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IMAGE SUPERIORITY MODERNIZATION USING SUPER RESOLUTION METHOD WITH DEEP LEARNING

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Abstract

In the rapidly evolving landscape of defense and surveillance systems, the need for high-quality imagery has become paramount for accurate decision-making and intelligence gathering. Traditional imaging systems often suffer from limitations such as low resolution due to long-range capture, poor lighting, and environmental factors. To address these challenges, image superiority modernization through the application of super-resolution techniques using deep learning has emerged as a transformative solution. This paper explores the implementation of deep learning-based super-resolution methods to enhance image quality in modern defense systems. Super-resolution algorithms, driven by convolutional neural networks (CNNs) and generative adversarial networks (GANs), can recover fine details from low-resolution images by learning complex mappings between low- and high-resolution data. These techniques outperform conventional interpolation methods by leveraging large-scale datasets and optimizing through advanced neural architectures. The proposed approach focuses on integrating these deep learning models into existing surveillance, reconnaissance, and targeting platforms to improve image clarity, object recognition, and situational awareness. By modernizing image superiority through super-resolution, this method can significantly enhance the operational capabilities of defense technologies, offering better precision, faster analysis, and improved mission success rates.

Keywords— *Image Superiority, Super-Resolution, Deep Learning, CNN, GAN, Image Enhancement.*

INTRODUCTION

Image Restoration can be defined as the process of removal or reduction of degradation in an image through linear or non linear filtering. Images with higher resolution are required in most electronic imaging applications such as remote sensing, medical diagnostics, and video surveillance. For the past decades, considerable advancement has been realized in imaging system. However, the quality of images is still limited by the cost and manufacturing technology . Super-resolution (SR) is a promising digital image processing technique to obtain a single high-resolution image (or sequence) from multiple blurred low-resolution images [1]. The basic idea of SR is that the low-resolution (LR) images of the same scene contain different information because of relative subpixel shifts; thus, a high-resolution (HR) image with higher spatial information can be reconstructed by image fusion. Subpixel motion can occur due to movement of local objects or vibrating of imaging system, or even controlled micro-scanning. Numerous SR algorithms have been proposed since the concept was introduced by Tsai and Huang in the year of 1984. Most of them operate in batch mode, i.e., a sequence of images are co-processed at the same time. Thus, these algorithms require a high memory resource to store the LR images and temporary data, and need a high computing resource as well. These disadvantages limit their practical application. There are a variety of SR techniques, including multi-frame SR and single-frame SR. for an overview of this issue. Our discussion below is limited to work related to quality multi-frame SR method, as it is the focus of our paper [2]. In modern defense and surveillance operations, the quality and clarity of captured images are critical for accurate analysis, decision-making, and mission success. However, many imaging systems face limitations in resolution due to factors such as long-range captures, atmospheric conditions, motion blur, and low-light environments. These challenges result in low-resolution images that lack the necessary detail for precise object identification, target recognition, and situational awareness [3]. Traditional methods for improving image resolution, such as interpolation or basic image enhancement techniques, often fall short in recovering fine details and enhancing image quality to the required levels. These limitations can hinder the effectiveness of surveillance and reconnaissance systems, leading to delays, misinterpretations, or missed opportunities in critical scenarios [4]. The problem lies in the need for an advanced solution that can overcome these limitations by significantly enhancing the resolution and quality of images captured in challenging conditions [5]. The challenge is to develop and implement a super-resolution method that leverages deep learning techniques, such as convolutional neural networks (CNNs) and generative adversarial networks (GANs), to recover high-quality images from low-resolution inputs. This method must be scalable, efficient, and adaptable to various operational environments to support modern defense and intelligence systems in achieving image superiority [6].

