Visibility Enhancement in Foggy Traffic Surveillance for Improved Vehicle Detection

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***Abstract*—Fog is one of the foremost causes of poor visibility leading to some serious road accidents. Videos captured under such prevailing weather conditions generally are very poor in contrast and clarity as atmospheric particles scatter the light involved. This study reports a video-based system for visibility enhancement and vehicle detection from fog or low-light traffic conditions that are feasible to work with in surveillance scenarios. A multi-stage processing pipeline is designed here using classical computer vision techniques to improve the visibility scene and make detection much more reliable. The methodology is divided into five major stages, namely foggy video frame acquisition, transmission map estimation using the Dark Channel Prior (DCP) method, enhancement using Contrast Limited Adaptive Histogram Equalization (CLAHE), adaptive gamma correction illumination correction, and vehicle detection using background subtraction and contour based analysis. Each of the above stages is significant in restoring degraded frames and facilitating their visibility so as to enable more accurate detection of moving vehicles. Experimental studies have shown that the proposed approach greatly improves visual clarity of such scenes affected by fog and is extremely efficient in vehicle detection under adverse weather conditions.**

***Index Terms*—Video enhancement, Fog removal, Adaptive gamma correction, Vehicle detection, Dark Channel Prior, CLAHE**

I. Introduction

Modern traffic systems have made ample utilization of vision-based techniques for various purposes such as monitoring traffic, speed estimation of vehicles, recognition of signal state, and accident detection [1]–[3]. Urban population growth being fixed while increased vehicle ownership due to higher disposable income formation has added to cars' number on-road in recent times. This influx has created a new board of issues-like traffic congestion, exceedingly long travel times, fuel wastage, and constant delay intersections. Hence, the demand for an intelligent and efficient traffic control system has become even more critical.

Regions have variously employed traditional systems to monitor and control traffic flow, including fixed-timing light signals, vehicle-actuated control mechanisms, inductive loops, and others like magnetic sensors. Although real-time information is relied on by these systems, they are limited in many respects. Almost always, installation will be burdensome infrastructurally for these systems, involving constant upkeep and usually with a very limited spatial coverage factor [5]. Camera-based surveillance approaches in the vision-based approach provide a good affordable and scalable solution. These can, in fact, mitigate the hardware limitations entrenching conventional systems by utilizing existing CCTV networks, channeling real-time video analysis for the purposes of traffic control on a dynamic basis.

Fog is one of the main weather phenomena responsible for traffic inefficiency and road crashes. Fog lowers visibility in video frames through the scattering of light by suspended particles in the atmosphere. It renders contrast lower, obscures object boundaries, and blurs. These factors severely affect many operations in image-processing and computer-vision applications such as feature extraction, object segmentation, motion tracking, and classification. Among the many effects of fog, vehicles become almost indistinguishable from the background, making reliable detection a challenge for humans and automated systems alike.

In the past, a variety of methods were suggested to counteract the degrading of visibility. Among these, polarizing filters and enhancement via multi-image processing have been proposed. Polarization-based analysis, such as Degrees of Polarization (DoP), is, however, a special hardware-and-multiple-image-inputs-enhanced methodology that cannot be easily deployed in an urban surveillance scenario. The aforementioned analysis methods diverge significantly regarding accuracy and robustness when atmospheric particles exhibit different densities and scales, further discouraging their use for practical applications.

These limitations motivate the present work, which presents a video enhancement and vehicle detection scheme suited to extreme foggy traffic conditions. The enhancement works by adaptive gamma correction and Contrast Limited Adaptive Histogram Equalization (CLAHE) for local contrast improvement.

As such, this work would hold a primary purpose of carrying out vehicle detection and enhancement under foggy traffic conditions. Thus, an adaptive Gamma correction combined with contrast-limited adaptive histogram equalization for local contrast enhancement is followed by image filtration and restoration techniques meant to suppress noise while retrieving

(a) Severe fog degradation obscuring vehicles

(b) Foggy traffic image with low visibility

Fig. 1: Example of foggy traffic surveillance images demonstrating the need for visibility enhancement.

fog-lost detail. This is made possible by using classical filters such as median filters and wiener filters to remove the image degradation caused by scattering in the environment [9].

