

Image Enhancement in Foggy Images using Dark Channel Prior and Guided Filter

Sachin Harné¹, Siddhartha Choubey², Abha Choubey³

¹Department of Computer Application, Shri Shankaracharya Technical Campus, Shri Shankaracharya Group of Institution, Bhilai, Chhattisgarh, India

^{2,3}Department of Computer Science and Engineering, Shri Shankaracharya Technical Campus, Shri Shankaracharya Group of Institution, Bhilai, Chhattisgarh, India

Corresponding author Email Id: sachin.harne2027@gmail.com

Abstract:

Haze is very apparent in images shot during periods of bad weather (fog). The image's clarity and readability are both diminished as a result. As part of this work, we suggest a method for improving the quality of the hazy image and for identifying any objects hidden inside it. To address this, we use the picture enhancement techniques of Dark Channel Prior and Guided Filter. The Saliency map is then used to segment the improved image and identify passing vehicles. Lastly, we describe our method for calculating the actual distance in units from a camera-equipped vehicle of an item (another vehicle). Our proposed solution can warn the driver based on the distance to help them prevent an accident. Our suggested technology improves images and accurately detects vehicles nearly 100% of the time.

Keywords: Haze, Vehicles, Dark channel before and directed filter, Saliency map, Image enhancement.

I. Introduction

In order to enhance a picture or extract valuable data from it, it must be digitised and subjected to a series of procedures known as "image processing." Multiple cameras now keep an eye on the area to ensure everybody's safety. In most cases, well-trained human operators will suffice to do this monitoring. However, it is impractical and prohibitively costly to monitor the images from several cameras simultaneously. In addition, the major benefit of surveillance video as an active, real-time medium is lost since it is now only utilised "after the fact" as a forensic tool. Putting cameras in lieu of human eyes is just half the battle; true success in visual surveillance also comes from automating as much of the process as feasible. Therefore, IVS becomes a hot area of study for computer vision researchers.

The recognition of foreground objects of interest inside a surveillance video sequence is one of the most crucial tasks of any intelligent visual surveillance system. Several methods are presented in the literature to detect objects. All these methods function best when lighting conditions are ideal, since the input photographs must have good visibility for the analysis to be successful. But there are times when this is not the case, including when recordings are shot in poor lighting or on a cloudy day. The visual quality has declined, and there has been a marked reduction in contrast. Traditional object identification algorithms have difficulty with these low-quality photos.

Similar to this, a murk is a dense cloud of small water droplets floating in the sky that filters out light. Some of the meteorological factors that may significantly alter images and films are darkness, smoke, rain, and snow. Outdoor vision systems that rely on image/video feature extraction or visual attention modelling for tasks like action identification, object detection, tracking and acknowledgment, scene analysis and classification, and photo indexing and retrieval can be severely impacted by these distortions. They often misidentify or completely miss items because to the poor lighting. The goal of enhancing visibility is necessary to get good tracking pictures. Since defocusing techniques are a hot topic for study in the field of computer vision, they have recently attracted a lot of interest. Image enhancement is used to highlight or sharpen picture components like borders or contrast in order to make the graphical representation more effective for display and analysis. To put it another way, the information richness of the data is not increased by this procedure. Grayscale and contrast adjustments, noise cancellation, sharpening and edging, filtration, interpolation and magnification, phoneycolouring, and so forth are all a part of this category. There are five broad categories for which image processing can be used. They are:

- Visualization allows one to see invisible things.
- Restoration and sharpening of images for increasing performance
- Image Search allows you to look for a certain image.

- The image's contents may be evaluated using the Pattern Measurement feature.
- Object recognition in images is an area of study known as "image recognition."

II. Literary review

In this part, we will look at the effects of seasonal fluctuations on image quality as well as the numerous approaches currently used to improve images.

1) Evaluation of different digital image de-fogging algorithms, Authors: Gagandeep Singh

Various methods for removing fog are discussed in this article. Defog, often known as visibility restoration, may refer to a number of different methods that automatically correct for or remove degradation introduced by digital picture capture. Multiple methods for dispelling fog are dissected here. It turns out that there are benefits and drawbacks to using a variety of approaches to clearing the fog. Methods to mitigate the noise seen in the final photos produced by preexisting fog removal algorithms were brushed over. However, until recently, there was little attention paid to combining CLAHE with Dark channels. Most studies also failed to consider the issue of uneven lighting.

