Journal on Electronic and Automation Engineering

Vol: 4(2), June 2025

REST Publisher; ISSN: 2583-6951 (Online)

Website: https://restpublisher.com/journals/jeae/

DOI: https://doi.org/10.46632/jeae/4/2/47

Low-Light Video Enhancement Using Improved Illumination Map and Retinex Theory

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Abstract: *Low-light video enhancement is crucial in applications such as surveillance, automotive systems, and medical imaging, where visibility is affected by poor light conditions. This project proposes a new method for low-light video enhancement based on the Retinex theory. The Retinex algorithm, which is widely used for image enhancement, divides an image into illuminant and reflectance components, simulating human visual perception. However, when applied to low-light videos, the standard Retinex algorithm faces challenges such as noise amplification and temporal anomalies.*

1. INTRODUCTION

The primary objective is to develop a method that can effectively enhance low-light video in real-time, providing clear, noise-reduced, and visually balanced images. Light mapping plays a key role in determining how light is distributed across a scene and guiding the enhancement process. Low-light video enhancement is a critical task in a variety of fields, including surveillance, entertainment, autonomous driving, and medical imaging. Since conventional cameras struggle to preserve both brightness and fine details in dark scenes, it is challenging to capture clear and detailed video in such environments, while at the same time reducing the impact of noise. Low-light video enhancement is an important area of research, especially in applications such as surveillance, medical imaging, and autonomous vehicles, where clarity and sharpness are essential in environments where reduced contrast is essential. Videos captured in low-light conditions often suffer from issues such as noise, low contrast, and poor visibility, which can significantly hinder their interpretation and analysis. A promising approach to address these challenges is based on the *Retinex theory*, which aims to separate reflectance (intrinsic properties of objects) from illumination (the lighting conditions in a scene). According to Retinex theory, an image can be modeled as the product of reflectance and illumination, and enhancing low-light images involves improving the illumination estimate while preserving the natural appearance. Conventional Retinex-based methods, while effective, sometimes face limitations in accurately estimating illumination, leading to artifacts such as unnatural colors or loss of detail in some areas. To overcome these limitations, recent developments propose the use of *enhanced illumination maps*, which refine the estimation of illumination by combining adaptive techniques, advanced filtering methods, or machine learning algorithms. This approach ensures better preservation of details and contrast, providing a more realistic The combination of Retinex theory with improved illumination maps is a promising solution for low-light video enhancement. By improving illumination estimation and refining the enhancement process, these methods can significantly improve the visual quality of videos captured under challenging lighting conditions, making them more suitable for practical applications in various fields.

2. LITERATURE REVIEW

1. LIME (Low-light Image Enhancement) – 2016

LIME is a low-light image enhancement method that focuses on efficient and sharp illumination map estimation. It employs structure priors to robustly estimate the illumination of the scene, which helps in enhancing visibility in dim regions. However, LIME is sensitive to noise and struggles to produce satisfactory results in extremely dark areas, where the estimation becomes less reliable.

2. Histogram Equalization – 2017

Histogram Equalization (HE) enhances image contrast by redistributing the intensity values across the image. It works by computing the cumulative distribution function of pixel intensities and then mapping the original pixel values to new values that enhance overall visibility. While effective in improving contrast, HE can sometimes over-enhance certain regions or introduce noise, especially in images with non-uniform lighting.

3. Retinex-based Enhancement – 1971

Inspired by the human visual system, Retinex-based enhancement techniques aim to decompose an image into its reflectance and illumination components. Using multi-scale processing, the algorithm adjusts the illumination while preserving the natural colors and details of the image. Though this approach produces visually pleasing results, it is computationally intensive and may struggle with scenes that exhibit high variance in brightness or color.

4. MF (Multi-scale Fusion)

Multi-scale Fusion enhancement techniques take both spatial and frequency domain information into account. These methods estimate illumination maps at different scales and then fuse them to produce the final enhanced image. While this can lead to better visual quality and contrast, the fusion process may introduce halo artifacts, especially around strong edges or transitions in brightness.

