Low Light Image Enhancement Using Python

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ABSTRACT----The poor signal-to-noise ratio (SNR) in low-light photos frequently results in significant sensor noise. Moreover, the noise is non-Gaussian and signal-dependent. We propose a novel denoising technique to tackle the issue by combining weighted total variation (TV) regularization with a Poisson noise model. The weighted Total Variation (T V) regularization effectively eliminates noise while preserving details, whereas the Poisson noise model retains the nature of the noise. Our suggested strategy performs better on NIQE scores than the most advanced techniques.

KEYWORDS----COOPERATIVE Intelligent Transport Systems (C-ITS), Convolutional Neural Network (CNN), Image Collection, CNN+Pyramid Model, Signal to Noise Ratio (SNR), Total Variation (TV) Image Segmentation Histogram Analysis, Image Processing, Image Filtering, Image Enhancement

I. INTRODUCTION

Co-operative Intelligent Transport Systems are an advanced technology allowing for autonomous vehicles to communicate with smart infrastructure and even traffic control centers for the creation of an ideal communication system. Such collaboration in its promotion enables C-ITS as a cornerstone toward the realization of smart cities and IoT.

Among other factors, the roadside units (RSUs), especially if fitted with computer vision, can be said to be a main part of Cooperative Intelligent Transportation Systems (C-ITS).

These RSUs provide complete information regarding traffic and increased range more so than sensors installed on cars. However, low-light challenges severely degrade the performance of vision-based RSUs leading to poor image quality as well as low visibility. In order to address this issue, a variety of image enhancement techniques have been investigated. Conventional methods such as histogram equalization, Retinex algorithms, and wavelet decomposition have demonstrated potential in specific circumstances. Nonetheless, their efficacy is constrained by the significant deterioration of details and colour information in low-light traffic images obtained from low-cost cameras. Deep learning-based methods, such as Dual-Channel DehazeNet, can obtain state-of-the-art performance but require tremendous amounts of training data, thereby making them highly challenging to engineer in practice. To overcome these limitations, context enhancement-based techniques, such as multi-sensor fusion (MSF) and multi-exposure fusion (MEF), have emerged as promising solutions. These techniques are able to significantly enhance image quality, even under difficult lighting conditions, by using information from various sources. This paper introduces a novel pseudo-multi-exposure fusion-based image enhancement algorithm using multi-source data fusion for improving images of low-light traffic conditions. Our approach integrates decision-level fusion of camera and radar data with pixel-level fusion of images taken at day and nighttime to effectively enhance image quality and highlight important traffic participants, including vehicles and pedestrians. The proposed methodology has been stringently tested using the Rope3D dataset as well as real nighttime images obtained from an Intelligent Roadside Surveillance System. We present the results to demonstrate the effectiveness and generalizability of our approach. The main contributions of this paper are as follows: This paper discusses a novel night colour image enhancement approach that integrates multi-sensor and pseudo-multi exposure fusion techniques. Multi-exposure sequences from day and night image pairs, created using a region-based tone mapping method. Utilizing the radar data, moving areas are detected in an image, and PDE-based luminance stretching is applied to highlight traffic targets. An improved weighting function for pyramid fusion has been designed which takes guidance information that results in high-quality traffic images. The rest of this paper is divided as follows: Section 2 contains a literature review relevant to MEF. Section 3 gives the proposed pseudo-multi-exposure fusion-based image enhancement algorithm. Section 4 deals with the experimental results, and finally, Section 5 concludes the paper along with possible future research directions

II. RELATED WORK AREA

In recent times, image dehazing has emerged as the main research area of scientists because it has a wide range of potential uses in fields like computer vision, remote sensing, and autonomous driving. Several methods have been introduced that alleviate the problems of haze from traditional methods and deep learning approaches. According to Sahu et al. (2022), they perform a comprehensive analysis of these techniques based on their pros and cons. The traditional methods mostly rely on the physical models of haze formation and removal, and the deep learning-based methods utilize the neural networks' ability to learn complex patterns from large datasets.

Multi-exposure image fusion (MEF) is another technique that significantly contributes to image quality enhancement, particularly in low-light and high-dynamic-range situations. Xu et al. (2022) do a comprehensive examination of various MEF techniques including the traditional ones drawing from a pixel-level fusion and the advanced methods using deep learning. Xu et al. (2022) developed an improved weight function-based MEF algorithm for capturing image details and thus producing high-quality fused

Object detection and classification are fundamental tasks in computer vision, with applications in autonomous driving, surveillance, and robotics. Liu et al. (2022) propose a novel radar-vision fusion approach based on enhanced evidence theory to improve the accuracy and robustness of object detection and classification in challenging conditions, such as low-light and adverse weather.

Low-light image enhancement is a widely encountered challenge because the desired light information is missing or at least not recorded as expected. Wang et al. (2022) have cited an approach of using a learning-based intensity mapping method that reasons the image-to-curve transformation and multi-exposure fusion for low-light images. The performance at which this methodology outshines others has been achieved by a CNN- trained by a pixel-wise intensity mapping function together with the images produced through the link of several iterations of the training process

III. METHODOLOGY

Image collection is gathering a very diverse range of visual content for various purposes, from personal enjoyment to professional use. Sourcing images from photography websites, stock photo libraries, social media sites, and personal photography, arranging them, and curating them may be part of it. A collection of images can help in artistic projects, marketing materials, educational resources, research purposes, or for personal documentation.

