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A Comparative Study of Methods to Improve Visibility in Low Light Images

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ABSTRACT: With the rise in availability of cameras, photography in various conditions such as low light has been on the rise. Due to low photon count, processed images are far from the scene as observed by human eyes. An increase in exposure while capturing the image led to better results, but in turn, increased the noise in the images. We look at the methods used to minimise this noise and increase the overall visibility of the image. We focus on low light images and how they are processed to obtain a perceptually good image. Some of the methods discussed here used traditional image processing pipelines to obtain results while others have used a data-based approach to overcome obstacles brought by image priors.

KEYWORDS- computer vision, convolutional neural networks, noise reduction, low light photography.

I. INTRODUCTION

One of the most important inventions, camera has been around for about 200 years now. It has helped preserve history, art and memories. It has led to a new art form of photography, where a photo tells a lot more than words can. There are various categories within photography, one of which is low light photography. This category involves taking images in low light, which involves scenes with lighting provided by sources such as street lights, moonlight.

Various methods have been used to improve visibility of scene. Some of them process a burst of images to obtain a single image, while others process a single image end-to-end to get the result.

II. EXISTING METHODS

2.1 Basic Methods

Digital cameras have had an important feature that has been taken for granted today. They have the ability to change their ISO on the fly. ISO here refers to the camera sensor's sensitivity to light. A high ISO means the sensor would be

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more sensitive to light and would increase the overall brightness of the image. This is the most basic method of improving visibility of a scene in low-light images.

Another basic method is to increase the exposure of the camera sensor. It can be controlled by two parameters: shutter speed and aperture. Shutter speed is the amount of time that the shutter remains open to capture the scene. A low shutter speed means that the shutter stays open for very small amount of time. The amount of light that enters the sensor is proportional to the time that the sensor is able to capture a light. For example, an image taken with shutter speed as 1/800 seconds would be darker than an image of the same scene taken with shutter speed as 1 second. A high exposure helps to get a brighter image as more photons can be captured by the camera sensor.

A camera works similar to the human eye. There exists an opening that allows light to enter a sensor that captures the light and convert it to an image. Aperture can be compared with the size of the pupil of the human eye. It controls the amount of light that can enter and be captured on the camera's sensor. A high aperture allows more light to enter and improve visibility in low-light images.

Low-light images captured this using traditional pipeline is not perceptually good as it has a high amount of amount of noise. Several denoising techniques are used to further improve the visibility within the image. One of the most used techniques is 3D transform-domain filtering (BM3D).

2.2 BM3D

In 2007, K. Dabov, A. Foi, V. Katkovnik, and K. Egiazarian proposed a novel image denoising strategy based on an enhanced sparse representation in transform domain [1]. The idea was to use 2D image fragments found using matching of reference blocks and group them into 3D data arrays. They called these 3D data arrays groups. Further, they used collaborative filtering for the 3D groups. The filtering was divided into 3 successive steps: 3D transformation of a group, shrinkage of the transform spectrum and an inverse 3D transformation. The estimated 2D fragments were then returned to their locations. Due to multiple matching 2D fragments, they would be required to aggregate to take advantage of the redundancy.

BM3D has outperformed other recent denoising techniques when used on real low light images [2]. BM3D fails to outperform other data driven techniques as they still rely on processed image data rather than raw sensor data. The method also relies on one image of the scene. Another method tackled low-light imaging using burst photography.

2.3 Burst Photography for high dynamic range and low-light imaging on mobile cameras

In 2016, Hasinoff et al [3] proposed a computational photography pipeline that can capture, align and merge a burst of frames to reduce noise and increase dynamic range. The pipeline takes in the burst of raw frames. It then aligns the burst to merge. Then it applies colour and tone mapping to produce a single full-resolution output.

The cameras in mobile phones allow auto exposure adjustment as the user moves the camera around. To get improved results in high dynamic range, they developed their own algorithm for adjusting the auto exposure within the mobile camera.

The major problem with burst images is that if the scene contains a moving object, it is at a different position in every frame. It becomes difficult to find the best position for the object. Hence, burst images introduce blurred objects, or ghosting if the objects move a lot faster than the shutter speed. To overcome this, they used temporal mean with alignment and merged it robustly to achieve almost zero blur compared to the temporal mean.

2.4 Learning to See in the Dark

At CVPR 2018, C Chen et al [4] proposed a pipeline for processing low-light images based on end-to-end training of a convolutional neural network on short exposure images and corresponding long exposure images. The neural network would be trained on raw sensor data rather than output images. This improves performances over other methods since this method does not rely on image priors, which are assumptions made about the image and its data prior to obtaining the image.

This method works by first training a fully convolutional neural network with short exposure images, which are captured in extreme low-light images. The architecture used in the neural network is U-net. Further they used 2 cameras to form the dataset required for training the neural network. The See-in-the-Dark dataset has images from Sony α7S II and Fujifilm X-T2. There are 5094 short exposure images with their reference long exposure images.

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III. FUTURE WORK

As of now, there are no methods that use a single capture on mobile cameras for low-light imagery. It was mentioned in [4] that the neural network they built provided compelling results with an iPhone. The raw images captured by mobile cameras are in DNG format and hence a different neural network must be trained on it to achieve better results. Further they use an external amplification ratio which can be made implicit similar to auto ISO.

IV. CONCLUSION

With the increasing reach of technology, low-light imagery has been on the rise. To improve visibility of scenes in low light images, several methods have come forward. A denoising method BM3D works very well to denoise an image, but works on image priors. Burst photography has helped improve visibility of scenes, but uses multiple images and hence brings the problems of working with burst images. Learning to See in the Dark uses raw data, avoiding image priors, but works best for cameras that have trained the network. There can be improvement made, with increasing visibility of scenes with the help of a single image captured on mobile camera.

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