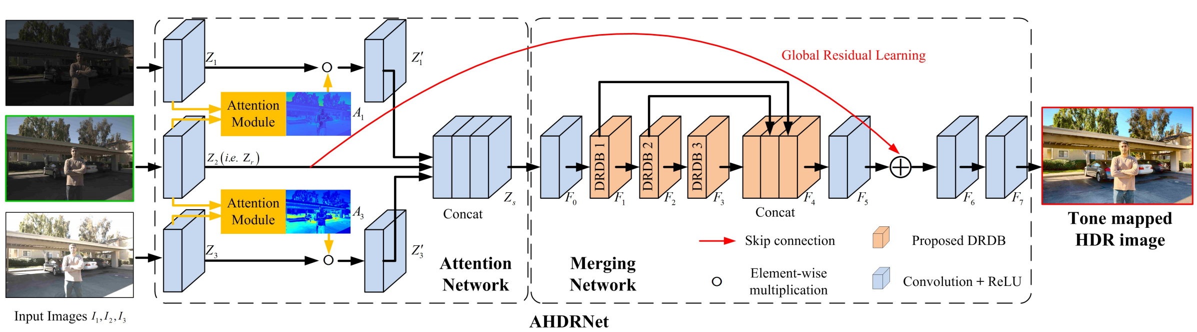


Figure 8. Overview of the AHDRNet architecture.

[21] and Tursun's datasets [22]. Computing the evaluation of metrics, PSNR- , PSNR-M, PSNR-L and HDR-VDP-2, AHDRNet performs best in comparasion with various state-of-art models.

Attention mechanism allows the AHDRNet to detect the important regions with large motion or saturation, putting the feature to the merging step. This characteristic brings amazing effects. Therefore, AHDRNet can generate high-quality HDR images even in the presence of large image motion and saturation, overcoming one of the biggest challenge HDR image faces, ghosting and saturating artifacts, thus offering the prospect of more extensive applications of HDR imaging.

### 3.4. Multi-Scale Dense Net for Multi-Iamge HDR

'Multi-scale Dense Networks for Deep High Dynamic Range Imaging' is written Yan, Gong, Zhang, Shi, Sun, Reid and Zhang, proposed in 2019 IEEE Winter Conference on Applications of Computer Vision. They adopt three independent networks to capture the multi-scale information from a sequence of bracketed exposure LDR images for reconstructing HDR image, and incorporate dense connections into U-Net to connect each layer to every other layer in a feed-forward fashion in order to use the features effectively and decrease the numbers of parameters.

#### 3.4.1 Model

The Multi-Scale Dense Net is consisted of three sub-networks on different scales to capture the high-level information, middle level features and local details. Accordingly the small scale is denoted by Dense U-Net1, the kernel size of which is $3 \times 3$, thus the coarsest-scale network has a large enough receptive field to see the whole patch. The middle and high scale are define by Dense U-Net2 whose kernel size is $5 \times 5$ and Dense U-Net3 whose kernel size is $7 \times 7$ respectively, showing in 9.

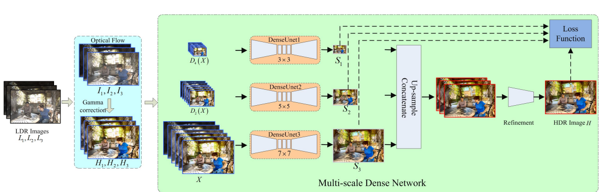


Figure 9. The architecture of Multi-Scale Dense Net.

Writers propose a refinement network, consisted by a convolutional layer and three ResBlocks which contains two convolutional layer and one ReLU activation as 10. The first convolutional layer is used to fuse the images, while the ResBlocks are used to refine the results and produce the final HDR image.

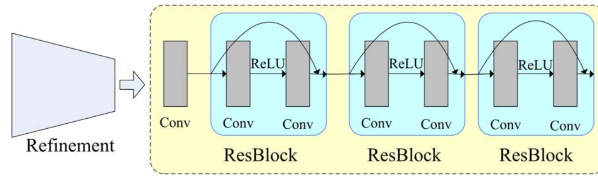


Figure 10. Details of the refinement network.

The loss function is designed to consider both each scale's loss and tonemapping loss, fitting to the model.

#### 3.4.2 Dataset and Discussion

Like many methods handling multi-image HDR reconstruction, the method uses the dataset created by Kalantari [9], too. Owing to the sample number of the dataset, it is hard to train a deep learning-based model if directly feed the full-size image to the network. Data augmentation is adopt to avoid over-fitting, with specifically description that randomly crop and flip the patches with $256 \times 256$ as training images.

