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LEARNING TO SEE IN THE DARK

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Abstract

Imaging in low light is challenging due to low photon count and low SNR. Short-exposure images suffer from noise, while long exposure can induce blur and is often impractical. A variety of denoising, deblurring, and enhancement techniques have been proposed, but their effectiveness is limited in extreme conditions, such as video-rate imaging at night. To support the development of learning-based pipelines for low-light image processing, we introduce a dataset of raw short-exposure low-light images, with corresponding long-exposure reference images. Using the presented dataset, we develop a pipeline for processing low-light images, based on end-to-end training of a fully-convolutional network. The network operates directly on raw sensor data and replaces much of the traditional image processing pipeline, which tends to perform poorly on such data. We report promising results on the new dataset, analyze factors that affect performance, and highlight opportunities for future work.

Introduction

Noise is present in any imaging system, but it makes imaging particularly challenging in low light. High ISO can be used to increase brightness, but it also amplifies noise. Postprocessing, such as scaling or histogram stretching, can be applied, but this does not resolve the low signal-to-noise ratio (SNR) due to low photon counts. There are physical means to increase SNR in low light, including opening the aperture, extending exposure time, and using flash. But each of these has its own characteristic drawbacks. For example, increasing exposure time can introduce blur due to camera shake or object motion.

Above fig illustrates our setting. The environment is extremely dark: less than 0.1 lux of illumination at the camera. The exposure time is set to 1/30 second. The aperture is f/5.6. At ISO 8,000, which is generally considered high, the camera produces an image that is essentially black, despite the high light sensitivity of the full-frame Sony sensor. At ISO 409,600, which is far beyond the reach of most cameras, the content of the scene is discernible, but the image is dim, noisy, and the colours are distorted.

Literature Survey

The challenge of fast imaging in low light is well known in the computational photography community, but remains open. Researchers have proposed techniques for denoising, deblurring, and enhancement of low-light images.

These techniques generally assume that images are captured in somewhat dim environments with moderate levels of noise. These techniques generally assume that images are captured in somewhat dim environments with moderate levels of noise.

Researches have proposed a method for the development of a deep neural network for conversion of low light short-exposure image to the corresponding long exposure image[1]. After several preliminary exploration they came to a conclusion to make use of U-Net[2] as the convolutional network for this proposed method.

EXISTING SYSTEM AND DRAWBACKS

Noise is present in any imaging system, but it makes imaging particularly challenging in low light. High ISO can be used to increase brightness, but it also amplifies noise.

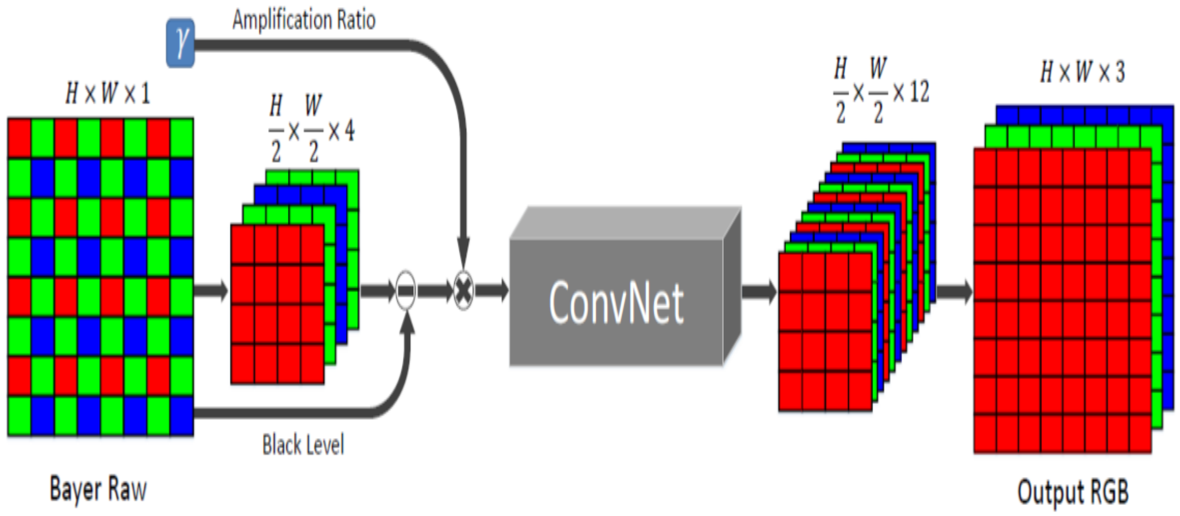
- Postprocessing, such as scaling or histogram stretching, can be applied, but this does not resolve the low signal-to-noise ratio (SNR) due to low photon counts.
- There are physical means to increase SNR in low light, including opening the aperture, extending exposure time, and using flash. But each of these has its own characteristic drawbacks.

