DeepHS-HDRVideo: Deep High Speed High Dynamic Range Video Reconstruction

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Input LDR Frames

Interpolated HDR Frames

Input LDR Frames

Fig. 1: Example of high speed HDR video generation using video interpolation. From a sequence of alternating exposure LDR frames at T = 0, 1, 2, 3, we generate multiple intermediate HDR frames between T = 1 and T = 2. Video frame interpolation allows us to augment the dynamic range at each timestamp, and recursively upscale the video frame-rate manifold. Our method can generate high quality HDR videos at arbitrarily high frame rates. More results are presented in the supplementary video.

Abstract—Due to hardware constraints, standard off-the-shelf digital cameras suffers from low dynamic range (LDR) and low frame per second (FPS) outputs. Previous works in high dynamic range (HDR) video reconstruction uses sequence of alternating exposure LDR frames as input, and align the neighbouring frames using optical flow based networks. However, these methods often result in motion artifacts in challenging situations. This is because, the alternate exposure frames have to be exposure matched in order to apply alignment using optical flow. Hence, over-saturation and noise in the LDR frames results in inaccurate alignment. To this end, we propose to align the input LDR frames using a pre-trained video frame interpolation network. This results in better alignment of LDR frames, since we circumvent the error-prone exposure matching step, and directly generate intermediate missing frames from the same exposure inputs. Furthermore, it allows us to generate high FPS HDR videos by recursively interpolating the intermediate frames. Through this work, we propose to use video frame interpolation for HDR video reconstruction, and present the first method to generate high FPS HDR videos. Experimental results demonstrate the efficacy of the proposed framework against optical flow based alignment methods, with an absolute improvement of 2.4 PSNR value on standard HDR video datasets [1], [2] and further benchmark our method for high FPS HDR video generation.

Keywords—Computational Photography, High Dynamic Range, Video Processing

I. INTRODUCTION

Digital videos are extremely rich sources of information that can convey meaningful stories through the lens of easily accessible and portable handheld cameras devices. Two roadblocks stand in the way of achieving this full potential - low dynamic range and sub-optimal frame rates. Due to limits in memory resources of the digital sensors, standard off-the-shelf cameras can capture only a narrow spectrum of light intensity levels (dynamic range) in a natural scene and only at limited frame rate.

Low dynamic range of standard camera sensors leads to loss of pixel information in the high and low illuminance regions of a scene, resulting in overexposed or underexposed images. And low frame rate cameras are unable to capture the swift movements of a scene and lose temporal precision. High speed (FPS) HDR videos can therefore widely benefit vision systems for autonomous vehicles, movie production, hand-held cameras for recording personal moments, and much more.

Recent works have explored many variations in convolutional neural networks (CNNs) for reconstructing artifact-free HDR images from multi-exposure bracketed images [3], [4], [5], [6] and even from single exposure LDR input images [7], [8], [9], [10]. These methods have been able to perform exceedingly well and generate high quality HDR images. The problem of HDR video reconstruction has however not been sufficiently explored, except for a few works [11], [12], [13], [14], [15]. Mainly all the previous works follow a common approach of matching the exposure of neighbouring frames to perform image alignment, and merging the aligned frames to generate an HDR video. Due to the alternating exposure nature of the source LDR frames, the high exposure frames generally have oversaturated regions and the low exposure frames have high frequency noise. Therefore, even after exposure matching, images have missing regions, which results in inaccurate alignment of the LDR images. This results in motion blur in the final HDR video.

In this work we show how in the right setting, HDR reconstruction can benefit from synthesising intermediate frames using video frame interpolation. We propose a novel approach for augmenting dynamic range by generating intermediate alternating exposure frames and merging them using an attention-based merge network. The pre-trained video interpolation network transfers knowledge from large scale pretraining on high FPS video datasets, and significantly improves motion compensation. This not only facilitates better HDR video synthesis, but can also be used to recursively increase the frame-rate of the generated HDR videos during inference.

So far, generating high FPS HDR videos has only been possible using event cameras [16] [17]. However, they suffer from low spatial resolution, and are very expensive and therefore less accessible. Our approach, however, can be used to convert an alternating exposure video captured from offthe-shelf cameras into a high FPS HDR video.