2) Research on image de-blurring algorithm using Dark-Channel Prior function based on Wavelet transform, Authors: Wu Sijiu, Zhang Haiyan

The study begins by contrasting image enhancement and restoration picture removal algorithms before moving on to investigate the fundamental principles of a dark channel image removal approach. The algorithm's shortcomings are explored. Additionally, a curvelet dark-channel prior is provided for use in an algorithm to eliminate blur in images. They consist of three stages: a three-channel wavelet transform of the picture, a dark-channel-based deblurring method for the low-frequency components, and a high-frequency component sharpening enhancement. The experimental findings demonstrate not only that the method is able to efficiently cut running time and enhance operating speed after deblurring a picture, but also that it can improve the image resolution and has superior performance in details.

3) Image acquisition in low-light circumstances by use of a physiologically model for contrast degradation, Authors: J.P. Oakley ; B. L. Satherley

Atmospheric particles, such as haze and fog, may drastically reduce picture contrast even in broad daylight. In cases when the scene geometry is known, the technique presented

in this paper may be used to mitigate this degradation. Contrast is decreased by both light reflected from the ground and light emitted toward the sensor by aerosol particles. This degradation may be roughly defined by a simple, physically grounded model with just three parameters. After the inverse issue is solved to get the three model parameters, the scattered and reflected flux contributions of each pixel are evaluated. We just take the pixel value and the thickness and remove the projected variance contribution to get the true variance contribution.

III. Proposed Methodology

In this section, we provide the theoretical underpinnings of the suggested fuzzy-based adaptive DCNN method, which was utilised to develop a better approach to loss estimation and augmentation of picture data by means of contour analysis, independent of seasonal variations. The current ones advocate for using CLAHE to get rid of sludge and turbidity and the Curvelet Transform to identify objects.

- In the first step, the colour image is changed to grayscale.
- After that, the median filter is applied to the grayscale image.
- The filtered image is processed with CLAHE.
- Curvelet Transform is then used to action on the improved picture.

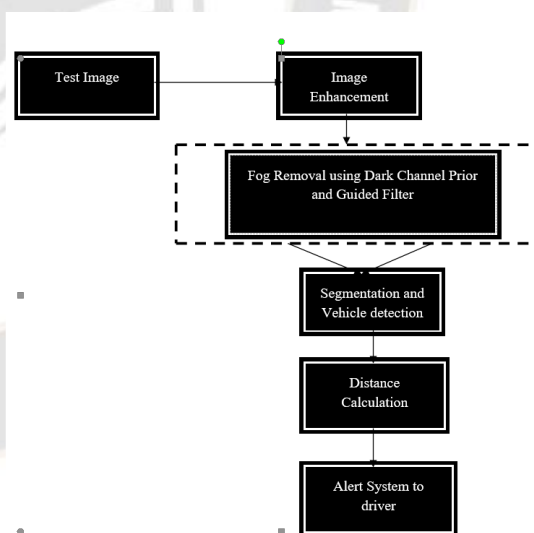


Figure 3.1: Workflow of Proposed System

3.1 Disadvantages of the current system:

- In the existing ones, a smaller amount of cloudiness/smear removal in the image is suggested.
- Decreased detection accuracy was one of the main issues.
- And in the current ones for driver notification, the distance computation is not implemented.

3.2 The proposed system:

The suggested approach takes use of a saliency map for object recognition and a controlled filter for enhancement. There are five stages to it.

Step 1: Collect test images from public database.

Step 2: The fog was taken out of the picture by extracting the prior transfer map from the dark channel. Further refinement was achieved by using a calibrated filter to rectify the blurred source.

Step 3: The salient map is used to segment the improved image and identify moving vehicles.

Step 4: The computed distance between the identified item and the webcam vehicle allowed for its safe transport. And then, at some point, the motorist received a warning that was computed in relation to the distance.