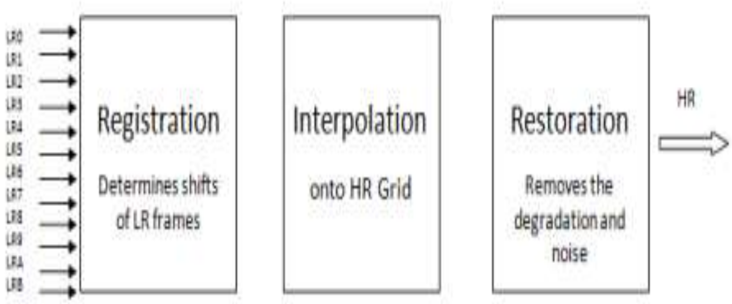

Figure 1: Common Super Resolution Flow Diagram

LITERATURE SURVEY

The basic assumption for increasing the spatial resolution is the availability of multiple LR images captured from the same scene. The LR images represent different “looks” at the same scene so LR images are sub sampled as well as shifted with sub pixel precision. If the LR images are shifted by integer units, then each image contains the same information and thus there is no new information that can be used to reconstruct an HR image. If the LR images have different sub pixel shifts from each other and if aliasing is present, then each image cannot be obtained from the others. Here new information contained in each LR image can be exploited to obtain an HR image. If we combine these LR images, SR image reconstruction is possible. There is a natural loss of spatial resolution caused by the optical distortions because of out of focus, diffraction limit, motion blur due to limited shutter speed, noise that occurs within the sensor or during transmission and insufficient sensor density in the process of recording a digital image. Existing system observed images of a real scene usually are in low resolution. This is due to some degradation operators. Moreover, in practice, the acquired images are decimated, corrupted by noise and blur. We assume that all low resolution images are taken under the same environmental conditions using the same sensor. A super resolution algorithm can be used to generate a high resolution image or image sequence [7]. The algorithm has been proposed to estimate sparse co-efficient using joint MAP estimator. A non local sparse model-based Bayesian framework is proposed for OCT restoration. The Laplacian distribution, normalized vector and GEV distribution is used for best good fit for modeling super resolution method is not fast as MAP solution. The aim of Super resolution (SR) is to generate a higher resolution image from lower to resolution images. Super resolution is based on the Laplacian+GEV model which shows the best goodness fit for modeling the images [8].

A related problem to SR techniques is image restoration, which is a well-established area in image processing applications. The goal of image restoration is to recover a degraded image, but it does not change the size of image. Restoration and SR reconstruction are closely related theoretically, and SR reconstruction can be considered as a second-generation problem of image restoration. One more problem related to SR reconstruction is image interpolation that has been used to increase the size of a single image. Comparisons between various SR techniques have been primarily concerned with what assumptions are made in modeling the SR problem. Some of these assumptions include assuming the blurring process to be known or that regions of interest among multiple frames are related through global parametric transformations. Signal-to-noise ratio, peak signal to noise ratio (PSNR), root mean squared error, mean absolute error, and mean square error (MSE) of super-resolved images versus interpolated images have all been used as objective measures of SR accuracy; however, the prominent method of presenting results in literature has clearly been subjective visual quality.

Detailed study of existing techniques in Super-Resolution was done with the help of different literatures available in journals and books. A Proliferation of literature is available in Super- resolution. Here highlight some of the key contributions. Super-resolution (SR) can be achieved using a single image or multiple images (image sets). In single image the input is single LR image. But in the case of multiple we take the different images of same scene it will give different looks of same scene. Based on the taxonomy of super-resolution technique based on the transformation domain super-resolution techniques are classified as two 1)spatial domain and 2)frequency domain. In spatial domain it is the normal image space. We perform operations directly on pixels. In frequency domain apply transforms (Fourier transform) convert it as frequency components and perform mathematical operations on this frequency components and again transform it into spatial domain for display purpose. Glasner et. Al combined the above two methods so as to obtain super - resolution from a single image. These single-frame super-resolution methods are also called Example based super-resolution described by Freeman et al. which states that to generate an up scaled image with desired number of pixels. The main aim of this paper is to check the performance of single-image and multiple image learning based super resolution method and compare it with the existing methods. Our aim is to achieve the good performance of the super-resolution algorithms by reducing the computational time and cost of the system and getting a good quality image. In order to do so we are extending previous method which was described. Also it has to be checked that the artifacts are reduced while a super resolved image is reconstructed. We call image super-resolution as image up scaling, image zooming, image magnification, image up sampling etc. Li et al proposed a non-iterative adaptive interpolation scheme for natural image sources. Sun et al proposed a Bayesian approach to image super resolution. Primal sketch priors are constructed and used to enhance the quality of the reconstructed high resolution image. Chang et al have generated a high resolution image from a single low resolution image, with the help of a single or multiple training images from scenes of the same or different types. Various methods are used to recover or obtain a high resolution