In summary, our key contributions are:

- We present a novel HDR video reconstruction framework for augmenting dynamic range by interpolating LDR video frames, instead of relying on error-prone exposure matching and image registration techniques for image alignment.
- 2) We present the first deep learning framework for HDR video frame interpolation, which can generate high resolution HDR videos at arbitrarily high frame-rates.
- 3) We present both quantitative and qualitative experiments to validate the superiority of the proposed HDR video generation method at both standard and high frame-rates.

II. RELATED WORKS

a) HDR imaging: HDR image generation has been extensively studied in the last few decades. Two major approaches have been adopted - 1) motion pixel rejection ([18], [19], [20], [21]) and 2) image alignment before merging ([22], [23], [24], [25], [26]). However these approaches either lose important information, when rejecting pixels, or fail to account for large motions in challenging cases, while performing image alignment. In the last few years, many deep convolutional neural network (CNN) architectures have been utilised to compose high quality HDR images. Methods like [3], [4], [6], [27], [28], [8], [29] have been successful in generating high quality HDR images using multi-exposure input images and have

been able to outperform classical approaches. The abilities of these deep networks have also been extended to generate decent HDR images from single LDR images [7], [30], [31], [32], [9], [10], [33], [34]. Recently, an attention-based network was proposed by [6] to eliminate motion discrepancies among multi-exposure images with large displacements to generate ghosting-free HDR images.

b) HDR video generation: Pioneer works in HDR video reconstruction, such as [11], [12] and [13], generated HDR video frames from alternating exposure input by using classical flow based approach to align neighbouring images to the reference image. [14] proposed to avoid exact correspondence estimation and use a maxium aposteriori estimation (MAP) resulting in superior performance over flow based methods. This process, however, entails heavy computation load. Some works like [35], [36] focus on generating HDR videos from singly exposed LDR videos. These methods exploit single image HDR generation methods and extend them to work with videos. Lately, works like [37], [38], [39] solve a closely related problem of SDRTV-to-HDRTV where HDR video is generated with HDR display in pixel domain unlike the standard LDR to HDR video generation in linear domain.

Recently, [15] proposed a deep CNN to generate HDR videos from alternating exposure LDR sequences. They were able to outperform existing methods and reduce the processing time by several orders using a CNN based flow-based network followed by an HDR merge network. Their merge network predict the weights of input LDR images to merge. Their approach is, however, unable to generate good results in challenging conditions with complex motion and high saturation (see Figures 6 and 7). Authors of [40] used the same flow and HDR merge network proposed by [15] and add deformable convolution module to improve the alignment.

In contrast to previous works, we propose to replace image alignment and registration based motion compensation with video frame interpolation which is used to generate alternate exposure images at each timestamp. Then, we merge the images using an attention-based merge network that synthesises HDR images from scratch instead of predicting weights of the input images.

III. METHOD

A. Overview

Given a video sequence of alternating exposure LDR images, I_1^H , I_2^L , I_3^H , I_4^H , ..., I_n^H , our goal is to generate corresponding ground truth HDR video sequence, H_1 , H_2 , H_3 , H_4 , ..., H_n . Here I_t^H and I_t^L denote the high and low exposure LDR images respectively at time step T = t.

Having a triplet of consecutive alternating exposure images $[I_{t-1}^H, I_t^L, I_{t+1}^H]$, the middle one being used as the reference, we aim to generate an HDR image \hat{H}_t that is aligned with the reference LDR frame at time T = t. To achieve this, we require both the high and low exposure frames at the reference timestamp. Since we already have the reference image, I_t^L at the base exposure, we artificially generate the alternate exposed image at the same instance t, i.e. \hat{I}_t^H . We do so



Fig. 2: Overview of the proposed method

by using a video frame interpolation network to generate \hat{I}_{t}^{H} from the similarly exposed input neighbouring frames, I_{t-1}^{H} and I_{t+1}^{H} . Now that we have two alternately exposed images at time T = t, we propose to fuse them using an attentionbased HDR merge network to generate an HDR image \hat{H}_{t} . The end-to-end framework can be visualised in Figure 2.