The CNN + Pyramid model, also known as Convolutional Neural Network with Pyramid architecture, is a deep learning framework designed for tasks such as image recognition and object detection. This model combines the properties of convolutional neural networks with the multi-scale feature representation of pyramid structures. Under this framework, the CNN component is processing input images hierarchically to extract features at several levels of abstraction by using layers of convolution.

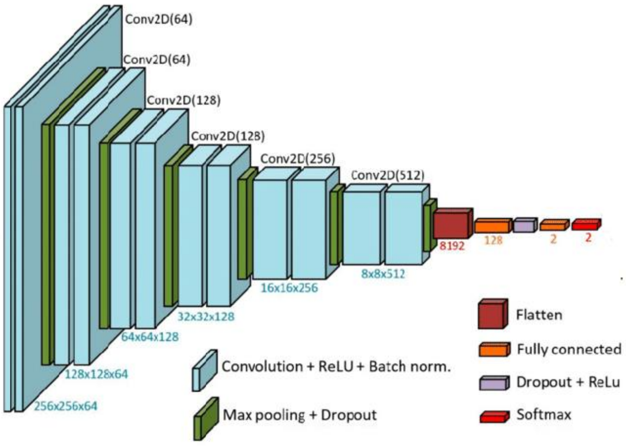
Image segmentation is one of the basic operations within computer vision. It's an operation that separates an image into several segments or regions according to specific features like colour or texture or intensity. In a nutshell, it is attempting to simplify image representation while abstracting all relevant information. The main objective of image segmentation is to divide the image into semantically meaningful parts so that it can be well understood, analyzed, and even managed in an efficient manner. Image segmentation is considered one of the very important tasks concerning computer vision due to the division of an image into several segments or regions based on certain characteristics such as colour, texture, intensity, with the objective of making the representation simple and relevant information being drawn out. The primary objective for image segmentation is to divide an image into semantically significant components so that there can be more effective analysis, comprehension, and manipulation of visual content.

Histogram analysis is perhaps one of the most simple techniques of image processing and computer vision as it analyzes the distribution of intensity of pixels in the image. Histogram is basically a graphical representation that shows the occurrence of a given intensity in an image by plotting darker pixels on the left end of the graph and brighter ones on the right end. The shape and features of the histogram can tell much about general brightness, contrast, and information in the present tones of an image.

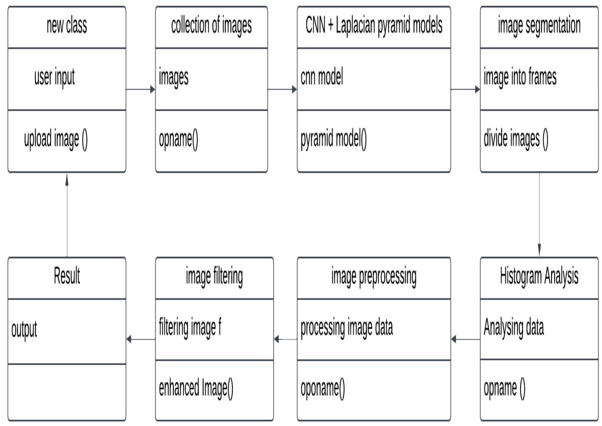
Image processing is referred to as the manipulation and analysis of digital images to extract useful information, improve the visual quality, or execute a particular task in any application. It applies a comprehensive set of techniques and algorithms used to manipulate images toward accomplishing some specific goals. Primary manipulative image processing operations include, and most often are used, in the following: namely resizing, cropping, rotating an image. More powerful and advanced image processing functions are filtering. Filtering: filtering modifies pixel values at given local neighbourhoods to help kill some noises, enhance details in features or bring out certain elements.

Image enhancement is the easiest form of image processing technique where the quality of digital images is enhanced and some of the image features are highlighted and noisiness minimized; contrast and brightness enhancement along with colour balancing is also considered. All this incorporates different techniques and algorithms meant to highlight certain aspects of an image without compromising the integrity and fidelity of the whole. Basic image enhancement involves brightness and contrast, whereby the intensity of a pixel is adjusted to make it brighter or darker. This enhances the contrast between different parts of the image.