3. BLOCK DIAGRAM

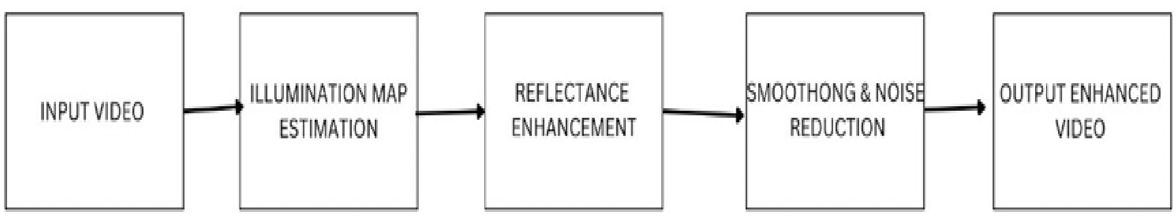

FIGURE 1. Steps for Low Light Video Enhancement

The process starts with a low-light input video, which suffers from issues such as low contrast, low visibility, noise, and color distortion due to insufficient light conditions. In this step, the input video is divided into individual frames. Frame extraction is necessary to allow frame-wise processing. This step makes it possible to apply enhancement techniques to each frame individually, ensuring detailed processing and control. The extracted frames are analyzed to estimate the illuminance map, which indicates the intensity of light in different parts of the frame. This map helps to identify underexposed areas and areas that need illuminance enhancement. An enhanced illuminance map is calculated to ensure a balanced illuminance distribution without overexposing bright areas. Once the illuminance map is estimated, Retinex-based reflectance enhancement is applied. This step aims to enhance the reflectance components of the frame, which include the inherent details, textures, and colors of objects. By adjusting reflectance and illumination, the visibility of dark areas is improved while preserving the natural look of the scene. After enhancing individual frames, temporal smoothing is applied to reduce flicker and ensure smooth transitions between frames. Noise reduction is also performed at this stage to reduce noise that may have been amplified when increasing brightness. This step helps maintain consistency across frames and produce a clean, noise-free output. In this step, the enhanced frames are recombined to create the final output video. This process involves reconstructing the frames in the correct order and ensuring that the enhanced video has smooth playback. The final output is an enhanced video with improved brightness, contrast, and visibility. The enhanced video has reduced noise, restored color balance, and has consistent temporal quality, making it more visually appealing and suitable for practical applications such as surveillance, video. Streaming and multimedia content creation. This process is designed to address the common challenges associated with low-light video enhancement by improving brightness, contrast, and noise levels. This section explains in detail how your proposed low-light video enhancement system works, covering each step of the process. The process includes decomposing the video into individual frames, estimating the enhanced illumination map, applying Retinex-based enhancement, and post-processing the frames to improve visual quality.

4. HARDWARE DESCRIPTION

The hardware requirements largely depend on the complexity of the algorithms, the desired video resolution, and the real-time performance expectations. However, the minimum hardware specifications for such a system can be outlined as follows:

Processor (CPU):

A capable CPU is essential for performing video processing tasks, especially if you are using traditional image processing algorithms. However, if you are using deep learning models (such as CNNs for luminance map estimation), more powerful CPUs or GPUs will be required. Minimum requirement: Intel Core i5 or AMD Ryzen 5 (quad-core processor or better) Clock speed: 2.5 GHz or higher.

Graphics Processing Unit (GPU):

Video enhancement algorithms, especially those that handle high-resolution video, can use significant amounts of RAM. If deep learning models are used, more memory is required to store intermediate results and model parameters. Minimum requirement: 8 GB of RAM For handling high-definition (HD) or 4K video or working with large neural networks, 16 GB or more of RAM is useful.

Operating System:

Minimum requirement: Windows 10/11 (64-bit) or Linux (Ubuntu 20.04 or higher) for deep learning frameworks such as TensorFlow, PyTorch, and OpenCV. The operating system must support all the drivers required for GPU acceleration and video processing.

Storage:

Fast storage is required to handle video files, intermediate results, and sample files. Using an SSD (Solid State Drive) can help reduce latency when loading video frames and samples, ensuring smooth processing.