PROPOSED SYSTEM AND ADVANTAGES

A variety of denoising, deblurring, and enhancement techniques have been proposed, but their effectiveness is limited in extreme conditions, such as video-rate imaging at night. To support the development of learning based pipelines for low-light image processing, we introduce a dataset of raw short-exposure low-light images, with corresponding long-exposure reference images.

Using the presented dataset, we develop a pipeline for processing low-light images, based on end-to-end training of a fully convolutional network. The network operates directly on raw sensor data and replaces much of the traditional image processing pipeline, which tends to perform poorly on such data. This project provides promising results on the new dataset, analyze factors that affect performance, and highlight opportunities for future work.

Architecture



Implementation

The raw data from an imaging sensor, the traditional image processing pipeline applies a sequence of modules such as white balance, demosaicing, denoising, sharpening, colour space conversion, gamma correction, and others. These modules are often tuned for specific cameras. Rather than operating on normal RGB images produced by traditional camera processing pipelines, we operate on raw sensor data.

For Bayer arrays, we pack the input into four channels and correspondingly reduce the spatial resolution by a factor of two in each dimension. For X-Trans arrays ,the raw data is arranged in 6x6 blocks; we pack it into 9 channels instead of 36 channels by exchanging adjacent elements. We subtract the black level and scale the data by the desired amplification ratio (e.g., x100 or x300). The packed and amplified data is fed into a fully-convolutional network. The output is a 12-channel image with half the spatial resolution. This half-sized output is processed by a sub-pixel layer to recover the original resolution. The ConvNet used is U-Net. The amplification ratio determines the brightness of the output. In our pipeline, the amplification ratio is set externally and is provided as input to the pipeline.

A Bayer filter is a colour filter array consisting of a mosaic for arranging RGB colour filters on a square grid of photosensors. The filter consists of one-fourth red, one-fourth blue and half green pixels as green colour is perceived more by our naked eye. After this the image is multiplied by an amplification ratio. This is then passed on to the convolutional neural network(U-Net) for training.

The U-Net architecture is built upon the Fully Convolutional Network and modified in a way that it yields better segmentation in medical imaging. Compared to FCN-8, the two main differences are (1) U-net is symmetric and (2) the skip connections between the down sampling path and the up sampling path apply a concatenation operator instead of a sum.

Results

input short exposure image with a exposure time of 1/10 seconds

output image for passed through the pipeline with amplification 300 (l1 loss 0.049201)

Conclusion and Future Scope

Usage of deep neural networks for processing short exposure images has demonstrated promising results, with successful noise suppression and correct colour transformation. This work opens many opportunities for the future research. In the future this helps to yield further improvements in the image quality. This leads a way to develop models which are generalized rather than working on specific image sensors.

- The model works only on the raw images
- The See in The Dark dataset does not contain real human images
- The amplification must be given explicitly
- The model only works on the raw images taken by a image sensor which produces Bayer raw image

The results obtained from the trained model are overwhelming. The time taken by the model to produce an output of an image is about 20-25 seconds on the system on a system with 8GB RAM. It will be even faster on system with better configuration.

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