B. Video frame interpolation and HDR merge network

For synthesising intermediate frames, we use the Depth Aware Video Interpolation (DAIN) method [41]. DAIN is a deep network that leverages depth information to formulate occlusion reasoning. This allows it to emphasise sampling of closer objects and facilitates robust frame interpolation. After generating an intermediate frame, the next part of the process is to merge the reference and the interpolated frame using an attention-based HDR merge network.

Attention networks for HDR reconstruction have proven to be state-of-the-art for learning attention maps to guide HDR image generation [6]. These learned soft attention maps are adept in dealing with misaligned LDR images and also help in picking appropriately exposed, unsaturated regions from each exposure variant.

The authors of [6] generate attention for high and low exposure images with respect to a reference exposure image. We instead do so in an alternate exposure setting. as shown in Figure 3, we generate attention directly between the high and low exposure images. We learn two attention units for attending to high exposure and low exposure images with respect to each other, and use that information to drive HDR reconstruction in a way that reduces saturation and alignment artifacts. For more details on DAIN and attention based HDR merge network, we refer the interested readers to [41] and [6].



Fig. 3: Architecture of the attention-based HDR merge network (HDRV). Given two alternate exposure LDR images, we first use the attention network to generate attention maps. These maps are then applied on the extracted features of the input LDR image. After concatenating the attention applied features and originally extracted features, these are propagated to the deep merge network.

C. High FPS Video Generation

In this section, we explore how the aforementioned networks can come together to generate high FPS HDR videos during inference. For example, to generate an intermediate HDR frame at time T = 2.5, we first generate the LDR images of the missing exposure at time T = 2 and T = 3 as shown below.

$$I_2^H = f_{interp}(I_1^H, I_3^H)$$
 (1)

$$\hat{I}_3^L = f_{interp}(I_2^L, I_4^L) \tag{2}$$

Now we have both exposure images at time T = 2, i.e. (\bar{I}_2^H, I_2^L) and T = 3, i.e. (I_3^H, \hat{I}_3^L) . We can use similar exposure frames at both instances (\hat{I}_2^H, I_3^H) and $I_2^L, \hat{I}_3^L)$ to generate intermediate frames of both exposures at T = 2.5, as shown below.

$$\hat{I}_{2.5}^{H} = f_{interp}(\hat{I}_{2}^{H}, I_{3}^{H}) \tag{3}$$

$$\hat{I}_{2.5}^{L} = f_{interp}(I_{2}^{L}, \hat{I}_{3}^{L}) \tag{4}$$

We can then merge the generated intermediate LDR frames $(I_{2.5}^H \text{ and } I_{2.5}^L)$ to obtain the final HDR image, $\hat{H}_{2.5}$ at time T = 2.5, as shown below.

$$\hat{H}_{2.5} = f_{HDR}(\hat{I}_{2.5}^H, \hat{I}_{2.5}^L) \tag{5}$$

This procedure can be extended to generate intermediate HDR frames recursively and can thus increase the frame-rate of HDR video.

IV. IMPLEMENTATION DETAILS

A. Dataset

The aforementioned network is trained on two publicly available HDR video datasets - [1] (13 scenes) and [2] (8 scenes). Just like [15], we reserve four scenes for the test set -CAROUSEL FIREWORKS, FISHING LONGSHOT, POKER FULLSHOT, and POKER TRAVELLING SLOW-MOTION. We prepare the dataset using the same approach described in [15]. From three consecutive HDR frames we generate 3 LDR images in an alternating exposure setting, with exposures



Fig. 4: HDR video frames generated from the proposed approach.

separated by one, two, and three stops. Where we choose a low exposure time randomly selected from a base high exposure. The HDR image is delinearised using $\gamma = 2.2$. We create randomly cropped patches from each video of size 256×256 . We also apply geometric transformations like 90 degrees rotation and flipping to augment the training data. Training data consists of about 21000 patches.

B. Loss functions

We calculate an L1 loss between the tonemapped generated HDR frame and the tonemapped ground truth HDR frame. It is imperative to tonemap the HDR images before calculating the loss because HDR loss is likely to be misrepesented due to the dominance of the highly illuminated regions in images with higher dynamic range.