Minimum requirement:

A SSD with at least 256 GB of storage for fast data retrieval. For large video datasets or if working with multiple high-resolution videos, 512 GB or more of SSD storage may be required.

5. SOFTWARE DESCRIPTION

This section provides a detailed description of the software components, technologies, tools, and libraries used to implement the low-light video enhancement system. The goal is to explain the software environment, frameworks, and algorithms that form the backbone of the implementation. The system can be implemented using one of the following programming languages, depending on your specific requirements:

MATLAB:

MATLAB (Matrix Laboratory) is a high-level programming and numerical computing environment widely used for image and video processing. MATLAB provides several built-in toolboxes that facilitate image enhancement, video processing, and Retinex-based applications.

The following MATLAB features and functions are relevant to the Low Light Video Enhancement project:

Image Processing Toolbox:

This toolbox provides essential functions for image enhancement, illumination estimation, and noise reduction. Some of the key functions that can be used include:

imadjust: Enhances image contrast using histogram stretching. histeq: Performs histogram equalization to enhance contrast. imfilter: Uses Gaussian filtering or guided filtering to smooth light maps. rgb2gray and gray2rgb: Converts RGB images to grayscale and vice versa, which is useful when processing illumination and reflectance maps.

Adaptive Histogram (CLAHE):

Performs a contrast-limited adaptive histogram equalization for local contrast enhancement. Log and Exp functions: Useful for applying logarithmic transformations in Retinex theory.

Video Processing Functions:

To handle video input and output: Video Reader: Reads video frames from the input video. Video Writer: Writes the enhanced video frames to a video file after processing. Read Frame: Extracts individual frames from the video for frame-by-frame enhancement. Using a loop, each frame can be processed individually and enhanced with a Retinex-based light map method.

4.2 MATLAB APP DESIGNER GUI EXPLANATION 4.2.1 Overview the GUI was created using MATLAB App Designer to make the enhancement process user friendly. The GUI includes:

- Two video display axes (Original and Enhanced)
- Three buttons:
- Load Video
- Enhance Video
- Export Video

Key Steps in MATLAB Implementation:

Reading Video Input: Use Video Reader to read the input low-light video. Extract individual frames using Read Frame for frame-by-frame processing. Creating a Light Map: Estimate the illumination map using Gaussian Smoothing (Imfilter) or guided filtering methods. Use adaptive smoothing to avoid over-enhancement in bright areas. Applying Retinex Theory: Decompose the frame into illumination and reflection components using a logarithmic transform. Enhance reflection while adjusting the illumination based on the estimated illumination map. Post-processing: Use contrast enhancement (Imajust, Histech) and denoising filters to remove noise from the enhanced frames. Use adaptive histogram (CLAHE) to enhance local contrast. Reconstructing the enhanced video: Use Video Writer to save the enhanced frames back into a video file. Specify the output video format, frame rate, and quality parameters.

OpenCV for Low-Light Video Enhancement:

OpenCV (Open-Source Computer Vision Library) is a widely utilized, open-source toolkit designed for computer vision and image processing tasks. It offers a vast array of functions tailored for both static images and dynamic video analysis, making it particularly suitable for implementing enhancement techniques in low-light video conditions. Among its many capabilities, OpenCV supports frame-by-frame video processing, Retinex-based operations, and a range of filtering and transformation tools essential for refining visual quality in dimly lit footage. Several key OpenCV libraries and functions play a central role in building an effective low-light video enhancement system. To handle video input and output, cv2.VideoCapture() is used to read the video file frame by frame, while cv2.VideoWriter() allows the processed frames to be compiled back into a final output video. For smoothing and illumination estimation, functions like cv2.GaussianBlur() apply Gaussian filters, and cv2.bilateralFilter() offers edge-preserving noise reduction. Additionally, cv2.ximgproc. guided Filter () provides guided filtering to improve the illumination map without losing important structural details. Color space conversions, necessary for separating luminance from chrominance, are carried out using cv2.cvtColor(), which enables transformation between RGB, grayscale, and other color models. In the context of Retinex theory, mathematical operations are essential; numpy.log () and numpy.exp() are employed for logarithmic transformations, while cv2.divide() performs pixel-wise division to compute the reflectance component. For improving contrast, cv2.equalizeHist() performs histogram equalization, enhancing visibility across varying lighting intensities. Lastly, cv2.fastNlMeansDenoisingColored() effectively reduces chromatic noise in color video frames, preserving visual clarity after enhancement.

