SATURATED REGION RECOVERY IN TONE-MAPPED HDR IMAGES

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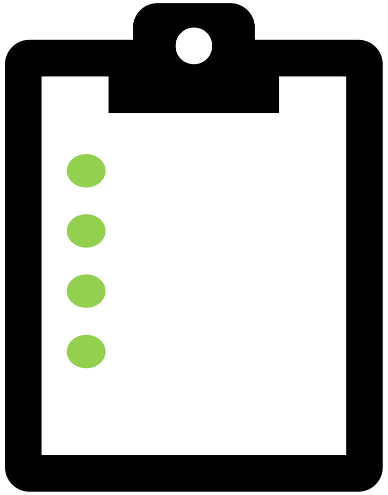


1. Introduction
Aim of the Study

- Tone-mapped High Dynamic Range (HDR) Images
- Over Exposed Pixels & Color Distortion
- Information Loss & Noise
- Correction of Saturated Pixels

Figure. Images containing saturated pixels

1. Introduction

- Over Exposed Regions ⟶ Scenes with High Contrast [1]

HDR : 96 bits/pixel
LDR*: 24 bits/pixel

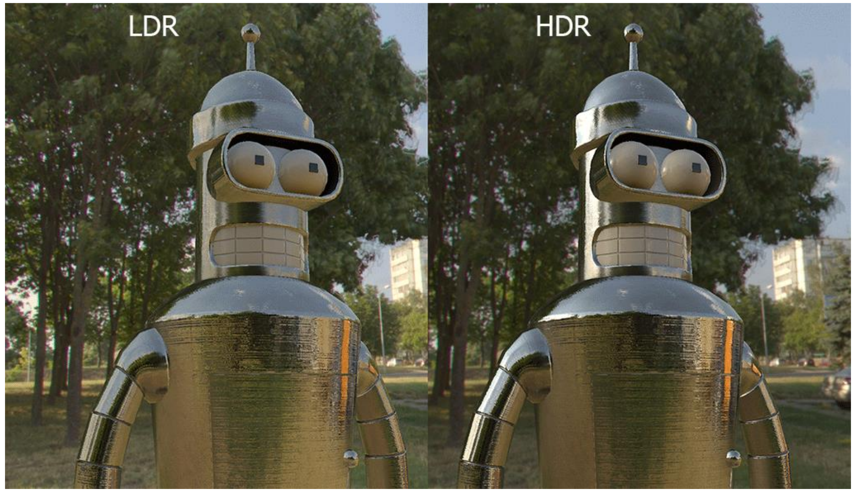


Figure. Robot, LDR and HDR comparison [2].

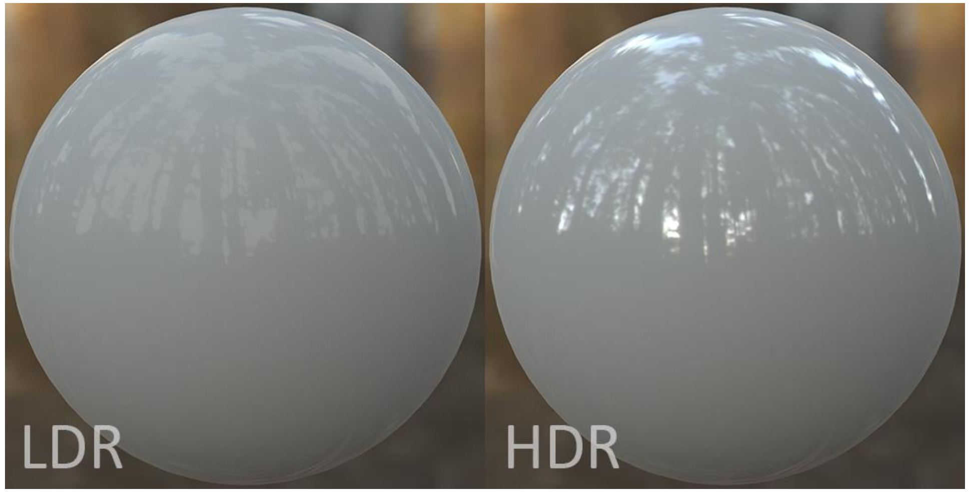


Figure. Sphere, LDR and HDR comparison [3].