(HR) image from one or more low resolution (LR) images. Pixel replication and nearest Neighbour interpolation are the standard interpolation techniques that tend to increase the pixel count or repeat the pixels without actually adding the image details. These techniques blur edges and other sharp details of the images but perform well in smoother regions. In conventional multi frame super- resolution methods, many low resolution images of the same scene with varying pixel shifts are taken as inputs and correspondence between high and low resolution patches is learned from a database which consists of LR and HR image pairs and then by applying this knowledge to a new low resolution (LR) image, and reconstruct the corresponding high resolution image. Purkait et al have proposed image zooming technique using fuzzy rule based prediction. In [, single image super-resolution algorithm based on spatial and wavelet domain is presented a survey on techniques and challenges in image super resolution reconstruction are discussed. Regularization literally means to remove the noise from an image. Total variation regularization methods leads to reduction in the artifacts while maintaining the sharp edges and textures. In this method, Learning based method using single image is combined with Intermediate Dictionary Learning in order to get an improved image quality. It is different from in the fact that in this case a single image is used for learning. Thus, a large database of images is not needed for checking co-occurrence between the image patches so there is no problem of data redundancy as only high resolution patches constitute its database.

METHODOLOGY

Resolution techniques can be broadly classified into interpolation-based, reconstruction-based, and learning-based techniques. Interpolation-based methods such as bicubic interpolation remain the bulwark of digital zoom in consumer software and devices, but produce blurring or ringing artifacts. Reconstruction-based techniques produce water-color like artifacts. As the performance has been achieved using learning-based, reconstruction based and interpolation based techniques, comparing with other methods learning based method give high quality image as output. In learning-based SR methods, a mapping from LR patches to their corresponding HR patches is learnt using set of LR-HR patch pairs. Most of them are memory and computation intensive due to formation of an LR-HR patch database or searching LRHR patch pairs within the same image. Direct nonlinear regression mapping between LR and HR patches gives good results with memory and time efficiency. According to technique principle and input and output data form, current super resolution algorithms can be divided into various types. The division standards also include transformation domain, the number of input image, color space and so on. Frequency domain and spatial domain are divided from the perspective of signal transformation domain. Based on input number of image, we can obtain single image based super resolution and multiple images based super resolution. According to technique principle, super resolution can be divided into three types, namely, interpolation based, reconstruction based and learning based. And among existing super resolution methods, reconstruction based method and learning based method are the most popular ones. Most multiple images based super resolution algorithms are reconstruction based methods. These algorithms assume that there is a target high resolution image and the low resolution observations have some relative geometric displacements from the target high resolution image. They usually exploit these differences between low resolution observations and the targeted high resolution image, and hence are referred to as reconstruction based super resolution algorithms. Super-Resolution techniques are mainly classified as

Interpolation Based Super-Resolution:

This method try to recover missing information from neighboring pixels. It is quite straightforward but the quality is not tolerate when the scaling factor is getting larger. Interpolation is a method of constructing new set of data points within the range of a discrete set of known data points. Disadvantage is produce blurring or ringing artifacts. Mainly used Interpolation based techniques are

a. Bilinear Interpolation :

