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Low Light Image Enhancement for Dark Images

Akshay Patil[*], Tejas Chaudhari, Ketan Deo, Kalpesh Sonawane, Rupali Bora

Information Technology, K. K. Wagh Institute of Engineering Education and Research, Nashik, India

Email address:
akshayspatil1411@gmail.com (A. Patil), tejaschaudhari22198@gmail.com (T. Chaudhari), ketandeo@gmail.com (K. Deo), 11kalpeshsonawane@gmail.com (K. Sonawane), rmbora@kkwagh.edu.in (R. Bora)

[*]Corresponding author

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Abstract: Image plays an important role in this present technological world and leads to progress in multimedia communication, various research fields related to image processing, etc. Low-light image enhancement specifically addresses images captured in low-light conditions such as nighttime, where the common goal is to brighten and improve the contrast of the image for better visual quality and show details that are hidden in darkness. Research fields that may assist us in lowlight environments, such as object detection, has glossed over this aspect even though breakthroughs-after breakthroughs had been achieved in recent years, most noticeably from the lack of low-light data (less than 2% of the total images) in successful public benchmark datasets such as PASCAL VOC, ImageNet, and Microsoft COCO. To improve image quality, these low-light images are needed to be enhanced. For this purpose, an exclusively dark dataset comprising of images captured in visible light only is proposed. Further, dehazing technique is used for haze removal, histogram equalization (HE) technique is used for contrast enhancement and denoising technique is used for noise removal. Experimental results demonstrate that the proposed method achieves a good performance in low light image enhancement and outperforms state-of-the-art ones in terms of contrast enhancement and noise reduction.

Keywords: Dataset, Dehazing, Denoising, Enhancement, Histogram Equalization, Low-light

1. Introduction

When one captures pictures in low-light conditions, the pictures usually suffer from low visibility. Besides degrading the visual aesthetics of pictures, this poor quality might also considerably degenerate the performance of the many pc vision and multimedia system algorithms that are primarily designed for high-quality inputs. Low–light setting is associate integral a part of our everyday activities. As day changes to night-time, the quantity of accessible lightweight decreases, inflicting the environment to be more and more dark, and later on touching the talents to perform even menial tasks because of lack of visibility.

Computer vision analysis and systems geared toward aiding folks in daily activities, further as improve safety and security may well be particularly useful in such conditions. However, low-light analysis unremarkably specialize in the image sweetening downside that hardly relates to helpful systems, or vision police investigation that demands pricey hardware, whereas a lot of connected domains like object detection are rarely given attention. Although vital breakthroughs are achieved one once another within the object detection domain, they plain trot out bright pictures whereas considerably lacking for low-light. This is often mostly because of a scarcity of accessible dataset to facilitate and benchmark the analysis during this space. Renowned public object datasets, PASCAL VOC, ImageNet, and Microsoft coco, vie associate integral role within the advancements as they supply massive scale information for several researchers to figure on or as challenges that promote progress in object detection and recognition.

Whereas datasets still grow in numbers, a replacement challenge arises within the style of information annotation as a result of it's troublesome for the human annotators to address the sheer numbers. This shortage of knowledge has obstructed each the understanding and development of pc vision in low-light environments. Thus, it's vital to maneuver the sector forward during this direction through the completely dark (ExDARK) dataset. It contains 7363 lowlight pictures from terribly low-light environments to twilight, and twelve object categories annotated on each image category level and native object bounding boxes. This info may facilitate a stronger understanding of the low-light development that specialize in objects, not like this trend of low-light analysis works wherever restricted samples were used for benchmarking sweetening algorithms, or camera dependent pictures like thermal imaging and close to infra-red for police investigation that are pricey and don't show realistic pictures. This paper presents 2 contributions. First, the completely Dark (ExDARK) dataset, is that the largest assortment of natural low-light pictures taken in visible radiation to-date with object level annotation. Secondly, associate object centered analysis of low-light pictures victimization the progressive algorithms in each handwoven and learned options for a stronger understanding of low-light vision and its distinction from vision with decent illumination is provided.

2. Motivation

When one captures pictures in low-light conditions, the pictures usually suffer from low visibility. This poor quality could considerably degrades the performance of the many computer vision and multimedia system algorithms that are primarily designed for high-quality inputs. These pictures will have low dynamic ranges with high noise levels that have an effect on the performance of computer vision algorithms. To make computer vision algorithms robust in low - light conditions, low-light image enhancement to improve the visibility of an image is the need of time.

3. Aim and Objectives of the Work

The aim of this project is to enhance the images that are captured in low – light conditions by using a proposed Exclusively Dark dataset. We believe this database could facilitate a better understanding of the low-light phenomenon focusing on objects, unlike the current trend of low-light research works where limited samples were used for benchmarking enhancement algorithms, or camera dependent images like thermal imaging and near infra-red for surveillance that are costly and do not show realistic images.

