CONTRAST ENHANCEMENT AND IMAGE COMPLETION

CNN-based Luminance and Color Correction for Ill-Exposed Images

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Introduction

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Introduction

About

- Clipping and its impact on an image
- Challenge for computer vision algorithms
- Post-processing CNN-Based model applied on the damaged images
- sRGB Color Space
- Restoration with aesthetic purposes
- Qualitative and quantitative metrics
  - Color correction
  - Texture
  - Image gradient
  - Structures

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Introduction

Efect of exposure on the intensity levels

Underexposure

Overexposure

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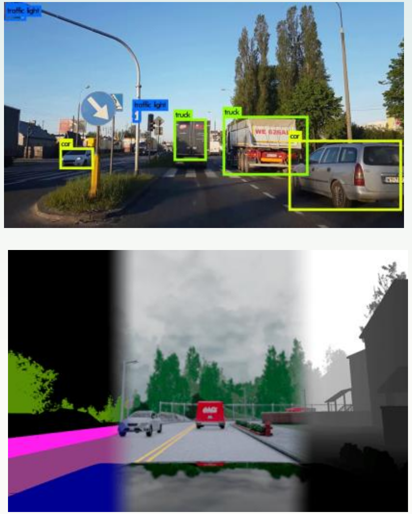
Introduction

Image Process

Different camera configurations

Quantization & Dynamic Range Compression

affect



Computer Vision

Related Work

Classic vs Learning-based Approaches

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Related Work

Classic approaches

- Histogram Equalization
  - Transforming intensity levels
  - Contrast Enhancement
- Techniques based on Color Constancy
  - Center / All (spatial interaction)
  - Color / Illumination (perceived color)
  - Color restoration and contrast enhancement
- Image Fusion-Based Techniques
  - Estimation of degradation
  - Weighted Restoration
- Inpainting
  - Filling regions

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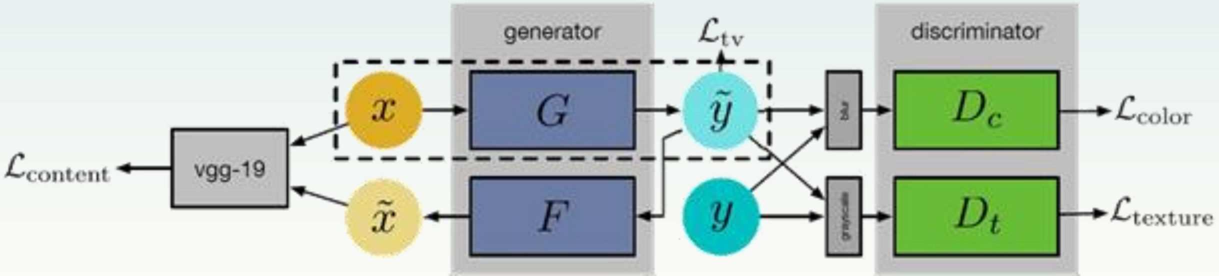
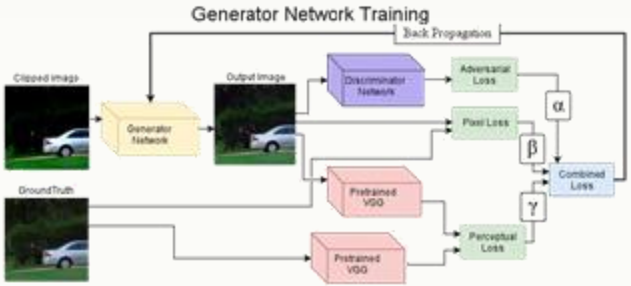
Related Work

Learning-based approaches

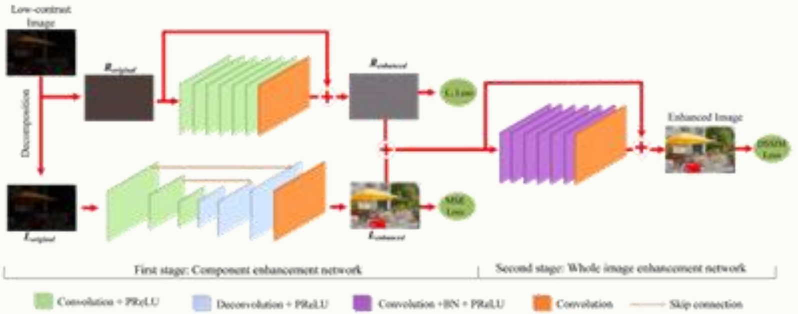
- Converge to an image transformation model from training data



Ignatov et al. (2018)



Honig and Werman (2018).



