ENHANCEMENT OF LOW LIGHT IMAGES

Amogh Joshi (01FE19BEC199), Chinmayee Mandi (01FE19BEC188), Sampada Malagi (01FE19BEC244), Palavi Kamat (01FE19BEC032)

Under the guidance of
Ujwala Patil, Ramesh Tabib, Chaitra Desai

KLE Technological University, Vidyanagar, Hubballi-580031, Karnataka, India

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Overview

Introduction to Low light images

- Images captured in low-light conditions are prone to suffer from low visibility.
- Image enhancement is the procedure of improving the quality and information content of original data.

Figure: Enhanced low light image

Motivation

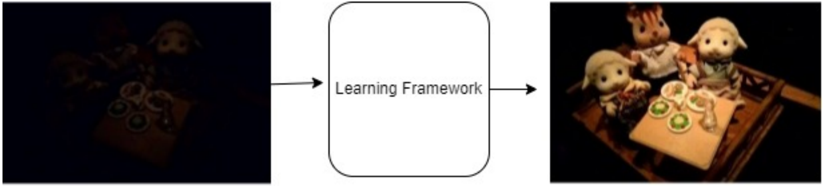


Figure: Enhanced low light image

- Images captured in low-light conditions being unpleasing to human vision, the enhancement of such images help the society have a beautiful vision of images without any external light source requirement for capturing of images.
- This being the basic motivation, we urge to work on applications of this concept to help the needy at the root level and also where possible.

Zero-Reference Deep Curve Estimation for Low-Light Image Enhancement(CVPR-2020)

A Deep Curve Estimation Network (DCE-Net) is devised to estimate a set of best-fitting Light-Enhancement curves (LE-curves) given an input image. The framework then maps all pixels of the input's RGB channels by applying the curves iteratively for obtaining the final enhanced image.

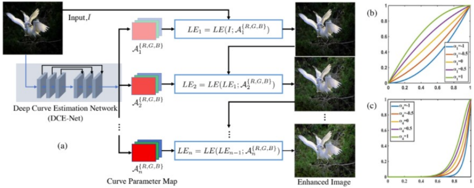


Figure: Architecture diagram of zero-dce

Literature Survey on Enhancement of Lowlight images

Learning to Restore Low-Light Images via Decomposition-and-Enhancement(CVPR-2020)

It presents a novel network that first learns to recover image objects in the low-frequency layer and then enhances high-frequency details based on the recovered image objects. In addition, a new low-light image dataset is prepared with real noise to facilitate learning.

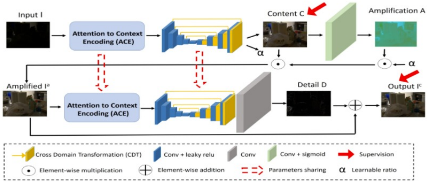


Figure: Architecture diagram of enhancement using decompostion and enhancement.

From Fidelity to Perceptual Quality: A Semi-Supervised Approach for Low-Light Image Enhancement(CVPR-2020)

The architecture here is divided into two parts: 1.recursive band learning : here the drbn is constructed to recover a normal light image based on low light input in recursive manner, 2.Band recomposition:the model here further learns to recompose the restored signals with perceptual quality guide.

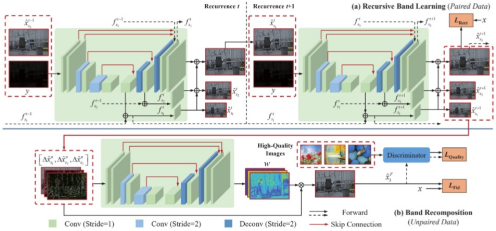


Figure: Architecture of semi-supervised approach for Low-Light image enhancement.

A New Low-Light Image Enhancement Algorithm using Camera Response Model(CVPR-2020)

A novel enhancement method using the response characteristics of cameras. First, we investigate the relationship between two images with different exposures to obtain an accurate camera response model. Then we borrow the illumination estimation techniques to estimate the exposure ratio map.

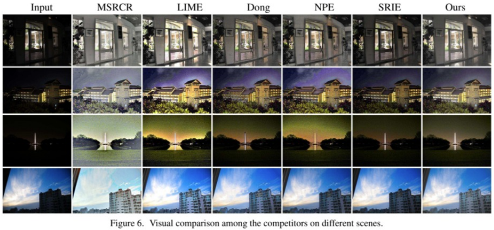


Figure: Architecture of camera response model.

