Enhancing Visibility of Low-Light Images using Deep Learning Techniques

M.Praveena, V.Pavan Kumar, R. Asha Deepika, Ch.Sai Raghavendhar, J.Rahul Sai Reddy

Abstract: Visualizing an image in the low light is still a challenging and an unaccomplished objective, due to low Signal Noise Ratio (SNR) and low photon count. Though many techniques on image processing have been proposed, such as deblurring and denoising, to increase the visibility of the image in the darkness, they have certain drawbacks and limitations. The model proposed in this paper is deep learning pipeline. We have trained two models in order to enhance the image, one is based up on the convolutional network with raw short exposure image with reference of its corresponding long exposure image. The second model is based on the separation of an image into its RGB (Red, Blue, Green) channels, and training an individual model for each channel. Both the models are tested and promising results are obtained in terms of the SNR, on the new datasets.

I. INTRODUCTION

Every image consists of noise, but its really high in those where there is low light. Brightness of the image can be raised to increase its visibility using high ISO, but it also raises the noise of image to the same extent. Techniques like histogram stretching, gamma correction can be used but they cannot resolve the low SNR problem due to less photon count. SNR can be increased to some extent taking measures like using a flash or raising the exposure time. But every method has its own drawbacks, like increasing the flash can reduce the visibility of objects in the image and raise in the exposure time leads to blurring of the image which in turn raises the noise.

Some approaches include methods like total variation, wavelet-domain processing, nuclear norm minimization, sparse coding, 3D-Transform-domain filtering(B3MD), Trainable non-linear reaction diffusion(TNRD), Sparse denoising auto-encoders(SSDA), Deep auto encoders etc.

In this paper, images with extremely low illumination and short exposure levels are concentrated. In this contrast, the images should be recreated entirely from raw data. As such, a pipeline is proposed which operates completely in data driven approach. The deep neural networks are trained in such a way that they learn the image processing pipeline technique for low light image data which includes the demosaicing, color transitions, image enhancement, reduction of noise. The training is done in end-to-end approach in order to avoid the accumulation of errors, and amplification of noise.

Existing models for preprocessing the low light images were evaluated mainly on the data that has images with added Gaussian noise. As far as our knowledge, there are no datasets available publicly for testing and training techniques to process the low-light images with varied real-time data depicting the ground reality. So, completely new data sets of raw images are being captured in low light and fast exposure have been collected. Each image with short-exposure has its corresponding long-exposure reference image with high quality. The observed results were quiet satisfactory as the image amplification is done up to 300 times with appropriate color transformations and successful noise reduction.

II. LITERATURE SURVEY:

Learning to see in the dark[1]: In this paper, The application of deep learning on the enhancing the visibility of low light images and application of artificial intelligence in image processing field have been elaborated.

Image processing with Neural Networks[2]: In this paper, we reviewed some image processing applications of the neural networks and an assessment on present and also future roles of neural networks, especially Kohonen feature maps, feed forward, and Hopfield neural networks is done.

U-Net Convolution networks in Biomedical Image Segmentation[3]: In this paper, the U-Net architecture is described clearly. This architecture uses up sampling and down sampling algorithms. It is applied when input is an image and an image for image segmentation is the output of the network.

III. RELATED WORK:

Low light image processing is computationally studied in this literature. It is a challenge to enhance images in low-light. Few traditional image processing techniques like de-noising, de-blurring and enhancement of low light images are used earlier. If high ISO is used to brighten the image, noise increases. Low signal-to-noise (SNR) still persists even when post-processing. Either due to object motion or shaking of camera

3.1. Image De-noising:

Image denoising is a process with which we reconstruct signal from a noisy one. Removing unwanted noise in order to restore the original image is the gist of image denoising.

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M.Praveena, Department of computer science and engineering Koneru Lakshmaiah Educational Foundation, Vaddeswaram. (Email: praveena.mandapati@kluniversity.in)

V.Pavan kumar, Department of computer science and engineering Koneru Lakshmaiah Educational Foundation, Vaddeswaram. (Email: pavanv1998@gmail.com)

R.Asha deepika, Department of computer science and engineering Koneru Lakshmaiah Educational Foundation, Vaddeswaram. (Email: ashadeepika123@gmail.com)

CH.Sai raghavendhar, Department of computer science and engineering Koneru Lakshmaiah Educational Foundation, Vaddeswaram. (Email: raghavlucky1209@gmail.com)

J.Rahul sai reddy, Department of computer science and engineering Koneru Lakshmaiah Educational Foundation, Vaddeswaram. (Email: jangarahulreddy@gmail.com)

Image denoising is simply a method of estimating the unknown signal from available noisy data. But the methods that exist right now work only to limited extend. So deep learning neural network is used for image de-noising.