3.3 Advantages of the proposed system

- The effectiveness in reducing turbidity is quite great.
- An extremely precise detection rate is achieved
- A distance calculator has been included for safety purposes.

IV. Results and discussion:

The fact is that MATLAB is used for both numerical calculations and symbolic calculations. The integration with a smart software for numerically expressing information is a further advantage. Having this coding skill has facilitated the growth of research and development resources in all of science and technology. The toolkit contains a comprehensive arrangement of standard calculations, functions, applications and representations. A variety of image processing tools are available to organize and analyze images that sort pixel determinations.

4.1 Haze removal function

For the aim of blurring only one image, we suggest a new previous - dark channel. The preceding dark channel was derived from data collected from outdoor, uncovered photos. We found that some pixels, dubbed "black pixels" because of their extremely low intensity in at least one RGB channel, are extremely prevalent in most little places that do not completely fill the sky. These dark pixels in this channel contribute significantly to the overall intensity of a turbid picture. Therefore, the number of opaque pixels may be used as a direct measure of turbidity transmission. A high-quality, turbidity-free image and an accurate depth map may be obtained using a combination of the turbidity imaging model and the controlled filter approach (up to scale). When working with distant objects, even in heavy haze, our method is physically sound and effective. When processing

an image, we don't depend on small differences in transmittance or surface shading. Multiple halo artefacts are seen in the finished product.

4.2 DCP-based image removal

where x represents the position of the image, I represents the fuzzy view, J represents the clear view, A represents the atmospheric circulation light, β represents the atmospheric effects coefficient, and d represents the depth of the scene. In this case, we typically give $e^{-\beta d}$ in the form of a transmission map.

$$I(x) = J(x)e^{-\beta d(x)} + A(1 - e^{-\beta d(x)}), I(x) = J(x)e^{-\beta d(x)} + A(1 - e^{-\beta d(x)}) \quad (1)$$

where β is the atmospheric scattering coefficient, d is the scene depth, x is the location in the image, I is the hazy image observed, J is the clear image, A is the global atmospheric light, and I in this instance, e^{-d} is often provided as a transmission map.

$$t(x) = e^{-\beta d(x)}, t(x) = e^{-\beta d(x)}. \quad (2)$$

Since we have $\beta \approx 0$ in the absence of cloud, we have $I \approx J$. However, β for fuzzy pictures, becomes significant. As scene depth rises, the direct attenuation component, $J(x)t(x)$, in Eq. (1), becomes less. In contrast, when scene depth rises, the value of the second part in Eq. (1), $A(1 - t(x))$ (air light), grows. After calculating A and t from I , the last step in picture deinterlacing is a simple integer value:

$$J(x) = I(x) - At(x) + A, J(x) = I(x) - At(x) + A. \quad (3)$$

However, it is not easy to make a rough estimate about A and t . Particularly, there are as many questions unanswered as there are pixels in the image since t fluctuates spatially with scene depth. Therefore, it is inappropriate to estimate t directly from I without making any necessary assumptions or use of prior knowledge.

He and his colleagues [10] undertook an experiment to determine what factors contribute to clear outdoor photos. It was found that there are dark pixels in the image field, with intensity values close to 0 for at least one colour channel. We may extrapolate the following characterisation of the dark channel from this:

$$J_{\text{tmav}}(x) = \min_{y \in \Omega(x)} (\min_{c \in \{r, g, b\}} J_c(y)), J_{\text{tmav}}(x) = \min_{y \in \Omega(x)} (\min_{c \in \{r, g, b\}} J_c(y)), \quad (4)$$

A dark channel is generated from the input picture using the DCP-based dehazing method, as shown in Eq. [10]. (4). The dark channel is then used to create a map of atmospheric light and transmission. Through Eq (3) and an improved transmission map, the original crisp image is reconstructed.

$$\text{Dark} \approx 0. \quad (5)$$

The value represented by the initials DCP stands for "dark channel pixel," and it is an approximation of zero.