Project objectives:

a) To propose a Low Light Image enhancement technique that is able to provide solutions for Exclusively Dark Dataset, fixing it and should find to proper solution.

b) To facilitate a better understanding of the low-light phenomenon focusing on objects using the proposed Exclusively Dark Dataset.

4. Literature Survey

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 [1].

Up to now, researchers have proposed a lot of contrast enhancement methods to improve the contrast of the low light images. Histogram equalization (HE) remapped input pixel values according to the probability distribution of the input image to make the enhanced image have a uniform distribution in its histogram and fully utilize the dynamic range [2].

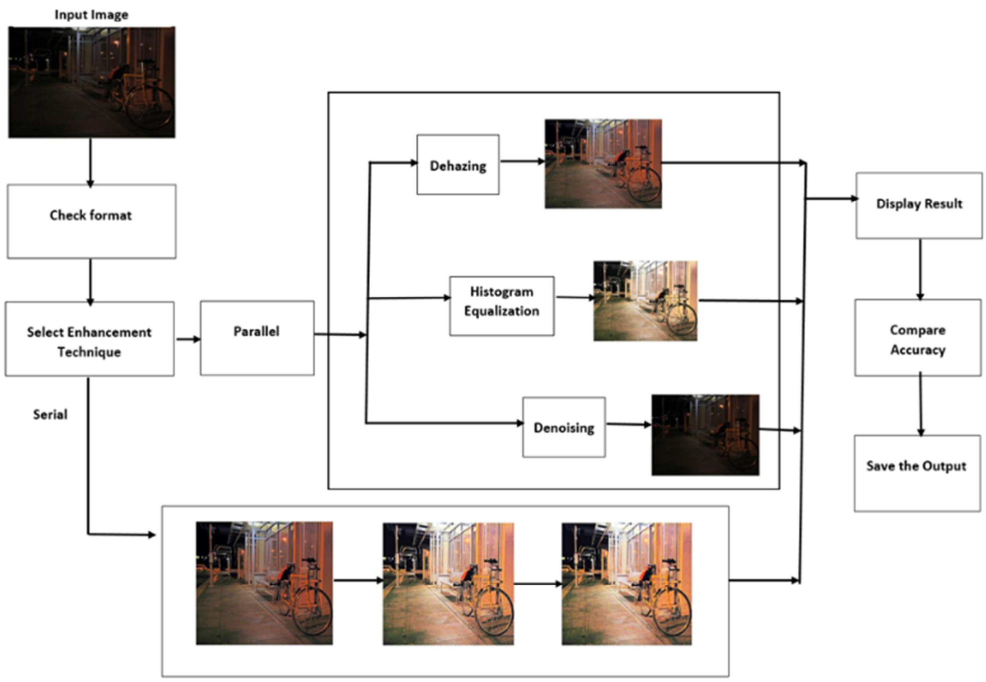

Figure 1. *Block Diagram.*

Low-light research commonly focus on the image enhancement problem that hardly relates to assistive systems, or night vision surveillance that demands costly hardware, whereas more related domains like object detection are seldom given attention. Though significant breakthroughs have been achieved one after another in the object detection domain, they evidently deal with bright images while significantly lacking for low-light [3].

The aim of this paper is to enhance the images that are captured in low – light conditions by using a proposed Exclusively Dark dataset. We believe this database could facilitate a better understanding of the low-light phenomenon focusing on objects, unlike the current trend of low-light research works where limited samples were used for benchmarking enhancement algorithms, or camera dependent images like thermal imaging and near infra-red for surveillance that are costly and do not show realistic images [4].

5. System's Proposed Architecture

A. SYSTEM ARCHITECTURE

The system architecture is as proposed in "figure 1". The user selects an image that is to be enhanced. The system checks for the correct format of the file chosen. Then user selects the enhancement technique that he wants to apply to the image. There are two options, first parallel processing where each option from dehazing, histogram equalization and denoising will be available separately. Second there is serial processing where all options are executed one by one automatically. Finally the result is displayed and the accuracy of the result is checked.

B. Aspiration for low-light image data

A significant motivation in the effort to introduce a singular low-light image dataset is that there is none that is available to the standards for research in this domain.

Table 1. *Low-light image data distribution.*

DATASET		Low-light image
	Training	149
Microsoft COCO	Validation	163
	Testing 2014	138
	Testing 2015	115
	Total	565
	Training	295
ImageNet	Validation	51
	Testing 2014	34
	Testing 2015	72
	Total	450
	Training	195
PASCAL VOC	Validation	43
	Testing 2014	98
	Testing 2015	17
	Total	353
TOTAL	2018	7363

Handling of Low-Light images: Based on the observation, it is found that low-light is commonly glossed over in object dataset analyses with the preferred emphasis on object instances, scale, occlusion, and quantity. This has also indirectly led many researchers to oversimplify the diversity and challenges of low light images. Considering very early computer vision works, such as well-known feature extractors, had already strove for illumination invariance in their design, it is understandable that many would consider illumination or low light condition.