3.2. Low-light image enhancement:

Different methods are being applied to improve the quality of images with dim-light. Histogram equalization is one such method, in which the whole image is represented in a histogram format and we try to balance the histogram. Gamma correction is another technique in which we increase the brightness of the regions which are dark while compress the pixels which are bright. These methods generally assume that representation of scene content in the images are fair enough.

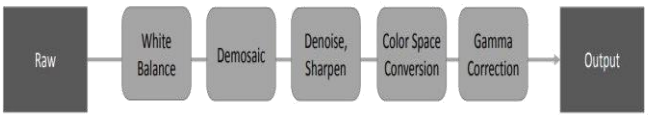
IV. PROPOSED-MODEL:

4.1 Pipeline:

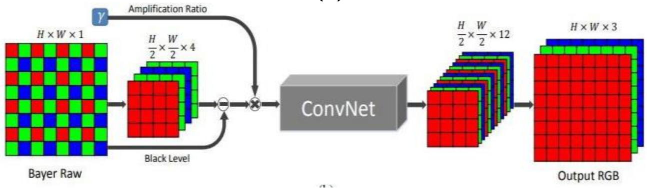
After getting the raw data, the traditional image processing pipeline applies a sequence of modules such as white-balancing, de-mosaicing, de-noising, sharpening of image, color space conversion and gamma correction. But using this traditional pipelining method we are not able to deal with fast low-light images successfully and also extreme low SNR are not handled correctly.

We propose to use an end-to-end learning for processing of low-light images. A fully convolutional network is used for training to perform image processing pipeline. We operate on raw-data images rather than images produced by traditional camera processing pipelines.

Fig 1(a) is the traditional image processing pipeline. Fig1(b) is the presented pipeline structure. We reduce the resolution in each dimension to half for Bayer arrays. The input is packed into four channels in each dimension. We subtract the black level and scale the data by the desired amplification. This amplified data is fed to the fully convolutional neural network This half-sized output is processed through a sub-pixel layer used to recover the image to its actual resolution.



1(a)



1(b)

Fig. 1(a) Traditional pipeline 1(b) Our pipeline

In the first method, the pipeline is applied on the image as a whole directly and the results are observed. Whereas in the second method, for further improvement the pipeline present in the Figure1(b) is applied thrice for three channels and the results are merged. For each channel the image intensity values of other two color channels are made zero before applying the pipeline.

4.2 Architecture

U_NET architecture is used in this model which is demonstrated in Fig.2 . The architecture consists of two parts. A contrasting path on the left side and an expansive path on the right side. In the contrasting path, the general convolutional network architecture is followed which consists of repeated two 3x3 convolutions. Each of these convolution operations are followed by a ReLU(Rectified Linear Unit) activation function with a max pooling operation of 2x2 with stride 2 for down sampling.

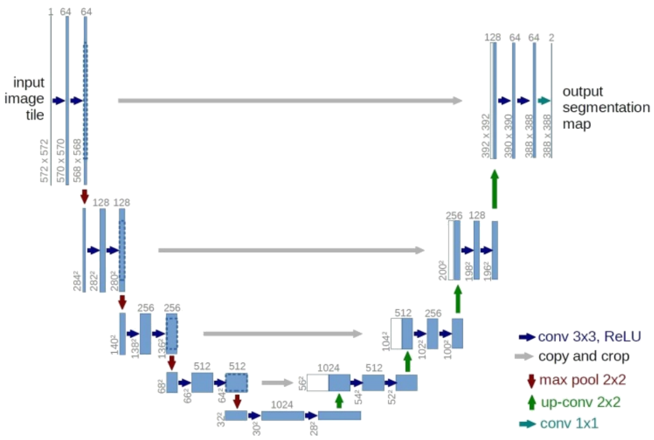


Fig. 2

At every downsampling operation, the feature channels will be doubled. Each step of the expansive path compromises of an upsampling of the feature map and then a 2x2 convolution(up convolution) is performed which is used to half the number of feature channels, the joining with the corresponding cropped feature map in the contracting path, followed by two 3x3 convolutions, each followed by an activation function which is ReLU. In each convolution operation the pixels at the border can be lost. To overcome such issues cropping is important.

4.3 ACTIVATION FUNCTION:

Activation function used in this architecture is ReLU.