Cai et al. (2018)

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Proposed CNN

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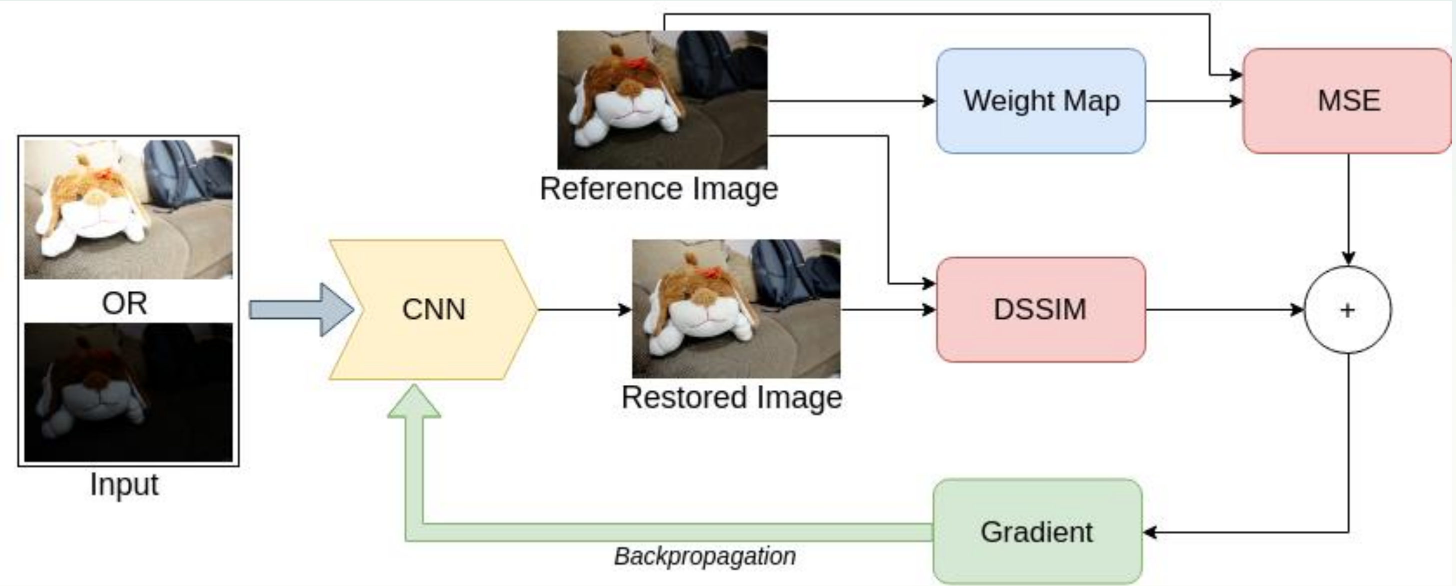
Proposed CNN

