

Dynamic Visual Quality Enhancement For Surveillance in Defense Environment

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ABSTRACT

Surveillance systems are widely used in defense environments to monitor activities and ensure security. However, images captured by surveillance cameras often suffer from low illumination, noise, blur, and poor contrast due to environmental conditions. These issues reduce the visibility of important objects and make analysis difficult. Therefore, improving the visual quality of surveillance images is essential for effective monitoring and security operations.

This work proposes a Dynamic Visual Quality Enhancement (DVQE) system that enhances the visual quality of surveillance images using image processing techniques. The system processes images through several stages, including image acquisition, preprocessing, noise reduction, contrast enhancement, and brightness adjustment. Techniques such as filtering, histogram equalisation, and gamma correction are applied to improve image visibility and reveal hidden details.

The enhanced images provide better clarity and improved structural information, making it easier to identify objects such as vehicles, people, and other important elements in surveillance footage. Experimental results show that the proposed method effectively improves brightness, contrast, and overall image quality, thereby supporting efficient monitoring and decision-making in defence surveillance environments.

Keywords: Image Enhancement, Surveillance System, Image Processing, Contrast Enhancement, Noise Reduction, Defense Monitoring.

I. INTRODUCTION

The purpose of image restoration is to compensate for or undo defects that degrade an image. Degradation may occur in several forms, such as motion blur, noise and camera misfocus. Motion blur is one of the common problems in photography and image acquisition systems. In many real-world situations, images are captured under challenging environmental conditions such as low light, bad weather or unstable camera movement. These conditions can significantly reduce the quality of the captured images and make them appear blurry, noisy or unclear.

Often, images of outdoor scenes are degraded by atmospheric conditions such as haze and fog, which reduce the visibility of the captured scene. Light reflected from objects is scattered by particles in the atmosphere, causing distant objects to appear less visible and resulting in reduced contrast and faded colours.

Restoration of images captured under such conditions has received increasing attention in recent years because of its importance in improving image clarity and visual quality.

Image restoration plays an important role in several real-world applications, including remote sensing, intelligent transportation systems, object recognition and surveillance. In remote sensing systems, the recorded bands of reflected light are processed to recover useful information from degraded images. These techniques help researchers and engineers analyse environmental conditions and detect important objects more accurately.

One of the major challenges in photography is capturing images in low-light environments. The quality of an image mainly depends on the number of photons reaching the camera sensor during exposure. When the lighting condition is poor, a longer exposure time is required to capture more photons. However, a long exposure time can cause motion blur if there is movement between the camera and the scene.

Camera shake caused by hand tremor is a common reason for image blur in many digital photographs. This problem becomes more significant when using handheld cameras in dim lighting conditions. Because the movement of the camera is random, each captured frame may contain different blur patterns. Therefore, image restoration and enhancement techniques are essential to reduce blur and improve the overall visual quality of the captured images.

II. LITERATURE SURVEY

Restoration and deblurring techniques have become an important research area in image processing due to the increasing use of digital imaging systems in surveillance, medical imaging, and defense applications. Motion blur and noise are common problems that degrade the quality of captured images, making it difficult to extract meaningful visual information. These degradations can occur due to camera shake, object motion, long exposure times, or environmental disturbances during image acquisition. To address these challenges, researchers have developed several image restoration algorithms that aim to recover high-quality images from degraded observations.

Boracchi and Foi [1] proposed a statistical modelling approach to evaluate the performance of image restoration algorithms

under motion blur conditions. Their method models the motion trajectory of the point spread function as a random process and analyses restoration performance using a Monte Carlo framework. The study investigates how exposure time and motion randomness affect the quality of restored images. By estimating restoration errors statistically, the approach helps determine optimal exposure settings that maximise image quality after deblurring.

Zhang et al. [2] introduced a multi-image blind deblurring algorithm based on a coupled adaptive sparse prior model. Their method estimates a sharp latent image from multiple degraded observations that may contain blur or noise. The algorithm uses a Bayesian-inspired penalty function that links the latent image, blur kernels, and noise levels together. This adaptive mechanism allows higher-quality images to contribute more significantly to the final reconstruction, improving the overall restoration performance even when the degradation characteristics of the images are unknown.

Park and Levoy [3] presented a gyroscope-based multi-image deconvolution technique to remove handshake blur in images captured by mobile cameras. Their system combines camera motion information obtained from a gyroscope with multiple captured frames to perform non-blind deconvolution. By accurately estimating camera motion and correcting drift errors in the gyroscope data, the proposed method improves the robustness and efficiency of the deblurring process. Experimental results demonstrate that combining sensor data with image processing techniques can significantly enhance image restoration performance.