Subsequently, these cleaned and enhanced video frames will be subjected to vehicle detection employing motion-based background change techniques coupled to contour analysis. Enhancement along with detection will provide the system with the real-time recognition of vehicles in lesser visibility, which is a crucial aspect for monitoring traffic and detecting violations or dynamic signal control.

Unlike previous techniques which mostly focused on the enhancement of still images, this work pertains to real-time video processing for frame-wise applications. The algorithm is now used to capture a video stream from a fixed surveillance camera positioned at a traffic intersection. Then, each frame is processed successively: the first step is denoising, and then contrast enhancement, and finally, object detection. The comparison of successive frames allows the system to catch moving objects, mainly vehicles, against a changing background, which is effective also in high fog levels.

In essence, this research work advances an intelligent vision-based vehicle detection system that can be classical computer vision techniques to enhance foggy video footage. The implementation is made on the MATLAB and OpenCV frameworks. Thus, this system provides a cost-effective solution for urban traffic control, in line with the ever-increasing demands for intelligent adaptive transportation systems, by improving visibility and reliable detection of vehicles under adverse weather conditions.

II. LITERATURE REVIEW

Video-based traffic surveillance is a field that has started to become mature and equally responsive to challenges stemming from poor visibility conditions, for instance fog or haze, or very poor light. These atmospheric disturbances seriously degrade the quality of images, which renders the vehicle detection tasks all the more difficult. Various classical and learning-based methodologies have been attempted in the literature to counter these effects and enhance the performance of object detection in harsh environments.

The early theoretical studies on which the implementation of algorithms was based were concerned with understanding how the weather would affect the quality of images. Narasimhan and Nayar [5], [6] proposed a theoretical framework that was chromatic for bad weather and developed algorithms for contrast restoration of weather-degraded images. They stressed the importance of visibility enhancement prior to the implementation of any detection-related tasks. Robby Tan [8], [11], with some background on physical image formation models, placed a lot of importance upon a single-image approach to visibility restoration, which later became a standard. Subsequently, Fattal [9] and He et al. [10] improved single-image enhancement via refined estimating of scene radiance and the introduction of the dark channel prior (DCP), ever since widely and commonly used. Their work essentially established the utility of image enhancement in benefit perception and object recognition in foggy scenes.

Subsequent works by Hautière et al. [11], [12], and [13] merged disparity contrast estimation and stereovision for prediction of visibility distance via onboard vehicles, rendering them adaptive for intelligent transportation systems. Alongside, adaptive histogram-based methods like CLAHE began functioning by locally pumping contrasts in foggy or underexposed regions without oversaturating image features. Gamma correction started to gain popularity due to its simplicity and easy computational load; on the other hand, the appropriate gamma value is still an issue. While Zhang and Ding [10] applied image filtering and enhancement to improve visibility under fog, Alwani and Tiwari [9] suggested algorithms for contrast enhancement that target the specific features of colored fog images.

Vehicle detection and tracking are equally integral parts of traffic surveillance, apart from the visibility enhancement. Early work by Dailey et al. [2] proposed algorithms to estimate mean traffic speed from uncalibrated video feeds, while Tai et al. [1] generated real-time image tracking techniques for enforcement and monitoring. Gaussian Gaussian Mixture Models (GMM) for background subtraction [18], together with edge detectors like the Canny operator and Hough Transform

[15], have found wide applications in traffic lane localization and distinguishing moving objects. Eventually, blob extraction and region growing methods [16] enabled precise vehicle segmentation by noise reduction and boundary refinement.