The deterioration model, to be more exact,

$$I(x) = J(x)t(x) + A(1-t(x)), I(x) = J(x)t(x) + A(1-t(x)), \quad (6)$$

We get the least intensity in the local field for each colour channel by dividing the two sides of Eq. (6):

$$\min_{y \in \Omega(x)} I_c(y) A_c = t(x) \min_{y \in \Omega(x)} J_c(y) A_c + (1-t(x)) \min_{y \in \Omega(x)} I_c(y) A_c = t(x) \min_{y \in \Omega(x)} J_c(y) A_c + (1-t(x)) A_c \quad (7)$$

Here, we assume that the nearby patch $\Omega(x)$, represented by the symbols $t(x)$ [10], has continuous transmission. This enables us to use Eq. (7) as follows to apply the min operator of the three colour channels:

$$\min_{y \in \Omega(x)} (\min_c I_c(y) A_c) = t(x) \min_{y \in \Omega(x)} (\min_c J_c(y) A_c) + (1-t(x)) \min_{y \in \Omega(x)} (\min_c I_c(y) A_c) = t(x) \min_{y \in \Omega(x)} (\min_c J_c(y) A_c) + (1-t(x)) A_c \quad (8)$$

According to the DCP approximation of Eq. (5), $t(x)$ can be represented as $t(x) = 1 - \min_{y \in \Omega(x)} (\min_c I_c(y) A_c) / A_c$. $t(x) = 1 - \min_{y \in \Omega(x)} (\min_c I_c(y) A_c) / A_c \quad (9)$

The transmission map $t(x)$ may then be derived from an estimate of the ambient light A . Most conventional detection methods start with a search for the most opaque pixels and use them to estimate a whole A frame. Dark channel pixel values strongly correlate with turbidity as we saw in Section 1.2.2. Selecting the ten percent brightest pixels in the dark channel and then using the colour with the greatest intensity value among those pixels yields the result for A [10].

4.3 Controlled filter

The `imguidedfilter` function applies an edge-preserving smoothing to a picture by taking into consideration the features of some other image (the guide image). The picture itself, a modified version of the image, or an entirely other image might all serve as a partner image. Like other filtering operations, guided image filtering considers the statistics of the region in the matching spatial neighbourhood of the guide picture to determine the value of each filter pixel. The structures are same if the hint and the image to be filtered are the same; the edge in the original image is identical to the edge in the clue image. In the event when the guiding image is I

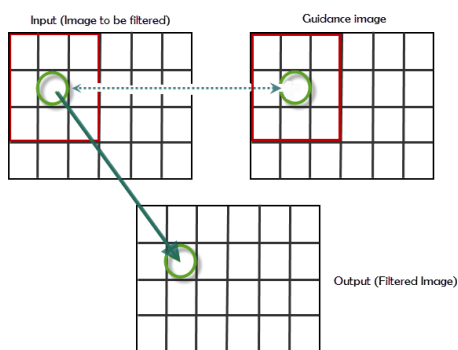


Figure 4.1: Guided Filter

First, we propose a generic linear translation-variant filtering method using a guide image I , an input picture p , and an output image q . I and p are both supplied by the programme and might be the same. We may easily interpret the filter's output at pixel I as a weighted average:

$$q_i = \sum_j W_{ij} (I)_j, \quad (1)$$

I and j are the indices of the individual pixels in. The guiding image I determines the filter's kernel, which makes the variable p irrelevant since it is a function of that image. This filter maintains linear for all values of p . The joint bilateral filter [12] is one specific example of such a filter.

The formula for the Wbf bilateral filtering kernel is as follows:

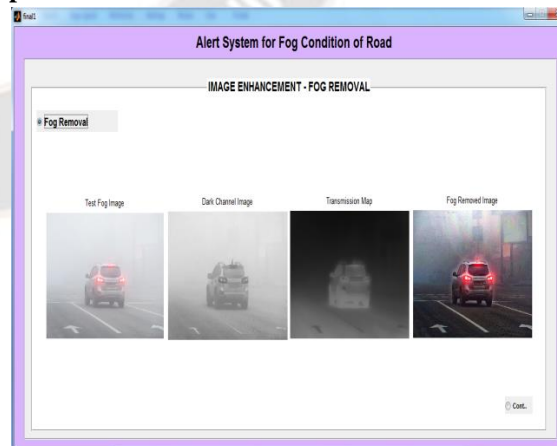
$$W_{bf}(I) = \frac{1}{K_i} \exp(-|x_i - x_j|^2 / (2\sigma_s^2)) \exp(-|I_i - I_j|^2 / (2\sigma_r^2)) \quad (2)$$

