DEEP HIGH DYNAMIC RANGE IMAGING USING DIFFERENTLY EXPOSED STEREO IMAGES

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Abstract

- High dynamic range (HDR) image formation from low dynamic range (LDR) images of different exposures is a well researched topic in the past two decades
 - Most of the developed techniques consider differently exposed LDR images that are acquired from the same camera view point
 - Assumes the scene to be static long enough to capture multiple images
- Proposed technique: Addresses the problem of HDR imaging from differently exposed LDR stereo images
 - An encoder-decoder based convolutional neural network (CNN)
 - Does not require the LDR stereo images to be explicitly rectified and disparity corrected before merging to HDR image
 - Unlike conventional stereo matching methods
- Training and evaluation
 - An existing benchmark dataset of HDR stereo images, DML-HDR
- The experiments have shown some interesting results in comparison to the state-of-the-art approaches
 - End-to-end network is found to perform equally well on LDR images that are obtained from both stereo framework and single viewpoint

Objectives and Motivation

- High dynamic range (HDR) images capture more information of a scene than their corresponding low dynamic range (LDR) images with a better representation of real world illumination
- Most of the existing commercial HDR image acquisition systems capture HDR images by merging multiple LDR images that are captured from the same camera center sequentially
 - For dynamic scenes, such sequential capturing method introduces non-linear deformations between LDR images due to motion of objects in the scene
- The conventional approach for HDR imaging from stereo LDR images is a pipelining of two stages: rectification and/or disparity correction, and HDR merging
 - These geometric corrections make the HDR merging process computationally expensive and time consuming
 - Heavy networks

Literature

- Assume the scene to be static, and capture multiple LDR images of the scene at different shutter exposures that are combined to a HDR image by radiance mapping^[1,2,3]
 - Since the LDR images are acquired from the same camera center sequentially, they lose structural consistency between them in a dynamic scene
- Align the sequential LDR images of a dynamic scene at a pivot point and locally register them for non-linear distortions, and then converted them to their linear exposure values and combine to obtain the HDR image using a deep convolutional neural network (CNN)^[4,5]
 - Not plausible for abruptly changing dynamic scenes due to loss of coherency between the LDR images
 - The non-linear warping introduces some artifacts for abrupt scenes
- Use differently exposed LDR stereo images for forming a HDR image^[6,7,8,9]
 - Require explicit geometric processes of rectification and disparity correction of stereo image pairs to account for perspective transformation between them
 - The HDR merging of the stereo images usually uses piecewise radiance mapping

- 6. M. Batz et. al., "High Dynamic Range Video Reconstruction from a Stereo Camera Setup", Sig. Proc.: Image Comm., vol. 29, no. 2, 2014
- 7. S. Ning, et. al., "HDR Image Construction from Multi-exposed Stereo LDR Images", Int. Conf. on Image Proc., 2010
- 8. W. J. Park et. al., "Stereo Vision-Based High Dynamic Range Imaging Using Differently-Exposed Image Pair", Sensors, vol. 17, no. 7, 2018
- 9. J. Bonnard, et. al., "Disparity-based HDR Imaging", arXiv CoRR, vol. abs/1905.07918, 2019

^{1.} P. E. Debevec and J. Malik, "*Recovering High Dynamic Range Radiance Maps from Photographs*", Int. Conf. Comp. Graph. and Interactive Techniques, 1997

P. Sen et. al., "Robust Patch-based HDR Reconstruction of Dynamic Scenes", Trans. Graph., vol. 31, no. 6, 2012

^{3.} S. W. Hasinoff et. al., "Burst Photography for High Dynamic Range and Low-light Imaging on Mobile Cameras", Trans. Graph., vol. 35, no. 6, 2016

^{4.} N. K. Kalantari and R. Ramamoorthi, "Deep High Dynamic Range Imaging of Dynamic Scenes", Trans. Graph., vol. 36, no. 4, 2017

^{5.} Q. Yan et. al., "Multi-Scale Dense Networks for Deep High Dynamic Range Imaging", Winter Conf. on Applications of Comp. Vis., 2019

- An encoder-decoder based deep-CNN architecture for merging two differently exposed LDR stereo images into a HDR image
- Does not explicitly require the tasks of rectification and disparity correction
- Resolves rectification and disparity correction, within a tailored range, inherently while forming the HDR image using two stages of network
 - Feature extraction stage
 - Feature fusion stage



Fig.1: Proposed network for HDR image formation by corresponding LDR stereo image pairs with different exposures