Bilinear interpolation is an extension of normal mathematical linear interpolation for interpolating functions of two variables (e.g.,x and y) on a rectilinear 2D grid. The main idea is to perform linear interpolation first in one direction(row), and then again in the other direction (coloumn). Bilinear interpolation is performed by finding linear interpolation between adjacent pixels. This can be done by finding the average gray value between two pixels and use that as the pixel value between those two. We can do this for the rows first, and then we take that result and expand the coloumns in the same way.

b. Bicubic Interpolation :

This is the Godzilla of pixel interpolation algorithms. It gives absolutely good results with negligible artifacts. But it requires an extreme number of complex calculations and it is very hard to understand. Bicubic Interpolation takes a weighted average of the 16 pixels to calculate its final interpolated value. Bicubic gives sharper images than other two methods. This techniques take more computational time. When time is not an issue then this technique give the best result among all other techniques.

c. Nearest Neighbour:

This method is performed by repeating pixel values. Pixel replication is used to increase the size of an image an integer number of times. It only considers one pixel: that is the closest one to the interpolated point. Requires the least processing time of all the interpolation algorithms. This has the effect of simply making each pixel bigger. Disadvantage: It produce jagged results Images obtained through photography are affected by various real-world factors, such as noise inherent to the camera imaging system, or blurring caused by the subject of the image being out of focus or in motion. These factors degrade important details, negatively impacting image quality. Super-resolution (SR) image reconstruction is specifically the technique of constructing high resolution (HR) images using single, multiple, or sequential low-resolution (LR) images in the case of degradation. It is widely used in security surveillance, medical imaging, remote sensing imaging, image processing research and public safety. Generally, the use of sequential images for SR reconstruction provides a better reconstruction effect than that of a single image. This difference is due to the relative motion between frames in image sequences, as information observable from different angles in a single scenario is non-redundant and complementary. In the field of digital image research, many researchers are committed to traditional image reconstruction. Although the use of single-frame images for reconstruction has been extensively studied, use multi-frame images to achieve higher resolution reconstructed images than single-frame images.

The advantage of multi-frame reconstruction is to use not only in-frame correlation in a single frame image, but also inter-frame correlation between multiple images. In order to take advantage of multi-frame images, generally involves image registration, fusion, and other techniques to compensate for the displacement between images. There are three main methods: frequency domain method, spatial domain method, and learning method: The benefits of the frequency domain method include it being easier to understand, as the algorithm model is based on the relationship between the image frequency domain, its calculating speed, as the computing hardware requirements are low, and its ease of application in practical engineering.

We propose a novel multi-frame SR image reconstruction process based on the Multi-grained Cascade Forest reconstruction algorithm (SRMCF), which is a learning method using chunking. First, a convolutional neural network is used to process image registration in advance, and then a simple deep forest model is used for recovery to fuse images and reach the final SR restoration.