Network Overview



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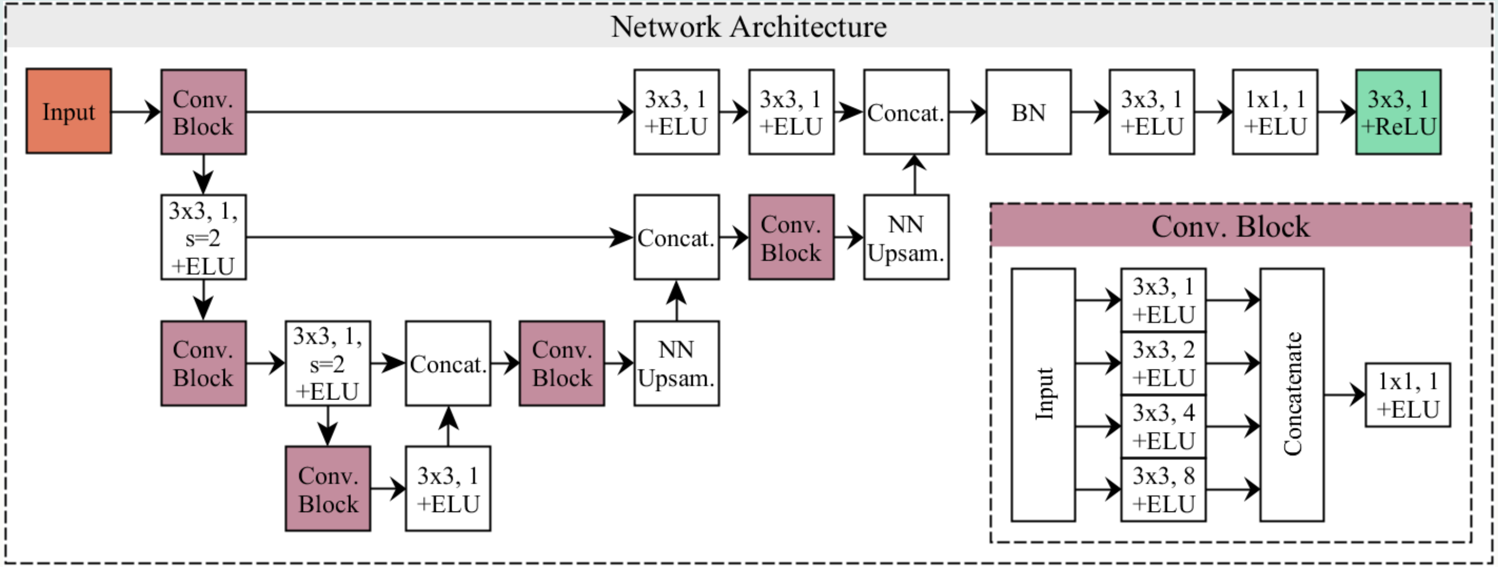
Proposed CNN

Network Structure



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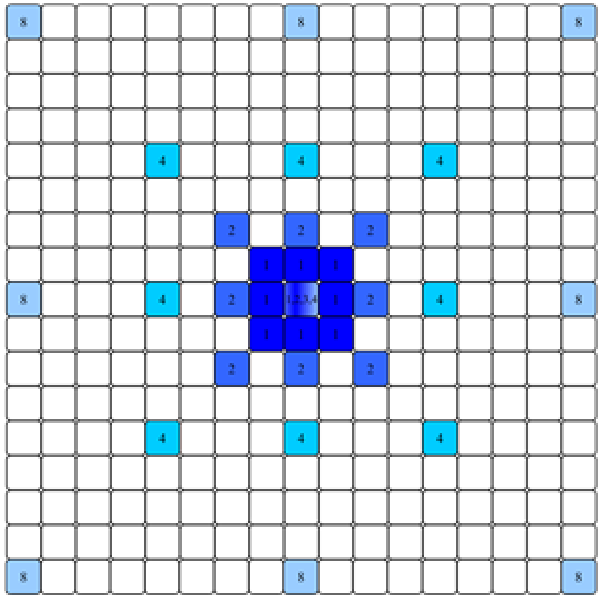
Proposed CNN

Network Structure: Key Aspects

- Larger Receptive Field with Dilated Convolutions
  - Context for filling large saturated regions
- Flow with integral image resolution
  - Local Feature Aggregation
- Exponential Linear Unit Internal Activation
  - Faster Convergence
- Instance Normalization
  - Contrast
- Trainable Downscaling
  - Convolution with step 2
- Trainable Upscaling
  - NN + Convolution



Dilated Convolution Block

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Proposed CNN

Network Structure: Loss Function

- Structural Dissimilarity (DSSIM)
  - 3x3 block
  - Luminance. Contrast and Structure
- Absolute Error (AE)
  - Low frequency evaluation
  - Little impact in terms of texture
  - Color
- Weighting
  - More impact in regions more susceptible to under and overexposure.