Šroubek and Milanfar [4] developed a robust multichannel blind deconvolution method to simultaneously estimate the original image and blur kernels from multiple degraded images. Their approach formulates the restoration problem as an optimisation task and solves it using an augmented Lagrangian framework. The algorithm incorporates regularisation techniques to improve stability in the presence of noise and large blur sizes while ensuring fast convergence. Similarly, Kundur and Hatzinakos [5] provided a comprehensive overview of blind image deconvolution methods and discussed the theoretical principles behind various restoration algorithms. Their work highlights the challenges, applications, and implementation issues associated with blind image restoration techniques.

In summary, previous studies have proposed several techniques to address image degradation caused by blur and noise. While these methods have shown promising results, many approaches require complex computations or additional hardware support. Therefore, there is a need for efficient and cost-effective image restoration systems that can enhance image quality using practical image processing frameworks. Based on these research insights, the proposed system focuses on improving image clarity and reducing blur using advanced image processing techniques for surveillance and monitoring applications. In addition, the system aims to produce clearer visual information that can support accurate analysis and decision-making. By applying effective enhancement and restoration methods, the proposed approach attempts to improve the overall visibility and usefulness of captured images in real-world environments.

Low light Image**Enhanced Image****Figure 1: Low-light & Enhanced Image**

III. SYSTEM ARCHITECTURE

The proposed Visual Quality Enhancement system is designed using a structured architecture that integrates image input modules, a processing unit, and an output display module. The architecture is divided into three main components: the Input Module, Processing Module, and Output Module. These components work together sequentially to enhance the quality of surveillance images and improve visual clarity for defense monitoring applications. The overall system ensures that captured images are processed effectively to produce clearer and more interpretable visual outputs.

Input Module

The input module is responsible for acquiring surveillance images or video frames from a local storage system or dataset. The collected images may contain several quality issues such as noise, low brightness, poor contrast, blur, or environmental distortions caused by fog, dust, or low-light conditions. These factors reduce the clarity of surveillance footage and make visual analysis difficult.

In this stage, the input images are converted into a suitable digital format for further processing. In some cases, colour images are transformed into grayscale format in order to reduce computational complexity while preserving essential structural information. This preprocessing stage ensures that the captured surveillance data is properly prepared before applying enhancement techniques.

Processing Module

The processing module acts as the core component of the proposed system. It is implemented using Python-based image processing techniques with the support of the OpenCV library. This module performs several enhancement operations to improve the visual quality of surveillance images. Initially, noise reduction techniques such as Gaussian filtering or median filtering are applied to remove unwanted disturbances while preserving important image details. After noise removal,

contrast enhancement is performed using histogram equalisation to improve the brightness and visibility of the image. Further enhancement is achieved using edge detection and sharpening filters that highlight object boundaries and structural features. These techniques help improve the visibility of important elements such as faces, vehicles, and other critical objects within the surveillance footage.

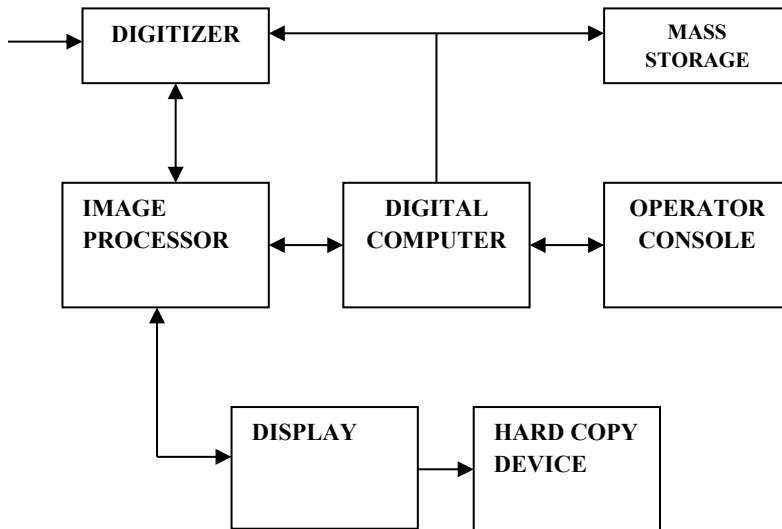


Figure 2: Block Diagram of Image Processing System

Output Module Display: The output module displays the enhanced surveillance image for monitoring and analysis. The system allows visual comparison between the original image and the processed image so that improvements in clarity and detail can be easily observed.