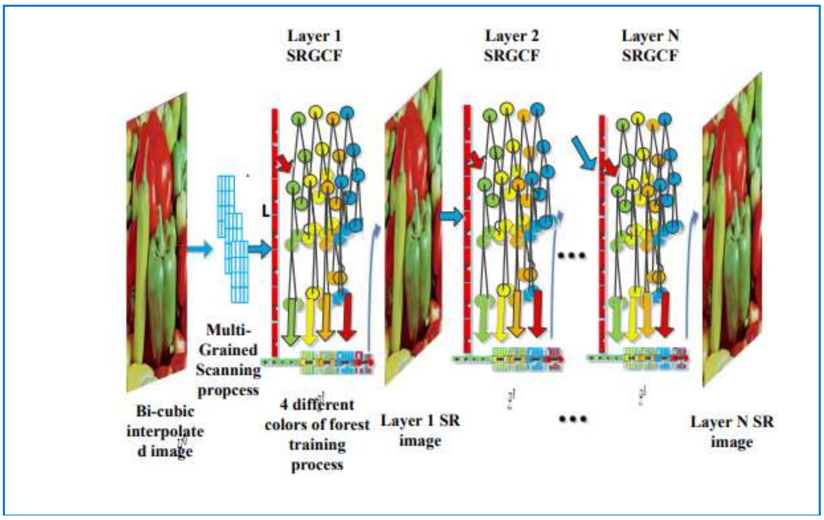

Figure 2: Flowchart showing Super Resolution Framework

Figure 2 showing the image layer activity for improving reconstruction quality of multi frame using super resolution method in which layer 1 gets different colors with training process and layer 2 re constructs and end giving super resolution image. First, multi-grained scanning is performed on the bicubic interpolation edge images. Then, the feature vectors obtained through scanning are used to repeatedly train the completely random forests and the ordinary random forests. As discussed above, the classification result of each layer, excepting the final layer, joins in the training of the next layer. In our method, the depth of the cascade forest is not a constant and is instead generated automatically according to the quality of the recovered image. When we finish training one layer, the recovered image is automatically evaluated. If the quality is not optimal, a new layer is constructed for training until an optimal restored image is obtained.

Image registration algorithm based on convolutional neural network

In the reconstruction of multi-frame images, due to camera shooting, lighting and other factors, a certain motion blur is generated during the imaging. In order to solve these problems, we need to register each image frame to compensate for displacement. The purpose of image registration is to solve the optimal coordinate transformation relationship between images and transform the registration image to spatially align it with the reference image. There are three kinds of image registration methods: region-based image registration, transform domain-based image registration and feature-based image registration. The feature-based image registration algorithm is the most mature and most widely used method among the three types. Its primary function is the detection and extraction of feature points. Existing feature-based registration methods include SIFT, SURF, ORB, etc. Although these methods have greatly improved the processing of feature points, they cannot detect a sufficient number of feature points when the multiframe image has appearance differences or when the detected feature points contain serious abnormal values. As a result, the registration effect is poor, and the algorithm is less robust. In order to guarantee the efficiency and effect of registration, this paper adopts a registration algorithm based on a convolutional neural network to register LR images. Image frame feature points are extracted by convolutional neural network. By making full use of the image frame information, the effect of registration is enhanced, and the robustness of registration is improved. Image registration algorithms based on convolutional neural network are mainly used to transform LR images to align with a reference image.

SRMCF-based super-resolution reconstruction algorithm for single frame images

Here, the SR reconstruction algorithm based on SRMCF is discussed, and then the SR algorithm based on SRMCF is constructed. The single-frame image reconstruction based on SRMCF is based on the Multi-grained Cascade Forest algorithm proposed according to Zhou [20], which simplifies the computational complexity by using its cascading forest structure, greatly reducing the time required for reconstruction. The quality of its image reconstruction is also higher than that of other reconstruction algorithms due to its first-level multiple training. The main step of this algorithm is to input a pair of HR images. If there is a corresponding LR, it will be input directly into the multi-particle scan for feature enhancement training. When the feature extraction training is completed, the model training will be carried out with the cascade forest, and then restored according to the model obtained from the training.

RESULT ANALYSIS:

Reconstructed HR images for different noise levels. Bar Graph showing histogram values raning from 500 to 2500 respectively from left to right and from maximum to minimum showing from 2500 to 0. The algorithm is simple and memory efficient and needs much less computing resource compared to batch-mode methods. Additionally, we employ a noise-adaptive parameter in classical steepest gradient optimization algorithm to avoid noise amplification and the over fitting of LR images. Our method is also compatible with color images. Experimental results on simulated and real-image sequences show that our online SR method has a good performance in restoring the details and missing information in LR images and has a real-time application prospect. Image super-resolution naturally requires large computing resources. A good choice is to just process the region of interest which can also simplify the motion model. The work to incorporate a tracking system and more complex motion model into the online SR framework is ongoing. The implementation of super-resolution methods using deep learning, specifically convolutional neural networks (CNNs) and generative adversarial networks (GANs), for image superiority modernization yields promising results in enhancing image quality in defense and surveillance applications. The super-resolution models significantly improve the resolution of low-quality images by generating finer details and clearer edges. Quantitative metrics such as Peak Signal-to-

Noise Ratio (PSNR) and Structural Similarity Index (SSIM) are used to evaluate the enhanced image quality. Super-resolution methods using deep learning show substantial improvements over traditional interpolation techniques, with higher PSNR and SSIM values indicating better visual accuracy and perceptual quality.