*Low dynamic range.

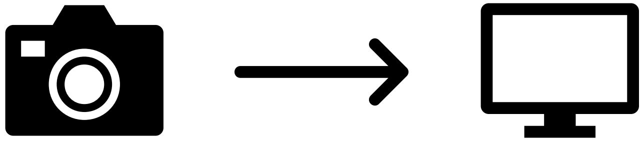
1. Honig, S. and Werman, M. *Image declipping with deep networks*, in IEEE International Conference on Image Processing. Athens, Greece. 7 – 10 October 2018.
2. LDR vs HDR 1, http://damart3d.blogspot.com/2016/12/hdr-vs-ldr-image-based-lighting.html, (15.07.20).
3. LDR vs HDR 2, https://sudonull.com/post/105920-HDR-vs-LDR-implementation-of-HDR-Rendering, (15.07.20).

1. Introduction

- ➢HDR Equipment Unaffordable

- ➢HDR-like Content from LDR Image Sequence [1] ⟶ MEF*

- ➢MEF ⟶ Jitter Effect [2] , Ghosting Effect [3]

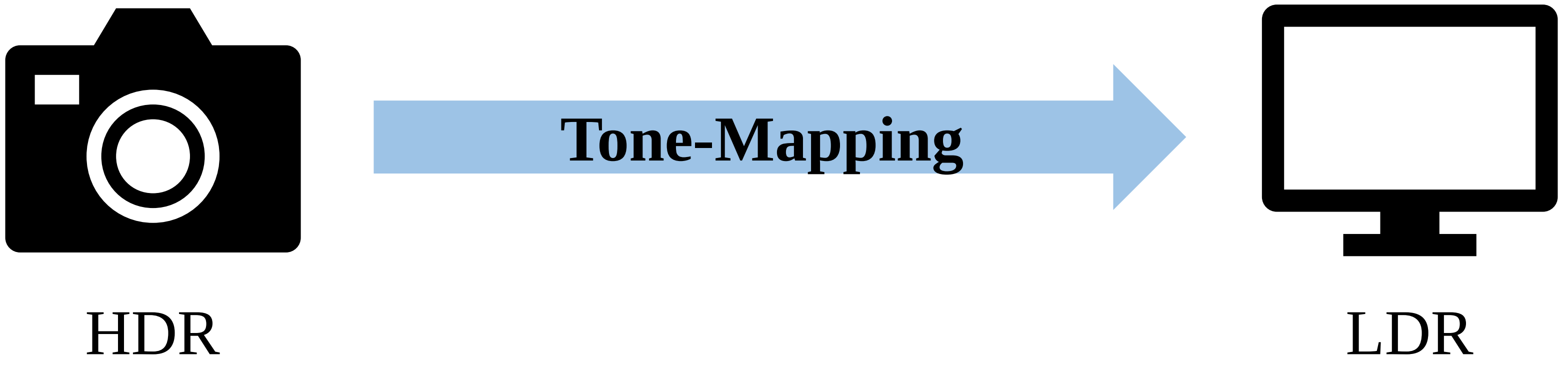


* Multi-Exposure Fusion.

1. O.Ulucan, D.Karakaya and M. Turkan. (2021) *Multi-exposure image fusion based on linear embeddings and watershed masking.* Signal Processing, Vol. 178, pp. 107791.
2. Angelov, P. (2012) Sense and avoid in UAS: research and applications. United Kingdom: John Wiley & Sons.
3. Cai, J., Gu, S. and Zhang, L. (2018) *Learning a deep single image contrast enhancer from multi-exposure images*, IEEE Transactions on Image Processing, Vol. 27(4), pp. 2049–2062.

1. Introduction

✕ Hardware, Human Operator, Environmental based Drawback



1. Introduction

Projected Pixels from HDR to LDR → Brighter or Darker → Detail Loss & Color Distortion

⚠ Clipping

If shortcoming can be eliminated with post-processing → Effective for High-Quality Content

1. Mantiuk, Radoslaw *et al.* (2009) *Color correction for tone mapping*, Computer Graphics forum, Vol. 28(2), pp. 193–202.