Implementation Steps Using Open CV:

To implement the low-light enhancement system using OpenCV, the process begins by reading the input video through cv2.VideoCapture() and breaking it down into individual frames. Each frame undergoes a sequence of enhancement operations. The first step involves estimating the illumination map, which can be accomplished by applying Gaussian blurring or guided filtering using cv2.GaussianBlur() or cv2.ximgproc. guided Filter () respectively. These filters smooth the brightness variations while preserving edges and significant features in the image. Next, the reflectance component is extracted using Retinex principles. This involves applying logarithmic transformations to the frame using NumPy functions such as log () to compress intensity values, followed by pixel-wise division (cv2.divide()) to isolate the reflectance from the illumination. The reflectance is then further enhanced by adjusting contrast and brightness, ensuring that dark regions are illuminated without distorting the overall image quality. Throughout the enhancement process, denoising techniques are also applied to suppress noise introduced during amplification, resulting in clearer, more visually consistent output frames. Once all frames are processed, they are written back into a single output video using cv2.VideoWriter(), producing a final enhanced video that exhibits improved brightness, reduced noise, and more natural-looking scenes in low-light conditions.

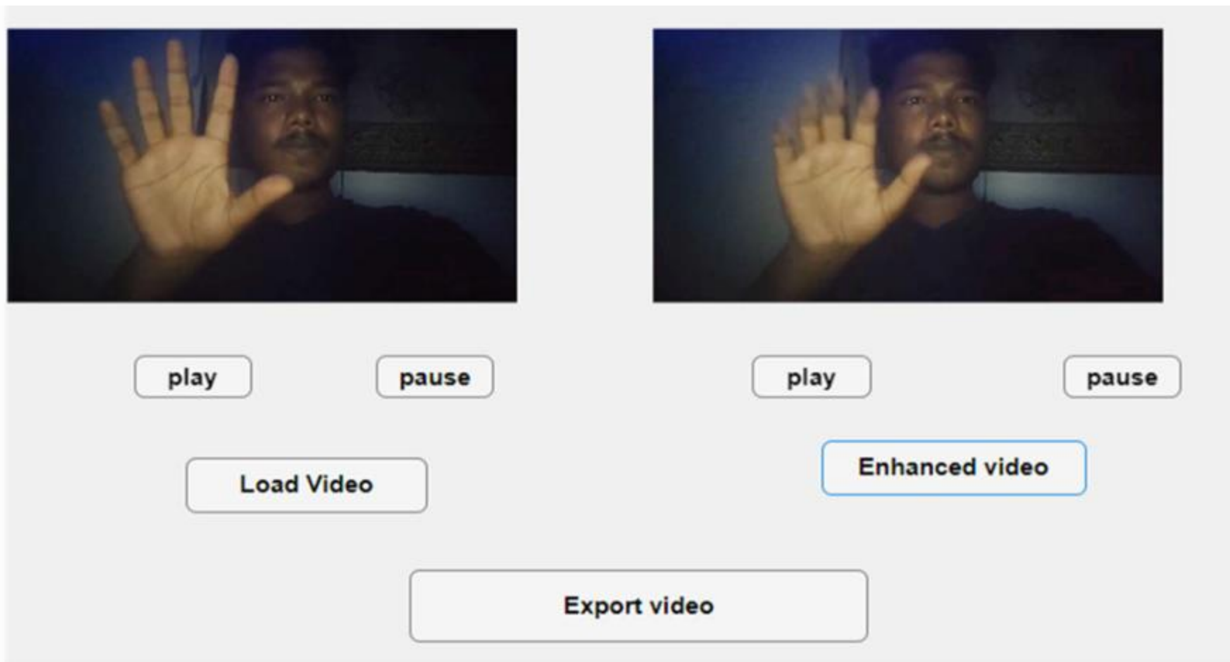

FIGURE 2. Enhanced Output

In combination with the Retinex theory, enhancing videos taken in low light conditions using a refined illumination map leads to a significant improvement in visual quality. This approach effectively addresses common issues such as poor contrast, limited visibility, and noise interference. At the heart of this method is the Retinex theory, which proposes that an image is a combination of two distinct components: reflectance, which represents the true colors and textures of objects, and illumination, which reflects the lighting conditions of the scene. By accurately estimating the illumination components, the algorithm can effectively distinguish between areas that are truly dark and areas that are simply underexposed due to illumination limitations.

The enhanced illumination map plays a key role in adaptively brightening only the necessary areas, while preserving the integrity of well-lit areas. This balance helps prevent overexposure and preserves important image details, resulting in videos with even greater brightness, improved textures, and realistic color representation. Furthermore, the method incorporates edge-preserving filters and noise-aware adjustments, which help suppress unwanted noise typically introduced during brightness enhancement. A key feature of this process is maintaining temporal consistency between video frames. By doing so, it prevents flicker and ensures that the visual flow remains consistent throughout the sequence—a necessary requirement for video applications.