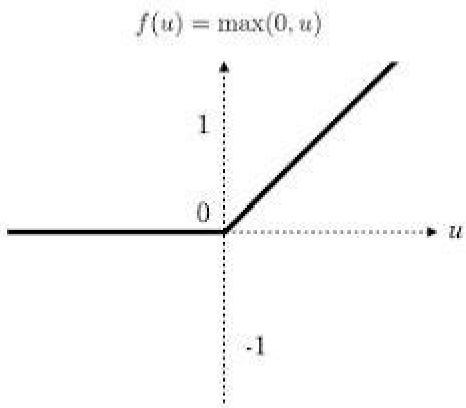


Fig 3 : Rectified Linear Unit

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V. EXPERIMENT:

5.1 Dataset

Most of the surviving methods proposed for processing of dark images are a ccessed using Artificial data and the real dark ima ges but not on the ground truth images. We have captured some images in dark with a fast snap. We h ave created the dataset with this data. For every im age we have captured dark, we have also captured the corresponding image with long snap which is high quality reference for the dark image. Multiple short exposure images can correspond to their long snap references.

The dataset which we have given consists of the images which are taken outside as well as inside. The outside images are usually captured at night times under some moonlight or roa d lights. The illuminance of the outside pictures was usually at a the range of about 0.2 lux and 5 lu x. The images captured inside are darker than the im ages captured outside. The inside images are captur ed under some different conditions of light and with some indirect lighting setup in a closed room. The dataset used is SID(See in Dark) dataset.

5.2 Training

We have made the networks to learn from the very basics using Adam optimizer and L1 loss. We train the networks with the raw data of the fast snap (short exposure) in their corresponding ground truth images (long exposure) in the sRGB. For training we apply some random rotations and flipping on a 512x512 image which is cropped ran domly for the data intensification. The learning spee d is about 10-4 at the former stage and after 2000 epochs it is reduced to 10-5. We train our netw ork for about 4000 epochs. Initially input is an image that is rather dark. This input while being trained is compared to other images of same model captured at different light exposures.

5.3 ACCURACY MEASURE – PSNR

Peak Signal to Noise Ratio: The PSNR slab calculates the PSNR between two images in decibels. This ratio is often used as a quality assurance between the compressed and original image. High PSNR value in turn refers to high quality of corresponding image.

Here we have two error metrics to assess the quality of the compressed image. They are PSNR and Mean Square Error(MSE). The PSNR value gives the peak error where as the increasing squared error concerning the compressed ima ge and actual image. The lesser MSE value, the lesser error.

To calculate the PSNR, the block first calculates the MSE using the succeeding equation.

$$MSE = \frac{\sum_{M,N} [I_1(m,n) - I_2(m,n)]^2}{M * N}$$

In the above equation, M repre sents the number of rows and N represents the number of columns of the input images. The PSNR value is measured using the succeeding equation.

$$PSNR = 10 \log_{10}\left(\frac{R^2}{MSE}\right)$$

VI. RESULTS:

In the traditional pipelining method, we can notice that the images produced in e xtremely low light conditions are suffering from severe color distortion and image noise. Even after a pplying the suitable denoising techniques the tra ditional pipelining method is not able to give the promising results in most of the cases.

So, here we are presenting the comparison of two different methods. In the former method, we build a single model and train it by capturing a image in different lightening conditions such as morning, afternoon, evening, night... Where as in the later method, we build individual models for each color channel i.e. red, green, blue. We train these models on their respective channels individually. So we will get separate output images for each model. There after we will get the resultant image by merging the output images of all individual channels.

6.1 METHOD 1 RESULTS:

Fig4.1 Ground Truth

6.2 METHOD 2 RESULTS:

Now, we can compare the two methods by testing them on extreme low light images. We can observe from the results that the former method results are with high noise and less color distortion while the later method has less noise and slightly high color distortion. If we go through the PSNR values , the second method is giving us the more promising results while compared to that of first method.

Fig.4.2 image of Method1
PSNR:30.933502786224537

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Fig-5.1

Fig-5.2

Fig-5.3

Fig-5.4 PSNR:35.433540041889266

Fig-5.1-output of blue channel, 5.2-output of green channel, 5.3-output of red channel

5.4-merged image of all above outputs.

6.3PSNR Values Comparison:

S.No	Image number	SNR of images tested on Model 1	SNR of images tested on Model 2
1	10032_00_250_	30.075880949230598	32.68209758190222
2	10203_00_250_	29.028864005020843	28.79201928644 9584
3	10191_00_300_	30.070349405274683	29.74464397234 2647
4	10203_00_100_	29.180667348920455	30.65436634329 702
5	0032_00_100_	30.933502786224537	35.43354004188 9266

VII. CONCLUSION:

In the paper, we have proposed the best methodology for enhancing the images in extreme low light conditions using the deep convolution networks(U-Net). From the above results we concluded that second model gives the better results than the first model but with slightly high color distortion. We can minimize this color distortion by adding the appropriate weights to each of the color channels. So, that the second model yields the promising results. We are intending to extend our work further by studying the generalized properties of low light imaging networks.

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