As suggested by [3], we use μ law for tonemapping because of it's differentiable nature. μ law brings the HDR data in the log domain, as shown below.

$$T(\hat{H}_t) = \frac{\log(1+\mu\hat{H}_t)}{\log(1+\mu)} \tag{6}$$

Here, T represents the tone mapping function and μ represents the amount of compression to be applied. We set μ as 5000 for our implementation.

C. Training strategy

We incorporate the following settings for training the HDR video network. For generating the intermediate LDR frames, we incorporate DAIN [41] as the video interpolation network, pre-trained on Vimeo90K dataset [42]. We only train the HDR merge network while keeping DAIN freezed. We use AdaMax optimizer [43] with β_1 and β_2 as 0.9 and 0.999 with the initial learning rate set to 5*e*-4. We trained the model for 40 epochs, with a batch-size of 6. It takes about 50 hours to train the model on an Nvidia RTX 5000 GPU. After 30 epochs the learning rate is reduced by half. At inference, it takes 5.6 seconds to generate one HDR frame of size 1900x1060.

V. EXPERIMENTS

We categorise the experiments into two parts (i) HDR video synthesis and (ii) High FPS HDR video synthesis. In the first subsection, we provide quantitative and qualitative comparisons against [15] for HDR video synthesis. In the second subsection, we evaluate our method for high FPS HDR video generation. We use three standard metrics for quantitative evaluation of the synthesized HDR data - PSNR, HDR-VDP-2 [44], HDR-VQM [45]. PSNR is calculated on the tonemapped HDR images using Equation 6, while the HDR-VDP-2 and HDR-VQM scores are calculated directly on the HDR frames. For displaying, we tonemap all the HDR images using the method of [46] with modifications as suggested by [11].

A. Evaluation of HDR video synthesis at standard frame rates

We evaluate our model on three seconds of the four publicly available HDR video sequences from [1], as described in section 4. For quantitative evaluation, we report the results of [15] on the generated output provided by the authors. For fair comparison, we choose the base high exposure of our input similar to that of [15] and the low exposure to be separated by three stops.

	PSNR	HDR-VDP-2	HDR-VQM
Kalantari[15]	40.67	74.15	85.51
Ours	43.03	79.76	89.58

TABLE I: Quantitative comparison of HDR video generation at ground-truth frame-rate.

1) Quantitative comparison: A quantitative comparison against the method of [15] for HDR video reconstruction has been presented in Table I. All the values are computed for each individual frame and averaged over all the frames of the four video sequences. A notable improvement over the previous method is observed across all the three metrics.

A higher PSNR score implies a higher pixel-level accuracy, indicating that the generated HDR frames are properly aligned with the ground truth HDR frames. HDR-VDP-2 and HDR-VQM scores implies that the generated frames are visually pleasing and temporally coherent.



Fig. 5: Comparison for HDR video reconstruction on the **POKER FULLSHOT scene.** Kalantari *et al*'s method [15] is unable to register the fast moving hand with the glass. In contrast, our method reconstructs it accurately.



Fig. 6: Comparison for HDR video reconstrution on the **POKER FULLSHOT scene.** Shape of the cards is distorted in the image generated by Kalantari *et al*'s method [15]. On the contrary, our approach accurately reconstruct the edges of the cards.



Fig. 7: Comparison for HDR video reconstruction on the CAROUSEL FIREWORKS scene. Due to the fast motion of lady, Kalantari *et al*'s method [15] is not able to registered the hand. On the contrary our method generates the image very close to ground truth.

2) *Qualitative comparison:* We argue that by completely eliminating the image registration process and by simply interpolating the intermediate frames, we are able to deal with large motions. As seen in Figure 5, Kalantari *et al* [15] is not able to register the fast moving hand of the man. Also the glass

in his hand has not been synthesised accurately. In Figure 6, the cards are distorted. Similarly, in Figure 7, hand of the lady has not been reconstructed properly. This blur is a result of inaccuracies of the image alignment process in scenes with large motions. Our method, however, is able to preserve the boundaries and spatial details more accurately and generate sharp images, with minimum motion blur. More comparisons and qualitative results are presented in the supplementary video.

B. Evaluation of High FPS HDR Video Synthesis

To evaluate the proposed method for high FPS video generation, and validate the generality of using video frame interpolation for HDR video generation. We study the effects of three video frame interpolation alternatives when combined with our attention-based HDR merge network (HDRV) on high frame rates.