The method performs pretty well compared with state-of-art methods, because of its splendid ability to capture features through independent three subnetworks which also realizes a coarse-to-fine scheme. This research is a great attempt to solve saturated and motion regions when reconstructing an HDR image.

### 3.5. SR-ITM for 4K HDR video

'Deep SR-ITM: Joint Learning of Super-Resolution and Inverse Tone-Mapping for 4K UHD HDR Applications' is written by Soo Ye, Jihyong and Munchurl, proposed in International Conference on Computer Vision (ICCV) 2019.

#### 3.5.1 Model

In the Deep SR-ITM model, the input image signal is decomposed into the base and detail layers, and separate feature extraction passes are designed for the two layers. Convolution operations are not suitable so modulation blocks are designed, which perform spatially-variant multiplication operations to modulate the local intensities.

The writers design a toy network, which is the simplified version of the Deep SR-ITM, to further analyze the effect of input decompositions and evaluate different types of modulations.

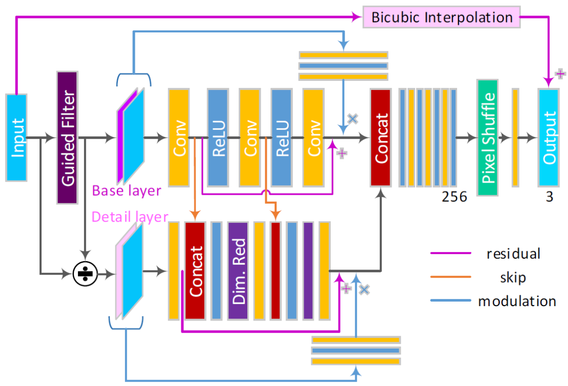


Figure 11. Architecture of the toy network.

#### 3.5.2 Dataset and Discussion

The dataset is constructed originally, collecting ten 4K-UHD HDR videos of 59, 818 frames in total from YouTube, among which 7 videos are used for training (44K frames) and 3 are left for testing. A modulation scheme is incorporated to boost the local contrast in the image signal amplitudes by introducing spatially-variant operations. Compared with many advanced methods, SR-ITM performs well in evaluation metrics like PSNR(dB), mPSNR(dB), SSIM, MS-SSIM and HDR-VDP(Q), which are trustworthy metrics to judge an HDR video.

# 4. Conclusion and Trend Prediction

## 4.1. Conclusion

Through the survey of classical and cutting-edge deep learning methods in HDR technology, it is found that researchers attempted to use a variety of deep learning networks for HDR image reconstruction, and proposed various models to specifically solve some HDR reconstruction challenges such as artifact removal to achieve better results. Meanwhile, the implementation details are constantly optimized, such as proposing new loss functions, datasets and activation functions, so as to make the deep learning model more suitable for HDR image and video reconstruction. In addition, scholars are also expanding the boundaries of HDR reconstruction technology, such as the application of spherical panoramas to broaden the application scene. It is expected that HDR technology will become more and more popular under the strong drive of deep learning methods.

## 4.2. Trend Prediction

Inspired by the excellent papers and brilliant ideas, plus the combing of the existing papers and finding the relationship of state-of-art methods, some predictions can be made about HDR technology evolution trendency in the near future.

#### 4.2.1 Keeping testing various models and optimazation in implementation details

It's sure that researchers will keep testing various deep learning models on the HDR reconstruction technology, as well as optimazing the implementation details like designing more suitable loss functions, activation functions, model architecture and so on. For instance, scholars may attempt to use RNN, or set up multi-scale attention model to guide HDR reconstruction. Also, mutual learning can be applied in three domains of HDR reconstruction, Single-Image HDR, Multi-Image HDR and HDR Video, to promote progress in each domain.

However, applying and mixing existing models and architectures is hard to make fundamental breakthrough. We are delight to hope more and more nice deep learning models would be come up with, therefore achieving great progress in HDR reconstruction and many other areas.

#### 4.2.2 Possible applications in image and video compression

Taking the advantage of advanced HDR reconstruction technology from LDR images or videos, it is very promising to apply this technology to image and video compressing, because LDR images and videos cost much more less memory than HDR images and videos. Therefore a compression method can be proposed, which enable to keep essential features of the image or video to ensure the correctness of the HDR reconstruction process, saving considerable memory.