Machine learning models, particularly SVMs trained on features like HOG, Haar cascades, and color histograms, have been shown to perform reliably in a structured environment of traffic. In contrast, state-of-the-art object-detection models such as YOLOv3 and Faster R-CNN have integrated with Kalman filters and Hungarian matching algorithms for real-time tracking [20], [21]. However, deep learning models are hampered by the need for large amounts of training data and intensive computational resources, placing limitations on their use in lightweight and edge-based systems.

On the other hand, SORT algorithm [21] works for fast reasonably accurate multi-object tracking but does not consider appearance features. A robust detector-tracker is also proposed using particle filters, region-based CNN segmentation, and hybrid SVM classifiers, but this comes at a higher computational cost. Complementary studies include traffic light detection [3], neural and fuzzy systems for traffic flow optimization [7], [8], and camera-based vehicle speed estimation [2], which give evidence for the enhanced amalgamation of intelligent computer vision into the world of traffic surveillance.

The proposal of this paper consists of a framework that combines classical vision methods for image enhancement such as adaptive gamma correction, CLAHE, and dehazing, with classical segmentation and tracking. This approach strives to retain high detection accuracy while satisfying computational speed, thereby favoring feasible deployment in resource-constrained or true-field systems for surveillance. The proposed system shall try to integrate insights from the various classical dehazing methods, machine learning classifiers, and efficient paradigms of tracking to restore the visibility and enhance vehicle detection performance in the case of degraded weather.

III. METHODOLOGY

Foggy traffic surveillance often induces traditional motion-based vehicle detection techniques to fail quite quickly because of blurred visibility and reduced contrast in the captured frames. In this context, we develop a classical computer vision pipeline in order to improve visibility for analytical vehicle detection in congested situations derived from foggy video, instead of motion difference or background subtraction-based approaches that usually fail in static situations or even with slow-moving vehicles. This focuses on emphasizing the spatial feature and visibility enhancement with a blend of frequencybased feature extraction and contrast enhancement methodology. The heart of our approach is represented by using the Gabor Wavelet Transform for feature extraction combined with three powerful image enhancing techniques, that is, Contrast Limited Adaptive Histogram Equalization (CLAHE), Dark Channel Prior (DCP), and Adaptive Gamma Correction (AGC).

With this workflow, video is acquired from a stationary camera, then images are taken from that video, which is then analyzed frame by frame. Each independent image is enhanced for visibility and makes vehicles more distinct even when shrouded in thick fog. Important steps of this workflow include process wherein frames converted into images, areas identified within these images for ROIs, classical techniques applied toward the enhancement of images, and detection strategy which relies on visual feature clarity, rather than movement.

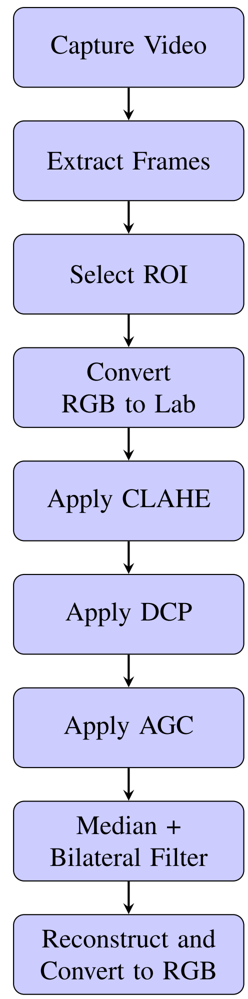


Fig. 2: Proposed Image Enhancement Pipeline

A. Image Representation

The very first input to the system is a real-time sequence of a fixed surveillance camera. The analog video signal is being digitized and further decomposed into discrete image frames. Each of those frames will find their representation either as a gray image or in a color space stage. If I(x,y) represents an image with size MxN, then a pixel location (x,y) would contain intensity values in the range [0, 255].

B. Region of Interest (ROI) Selection

When it comes to foggy traffic surveillance, the processing of the whole image can be computationally expensive and unnecessary. Thus, the selection of regions of interest is performed for efficiency and accuracy. These regions usually pertain to road segments or areas where vehicles are expected to appear. The selectivity helps in less burden on processing and increases subsequent enhancement techniques' effectiveness by isolating areas severely affected by fog degradation.