1) Quantitative Evaluation: In this section, we review the performance of our model in synthesising high FPS HDR video from a sequence of alternating exposure LDR frames. For this evaluation, we use the POKER TRAVELLING SLOW-MOTION scene because this is the only high FPS HDR video scene in the existing datasets. We report the PSNR, HDR-VDP-2 and, HDR-VQM scores on six seconds of this scene, for 1x, 2x, 4x, and 8x frame rates. We compare the performance of the three video interpolation networks combined with our HDRV network. 1) DAIN [41], 2) Super SloMo [5] and, 3) Modified flow network of [15]. The flow network proposed in [15] uses three input images and generate two flow maps to align both the first and the third image to the reference image. We modify it into an interpolation network. To do so, we predict two output flow maps, and generate a visibility mask to get the final interpolated image as done in Super SloMo [5]. We then use these pre-trained networks along with our HDR merge network.

	FPS = 1x	FPS = 2x	FPS = 4x	FPS = 8x
Kalantari[15]	44.07	40.41	37.01	33.54
Super SloMo[5]	45.42	43.33	40.18	35.57
DAIN[41]	46.54	45.26	42.22	37.82

TABLE II: PSNR scores on High FPS HDR video synthesis of three video frame interpolation networks combined with our HDRV network at FPS=1x, 2x, 4x, and 8x

	FPS = 1x	FPS = 2x	FPS = 4x	FPS = 8x
Kalantari[15]	76.35	69.67	61.2	56.4
Super SloMo[5]	81.07	75.56	68.6	61.25
DAIN[41]	84.27	80.51	73.59	65.46

TABLE III: HDR-VDP-2 scores at FPS=1x, 2x, 4x, and 8x

As seen in the Tables 2, 3, and 4, we are able to generate high frame-rate HDR videos from all the three models with good accuracy. We achieve the best results on (DAIN +



Fig. 8: Our results on the POKER TRAVELLING SLOW-MOTION scene at FPS = 8x. We generate seven HDR intermediate frames between two input frames at T = 0 and T = 8. As can be seen, the interpolated HDR frames do not suffer from any artifacts or motion blur.

DAIN[41]	86	85.58	84.59	82.74
Super SloMo[5]	84.94	83.88	82.43	80.09
Kalantari[15]	84.11	82.51	80.76	77.89
	FPS = 1x	FPS = 2x	FPS = 4x	FPS = 8x

TABLE IV: HDR-VQM scores at FPS=1x, 2x, 4x, and 8x

HDRV) model. As we move towards higher FPS, we see a drop in the accuracy. This is due to the fact that interpolating intermediate frames gets more difficult with more sparsely sampled input. However, the videos generated are temporally coherent and spatially sharp even for 8x frame rate upscaling. As seen in Figure 8, seven intermediate frames have been generated between the input frames at T = 0 and T = 8, using (DAIN+HDRV) upscaling the frame rate to 8x. The generated frames have smooth motion and are temporally coherent. This experiment validates the generality of using video interpolation for HDR video synthesis.



HDR Frame at T = 1

Fig. 9: Comparison for high FPS HDR video generation on the CAROUSEL FIREWORKS SCENE. We show the results on 4x upscaled frame-rate by generating three intermediate frames between T = 0 and T = 1.

2) *Qualitative Evaluation:* For qualitative evaluation, we show our results on the POKER FULLSHOT and CAROUSEL FIREWORKS scenes by upscaling the frame-rate to 4x. These are low frame rate input videos with fast motion. It can be seen in Figure 9 that (DAIN+HDRV) is able to interpolate the fast moving swing of the ride with minimum motion blur.



HDR Frame at T = 1

Fig. 10: Comparison for high FPS HDR video generation on the POKER FULLSHOT SCENE.

However, the interpolation networks of Kalantari *et al.* [15] and Super SloMo [5] produce severe artifacts in large motions. In Figure 10, we can see that the hand is distorted in Kalantari *et al.* approach, while Super SloMo and DAIN generate much better interpolations. This experiment suggests that the quality of high FPS HDR video synthesis heavily relies on the video frame interpolation model. More results on HDR video frame interpolations at very high FPS upto 8x are presented in the supplementary video.

