Heuristic Approach for Low Light Image Enhancement using Deep Learning

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Abstract - *Because of low Signal to Noise Ratio (SNR) and low photon count, low light imaging becomes more challenging. Images taken in a short exposure get affected by noise while images taken in a long exposure can be blurry. Different methods like image deblurring, image enhancement, and denoising are existing, but at extreme conditions their effectiveness is limited. For the development of a learning-based pipeline, a dataset that includes raw short exposure low light images and corresponding long exposure images is used. DNN based approach operates on raw data from the sensor and works effectively. It outperforms the traditional image processing method which shows poor results on such raw sensor data*

Keywords- SNR, Bayer array, Black level, CNN, etc.

1. INTRODUCTION

Noise makes imaging more challenging in low light. High ISO is used for increasing brightness, but it also amplifies noise. Many post-processing techniques, such as scaling or histogram stretching, can be applied to reduce noise, but as the photon count is low, this does not resolve the low signal-to-noise ratio (SNR). There are other alternative ways to increase SNR in low light, like opening the aperture, extending exposure time, and using flash. But each technique has its own drawbacks. For example, if the exposure time is increased it can introduce blur or object motion.

Many researchers have proposed techniques for deblurring, denoising, and enhancement of low-light images.[10,9,8] These techniques generally assume that images are captured with moderate levels of noise in dim environments. In extreme low-light imaging, the traditional camera processing pipeline fails and the image needs to be constructed again from the raw sensor data. When the environment is extremely dark with very little illumination at the camera. The exposure time is set to 1/30 second and the aperture is set to f/5.6. At high ISO ie. ISO 8,000, which is normally considered high, the camera produces an essentially black image, despite the high light sensitivity of the full-frame Sony sensor. The content of the scene is visible at extremely high ISO ie. ISO 409,600, which is considered to be far beyond the reach of most of the cameras. But the image produced is dim, noisy, and even the colors are distorted. Even state-of-the-art denoising techniques [13] fail to eliminate such noise and do not address the color bias. Using a burst of images is an alternative approach [11,8], but in extreme low-light conditions burst alignment algorithms may fail.

The challenges of extreme low-light photography can be addressed by an image processing pipeline using a data-driven approach. More precisely, we will train deep neural networks to learn the image processing pipeline for raw data of low light images, which includes color transformations, image enhancement, noise reduction and demosaicing. The pipeline will be trained end-to-end to avoid amplification of noise and error accumulation.

2. OBJECTIVES

The deep neural networks will be trained to learn the image processing pipeline for low light raw data which includes methods like color transformations, demosaicing, noise reduction, and image enhancement. Different amplification ratio can be externally set so as to adjust the brightness level of the output image.

3. RELATED WORK

A short review of existing methods is as follows:

3.1. Image Denoising

Denoising is more significant in image processing. The goal of image denoising approaches is reserving the details of an image and eliminating the random noise as far as possible. Techniques such as total-variation[7], wavelet-domain processing[5], sparse coding[4,2], nuclear norm minimization[3], and 3D transform-domain filtering (BM3D)[6] are being used in many approaches. Smoothness, sparsity, low rank, or self-similarity are the specific image priors on which these methods are often based. The application of deep networks to denoising has also been explored by many researchers, including stacked. These data-driven methods can compete with state-of-the-art classic techniques such as BM3D and sparse coding when trained on certain noise levels. BM3D outperforms more recent techniques on real images[13].

3.2 Low Light Image Enhancement

To enhance the contrast of low-light images a variety of techniques have been applied. Histogram equalization is the most popular technique, which balances the histogram of the entire image. Another widely used technique is gamma correction. It used to increase the brightness of dark regions while compressing bright pixels. More global analysis and processing is performed by more advanced methods. But, all these methods generally assume that the low light images already contain a good representation of the contents of the scene.

4. TERMINOLOGIES

4.1. Convolutional Neural Network:

CNN is a deep learning algorithm which takes an input image, assigns importance to the various aspects of the image and differentiate one from the other. It has a convolutional and pooling layer.