Knowing low-light images: We believe that the characterization of the low-light condition as just "illumination variation" is insufficient as the "variations" encompass much more. For example, low light condition can emerge depending on the time of the day, location, and the availability of light sources and their types. The combination of these three factors can create a great deal of disparity between image to image or even within an image itself. Low-light imaging enhancement is a computational photography pipeline that processes raw data from camera sensor to construct the enhanced RGB output. Though, rather than disregarding the milestones of researches so far, we simply believe that a gap has been overlooked in the common analysis, which we intend to fill in for a more thorough understanding of computer vision.

Examples of low light images:

Figure 2. *Low-light Images.*

C. Data Collection

The dataset currently has 7,363 images with 12 object classes Bicycle, Boat, Bottle, Bus, Car, Cat, Chair, Cup, Dog, Motorbike, People and Table. Most of the low light images are downloaded from internet websites and research engines, namely Flicker.com, Photobucket.com, Imgur.com, Gettyimages.com.

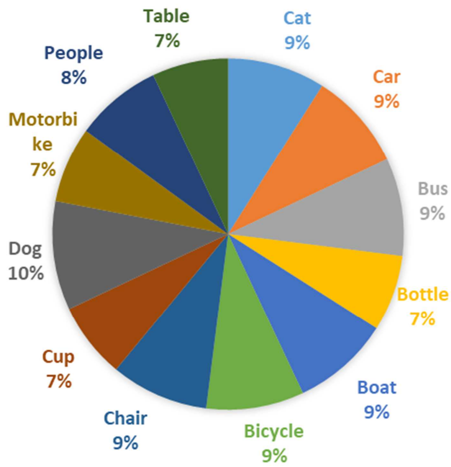

Figure 3. *Object classes in dataset.*

D. Types of Low-Light

1. Low: Images with low visible details.
2. Ambient: Images with weak illumination and light

source is not captured within.

3. Object: Images where there is brightly illuminated object but surroundings are dark and the light sources is not captured within.
4. Single: Images where single light source is visible.
5. Weak: Images with multiple visible but weak light sources.
6. Strong: Images with too bright light sources and multiple visible sources.
7. Screen: Indoor images with visible bright screens (i.e. computer monitors, televisions).
8. Window: Indoor images in which window is light source.
9. Shadow: Outdoor images captured in daylight with but the object are shrouded in shadows.
10. Twilight: Outdoor images captured during twilight (i.e. time of day between dawn and sunrise, or between dusk and sunset).

6. Techniques

A. Dehazing

Image dehazing refers to procedures that attempt to remove the haze amount in a hazy image and grant the degraded image an overall sharpened appearance to obtain a clearer visibility and smooth image.

Objects far from camera are blurry more than those near the camera, which means that the amount of blur in a given hazy image increases with the distance from camera. In contrast, we have that the depth of the image is defined by distance from camera to the farthest point in the image, thus, the amount of blur in a given hazy image increases.

Figure 4. *Image with haze.*

Figure 5. *Image with haze removed.*

Algorithm:

Input: Hazy image I (x)

Output: Airlight $\hat{A}$, t-map $\hat{t}(x)$, dehazed image $\hat{L}(x)$

1. Detect "co-occurring pairs":

(a) Extract structured (high-variance) patches from image I (x).

(b) Search for matching patches (with high normalized-correlation).

2. Extract Pairwise haze parameters for each pair:

(a) Estimate relative t-values t2/t1.

(b) Estimate their shared airlight.

3. Estimate Global haze parameters:

(a) Recover global airlight $\hat{A}$ using all pairwise airlight estimates.

(b) Recover dense t-map $\hat{t}(x)$ which:

(i) is smooth, and (ii) satisfies the sparse pairwise constraints.

4. Recover haze-free $\hat{L}(x)$: $\hat{L}(x)=(I(x)-\hat{A})/\hat{t}(x)+A$

B. Histogram Equalization

Histogram equalization is one of the fundamental tools in the image processing. It is a technique for adjusting the pixel values in image to enhance the contrast by making those intensities more equal across the board.