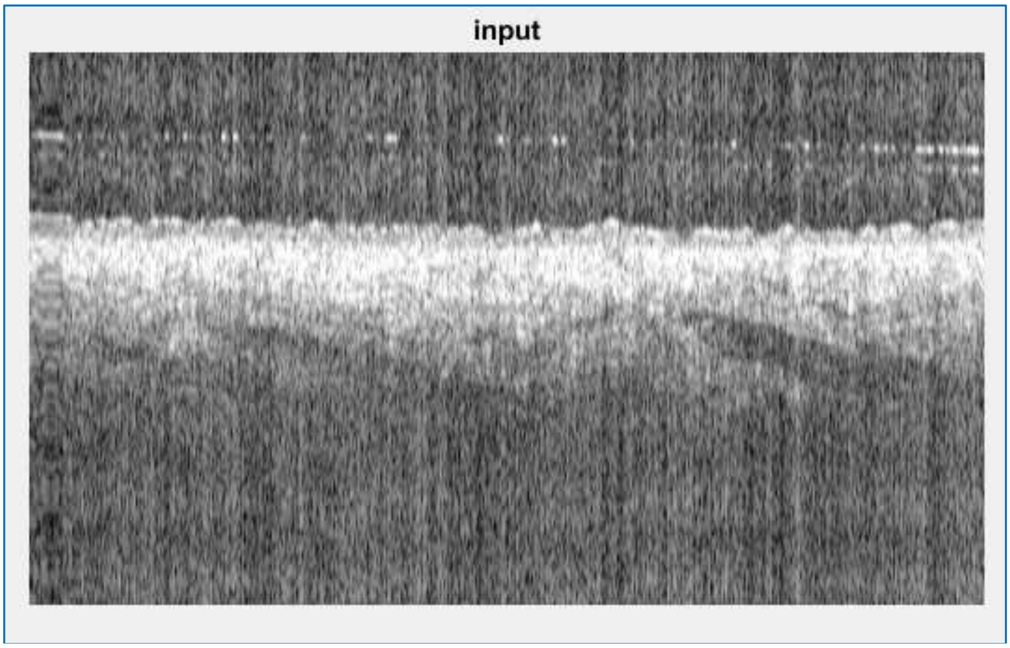

Figure 3: Input of LR Image to remove blur using multifare SR Technique

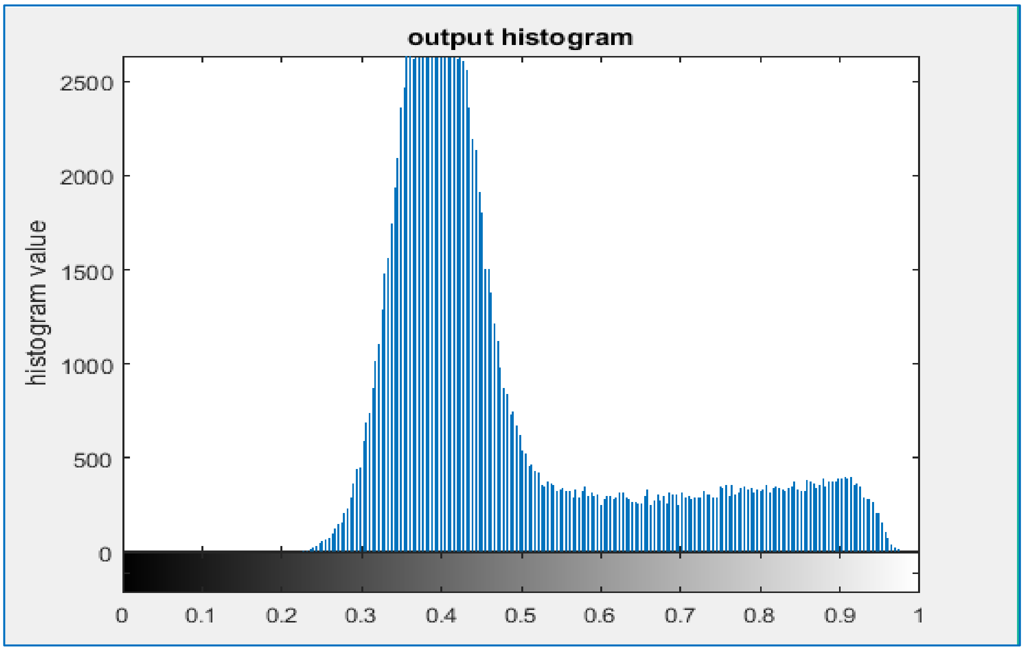

Figure 4: Bar Graph showing noisy Histogram of SR Image

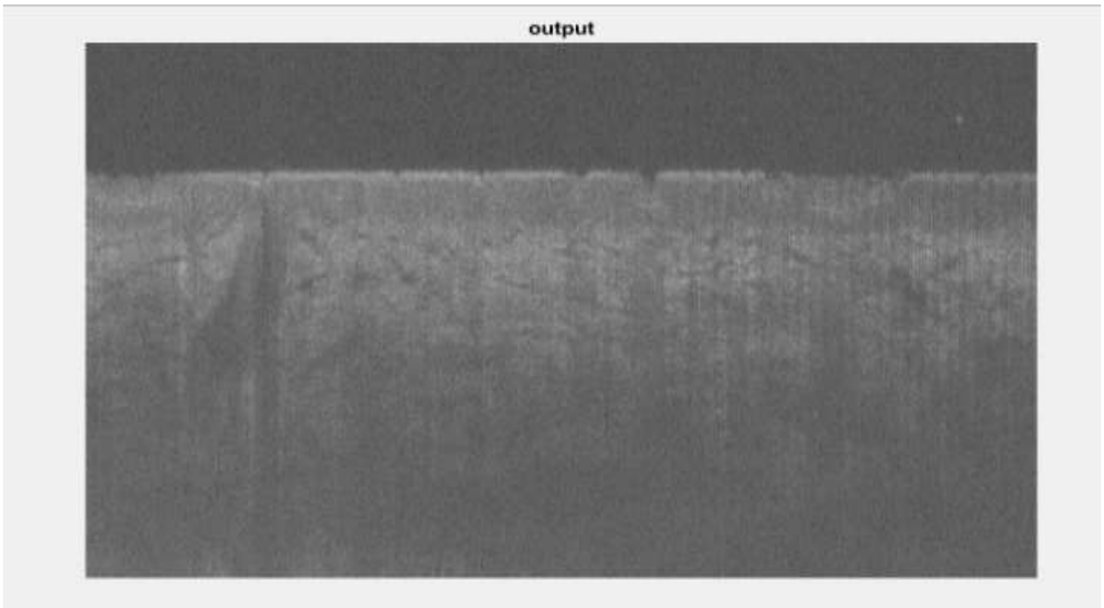

Figure 5: Output Showing blurs and noisy removed using multi frame SR Technique

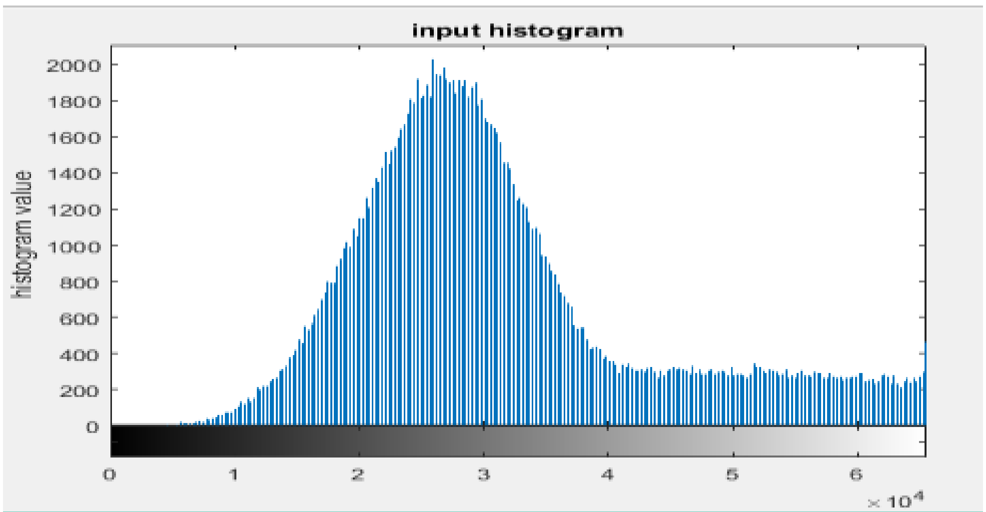

Figure 6: Bar Graph showing noisy Histogram of LR Image

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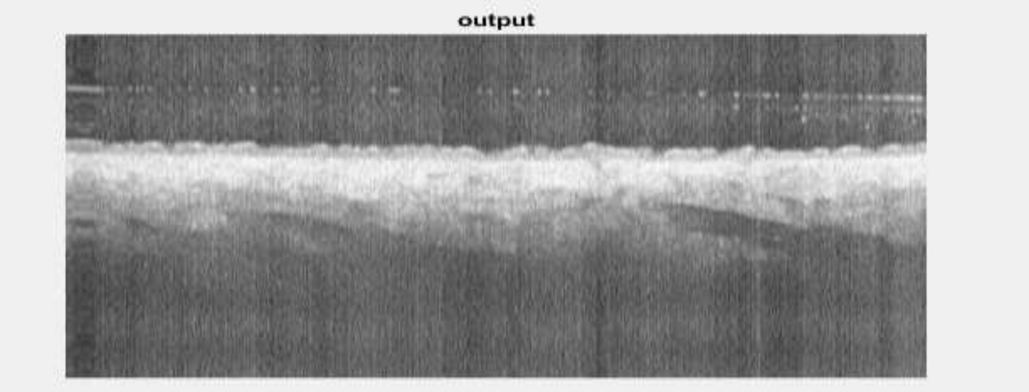

Figure 7: Output Showing Accurate multi frame

CONCLUSION

The modernization of image superiority using super-resolution methods powered by deep learning represents a significant advancement in the capabilities of defense and surveillance systems. By leveraging deep learning architectures such as convolutional neural networks (CNNs) and generative adversarial networks (GANs), this approach overcomes the limitations of traditional image enhancement techniques. It successfully restores fine details, improves clarity, and enhances the overall quality of low-resolution images captured under challenging conditions. The integration of these advanced super-resolution methods enables more accurate object recognition, target identification, and situational awareness, which are critical in defense and intelligence operations. The analysis shows substantial improvements in key metrics like Peak Signal-to-Noise Ratio (PSNR) and Structural Similarity Index (SSIM), reflecting better visual quality. Additionally, deep learning-based techniques provide adaptive solutions across different environments, including long-range surveillance, low-light conditions, and motion blur, making them highly versatile. The adoption of super-resolution methods using deep learning is a crucial step in modernizing image superiority for defense and surveillance systems. This approach not only enhances visual information but also provides a strategic advantage by enabling more precise and timely decision-making in mission-critical scenarios.

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