1. Convolutional layer, convolve area of input data into smaller areas by detecting important parts within input data.
2. Pooling layer reduces the size of representation to reduce the computation in the network

4.2 Bayer Filter

A Bayer filter checker is a Color Filter Array (CFA). On a square grid of photosensors, it is used for the arrangement of RGB color filters. In most of the single-chip digital image sensors used in digital cameras, a particular arrangement of color filters is used to generate a color image. The filter pattern is 25% blue, 25% red and 50% green. Bayer pattern image is the output of Bayer-filter cameras which is raw.

5. DNN BASED APPROACH

5.1. Neural Network

A Network of interconnected neurons is called a Neural network. A neuron ie. An artificial neuron works like a human neuron cell. The neural network contains an input layer, a hidden layer, and an output layer. A deep neural network is a neural network with more than 2 hidden layers.

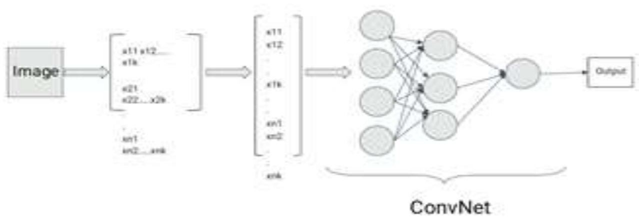

Figure 1: General workflow

There are four stages of neural network:

1. Initialization: Weights are applied to each neuron
2. Forward Propagation: Inputs from a training set are passed through the neural network and output is computed.
3. Error function: The difference between correct output and output of the trained model. By calculating error we can say how much the model is accurate.
4. Backpropagation: It is a technique used to change the weights for the neurons in order to minimize the error.

Repeat these steps until the predicted output become closer to the actual output.

5.2. System Description

We will use SID(See in the dark) dataset it has low exposure images each corresponding to high exposure images. Data is divided into the training-testing dataset. Generally, images are represented in matrix form. Before training the system we need to apply some data preprocessing.

Steps to train the pipeline:

1. Reduce the spatial resolution of the image and then subtract the black level.
2. An amplification ratio is added to increase the brightness of the image.
3. After, this images are fed to the training model i.e CNN.
4. After training the model we need to recover the original resolution of the image.
5. The expected output will be displayed with enhanced and noise-free images.

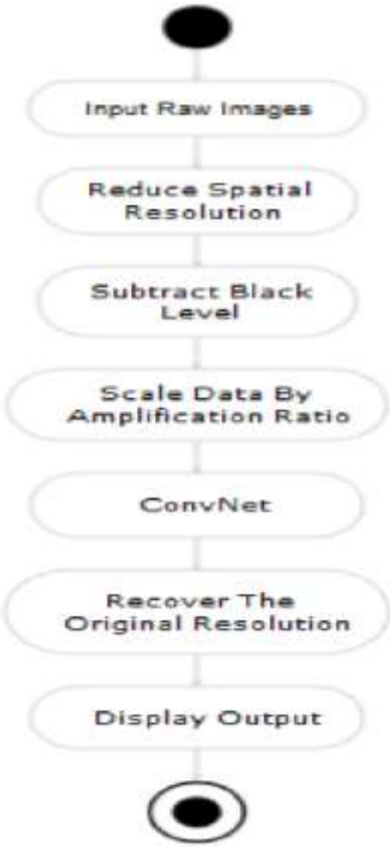

Figure 2: System workflow

6. CONCLUSIONS

The development of a data-driven approach that enables extreme low light imaging was studied. We will implement a simple pipeline that improves upon traditional processing of low-light images using See in the Dark dataset. The pipeline will be based on end-to-end training of a fully convolutional network. Traditional image processing pipeline performs poorly on such raw sensor image data. This network replaces most of the traditional image processing pipeline by directly working on raw sensor data.

A traditional pipeline does not effectively handle the noise and color bias in the image data. This method will help to overcome the traditional methods and will enhance the short exposure images with suppression of noise and correct color transformation. In the future, we can also experiment with this method on different datasets.

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