- Image references
 - Left camera view: Low exposure (*I*_llow)
 - Right camera view: High exposure $(I_{r^{high}})$
 - HDR image view: Left camera view (I_{hdr})
- The network learns the function $f(\bullet)$ by regressing over the HDR image of left camera view (I_{lhdr})
 - $I_{hdr} = f(I_{llow}, I_{rhigh})$
 - Subject to preset γ-correction
 - Loss function
 - $\Lambda_1 = \|I_{hdr} I_{lhdr}^{(\gamma)}\|_1$, the L_1 distance between I_{hdr} and γ -corrected I_{lhdr} and $\gamma = \frac{1}{2.2}$
- The fused HDR image is obtained by regressing directly on the reference HDR image of left camera view
 - No explicit consideration of disparity map or transformation function between the LDR images
 - Analogously seen to address three issues together: rectification, disparity correction, and HDR fusion
 - Separately dealt by individual steps in conventional approaches
- Results are evaluated with an inverse γ -mapping to match with the original scale of high dynamic range

- Feature extraction
 - Dense features computed from the concatenated LDR stereo images, *H*×*W*×6
 - Employ 10 consecutive 2-D convolutional layers
 - At each layer, 16 filters of stride 1 are used (refer Fig.1 for filter size, *h*×*w*, in each layer)
 - Aggregation by residual connections after ten layers
 - Feature volume assembly of *H*×*W*×160 for each image pair
 - Spatial support of feature volume
 - Spans a spatial range of 0 100 pixels in horizontal direction for disparity correction
 - Spans a spatial range of 0 30 pixels in vertical direction for rectification
 - Realized by varying the filter sizes that gradually increases with the depth of the network
 - Provides different extents of spatial coverage at different layers that are aggregated by depth concatenation
- Feature fusion
 - Computed by simple encoder-decoder module
 - The fused feature volume assembly of *H*×*W*×160 is reduced to a dimension of *H*×*W*×3 using 1×1 filters, which is regressed over the reference HDR image



Fig.2: Layer representation of encoder-decoder module used in our network.

Dataset

- The network is trained using a stereo HDR video dataset, DML-HDR^[1,2]
- The DML-HDR dataset consists of several stereo HDR videos that are acquired by RED SCARLET-X HDR motion footage capable camera
- Each video consists of hundreds of frames at Full HD resolution with a frame rate of 30 fps
- The image frames in the dataset have varied characteristics comprising of different composition, illumination, ambience, objects, etc., that are captured in both indoor and outdoor environments
- Data augmentation
 - Random rotations between -2° to 2° $\,$
 - Trained with image patches of size 256×512 that are randomly extracted from the training images with repetition
- HDR image visualization: Tone mapped to fit the dynamic range of normal displays^[3]

^{1.} A. B. Dehkordi, et. al., "Compression of high dynamic range video using the HEVC and H.264/AVC standards", Int. Conf. Heterogeneous Networking for Quality, Reliability, Security and Robustness, 2014

^{2.} M. Azimi et. al., "Evaluating the performance of existing full-reference quality metrics on high dynamic range (HDR) video content", 2018

^{3.} Z. Farbman et. al., "Edge-Preserving Decompositions for Multi-Scale Tone and Detail Manipulation", Trans. Graph., vol. 27, no. 3, 2008

<u>Results</u>





Fig.3: Example of 'Walking on Snow'





Fig.4: Example of 'Strangers'



Fig.5: Example of 'UBC'



- Qualitative assessment
 - Manual observation in comparison against the ground truth data
 - No visibly implausible artefacts are observed in the HDR rendered images obtained from the proposed technique
- Quantitative assessment
 - Three quality metrics of HDR visual data evaluation: PSNR, SSIM, and HDR-

VDP-2	Methods	PSNR	SSIM	HDR-VDP-2
	Ning et. al. ^[2]	39.87	0.83	72.23
	Bonnard et. al. ^[4]	43.28	0.93	89.37
	Park et. al. ^[3]	40.93	0.86	78.58
	Batz et. al. ^[1]	44.18	0.91	88.29
	Proposed approach	45.96	0.95	93.89

- 1. M. Batz et. al., "High Dynamic Range Video Reconstruction from a Stereo Camera Setup", Sig. Proc.: Image Comm., vol. 29, no. 2, 2014
- 2. S. Ning, et. al., "HDR Image Construction from Multi-exposed Stereo LDR Images", Int. Conf. on Image Proc., 2010
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- 4. J. Bonnard, et. al., "Disparity-based HDR Imaging", arXiv CoRR, vol. abs/1905.07918, 2019

Fig.6: Example of image acquisition by a stereo setup comprising of two mobile phones



Conclusion

- A two staged deep CNN based technique for forming HDR images using differently exposed LDR stereo image pairs is presented
 - Feature extraction phase and feature fusion phase
 - The network learns a function for combining the stereo LDR image pairs to a higher dynamic range
- Designed to handle geometric corrections like rectification and disparity correction between the LDR image pairs implicitly within a specific range
- The results are qualitatively and quantitatively shown to be at par with state-of-the-art techniques
- Future work
 - Future directions are laid towards forming HDR videos using LDR stereo framework
 - Applicability to render high quality and flicker-free HDR videos is yet to be explored

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