SYSTEM ARCHITECTURE

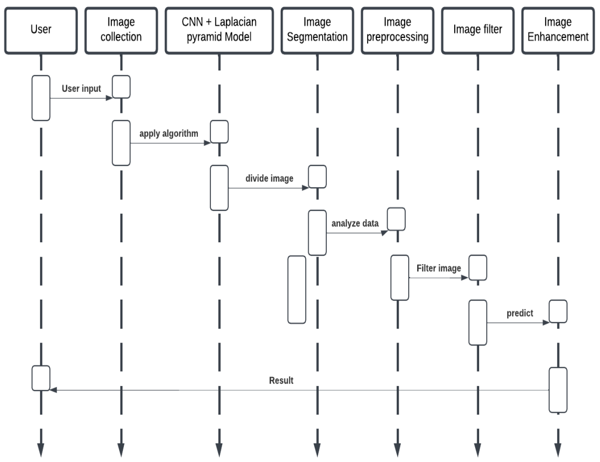


Class diagram



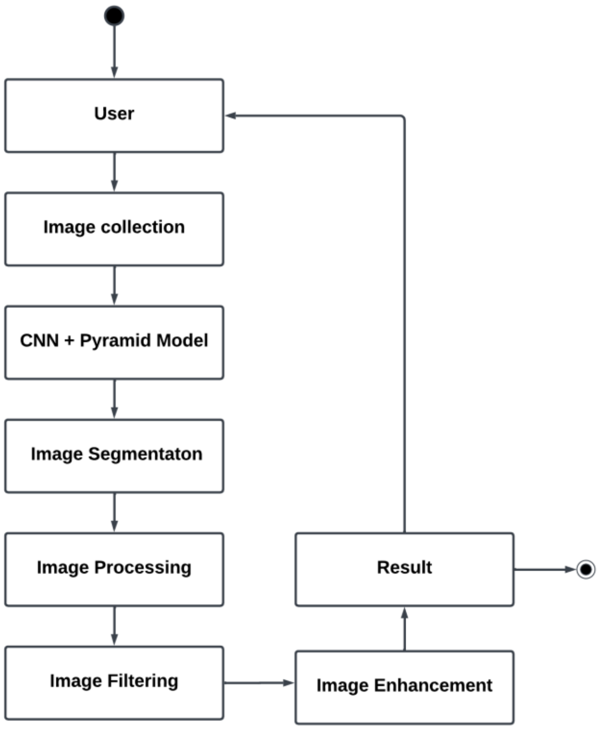
This class diagram portrays classes and their relevant attributes and methods in terms of this security verification. Above is the class diagram of different classes that result in our project.

Sequence diagram



A sequence diagram in Unified Modelling Language (UML) shows how processes work together and in what order. It comes from a Message Sequence Chart. This diagram displays object interactions in the order they happen over time. It shows the objects and classes that play a part in a scenario. It also reveals the order of messages these objects send to each other to make the scenario work.

State diagram



State diagram are the less formal diagrams for illustrating the workflows of stepwise activities & actions in the presence of choice, iteration and concurrency. State diagrams which depict the system in question are defined in the form of a number of states; sometimes it exactly is, while at other times it is a valid simplification. Different varieties of state diagrams also exist, which differ a bit and have distinct semantics

IV. RESULT AND ANALYSYIS

Better Picture Quality:

More Accurate Colours: The two-way area segmentation method helps keep colours looking natural cutting down on weird colour issues that often show up in dark photos.

More Detail and Contrast: By using reverse tone mapping, the system can boost the overall look of the picture making small details easier to see and improving the contrast.

*Clearer Moving Object*s: The highlighting approach, which zeros in on finding and making moving things stand out, can really improve how well you can see cars and people in low light, which could lead to safer roads.

INPUT IMAGE

The above image is the input image we can not see the objects In the Image clearly but after implementing this project we can clearly see all the objects in the image clearly when compared to before implementation of this project

You can clearly see the use of this project

OUTPUT IMAGE

Cutting-Edge Smart Transportation Systems:

Better Object Detection and Tracking: Clear pictures can make object detection and tracking systems work better. This matters for things like self-driving cars and keeping an eye on traffic.

Fewer Accidents: By making it easier to see, the system can help cut down on crashes when it's dark out.

Smarter Traffic Analysis: The clearer images can help us understand traffic patterns more. This leads to better ways to manage and plan for traffic.

V. CONCLUSION

For multi-object detection and recognition in the Intelligent Roadside Surveillance System, we propose an efficient flowchart for night image enhancement by using data fusion at the multi-source level. The intelligent roadside system has its suitability through the applicability of various schemes related to multi-sensor fusion when using a fixed field of view and simple multi-sensor fusion. Two important fusions are decision-level between the camera and radar data and pixel-level between daytime images and nighttime images.

VI. FUTURE SCOPE

This project can be developed in various ways in the future and further enhanced in several aspects to improve nighttime roadside images quality for intelligent transportation systems. This may be done through further refinement and optimization of the proposed bidirectional area segmentation-based inverse tone mapping technique, ensuring that it reaches better levels of natural color representation preservation, besides the improvement of the overall quality of the images. Future work may also be directed to further optimize the highlighting technique, perhaps by adding advanced motion tracking algorithms or machine learning approaches toward accurate identification and highlighting of moving objects. Another potential area that can be developed toward future improvement is new sensor technologies or data fusion strategies that enhance the effectiveness of pyramid-based fusion to generate even better images. Further experimentation and validation with larger and more diverse datasets could come up with interesting information concerning the robustness and generalizability of the proposed method to be potentially deployed in real-world intelligent transportation systems. To summarize, future improvement may continue to push the bound of nighttime image enhancement towards safer and more efficient transport systems.

VII. REFERENCES

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