$$\mathcal{L}(a,b) = \lambda|0.5-b|\circ L_2(a,b) + (1-\lambda)DSSIM(a,b)$$

Weight Map

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Proposed CNN

Model Adjustment

- 70% training data / 30% test data
- Adam Optimizer
- Mini-batches
  - 8 images
  - Resolution from 512px up to 1280px
- Weight Initialization
  - N (μ, σ) as in Glorot and Bengio (2010)
- Early Stopping Criteria:
  - 300 batches processed without significant improvement in MSE

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Datasets

Getting data to adjust a model
Large and Diverse

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Datasets

Creating Synthetic Clipping

- MIT-Adobe FiveK Dataset
- Synthetic ill exposure by:
  - Deliberatelly truncating a % of the pixels
  - Aplying power transformations to distort intensity levels
- Easy to extend and infinite training samples

$$C_{ij} = \begin{cases} P_{LT}, & I_{ij} \leq P_{LT} \\ I_{ij}, & P_{LT} \leq I_{ij} \leq P_{HT} \\ P_{HT}, & I_{ij} \geq P_{HT} \end{cases}$$

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Datasets

A6300: Real Ill Exposed Paired Image Sets

- A6300 by Steffens et al. (2018)
  - Sets of 4 images for each scene
  - Exposure value (EV) ranging from EV -0.7 up to EV +0.7
  - HDR Composition as ground-truth
  - Sony a6300 camera

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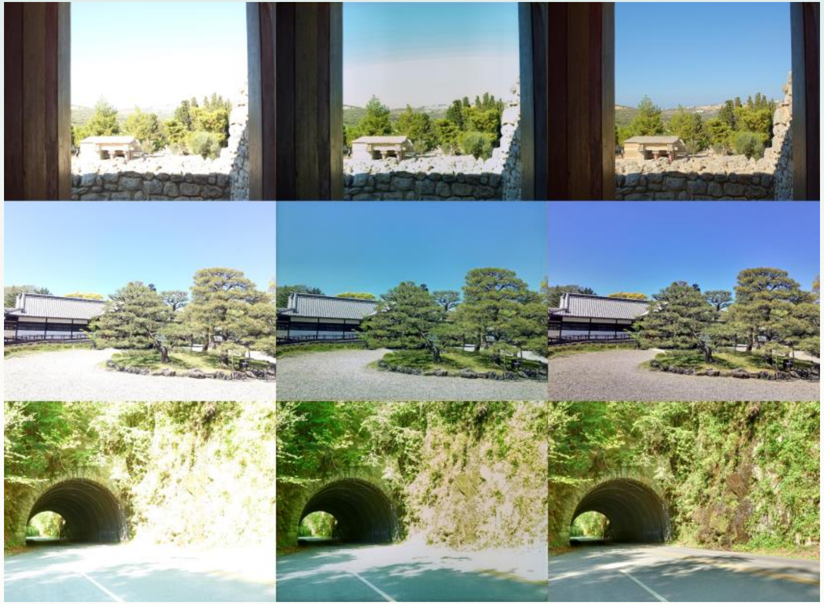
Results

Results

Qualitative Results for Under-Exposed Images

Underexposure



Overexposure

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Results

Top 1 per quality measure for ill-exposed images

FiveK Dataset with hard clipping							
Model	PSNR	MAE	SSIM	Sobel IoU	Canny IoU	Hist. Diff	GMSD
Ours	**2.359E+01**	**6.234E-02**	**9.142E-01**	**7.991E-01**	**6.229E-01**	**3.246E-03**	**2.025E-05**
U-net	2.186E+01	7.563E-02	8.559E-01	6.777E-01	5.150E-01	3.417E-03	3.303E-05
Can24	1.922E+01	1.235E-01	8.316E-01	6.923E-01	4.687E-01	5.007E-03	4.292E-05
DHE	1.529E+01	1.581E-01	7.300E-01	5.548E-01	3.005E-01	4.890E-03	8.671E-05
Ying	1.503E+01	1.887E-01	7.240E-01	6.087E-01	3.797E-01	5.580E-03	6.751E-05
Fu	1.579E+01	1.673E-01	7.544E-01	6.278E-01	3.486E-01	5.113E-03	6.275E-05
None	1.853E+01	1.463E-01	7.776E-01	7.450E-01	5.938E-01	4.569E-03	4.674E-05