Once the ROI is determined, the conversion of the input image will take place from RGB to a perceptually uniform color space, either Lab (L*, a*, b*) or HSV (Hue, Saturation, Value), for the processing purposes associated with intensities. The intensity (luminance) or value channel is extracted, whereby the most relevant structural information pertinent to fog is contained.

C. Visibility Enhancement Techniques

1) Contrast Limited Adaptive Histogram Equalization (CLAHE): Contrast Limited Adaptive Histogram Equalization (CLAHE) is a method that enhances local contrast while reducing the amplification of noise, which is often a side effect of conventional histogram equalization. The fundamental mechanism of CLAHE is to divide the image into small contextual regions or tiles and apply histogram equalization independently to each tile. This localized approach allows for improved contrast in specific areas of the image while avoiding the over-amplification of noise.

To control the extent of enhancement, CLAHE introduces a clip limit that restricts contrast amplification within each tile. This parameter prevents over-enhancement and ensures that the histogram equalization remains bounded.

Let $I(x, y)$ be the grayscale intensity value of the image. CLAHE is applied to the image as follows:

$$I(x, y) = \text{CLAHE}(I(x, y), \text{clipLimit}, \text{tileGridSize}) \tag{1}$$

2) Dark Channel Prior (DCP): Single image haze removal based on *Dark Channel Prior (DCP)* is a broadly-known technique for defogging. The principle stems from the empirical observation that in non-sky patches of outdoor images, at least one color channel exhibits very low intensity at some pixels. This results in what is referred to as the *dark channel* of the image.

In the presence of fog or haze, atmospheric scattering causes light to be diffused, leading to brighter pixel values across all color channels. As a result, the dark channel becomes significantly brighter in foggy conditions, thus allowing it to serve as an indicator of haze concentration.

Mathematically, for an input RGB image I, the dark channel $D(x, y)$ is computed over a local patch $\Omega(x, y)$ centered at pixel (x, y):

$$D(x, y) = \min_{c \in \{R,G,B\}} \left(\min_{(x',y') \in \Omega(x,y)} I^c(x', y') \right) \tag{2}$$

where c is the color channel, and $\Omega(x, y)$ is the local patch around (x, y).

The DCP is then used to estimate the *transmission map* $t(x, y)$, which represents the portion of scene radiance that reaches the camera:

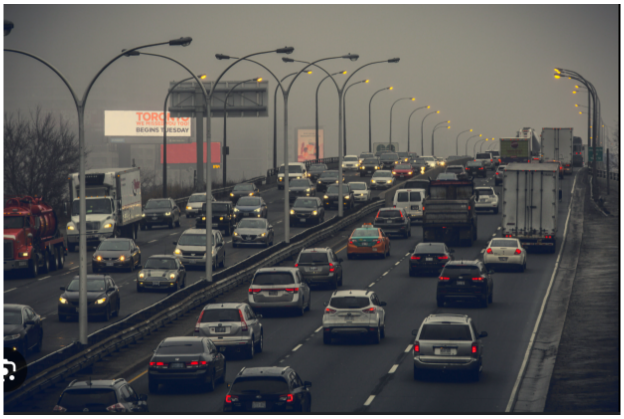
$$I(x, y) = J(x, y)t(x, y) + A(1 - t(x, y)) \tag{3}$$

3) Adaptive Gamma Correction: Adaptive Gamma Correction is an advanced, nonlinear mode of image enhancement used for foggy photos or pictures taken from a distance with low visibility. Generally speaking, the gamma correction used in these video systems tends to take care of the nonlinearities of display systems and the dynamic range that is used more effectively by feeding the raw data through these systems for viewing. The standard gamma correction is defined by the power-law transformation:

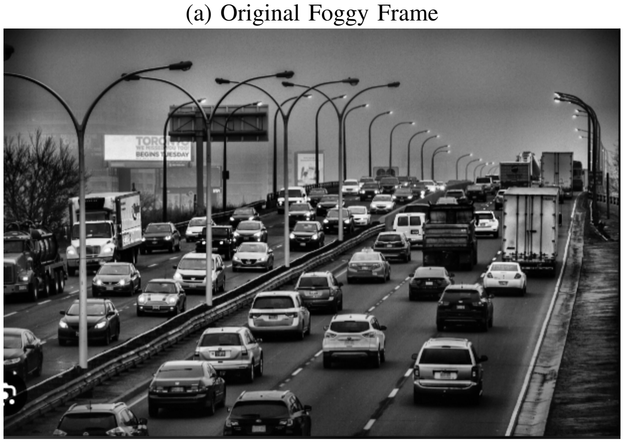
$$V_{\text{out}} = A \cdot V_{\text{in}}^{\gamma} \tag{4}$$

where V_{in} is the input intensity, V_{out} is the output intensity, A is a constant (typically 1), and γ is the gamma value.

Thus, it is insufficient in the case of foggy traffic footage, since the level of illumination varies across the scene: darker regions are enhanced more than already bright ones much in the same way as area-based adaptive thresholding. The gamma correction is done at the end, after the contrast, enhancement processes like CLAHE and dark channel prior have taken place and will add to how refined the visual output will appear to be. This combination makes the visibility improvements of distant vehicles and road boundaries without producing too much saturation around the brighter areas of the frame, making it particularly useful for foggy traffic surveillance videos under highly variable lighting conditions.



(a) Original Foggy Frame



(b) Enhanced Output Frame

Fig. 3: Comparison of input and output frames before and after applying the enhancement pipeline

D. Filtering and Image Smoothing

Filtering and smoothing operations are some of the important functions of image preprocessing, especially when visibility is hindered considerably by heavy fog. The main concern is the elimination of noisy images and the improved highlighting of important structure, namely rebates, lane markings, and boundaries of the road while keeping preserved the important edges of an image.

The extent to which we applied smoothing is primarily between the two events: contrast enhancement followed by the detail enhancement of the resulting image and removal of residual noise or artifacts introduced during dehazing. A median filter works best to remove salt-and-pepper noise from an image without blurring its sharp edges. It works quite differently from linear filters, as it preserves edge integrity because each pixel value is replaced by its median in light intensity in a certain neighborhood.

Smoothing is edge preserving and is also done using a Bilateral Filter; it is a non-linear filter. It looks at spatial proximity as well as the similarity in radiometry of the neighboring pixels. It works well to remove noise while maintaining relevant edge information required for shape retention of vehicles and road features in foggy scenes.

We then return to improve visibility and remove leftover fog-like artifacts by using the Dark Channel Prior (DCP) guided filtering procedures. Thus, estimating the transmission map through DCP will smooth the transmission map with a guided filter while keeping the structure of the original image, which produces a result in defogging closer to the more natural and aesthetically pleasing form.

This combination helps give an enhanced sharpening-shaping effect to the much-needed details and then keeps the haze artifacts in check all without creating the condition of noise overamplification or visual distortion. Final output frames would be clear, uniform, and ready for accurate vehicle detection.

E. Step-by-Step Algorithm

1) Capture video from a static surveillance camera.
2) Extract individual frames from the video stream.
3) Select Region of Interest (ROI) focusing on road areas.
4) Convert RGB frames to Lab color space for better contrast handling.
5) Apply CLAHE to the L* channel for local contrast enhancement.
6) Apply Dark Channel Prior (DCP) to estimate and remove fog.
7) Perform Adaptive Gamma Correction to enhance darker regions.
8) Apply image filtering (e.g., median filter) to reduce noise.
9) Reconstruct the enhanced image and convert it back to RGB.
10) Repeat the above steps for all frames to produce the final enhanced video.