2. Proposed Method

- One channel or two jointly clipped channels $\longrightarrow$ Pixel based
- Three jointly clipped channels $\longrightarrow$ Patch based

To the best of available knowledge

First individual approach for all cases

First study employing LE* in this research domain

2. Proposed Method

2.1 One Channel Correction via Linear Embeddings

- Pixel / Patch ⟶ Linear combination of neighbours [1]

Neighbour Embedding

Reconstruction of pixels or small regions from its neighbours [2]

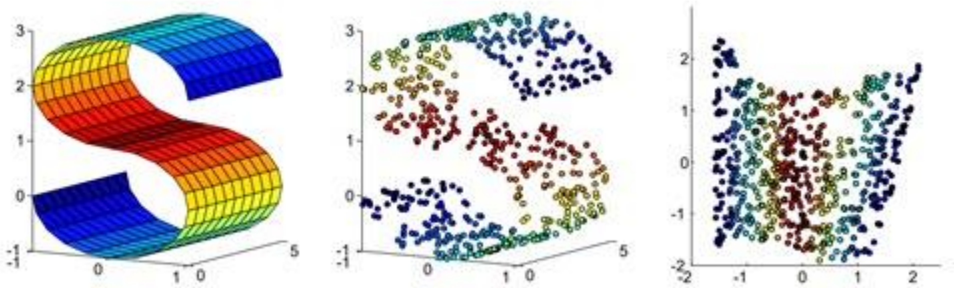


Figure. Neighbor preserving mapping via LLE [2].

- LLE* preserves the structure of a manifold [2]

* Locally linear embeddings.

1. Türkan, M., Thoreau, D. and Guillotel, P. *Optimized neighbor embeddings for single-image super-resolution*, in IEEE International Conference on Image Processing. Melbourne, VIC, Australia. 15-18 September 2013.
2. Roweis, S. T. and Saul, L. K. (2000). Nonlinear dimensionality reduction by locally linear embedding, Science, Vol. 290(5500), pp. 2323–2326.

2. Proposed Method

2.1 One Channel Correction via Linear Embeddings

- Thresholding at 235 in R, G, B of image I separetely $\longrightarrow$ Binary Mask

Two Assumptions

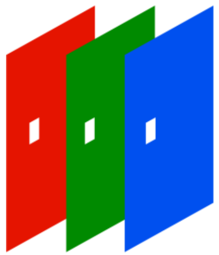


Figure. Channel-wise neighbours.

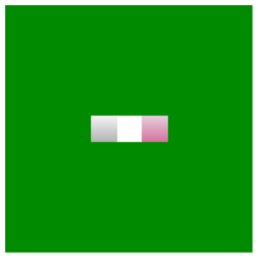


Figure. Pixel-wise neighbours $\mathcal{N}_1$, $\mathcal{N}_2$.

Table. Gradient angles in degrees and the corresponding positions of neighbours in I for clipped pixel α at row, column (r, c) are demonstrated.

Angle (degrees)	$\mathcal{N}_1$	$\mathcal{N}_2$
[0, 45] or [181, 225]	$(r-1, c+1)$	$(r+1, c-1)$
[46, 90] or [226, 270]	$(r-1, c)$	$(r+1, c)$
[91, 135] or [271, 315]	$(r-1, c-1)$	$(r+1, c+1)$
[136, 180] or [316, 360]	$(r, c-1)$	$(r, c+1)$

2. Proposed Method

2.1 One Channel Correction via Linear Embeddings

- Let us assume that α is in R then w_α^G , $w_\alpha^{B\,*}$;

$$\{w_\alpha^G , w_\alpha^B \} = \underset{\{w_1,w_2\}}{\operatorname{argmin}} \left\| \begin{bmatrix} R_{\mathcal{N}_1} \\ R_{\mathcal{N}_2} \end{bmatrix} - \begin{bmatrix} G_{\mathcal{N}_1} & B_{\mathcal{N}_1} \\ G_{\mathcal{N}_2} & B_{\mathcal{N}_2} \end{bmatrix} \begin{bmatrix} w_1 \\ w_2 \end{bmatrix} \right\|_2^2 \quad \text{(Eqn.1)}$$

$$s.t.\, w_1 + w_2 = 1^{**}$$

$$R_\alpha = w_\alpha^G \cdot G_\alpha + w_\alpha^B \cdot B_\alpha \quad \text{(Eqn.2)}$$

* w_α^G and w_α^B represent the reconstruction weights for G and B respectively.
** For translation and rescaling invariance.