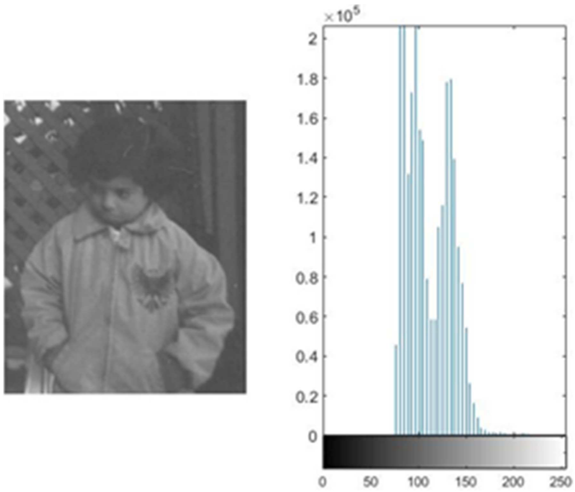

Figure 6. *Original Image with Histogram.*

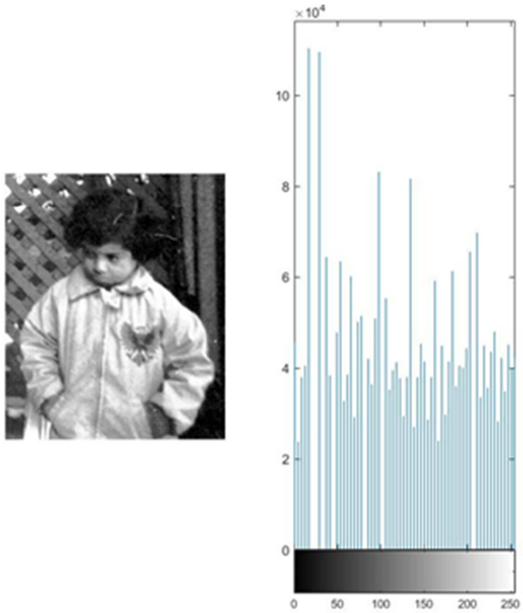

Figure 7. *Image after Histogram Equalization.*

Algorithm:

1. Find the frequency of each pixel value.

Consider a matrix $A=\begin{matrix} 1 & 4 & 2 \\ 5 & 1 & 3 \\ 1 & 2 & 4 \end{matrix}$ with no of bins=5.

The pixel value 1 occurs 3 times.

Similarly the pixel value 2 occurs 2 times and so on.

2. Find the probability of each frequency.

The probability of pixel value 1's occurrence=frequency (1) / no of pixels i.e. 3/9.

3. Find the cumulative histogram of each pixel:

The cumulative histogram of 1=3.

Cumulative histogram of 2=cumulative histogram of 1 + frequency of 2=5.

Cumulative histogram of 3=cumulative histogram of 2 + frequency of 3=6.

4. Find the cumulative distribution probability of each pixel-

CDF of 1=cumulative histogram of 1/no of pixel=3/9.

5. Calculate the final value of each pixel by multiplying CDF with (no of bins);

CDF of 1=(3/9)*5=1.667. Round of the value.

6. Now replace the final values: $\begin{matrix} 2 & 4 & 3 \\ 5 & 2 & 3 \\ 2 & 3 & 4 \end{matrix}$

The final value for bin 1 is 2. It is placed in the place of 1 in the matrix.

C. Denoising

Most Images remain affected by the presence of noise i.e. unwanted signals leading to challenging analysis of images. Image de-noising is a process of removal of unwanted disturbances from the image making image interpretation and analysis easier. The process of image de-noising is achieved by filtering the unwanted noise and accentuating the features and quality of an image.

Figure 8. *Image with noise.*

Figure 9. *Denoised Image.*

Algorithm:

1. Select an image to remove noise
2. Apply median filtering techniques

redChannel=p (:,:, 1);
greenChannel=p (:,:, 2);
blueChannel=p (:,:, 3);

3. Median Filter the channels:

redMF=medfilt2 (redChannel, [3 3]);
greenMF=medfilt2 (greenChannel, [3 3]);
blueMF=medfilt2 (blueChannel, [3 3]);

4. Concatenate all 3 channels

rgbFixed=cat (3, redMF, greenMF, blueMF)

5. Display the output image.

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Biography

Akshay Patil. Currently pursuing bachelor's degree in Information Technology Engineering from K. K. Wagh Institute of Engineering Education and Research, Nashik, India.

Tejas Chaudhari. Currently pursuing bachelor's degree in Information Technology Engineering from K. K. Wagh Institute of Engineering Education and Research, Nashik, India.

Ketan Deo. Currently pursuing bachelor's degree in Information Technology Engineering from K. K. Wagh Institute of Engineering Education and Research, Nashik, India.

Kalpesh Sonawane. Currently pursuing bachelor's degree in Information Technology Engineering from K. K. Wagh Institute of Engineering Education and Research, Nashik, India.

Prof. Rupali M. Bora. Currently working as an Assistant Professor in Information Technology department of K. K. Wagh Institute of Engineering Education and Research, Nashik, India.