In addition, the enhanced images can be stored in the local system for future investigation, documentation, or reporting purposes. By producing clearer and sharper images, the system helps security personnel analyse surveillance footage more effectively and supports faster decision-making in defence monitoring environments.



Figure 3: Output Module Detection Results

IV. METHODOLOGY

The methodology of the proposed Dynamic Visual Quality Enhancement system describes the step-by-step process

used to improve the visual quality of surveillance images captured in defense environments. The system processes surveillance images using image enhancement techniques and evaluates the improvement using image quality metrics. The overall process consists of several stages including image acquisition, preprocessing, enhancement, quality evaluation, and visualisation.

Image Acquisition

The first step of the proposed system involves acquiring surveillance images from a local dataset or camera source. These images may be captured in defence environments such as borders, military zones, or security areas. Due to environmental conditions such as low illumination, fog, haze, or sensor noise, the captured images may appear dark, blurry, or distorted.

The images are uploaded into the system through a user interface developed using Streamlit. Once the image is uploaded, it is converted into a suitable format and loaded into the Python processing environment using OpenCV libraries.

Image Preprocessing

After the image is loaded, preprocessing operations are performed to prepare the image for enhancement. In this stage, the image is converted into the required colour format and resized if necessary. Preprocessing helps remove unnecessary variations in the image and ensures that the enhancement algorithms operate efficiently.

Noise reduction and normalisation techniques are also applied during preprocessing. These operations help improve the stability of the enhancement process and ensure that the image data is suitable for further processing.

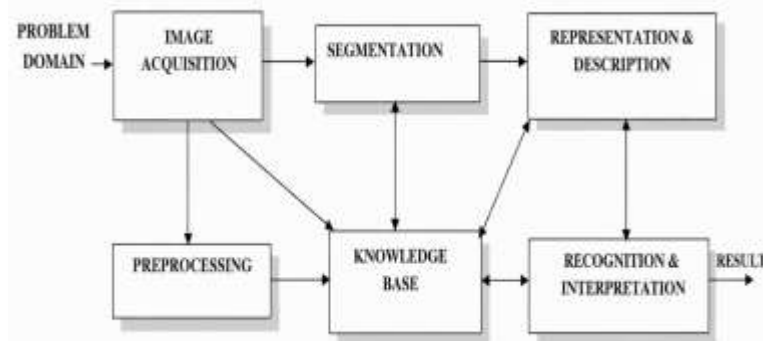


Figure 4: Block Diagram of Fundamental Sequences Involved in an Image

Image Enhancement

The image enhancement stage is the core component of the proposed system. In this stage, visual quality improvement techniques are applied to enhance the brightness, contrast, and visibility of the surveillance images.

The system uses Contrast Limited Adaptive Histogram Equalisation (CLAHE) to enhance image contrast and improve visibility in low-light conditions. CLAHE works by redistributing pixel intensity values locally across the image to reveal hidden details.

After contrast enhancement, gamma correction is applied to further improve brightness and illumination. Gamma

correction adjusts the intensity levels of the image to produce a more natural and visually clear output. These enhancement techniques help reveal important details that may be hidden in dark or noisy surveillance images.

Image Quality Evaluation

Once the image enhancement process is completed, the system evaluates the quality of the enhanced image using quantitative image quality metrics.

The Mean Squared Error (MSE) metric measures the difference between the original image and the enhanced image. Structural Similarity Index Measure (SSIM) is used to analyze the structural similarity between the two images and determine how well the enhanced image preserves the original image structure.

In addition to these metrics, brightness and contrast values are also calculated to analyze the improvement in image visibility.

Image Processing Fundamentals

Digital image processing is the technique of manipulating images using computer-based algorithms. In most applications, images are first captured through cameras or sensors and then converted into digital format. This conversion process includes sampling and quantization, which transform visual information into numerical data. Once the image becomes digital, different processing techniques can be applied to improve its quality or extract useful information. These operations help in analyzing, enhancing, or modifying the image depending on the application.

Image Processing Techniques

Image processing involves several techniques that are used to modify or analyze digital images for better interpretation and processing.