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Results

Top 1 per quality measure for ill-exposed images

A6300 Dataset with multiexposure bracketing							
Model	PSNR	MAE	SSIM	Sobel IoU	Canny IoU	Hist. Diff	GMSD
Ours	**1.780E+01**	**1.233E-01**	**8.628E-01**	**6.148E-01**	**3.903E-01**	**5.754E-03**	**3.707E-05**
U-net	1.640E+01	1.481E-01	8.332E-01	5.551E-01	3.536E-01	6.674E-03	4.376E-05
Can24	1.404E+01	2.045E-01	7.987E-01	5.287E-01	3.321E-01	7.493E-03	5.310E-05
DHE	1.436E+01	1.836E-01	7.810E-01	5.314E-01	3.006E-01	6.941E-03	9.072E-05
Ying	1.312E+01	2.595E-01	7.756E-01	5.915E-01	3.509E-01	7.846E-03	8.189E-05
Fu	1.153E+01	2.946E-01	7.241E-01	5.387E-01	3.273E-01	8.534E-03	9.466E-05
None	9.666E+00	3.419E-01	5.722E-01	4.584E-01	2.213E-01	9.365E-03	1.164E-04

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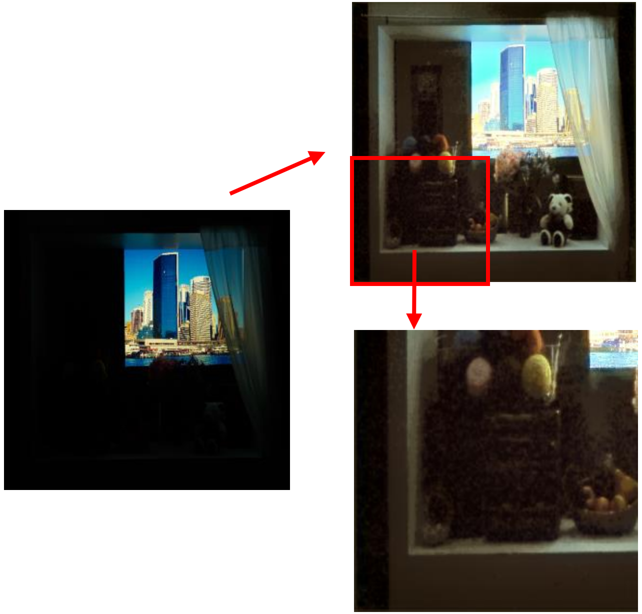
Results

Known Limitations

- Limitations on filling and retrieving texture details in large areas
- Scene semantics for restoring severely affected images
  - Imagination and Filling
- Block Artifacts from JPEG Compression
  - Low contrast regions
  - Abrupt transition zones (block edges)
  - Soft textures and transitions can not be retrieved



Block Artifacts

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Conclusion

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Conclusion

What has been done

- Saturation, underexposure and compression artifacts
- End-to-end model
- Evaluation using various quality indices
  - CNN generally superior to classical methods
  - Results significantly better than compared models
  - Good texture, contrast and color preservation
- Limitations
  - Severe saturation (large areas)
  - Enhancement of block artifacts

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Conclusion

Future Work

- Work on the identified limitations
- Explore Additional information
  - Metadata (fill and de-blocking)
  - Semantics / Content (fill in)
- Perceptual loss (de-blocking)
- Total Variance (de-blocking)
- Specialized sub-networks (semantics, enhancement, intensity, de-blocking)
- Compare with directly related models
  - Cai et al. (2018)
  - Ignatov et al. (2018)
  - Honig and Werman (2018)
  - Hu et al. (2018)

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Q&A

Please email the tricky questions

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Code and trained model:

http://tiny.cc/93bzcz