Such improvements not only make the final output more visually appealing to human viewers, but also make it more suitable for advanced computer vision tasks such as tracking, surveillance, and visual analysis in low-light environments. The combination of enhanced illumination mapping with Retinex theory creates a robust and efficient framework for low-light video enhancement.

In practice, the algorithm processes each video frame independently. Initially, an enhanced illumination map is generated for each frame. Then, using Retinex-based decomposition, the image is divided into luminance and reflectance layers. Various techniques, including adaptive gamma correction and histogram equalization, are used to enhance the luminance components. To reduce noise, methods such as BM3D filtering or advanced deep learning-based denoising are used.

To maintain consistency across frames and prevent significant changes, motion estimation and compensation techniques - such as optical flow - are used. These methods ensure that object movements are accounted for during enhancement. In addition, temporal filtering helps to reduce sudden brightness changes, resulting in a visually stable and coherent video output.

Compared to conventional low-light enhancement techniques, this proposed approach demonstrates significant advantages. It not only excels in subjective visual quality, but also in objective performance metrics such as Peak Signal-to-Noise Ratio (PSNR), Structural Similarity Index (SSIM), and Natural Image Quality Estimator (NIQE). Enhanced videos created by this method exhibit better detail preservation, more accurate color representation, and reduced noise levels. Furthermore, this technique is optimized for computational efficiency, making it practical for real-time or large-scale processing tasks.

6. APPLICATIONS, ADVANTAGES AND DISADVANTAGES

Applications

Surveillance and Security Systems

Video enhancement plays a key role in the performance of security systems operating in low-light environments, especially at night or in poorly lit areas. Improved video clarity helps to better identify unauthorized entries, suspicious behavior, or criminal activity, thereby strengthening security measures and assisting law enforcement in incident response and evidence collection.

Autonomous Driving Systems

For self-driving vehicles, camera-based perception is essential for detecting roadways, pedestrians, and obstacles. In low-light situations - such as driving at night or navigating through tunnels - improved video quality is crucial. Video enhancement in low light improves the visibility of the driving environment, ensuring safe and reliable autonomous navigation.

Medical Imaging and Endoscopy

During minimally invasive procedures, medical cameras often operate in dimly lit internal areas of the human body. Enhancing these videos helps medical professionals obtain clearer images, which supports more accurate diagnosis and facilitates precise surgical interventions, ultimately improving patient outcomes.

Underwater Research and Exploration

Due to limited sunlight penetration underwater, capturing well-lit footage is challenging. Underwater video enhancement is essential for scientific fields such as marine biology, underwater archaeology, and oceanography, where detailed footage is critical for research and analysis.