VI. CONCLUSION

We present a novel HDR video reconstruction framework from a sequence of alternating exposure LDR frames. We propose to use video frame interpolation to generate the missing exposure frames instead of relying on image registration techniques. We show that any video interpolation model pretrained on large scale high FPS LDR video datasets can be directly used to reconstruct an HDR video. We validate its generality by performing extensive experimentation using various video interpolation methods. Moreover, we extend the proposed framework to generate high FPS HDR videos by recursively interpolating the LDR frames. This is the first method to generate high FPS HDR videos from off-the-shelf digital cameras.

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REFERENCES

- J. Froehlich, S. Grandinetti, B. Eberhardt, S. Walter, A. Schilling, and H. Brendel, "Creating cinematic wide gamut HDR-video for the evaluation of tone mapping operators and HDR-displays," in *Digital Photography X*, N. Sampat, R. Tezaur, S. Battiato, and B. A. Fowler, Eds., vol. 9023, International Society for Optics and Photonics. SPIE, 2014, pp. 279 – 288. [Online]. Available: https://doi.org/10.1117/12.2040003
- [2] J. Kronander, S. Gustavson, G. Bonnet, A. Ynnerman, and J. Unger, "A unified framework for multi-sensor hdr video reconstruction," *Signal Process. Image Commun.*, vol. 29, pp. 203–215, 2014.
- [3] N. K. Kalantari and R. Ramamoorthi, "Deep high dynamic range imaging of dynamic scenes," ACM Transactions on Graphics (Proceedings of SIGGRAPH 2017), vol. 36, no. 4, 2017.
- [4] S. Wu, J. Xu, Y. Tai, and C. Tang, "Deep high dynamic range imaging with large foreground motions," in *Computer Vision - ECCV* 2018 - 15th European Conference, Munich, Germany, September 8-14, 2018, Proceedings, Part II, ser. Lecture Notes in Computer Science, V. Ferrari, M. Hebert, C. Sminchisescu, and Y. Weiss, Eds., vol. 11206. Springer, 2018, pp. 120–135. [Online]. Available: https://doi.org/10.1007/978-3-030-01216-8_8
- [5] H. Jiang, D. Sun, V. Jampani, M. Yang, E. Learned-Miller, and J. Kautz, "Super slomo: High quality estimation of multiple intermediate frames for video interpolation," in 2018 IEEE/CVF Conference on Computer Vision and Pattern Recognition, 2018, pp. 9000–9008.
- [6] Q. Yan, D. Gong, Q. Shi, A. van den Hengel, C. Shen, I. Reid, and Y. Zhang, "Attention-guided network for ghost-free high dynamic range imaging," in *The IEEE Conference on Computer Vision and Pattern Recognition (CVPR)*, 2019.
- [7] G. Eilertsen, J. Kronander, G. Denes, R. Mantiuk, and J. Unger, "Hdr image reconstruction from a single exposure using deep cnns," ACM *Transactions on Graphics (TOG)*, vol. 36, no. 6, 2017.
- [8] Y. Endo, Y. Kanamori, and J. Mitani, "Deep reverse tone mapping," ACM Transactions on Graphics (Proc. of SIGGRAPH ASIA 2017), vol. 36, no. 6, Nov. 2017.
- [9] Z. Khan, M. Khanna, and S. Raman, "Fhdr: Hdr image reconstruction from a single ldr image using feedback network," 2019 IEEE Global Conference on Signal and Information Processing (GlobalSIP), pp. 1– 5, 2019.
- [10] M. S. Santos, R. Tsang, and N. Khademi Kalantari, "Single image hdr reconstruction using a cnn with masked features and perceptual loss," *ACM Transactions on Graphics*, vol. 39, no. 4, 7 2020.
- [11] S. B. Kang, M. Uyttendaele, S. Winder, and R. Szeliski, "High dynamic range video," in ACM SIGGRAPH 2003 Papers, ser. SIGGRAPH '03. New York, NY, USA: Association for Computing Machinery, 2003, p. 319–325. [Online]. Available: https://doi.org/10.1145/1201775.882270
- [12] S. Mangiat and J. D. Gibson, "High dynamic range video with ghost removal," in *Optical Engineering + Applications*, 2010.
- [13] N. K. Kalantari, E. Shechtman, C. Barnes, S. Darabi, D. B. Goldman, and P. Sen, "Patch-based High Dynamic Range Video," ACM Transactions on Graphics (TOG) (Proceedings of SIGGRAPH Asia 2013), vol. 32, no. 6, 2013.
- [14] Y. Li, C. Lee, and V. Monga, "A maximum a posteriori estimation framework for robust high dynamic range video synthesis," *IEEE Transactions on Image Processing*, vol. 26, no. 3, pp. 1143–1157, 2017.
- [15] N. K. Kalantari and R. Ramamoorthi, "Deep hdr video from sequences with alternating exposures," *Comput. Graph. Forum*, vol. 38, pp. 193– 205, 2019.
- [16] H. Rebecq, R. Ranftl, V. Koltun, and D. Scaramuzza, "High speed and high dynamic range video with an event camera," *IEEE Transactions* on Pattern Analysis and Machine Intelligence, vol. 43, pp. 1964–1980, 2021.
- [17] —, "Events-to-video: Bringing modern computer vision to event cameras," in *Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition (CVPR)*, June 2019.
- [18] T. Grosch, "Fast and robust high dynamic range image generation with camera and object movement," 01 2006.
- [19] K. Jacobs, C. Loscos, and G. Ward, "Automatic high-dynamic range image generation for dynamic scenes," *IEEE Computer Graphics and Applications*, vol. 28, 2008.
- [20] F. Pece and J. Kautz, "Bitmap movement detection: Hdr for dynamic scenes," in 2010 Conference on Visual Media Production, 2010, pp. 1–8.