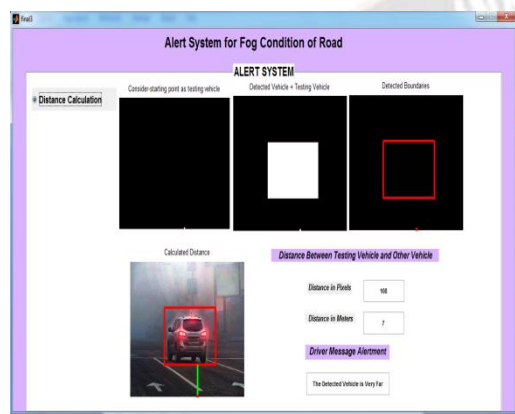
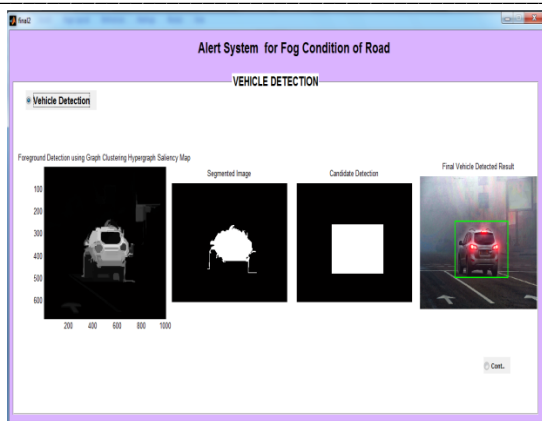
where x is the position in pixels and K_i is a normalising parameter that makes $\sum_j W_{bf}(I) = 1$. Using the s and r parameters, similarity in both spatial and intensity/color space may be adjusted. In the center, when I and p are equal, the hinged bilateral filter reverts to the standard bilateral filter [1]. The kernel and the controlled filter are explained in detail. A local linear model between the filter's input I and output q is required for the guided filter to operate. We suppose that q is a linear transformation of I in a window of size k where k is the number of pixels.

4.4 Working Of Object Detection

The saliency area may be obtained by thresholding the saliency map to generate a binary mask, which is the quickest and most straightforward method. The outcome of the picture segmentation is added to the saliency map for more precise detection of interesting elements.

Output:





V. Conclusion:

Image enhancement, the subject of this article, is one of the most recent areas of emphasis in the science of image processing. The authors of this work filter photos of fog by using the Guided Filter with Dark Channel Prior. After the Saliency map has been used to improve the fog image, the cars must be extracted. At last, the separation between the detected vehicle and the camera's own vehicle is determined. This means that drivers may benefit from a decreased frequency of vehicle-to-vehicle collisions on roads and highways if an efficient automatic vehicle recognition and warning system is in place.

Case 2:



References

- [1]. Gagandeep Singh1, Gagandeep Singh2: EVALUATION OF VARIOUS DIGITAL IMAGE FOG REMOVAL ALGORITHMS :International Journal of Advanced Research in.
- [2]. Research for Image Haze-Removal Algorithm Using the Dark-Channel Prior Based on Wavelet Transform The Open Cybernetics & Systemics Journal, 2015, 9, 1378-138.
- [3]. John P. Oakley, Member, IEEE, and Brenda L. Satherley:Improving Image Quality in Poor Visibility Conditions Using a Physical Model for Contrast Degradation- IEEE TRANSACTIONS ON IMAGE PROCESSING, FEBRUARY 1998.
- [4]. Kaiming He, Jian Sun, and Xiaoou Tang, Fellow:Single Image Haze Removal Using Dark Channel Prior- IEEE Computer and Communication Engineering Vol. 3, Issue.
- [5]. Jharna Majumdar1, Santhosh Kumar K L2:MODIFIED CLAHE: AN ADAPTIVE ALGORITHM FOR CONTRAST ENHANCEMENT OF AERIAL, MEDICAL AND UNDERWATER IMAGES Volume 5, Issue 11, November (2014).
- [6]. W. Yang, R. T. Tan, J. Feng, J. Liu, Z. Guo, and S. Yan. Deep joint rain detection and removal from a single image. In Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition, 2017.
- [7]. H. Yong, D. Meng, W. Zuo, and L. Zhang. Robust on-line matrix factorization for dynamic background subtraction. IEEE Transaction on Pattern Analysis and Machine Intelligence, 2017.