Restoring Extremely Dark Images in Real Time(CVPR-2020)

A new deep learning architecture for extreme low-light single image restoration, despite of its fast lightweight inference, produces a restoration that is perceptually at par with state-of-the-art computationally intense models. To achieve this, we do most of the processing in the higher scale-spaces, skipping the intermediate-scales wherever possible.

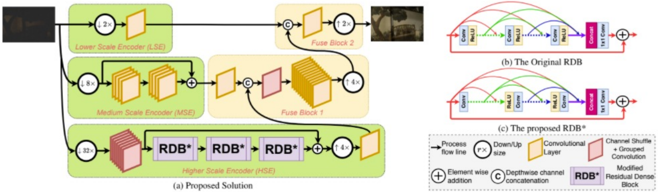


Figure 3. Architectural details of the proposed model. Depth of convolutional layer is roughly proportional to number of o/p features.

Figure: Architecture of Restoring Extremely Dark Images in Real Time

Problem Statement and Objectives

Problem Statement

To propose a Learning based technique for Enhancement of images captured in low light conditions.

Objectives:

1. Experiment on available learning based architectures towards Low light image enhancement.
2. Develop a learning based technique for enhancement of low light paired images of high ISO, low ISO and high exposure, low exposure.
3. Propose a learning based architecture to enhance the images captured in low light condition.
4. Demonstrate the results of the proposed methodology using the available data-set and compare the results with state-of-the-art methods

Approach

1: CWAN Architecture

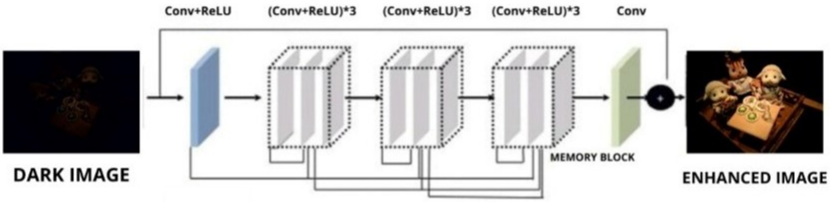


Figure: CWAN Architecture

2: Unet Architecture

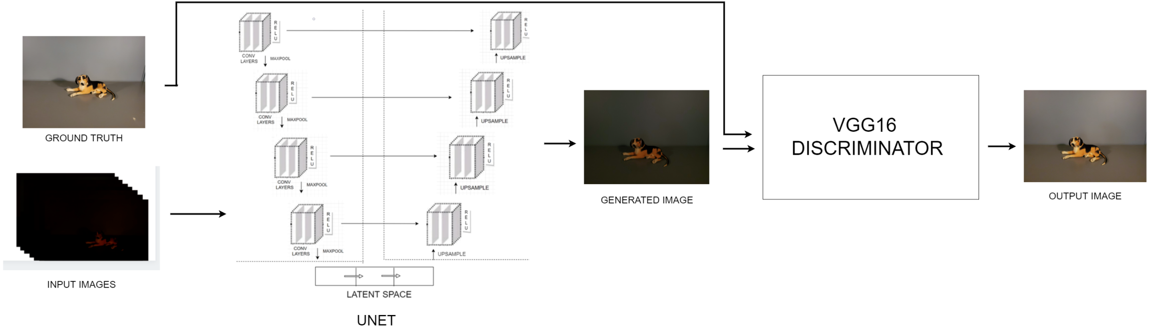


Figure: Unet Architecture

Proposed Block Diagram: Training phase.

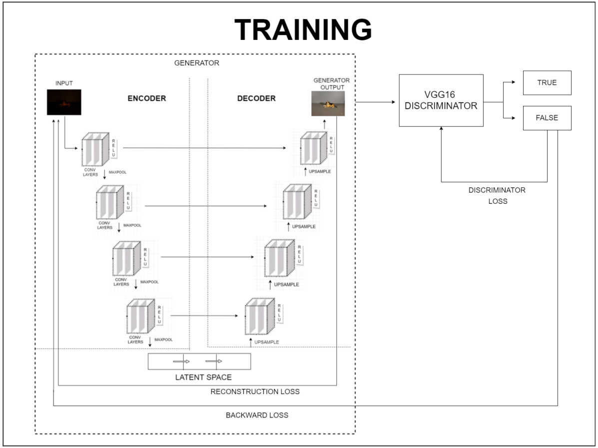


Figure: Training phase block diagram

Proposed Block Diagram: Testing phase.