- [21] S. Raman and S. Chaudhuri, "Reconstruction of high contrast images for dynamic scenes," Vis. Comput., vol. 27, no. 12, p. 1099–1114, Dec. 2011. [Online]. Available: https://doi.org/10.1007/s00371-011-0653-0
- [22] L. Bogoni, "Extending dynamic range of monochrome and color images through fusion," in *Proceedings 15th International Conference on Pattern Recognition. ICPR-2000*, vol. 3, 2000, pp. 7–12 vol.3.
- [23] J. Hu, O. Gallo, and K. Pulli, "Exposure stacks of live scenes with hand-held cameras," in *Computer Vision – ECCV 2012*, A. Fitzgibbon, S. Lazebnik, P. Perona, Y. Sato, and C. Schmid, Eds. Berlin, Heidelberg: Springer Berlin Heidelberg, 2012, pp. 499–512.
- [24] P. Sen, N. K. Kalantari, M. Yaesoubi, S. Darabi, D. B. Goldman, and E. Shechtman, "Robust patch-based hdr reconstruction of dynamic scenes," *ACM Trans. Graph.*, vol. 31, no. 6, Nov. 2012. [Online]. Available: https://doi.org/10.1145/2366145.2366222
- [25] J. Hu, O. Gallo, K. Pulli, and X. Sun, "Hdr deghosting: How to deal with saturation?" in 2013 IEEE Conference on Computer Vision and Pattern Recognition, 2013, pp. 1163–1170.
- [26] O. Gallo, A. Troccoli, J. Hu, K. Pulli, and J. Kautz, "Locally non-rigid registration for mobile hdr photography," in 2015 IEEE Conference on Computer Vision and Pattern Recognition Workshops (CVPRW), 2015, pp. 48–55.
- [27] Q. Yan, D. Gong, P. Zhang, Q. Shi, J. Sun, I. Reid, and Y. Zhang, "Multiscale dense networks for deep high dynamic range imaging," in 2019 IEEE Winter Conference on Applications of Computer Vision (WACV), 2019, pp. 41–50.
- [28] Q. Yan, L. Zhang, Y. Liu, Y. Zhu, J. Sun, Q. Shi, and Y. Zhang, "Deep hdr imaging via a non-local network," *IEEE Transactions on Image Processing*, vol. 29, pp. 4308–4322, 2020.
- [29] Y. Niu, J. Wu, W. Liu, W. Guo, and R. W. H. Lau, "Hdr-gan: Hdr image reconstruction from multi-exposed ldr images with large motions," *IEEE Transactions on Image Processing*, vol. 30, pp. 3885–3896, 2021.
- [30] S. Lee, G. H. An, and S.-J. Kang, "Deep recursive hdri: Inverse tone mapping using generative adversarial networks," in ECCV, 2018.
- [31] S. Lee, G. H. An, and S. Kang, "Deep chain hdri: Reconstructing a high dynamic range image from a single low dynamic range image," *IEEE Access*, vol. 6, pp. 49913–49924, 2018.
- [32] D. Marnerides, T. Bashford-Rogers, J. Hatchett, and K. Debattista, "ExpandNet: A Deep Convolutional Neural Network for High Dynamic Range Expansion from Low Dynamic Range Content," *Computer Graphics Forum*, 2018.