- [8]. F. Yu and V. Koltun. Multi-scale context aggregation by dilated convolutions. *Computer Vision and Pattern Recognition*, 2016.
- [9]. M. D. Zeiler, D. Krishnan, G. W. Taylor, and R. Fergus. De-convolutional networks. In *IEEE Winter Conference on Applications of Computer Vision*.
- [10]. K He, J Sun, X Tang, *Proceedings of IEEE Computer Society Conference on Computer Vision and Pattern Recognition (CVPR, Miami, 2009)*, pp. 1956–1963.
- [11]. H. Zhang and V. M. Patel. Convolutional sparse and low-rank coding-based rain streak removal. In *IEEE Winter Conference on Applications of Computer Vision*, 2017.
- [12]. C. Hsieh, J. Chen and Q. Zhao, "A modified DCP based dehazing algorithm", *2018 IEEE International Conference on Systems Man and Cybernetics (SMC)*, pp. 1779-1784, 2018.
- [13]. B. Li et al., "Benchmarking single-image dehazing and beyond", *IEEE Transactions on Image Processing*, vol. 28, no. 1, pp. 492-505, Jan. 2019
- [14]. X. Min, G. Zhai, K. Gu, X. Yang and X. Guan, "Objective quality evaluation of dehazed images", *IEEE Transactions on Intelligent Transportation Systems*, vol. 20, no. 8, pp. 2879-2892, Aug. 2019.
- [15]. Zahid tufail, Khawar khurshid, et al. "Improved Dark Channel Prior for Image Defogging Using RGB and YCbCr Color Space", *IEEE Access*, 6 (May. 2018), pp. 32576-32587
- [16]. S. Salazar-Colores, E. Cabal-Yepez, J.M. Ramos-Arreguin, G. Botella, L.M. Ledesma-Carrillo, S. Ledesma, "A Fast Image Dehazing Algorithm Using Morphological Reconstruction," *IEEE Transactions on Image Processing*, 28 (5) (May 2019), pp. 2357-2366.
- [17]. Cai, Bolun & Xing, Xiaofen & Xu, Xiangmin. (2017). Edge/structure preserving smoothing via relativity-of-Gaussian. 250-254. 10.1109/ICIP.2017.8296281.
- [18]. Vignesh, R & Simon, Philomina. (2019). Single Image Defogging Based on Local Extrema and Relativity of Gaussian: Theory and Applications, *ICHSA 2018*.10.1007/978-981-13-0761-4_42.
- [19]. W. Ren, S. Liu, H. Zhang, J. Pan, X. Cao, M.-H. Yang, Single image dehazing via multi-scale convolutional neural networks. In *European Conference on Computer Vision*, Springer (2016), pp. 154-169.
- [20]. Y. Peng, Z. Lu, F. Cheng, Y. Zheng and S. Huang, "Image Haze Removal Using Air light White Correction, Local Light Filter, and Aerial Perspective Prior," in *IEEE Transactions on Circuits and Systems for Video Technology.*, 2019
- [21]. S. Salazar-Colores, E. Cabal-Yepez, J.M. Ramos-Arreguin, G. Botella, L.M. Ledesma-Carrillo, S. Ledesma, "A Fast Image Dehazing Algorithm Using Morphological Reconstruction," *IEEE Transactions on Image Processing*, 28 (5) (May 2019), pp. 2357-2366