2. Proposed Method

2.1 One Channel Correction via Linear Embeddings

Figure. Image (I) with one-channel clipped pixels in magenta, map G and one channel corrected image (I_1).

- Mapping all pixels $\longrightarrow$ 8-bit image
- Map G $\longrightarrow$ Erosion, morphological reconstruction, dilation and a second morphological reconstruction
- Sliding Window operation $\longrightarrow$ $I_1 = G \cdot I_{SW} + (1 - G) \cdot I$ (Eqn.1)

2. Proposed Method

2.2 Two Channel Correction via Difference of Pixel Intensities

Masks of $\{R, G\}$, $\{R, B\}$ and $\{G, B\}$ jointly clipped pixels

Connected components processed individually

✓ More sensitive

Determination of the pixel with the highest priority

➢ Pixel with highest confidence & located at strong edges / structures [1]

Priority of a pixel x∈ β* ⟶ C(x).D(x) (Eqn.1)

$$C(x) = \frac{\sum_{\gamma \epsilon P_x \cap S} C_\gamma}{|P_x|} \quad \text{(Eqn.2)} \qquad D(x) = \frac{|\nabla I_x^{\perp} \cdot \omega_x|}{255} \quad \text{(Eqn.3)}$$

C: confidence term
D: data term
γ : most likely candidate to match x
P_x :a patch of size 5×5 pixels centred around x
$|P_x|$: the number pixels in P_x
ω_x: unit vector orthogonal to the contour

* contour

1. Criminisi, A., Pérez, P. and Toyama, K. (2004) *Region filling and object removal by exemplar-based image inpainting*, IEEE Transactions on Image Processing, Vol. 13(9), pp. 1200–1212.

2. Proposed Method

2.2 Two Channel Correction via Difference of Pixel Intensities

Neighbours of α possess a similar intensity value with the pixel of interest

Gradient map of the image I_1

✓ Avoid incorrect estimations at sharp color changeovers

Third non-clipped channel is used for saturation correction

- R and B are clipped

$$R_\alpha = G_\alpha + \frac{\left(R_{\mathcal{N}_1} - G_{\mathcal{N}_1}\right) + \left(R_{\mathcal{N}_2} - G_{\mathcal{N}_2}\right)}{2} \quad \text{(Eqn.1)}$$

$$B_\alpha = G_\alpha + \frac{\left(B_{\mathcal{N}_1} - G_{\mathcal{N}_1}\right) + \left(B_{\mathcal{N}_2} - G_{\mathcal{N}_2}\right)}{2} \quad \text{(Eqn.2)}$$

If the differences have distinct signs

→ Offset according to absolute values

→ Sign determined by the largest difference magnitude

2. Proposed Method

2.2 Two Channel Correction via Difference of Pixel Intensities

Figure. I_1 with two-channel clipped pixels in magenta, I_2, and I_2 with three-channel clipped pixels in magenta.

2. Proposed Method

2.3 Three-channel Correction via Gradient-guided Block-search

Most challenging step	Block-search approach partly based on exemplar-based inpainting [1]	Mask & Connected components are extracted	Priority computation

- Search-Region Formation ⟶ 11-pixel distance from the connected component border
- 4 pixels in the local patch gradient direction ⟶ Directed Template

1. Criminisi, A., Pérez, P. and Toyama, K. (2004) *Region filling and object removal by exemplar-based image inpainting*, IEEE Transactions on Image Processing, Vol. 13(9), pp. 1200–1212.

2. Proposed Method

2.3 Three-channel Correction via Gradient-guided Block-search

- 5x5 window through search region ⟶ Centring pixel of the minimum intensity distance window

- Closest 8 spatial neighbours of α ⟶ Replaced with the obtained value to avoid sharp color changeovers and probable artefacts

Figure. I_3 and I_3 with two- and three-channel clipped pixels in magenta.

2. Proposed Method

2.4 Post-processing

- *CIELab* ⟶ Process perceptually similar colors & Only preserve perceptually significant edges
- Two- and three-channel correction masks are combined

Reasons

Smoothen possible pixels non declipped in two channel correction process

Make areas more uniform after the block-search

Bilateral filter is adopted [1]

Figure. Input and output images.