- [33] Y.-L. Liu, W.-S. Lai, Y.-S. Chen, Y.-L. Kao, M.-H. Yang, Y.-Y. Chuang, and J.-B. Huang, "Single-image hdr reconstruction by learning to reverse the camera pipeline," 2020 IEEE/CVF Conference on Computer Vision and Pattern Recognition (CVPR), pp. 1648–1657, 2020.
- [34] J. H. Kim, S. Lee, S. Y. Jo, and S.-J. Kang, "End-to-end differentiable learning to hdr image synthesis for multi-exposure images," in AAAI, 2021.
- [35] S. Liu, G. Zhong, S. De Mello, J. Gu, V. Jampani, M.-H. Yang, and J. Kautz, "Switchable temporal propagation network," in *Proceedings* of the European Conference on Computer Vision (ECCV), 2018, pp. 87–102.
- [36] G. Eilertsen, R. K. Mantiuk, and J. Unger, "Single-frame regularization for temporally stable cnns," in *Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition*, 2019, pp. 11176–11185.
- [37] S. Y. Kim, J. Oh, and M. Kim, "Deep sr-itm: Joint learning of superresolution and inverse tone-mapping for 4k uhd hdr applications," 2019 IEEE/CVF International Conference on Computer Vision (ICCV), pp. 3116–3125, 2019.
- [38] S. Kim, J. Oh, and M. Kim, "Jsi-gan: Gan-based joint super-resolution and inverse tone-mapping with pixel-wise task-specific filters for uhd hdr video," *Proceedings of the AAAI Conference on Artificial Intelligence*, vol. 34, pp. 11 287–11 295, 04 2020.
- [39] X. Chen, Z. Zhang, J. S. Ren, L. Tian, Y. Qiao, and C. Dong, "A new journey from sdrtv to hdrtv," 2021.
- [40] G. Chen, C. Chen, S. Guo, Z. Liang, K.-Y. K. Wong, and L. Zhang, "Hdr video reconstruction: A coarse-to-fine network and a real-world benchmark dataset," *ArXiv*, vol. abs/2103.14943, 2021.
- [41] W. Bao, W.-S. Lai, C. Ma, X. Zhang, Z. Gao, and M.-H. Yang, "Depthaware video frame interpolation," in *IEEE Conference on Computer Vision and Pattern Recognition*, 2019.
- [42] T. Xue, B. Chen, J. Wu, D. Wei, and W. T. Freeman, "Video enhancement with task-oriented flow," *International Journal of Computer Vision* (*IJCV*), vol. 127, no. 8, pp. 1106–1125, 2019.

- [43] D. Kingma and J. Ba, "Adam: A method for stochastic optimization,"
- [45] D. Klight and J. Ba, Adah. A method for stochastic optimization, *International Conference on Learning Representations*, 12 2014.
 [44] R. Mantiuk, K. J. Kim, A. G. Rempel, and W. Heidrich, "Hdr-vdp-2: A calibrated visual metric for visibility and quality predictions in all luminance conditions," *ACM Trans. Graph.*, vol. 30, no. 4, Jul. 2011.
- [Online]. Available: https://doi.org/10.1145/2010324.1964935
 [45] M. Narwaria, M. Perreira Da Silva, and P. Le Callet, "Hdr-vqm," *Image Commun.*, vol. 35, no. C, p. 46–60, Jul. 2015. [Online]. Available: https://doi.org/10.1016/j.image.2015.04.009
 [46] E. Reinhard, "Photographic tone reproduction for digital images," 2002.