IV. Result

The proposed enhancement algorithm was tested using several frames of foggy traffic surveillance video recordings. The intention behind the enhancement algorithms was to clear the vision for vehicle detection during adverse weather conditions. The methods proposed integrate the classical image enhancement techniques such as CLAHE for boosting local contrast, Dark Channel Prior for haze removal, and Adaptive Gamma Correction to give the last touch.

A. Evaluation Metrics

Shannon Entropy (SE) measures the information content or randomness present in an image. It is a statistical metric used to quantify the uncertainty or complexity of pixel intensity distribution. A higher entropy value generally indicates that the image contains more details and richer visual information, which is desirable after enhancement.

Contrast Improvement Index (CII) quantifies the enhancement in contrast between the original (foggy) image and the processed (enhanced) image. It is calculated as the ratio of the contrast of the enhanced image to the contrast of the original image. A CII value greater than 1 indicates an

Fig. 4: Shannon Entropy (SE) comparison before and after enhancement. Although entropy decreases slightly after enhancement, the visual quality and contrast are improved, suggesting noise reduction and better feature visibility.

Fig. 5: Contrast Improvement Index (CII) comparison before and after enhancement for foggy traffic images. The proposed enhancement pipeline shows notable improvements in some cases, especially for images with low initial contrast.

improvement in image contrast, reflecting better visibility and clarity.

A clear improvement of image quality was seen after the algorithm implementation. Fog and low-contrast parts mostly diminished, revealing hitherto masked elements of the roadway, such as lane markings, the shapes of vehicles, or boundaries along the roadside. Processed frames had revealed increased visibility in near and far-reaching areas of the scene; this is, hence, crucial for real-time monitoring and detection of vehicles.

Specifically, use of Adaptive Gamma Correction at the final stage helped preserve brightness levels across the frame, optimally brightening the darker regions and avoiding saturating well-lit areas. This resulted in such balanced images where vehicles and obstacles seem to appear clearly than in the first phase under typical lighting conditions found in foggy environments.

Altogether, the enhanced video frames would give accurate detection of vehicles and estimation of traffic density. The amount of visible improvement lends credence to analysis and decision-making by modern intelligent transportation systems, especially for adaptive traffic signal control and accident prevention in low-visibility conditions. This proposed classical approach of computer vision proves to be indeed a reliable and efficient solution for scenarios of real-world foggy traffic surveillance.

TABLE I: Shannon Entropy Before and After Enhancement

Image	Entropy Before	Entropy After
fog image1	5.7543	5.6688
fog image2	6.9199	7.4822
fog image3	6.0395	6.1881
fog image4	6.9667	7.5065
fog image5	5.7543	5.6688

TABLE II: Contrast Improvement Index Before and After Enhancement

Image	CII Before	CII After
fog image1	1.1135	1.0000
fog image2	0.6905	1.0000
fog image3	0.9139	1.0000
fog image4	0.6766	1.0000
fog image5	1.1135	1.0000

V. Conclusion

The project developed a complete image enhancement framework to help in enhancing the visibility of road traffic surveillance videos affected by fog. The methodology involved a sequence of contrast enhancement techniques, such as Contrast Limited Adaptive Histogram Equalization (CLAHE), Dark Channel Prior (DCP), and Adaptive Gamma Correction (AGC), solving specific problems imposed by low-visibility situations.

The techniques employed not only improved the clarity of the images by enhancing contrast and attenuating atmospheric scatter but also adaptively adjusted luminance across different regions in the scene. This improvement goes a long way in helping to delineate the vehicles from the road boundary, making vehicle detection and subsequent traffic analysis more efficient.

The results indicate that the proposed enhancement pipeline is a solid solution to the problem of visibility in foggy traffic footage. The approach can be applied with real-life advantages in traffic monitoring systems, especially where diversely changing lighting and mal-weather conditions are concerned. Future work may involve adding segmentation or object detection modules for automating vehicle counting, hence aiding in overall traffic management efficiency.

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