- Bilateral filter ⟶ Degree of smoothing: variance of all pixels to be applied
  Neighbourhood size: 101
  Standard deviation of spatial Gaussian smoothing kernel: 10

1. Tomasi, C. and Manduchi, R. *Bilateral filtering for gray and color images*, in IEEE International Conference on Image Processing. Bombay, India. 7 January 1998.

3. Experimental Results

Dataset

Dino, Sink, Exploratorium, Watering Can and *Butterflies* are courtesy of Erik Reinhard & Tania Pouli

Belgium House, Landscape, Memorial and *Mountain* belong to the study of Yeganeh & Wang [1]

Figure. The dataset: *Dino, Sink, Exploratorium, Watering Can, Butterflies, Belgium House, Landscape, Memorial, Mountain*.

- Experimental Setup: Intel(R) Core (TM) i7-8500U CPU @1.80 GHz 4-Core 8GB RAM machine using MATLAB R2019b
- Comparisons: Masood [2] and Steffens [3]
- Proposed: 11.56sec, Masood: 7.90sec, Steffens: 24.03sec

1. Yeganeh H. and Wang Z. (2012) *Objective quality assessment of tone-mapped images*, *IEEE Transactions on Image Processing*, vol. 22 (2), pp. 657–667.
2. Masood, S. Z., Zhu, J. and Tappen, M. F. (2009) *Automatic correction of saturated regions in photographs using cross-channel correlation*, Computer Graphics Forum, Vol. 28(7), pp. 1861–1869.
3. Steffens, C. R. , Huttner, V. , Messias, L. R. V., Drews, P.L.J. , Botelho, S.S.C. and Guerra, R.S. *CNN-based luminance and color correction for ill-exposed images*, in IEEE International Conference on Image Processing., Taipei, Taiwan, 22-25 September 2019.

3. Experimental Results

- Peak-to-Signal Ratio (PSNR) & Structural Similarity Index (SSIM) & Visual Information Fidelty (VIF)

Higher scores: Better outcomes

range [0; 1] Results closer to 1: Superior perceptual quality

Table. Statistical comparisons of Masood, Steffens and the proposed algorithm.

	Masood			Steffens			Proposed		
	PSNR (dB)	SSIM	VIF	PSNR (dB)	SSIM	VIF	PSNR (dB)	SSIM	VIF
Dino	27.481	0.979	0.851	15.082	0.884	0.722	36.830	0.995	0.927
Sink	28.856	0.979	0.780	18.055	0.889	0.732	32.492	0.995	0.963
Exploratorium	26.549	0.963	0.838	14.220	0.768	0.492	29.820	0.980	0.977
Watering Can	30.502	0.985	0.872	15.049	0.863	0.708	29.365	0.974	0.991
Butterflies	22.872	0.961	0.741	13.588	0.827	0.724	32.070	0.972	0.988
Belgium House	30.929	0.990	0.912	21.333	0.792	0.705	51.997	0.999	0.989
Landscape	41.155	0.997	0.979	18.247	0.828	0.774	47.566	0.999	0.990
Memorial	35.713	0.996	0.944	22.574	0.884	0.742	37.974	0.995	0.983
Mountain	20.534	0.953	0.878	13.766	0.738	0.702	38.505	0.983	0.949
Average	29.399	0.978	0.866	16.879	0.830	0.700	**37.402**	**0.988**	**0.973**

3. Experimental Results

Figure. *Butterflies*, (Left-to-right): Input, Masood, Steffens and Proposed.

3. Experimental Results

Figure. *Watering Can*, (Left-to-right): Input, Masood, Steffens and Proposed.

Figure. *Landscape*, (Left-to-right): Input, Masood, Steffens and Proposed.

3. Experimental Results

Figure. *Memorial*, (Left-to-right): Input, Masood, Steffens and Proposed.

Figure. *Belgium House*, (Left-to-right): Input, Masood, Steffens and Proposed.

4. Conclusion

- Information loss in highlights may occur due to clipping
- Adopting LE for the first time
- Constructing a case-oriented algorithm
- On average both visually and statistically superior results
- Can be extended for raw/processed LDR images

- Recover low-light regions in tone-mapped images

Thank you for listening!