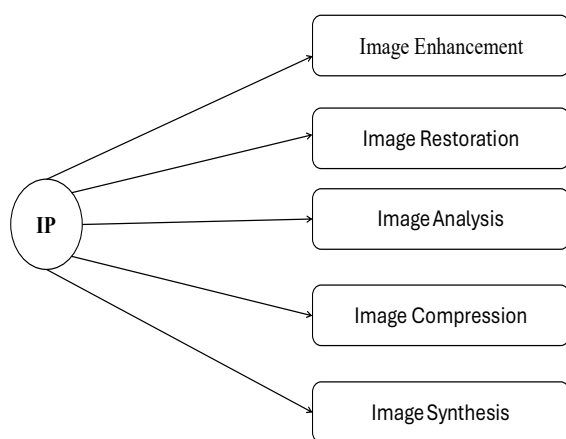


Figure 5: Image Processing Techniques

Image Enhancement: Image enhancement focuses on improving the visual appearance of an image. Techniques such as contrast adjustment, brightness correction, noise reduction, and sharpening are commonly used. The purpose is to make the image clearer and easier to interpret without changing the original information present in the image.

Image Restoration: Image restoration aims to recover an image that has been degraded due to noise, blur, motion, or other distortions. This method relies on mathematical models that estimate the degradation and attempt to reconstruct the original image as accurately as possible.

Image Analysis: Image analysis is used to extract meaningful information from images. It involves identifying objects, measuring features, and classifying patterns within the image. This technique is widely used in machine vision systems and automated inspection applications.

Image Compression: Image compression reduces the amount of data required to represent an image. By removing redundant or unnecessary information, the image size becomes smaller, which helps in efficient storage and faster transmission. Compression methods are mainly categorized into lossless and lossy techniques.

Image Synthesis: Image synthesis refers to the generation of images using computer algorithms rather than capturing them directly through cameras. These images can be created from other images, mathematical models, or graphical data and are commonly used in simulations, graphics, and visualization.

V. IMPLEMENTATION AND RESULTS

The proposed Dynamic Visual Quality Enhancement (DVQE) system was implemented using Python with OpenCV, NumPy, Matplotlib, and deep learning frameworks such as PyTorch and TensorFlow. Surveillance images captured under low-light conditions, motion blur, noise, fog, and other environmental disturbances were used for testing. Initially, images were acquired from CCTV cameras, drones, or stored datasets and underwent preprocessing, including resizing, normalization, noise filtering, and color correction, to ensure uniform input for further enhancement. The enhancement process combined traditional techniques like CLAHE for contrast improvement and gamma correction for brightness adjustment with deep learning models such as Zero-DCE or convolutional neural networks that automatically adjusted illumination, contrast, and structural details without requiring reference images.

Enhanced images were evaluated using metrics such as Mean Squared Error (MSE), Structural Similarity Index Measure (SSIM), brightness, and contrast to quantify improvements. The enhancement pipeline improved visual clarity, preserved structural information, and reduced noise, making objects such as vehicles, personnel, and drones more distinguishable. These enhanced frames were then processed through an object detection module using YOLO, which achieved higher accuracy due to the improved image quality.

The system also included a real-time monitoring dashboard developed with Streamlit, allowing visualization of original and enhanced images, quality metrics, histograms, and brightness versus contrast analysis. Testing under various conditions demonstrated that the DVQE system effectively improved image clarity, visibility, and structural details, enabling better situational awareness. The combined use of traditional and deep learning-based enhancement ensured adaptability across multiple environmental conditions.

The implementation confirms that local processing of images without reliance on cloud-based computation provides fast and reliable results. The integration of preprocessing,

enhancement, quality assessment, and object detection modules ensures end-to-end automation of the surveillance analysis workflow. Evaluated results show significant improvement in sharpness, brightness, and contrast, reducing visual ambiguity and enhancing interpretability.

Overall, the DVQE system provides a practical and cost-effective solution for defense surveillance by improving monitoring efficiency, enabling accurate detection of potential threats, and enhancing decision-making for security personnel. The results indicate that combining traditional image processing techniques with deep learning-based enhancement offers robust performance across diverse surveillance scenarios.

The system's successful implementation demonstrates that AI-driven image enhancement can overcome limitations of classical methods, such as high computational complexity and poor restoration in low-light or blurred images. By fusing multiple techniques and evaluating improvements with quantitative metrics, the DVQE framework ensures reliable, intelligent, and real-time surveillance support for defense environments.