Traffic Surveillance and Accident Analysis

Traffic surveillance systems typically operate under a variety of lighting conditions. Enhancing video from street-level CCTV cameras improves the visibility of vehicles and pedestrians, helping to accurately monitor traffic patterns, identify violations, and investigate road accidents more effectively.

Film Production and Video Post-Processing

In the entertainment industry, low-light enhancement tools provide filmmakers with the ability to refine footage captured in dim lighting without the need for expensive and time-consuming reshoots. These technologies allow for digital lighting adjustments during post-production, helping to maintain visual quality and cinematic consistency across scenes.

Advantages

Improved visibility in dark scenes: By accurately assessing and adjusting the brightness, this method significantly improves brightness and contrast, making objects and details more visible in low-light videos.

Natural color preservation: The Retinex principle separates reflection and illumination, allowing the enhancement to brighten the video without distorting the natural colors, which often occurs in basic adjustments.

Reduced noise amplification: Unlike simple brightness enhancement, this approach reduces noise amplification by combining denoising techniques in both dark and bright areas and preserving structure.

Edge and detail preservation: The improved illumination map maintains edge sharpness and texture, avoiding the blurring or halo effects common in many enhancement methods.

Real-time capability: Optimized versions of the algorithm can be efficiently executed, allowing real-time optimization on live systems such as cameras or mobile devices.

Improved perceptual quality: The optimized videos not only perform better in terms of metrics such as PSNR and SSIM, but also look better to the human eye, which is important for end-user satisfaction.

Disadvantages

Color distortion: Redye-based methods often increase brightness at the expense of accurate color reproduction. Over-enhancement or mis-estimation of luminance maps can lead to unnatural-looking colors.

Overexposure in bright areas: If not carefully balanced, bright areas can become overexposed after enhancement, potentially losing detail.

Limited performance in very dark scenes: In very low light, there may not be enough detail to recover even with enhancement techniques.

Computational complexity: Enhanced luminance map estimation involves solving optimization problems, which can be computationally expensive, especially for real-time video processing.

7. CONCLUSION AND FUTURE SCOPE

In conclusion, low-light video enhancement using an improved illumination map combined with Retinex theory represents a significant advance in the field of image and video processing. The integration of Retinex theory, which divides an image into illuminance and reflectance components, provides a robust framework for improving the visibility of low-light scenes by addressing both global and local lighting conditions. By using an improved illumination map that more effectively adapts to spatial variations in illumination, this method overcomes the limitations of traditional low-light enhancement techniques that often introduce noise or degrade image quality. The proposed method not only improves the brightness and contrast of the video, but also preserves the natural appearance of the scene by maintaining the stability of reflectance. This approach results in clear, detailed visual information in challenging low-light environments, making it particularly useful for applications such as surveillance, autonomous driving, and nighttime photography. Furthermore, the method's ability to balance brightness with fine details ensures that the enhanced video retains a high level of realism and quality, even in the most difficult lighting conditions. Overall, this improved technique provides a more accurate and effective solution for low-light video enhancement, which provides a solid foundation for further research and development in this area. Future work could focus on real-time applications, improving computational efficiency, and extending the method to handle even more complex lighting scenarios such as dynamic lighting changes or extreme low-light conditions. Developing lightweight and optimized algorithms for real-time low-light video enhancement. Implementing parallel processing using GPU acceleration and optimized libraries such as CUDA or OpenCL (30 FPS or higher). Using hardware-accelerated deep learning methods (e.g., TensorRT optimization) to improve inference speed while maintaining video quality. Develop adaptive illumination estimation algorithms that can adjust enhancement parameters based on visual context, brightness levels, and motion information. Explore contextual awareness techniques that use spatial and temporal information to improve the accuracy of light mapping in video scenes. Use reinforcement learning to dynamically learn the best illumination parameters for different video scenes. Enhance videos captured by onboard cameras during nighttime driving, improving object detection and visual comprehension in low light conditions. Enhance security footage in low light environments to improve face recognition, object detection, and anomaly detection. Use low light enhancement techniques to improve the visibility of endoscopic or microscopic videos captured in low light. Enhance low light videos in real time to enhance AR/VR experiences, especially for nighttime outdoor activities.

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