#### 4.2.3 Being smaller and faster, thus accessible to cheap devices

It can be predicted that the model and algorithm handling HDR image and video reconstruction will be smaller and faster, which means that the model is memory-cost friendly and is fast enough to give the output without waiting. Therefore, with smaller and faster models, the phones and cameras can get the HDR image the moment user takes the picture, while the feature that the model only consumes a few memory allows it to be stored in cheep or even outdated devices.

#### 4.2.4 Mixing with non deep learning based methods to get better results

There are many valuable academic achievement on non deep learning based methods for HDR reconstruction, such as some traditional algorithm and brilliant methods putting physical property in good use. Deep learning based methods can get inspiration from these great achievements for better performance and results.

#### 4.2.5 Broadening application areas in VR, games and so on

The HDR reconstruction technology for spherical panoramas opens us to new idea that HDR technology has a broader application in many areas. For example, HDR mode in games for better simulation, HDR VR for greater visual experience, updating of camera hardware for better HDR construction or reconstruction, HDR together with high resolution and so on. All the areas are promising to explore.

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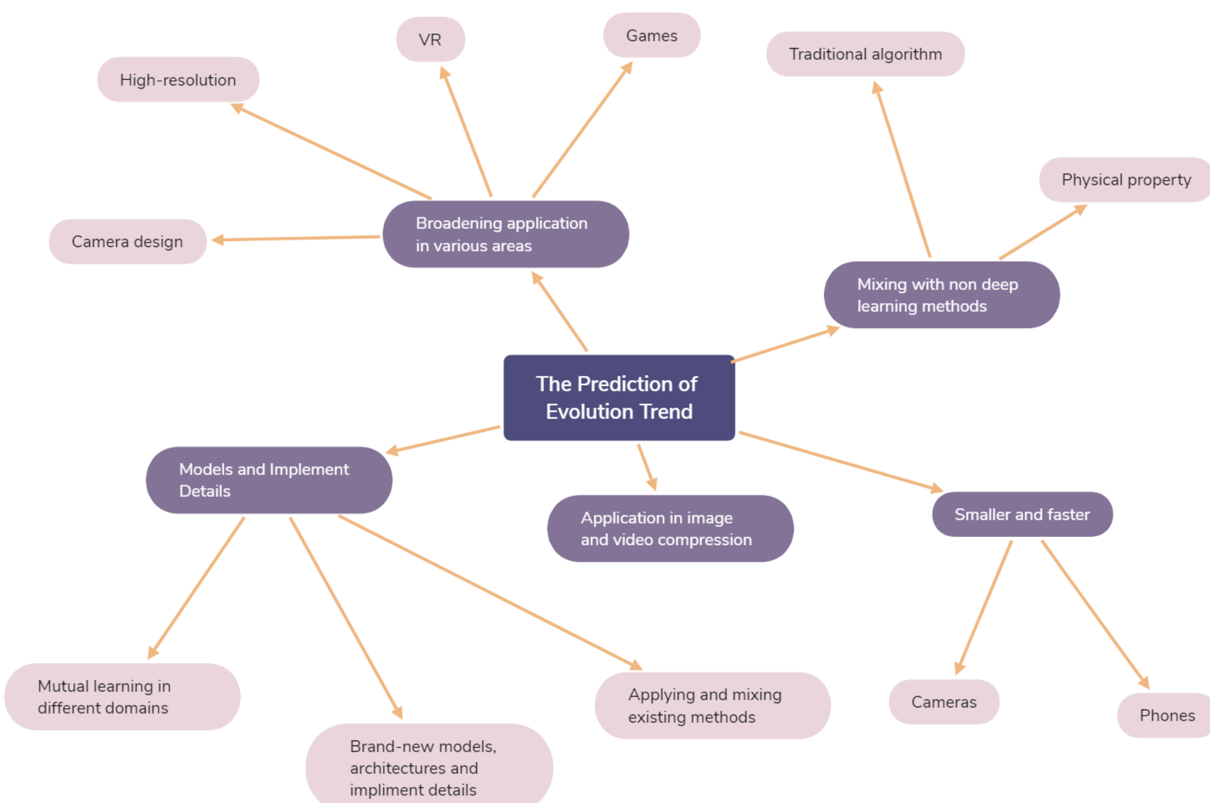


Figure 12. The Prediction of Evolution Trend. Each branch presents a possible breakthough point.

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