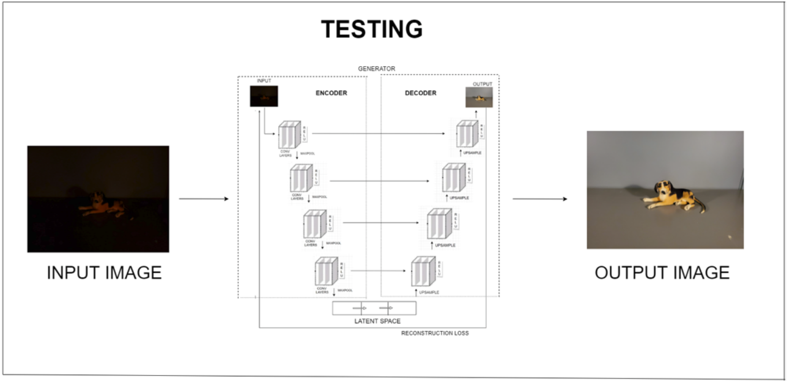
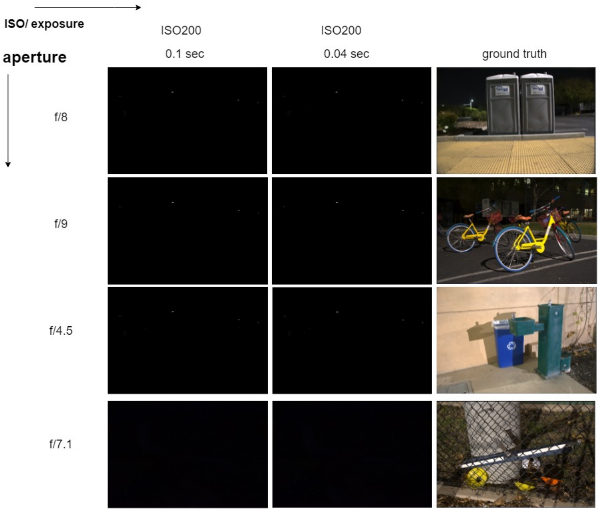


Figure: Testing phase block diagram

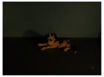
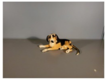
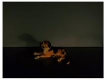
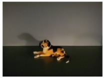
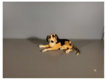
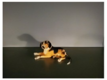
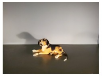
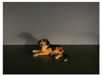
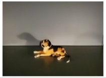
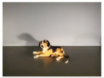
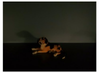
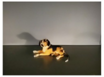
Data-set Analysis

- Sony Data-set



Data-set Analysis

- Custom Data-set

Exposure \ ISO	50	100	200	400	600	Ground Truth
1/125						
1/90						
1/60						
1/50						
1/45						

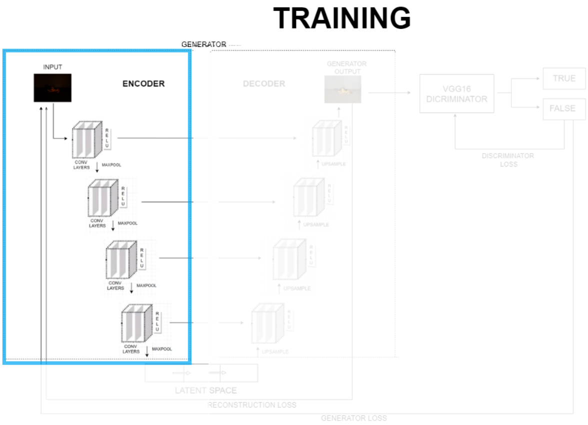


Figure: Training phase: Encoder

Figure: Training phase: Latent space

Plan of Action

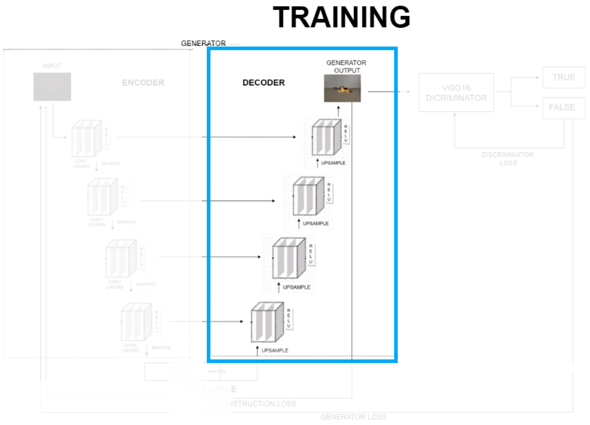


Figure: Training phase: Decoder

Figure: Training phase: Discriminator

Experimental setup

Evaluation metrics:

We evaluate the results generated by the proposed architecture using Peak Signal to Noise Ratio[4] (PSNR) and Structural Similarity Index Measure (SSIM)[6] evaluation metrics. PSNR[4] and SSIM are defined as:

$$PSNR[4] = 10log_{10}(\frac{P_{signal_{max}}}{MSE}) \tag{1}$$

where $p_{signal_{max}}$ is the maximum power of the signal

$$SSIM[6] = \frac{(2\mu_x\mu_y + C_1)(2\sigma_{xy} + C_2)}{(\mu_x^2 + \mu_y^2 + C_1)(\sigma_x^2 + \sigma_y^2 + C_2)} \tag{2}$$

where $\mu_x\mu_y\sigma_x\sigma_y and \sigma_{xy}$ are means, standard deviations and covariances for two images x and y.

Evaluation metrics:

$$GAN\ \ LOSS[3] = Ex[log_(D(x)) + Ez[log(1 - D(G(z)))] \tag{3}$$

where,

$z\ \ represents\ \ the\ \ latent\ \ space$
$D(x)\ \ is\ \ the\ \ output\ \ of\ \ the\ \ discriminator$
$Ex\ \ is\ \ the\ \ real\ \ value\ \ over\ \ all\ \ data\ \ instances\ \ x\ \ is\ \ the\ \ input\ \ vector.$
$G(z)\ \ Generator\ \ output\ \ vector.$
$D(G(z))\ \ is\ \ the\ \ discriminator's\ \ estimate\ \ of\ \ probability\ \ that\ \ a\ \ fake\ \ instance\ \ is\ \ real.$
$Ez\ \ is\ \ the\ \ expected\ \ over\ \ all\ \ random\ \ inputs\ \ to\ \ the\ \ generator.$

Experimental setup

$$Generator\ \ Loss = \Delta\theta g \frac{1}{m} \Sigma log(1 - D(G(z^i))) \tag{4}$$

where,
m repesesnts the number of samples.
$D(G(z^i))$ represents the discriminator output with generator output vector as an input.

$$Discriminator\ Loss = \Delta\theta g \frac{1}{m} \Sigma[log(D(x^i) + log(1 - D(G(z^i)))] \tag{5}$$

where,
m repesesnts the number of samples.
$D(G(z^i))$ represents the discriminator output with generator output
D(x^i) *represents the the noise input given to the discriminator.*

Experimental Results

Parameters	LDC	LAMBA	LAMBA(SONY)[5]†
PSNR	**29.56**	28.66	25.4994
SSIM	**0.799**	<u>0.790</u>	0.52511

The above table represents all the experimentation results.The best results are represented in bold and the second best is underlined.

Results obtained using sony data-set:

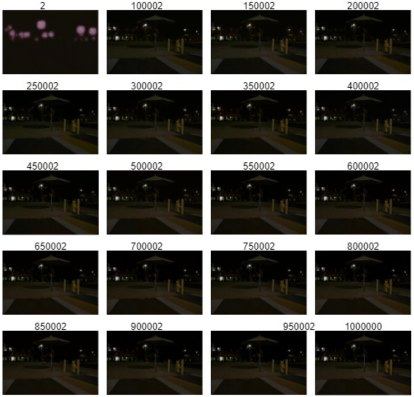


Figure: Results of Lamba architecture with Sony dataset.

Results obtained using custom dataset:

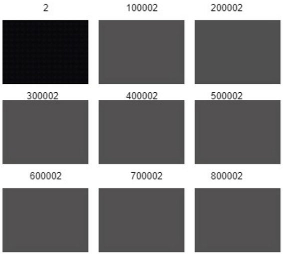


Figure: Results of Lamba architecture with custom dataset.

Reference I

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Reference II

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