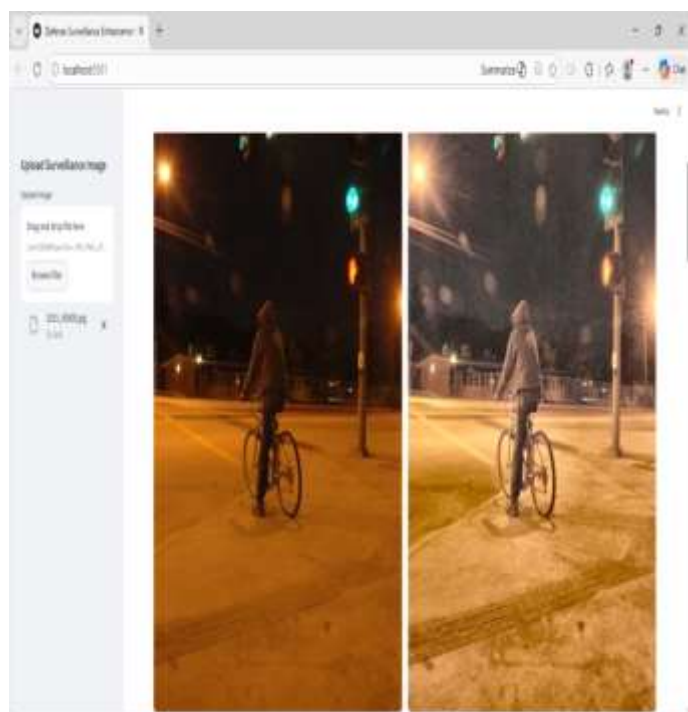


Figure 6: Implemented Result and Output Image

	Metric	Value
0	MSE	116.7986
1	SSIM	0.5127
2	Brightness	113.0260
3	Contrast	48.3385

Figure 7: Image Quality Metric

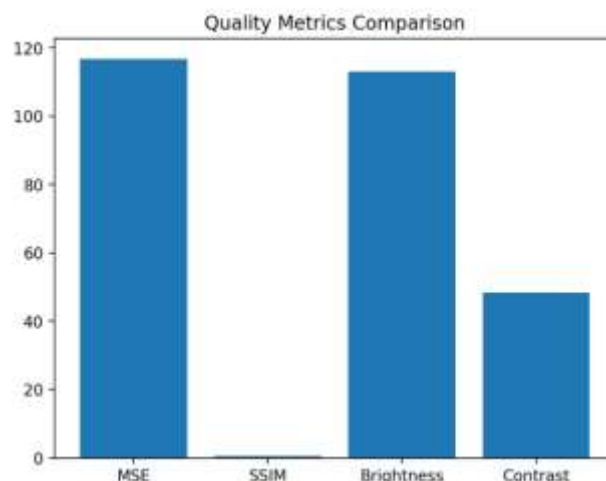


Figure 8: Image Quality Metrics Comparison

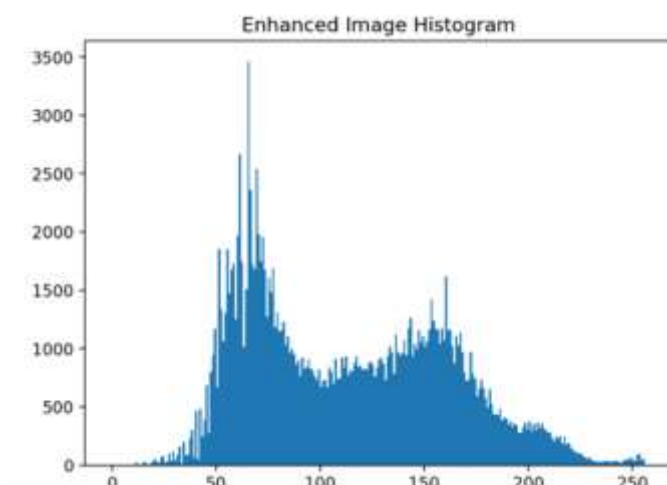


Figure 9: Enhanced Image Histogram

VI.CONCLUSION

The Dynamic Visual Quality Enhancement (DVQE) system for surveillance in defense environments effectively addresses the challenges posed by low-light, foggy, or noisy conditions. By integrating deep learning-based image enhancement techniques with real-time video processing, the system significantly improves the clarity, brightness, and contrast of surveillance footage.

Enhanced visual quality allows for more accurate object detection using models such as YOLO, enabling defense personnel to identify vehicles, humans, drones, or suspicious activities with greater reliability. The system also provides quantitative evaluation through metrics like PSNR and SSIM, ensuring that the structural integrity of images is preserved while reducing noise and distortion.

Overall, the DVQE framework offers an intelligent, automated solution for real-time surveillance monitoring, enhancing situational awareness, reducing response times, and supporting more informed decision-making in defense operations. Its modular design, combining acquisition, preprocessing, enhancement, quality assessment, and monitoring, makes it adaptable and scalable for various defense scenarios.

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