I.J. Image, Graphics and Signal Processing, **2024, 5, 91-104**
Published Online on October 8, 2024 by MECS Press (http://www.mecs-press.org/)
DOI: 10.5815/ijigsp.2024.05.07

Image De-Weathering Using Median Channel Technique and RGB-based Transmission Map for Autonomous Vehicles

P. Raja*
Sri Manakula Vinayagar Engineering College, Department of Electronics and Communication Engineering, Puducherry, Zip code– 605107, India
E-mail: rajashruthy@gmail.com
ORCID iD: https://orcid.org/0000-0002-9818-6004
*Corresponding Author

Sowmiya. M
Sri Manakula Vinayagar Engineering College, Department of Electronics and Communication Engineering, Puducherry, 605107, India
E-mail: sowmiya130402@gmail.com

Subathra. V
Sri Manakula Vinayagar Engineering College, Department of Electronics and Communication Engineering, Puducherry, 605107, India
E-mail: velayoudamsubathra@gmail.com

Sarah. S.
Sri Manakula Vinayagar Engineering College, Department of Electronics and Communication Engineering, Puducherry, 605107, India
E-mail: sarahsahabdeen@gmail.com

Received: 08 March, 2023; Revised: 20 May, 2023; Accepted: 12 March, 2024; Published: 08 October, 2024

Abstract: Static weather conditions like fog, haze, and mist in hilly and urban areas cause reduced road visibility. Due to different weather conditions, autonomous vehicles cannot identify objects, traffic signs, and signals. So, this leads to many accidents, endangering living beings' lives. The significance of this work lies in its aim to develop a model that can provide clear visibility for autonomous vehicles during bad weather conditions. Image restoration is one of the important issues in the image processing field as the images may be of low contrast and quality due to restricted visibility and, the development of a model that reduces the halos and artifacts produced in the image using the Median Channel based Image Restoration (MCIR) technique has significant research value. In this technique, the image restoration is done by calculating the atmospheric light and the transmission map using the MCIR technique and patching the pixels for different patch sizes. The Dark Channel Prior (DCP) method and the MCIR technique are compared for different patch sizes by evaluating the output images using the PSNR, SSIM, and MSE metrics. The results show that MCIR technique provides better Peak Signal-to-Noise Ratio (PSNR), Mean Square Error (MSE), and Structural Similarity Index Measure (SSIM) values than the DCP method with reduced halos and artifacts. This result highlights the effectiveness of the MCIR technique for image restoration. The software model developed can be applied to autonomous vehicles and surveillance cameras for the restoration of the images, which can improve their performance and safety.

Index Terms: Median Channel, Static Patching, Atmospheric Light Estimation, Transmission Map, Autonomous Vehicles

1. Introduction

Autonomous vehicles are prepared to work well in typical weather conditions, but limited work is done for them to operate in weather conditions like fog, haze, and mist in hilly and urban areas because of reduced road visibility. They cannot identify objects, traffic signs, and signals in such weather conditions. So, this leads to many accidents, endangering living beings' lives. This work aims to develop a model that can provide clear visibility for autonomous vehicles and surveillance cameras during bad weather conditions with reduced halos and artifacts. The existing autonomous cars use LiDAR [1,2,3,4] and Radar [5] but it suffers from poor image quality because when radio waves are transmitted and bounced off objects, only a small fraction of the signal gets reflected back to the sensor, and they also pick up noise which affects the quality of the image. They also produce echo signals, reflections of radio waves that are not directly from the objects being detected. So, cameras are being used to capture the foggy or hazy surroundings and de-weather them using the MCIR method by calculating the Atmospheric Light and the Transmission map which is applied to different patch sizes of the image. This de-weathered data can now be used by the system to view the surrounding clearly and identify the traffic signs and signals already present in their dataset.

The article also provides a comparison of the different recovered images obtained for different patch sizes such as 3×3, 15×15 and 30×30 using the DCP method [6] and the MCIR technique. The evaluation of the recovered images obtained is done by using the PSNR, MSE, and SSIM metrics. The article is structured as follows. Section 2 presents the related works done for de-weathering a foggy image. The next section 3, is devoted to the description of the MCIR method. Then, section 4 provides the simulation results and the qualitative and quantitative comparison and section 5 discusses the detailed conclusion and the future scope.

2. Related Works

The input foggy or hazy image captured from the surroundings is to be de-weathered using the software model and the recovered image will be used by the autonomous cars to identify the objects on the road. This section discusses the related works which is used to de-weather a foggy or hazy image fed as input to the software system. Histogram Equalization (HE) is a technique used in image processing to enhance the contrast of an image by modifying its intensity distribution. The objective of histogram equalization is to transform the image so that the histogram is uniform or equally distributed across all intensity levels. Adaptive Histogram Equalization (AHE) method [7] is appropriate for raising the local contrast and sharpening the edges by dividing the image into small windows and performing HE on it. Fog and haze reduce contrast and visibility in images, necessitating image defogging. One method to enhance contrast is to redistribute pixel intensities based on local histogram analysis. This approach applies adaptive contrast enhancement to each region of the image, based on its unique features. As a result, the image may appear clearer and more detailed, revealing previously obscured details. This provides a more balanced and natural-looking image and also preserves image features reducing the loss of image details. AHE can alter the brightness information over an image and sometimes over-enhance the bright regions of an image which is overcome by the Contrast enhancement using brightness preserving bi-histogram equalization [8] which produced images retaining their brightness with better-improved contrast. Histogram equalization divides the histogram into equal halves for dark and bright pixels. Each half is processed separately to plot the frequency of pixel intensities in the image. This technique maintains natural brightness levels while enhancing contrast and visibility, revealing features previously obscured by fog.

The input foggy or hazy image captured from the surroundings is to be de-weathered using the software model and the recovered image will be used by the autonomous cars to identify the objects on the road. This section discusses the related works which is used to de-weather a foggy or hazy image fed as input to the software system. Histogram Equalization (HE) is a technique used in image processing to enhance the contrast of an image by modifying its intensity distribution. The objective of histogram equalization is to transform the image so that the histogram is uniform or equally distributed across all intensity levels. Adaptive Histogram Equalization (AHE) method [7] is appropriate for raising the local contrast and sharpening the edges by dividing the image into small windows and performing HE on it. Fog and haze reduce contrast and visibility in images, necessitating image defogging. One method to enhance contrast is to redistribute pixel intensities based on local histogram analysis. This approach applies adaptive contrast enhancement to each region of the image, based on its unique features. As a result, the image may appear clearer and more detailed, revealing previously obscured details. This provides a more balanced and natural-looking image and also preserves image features reducing the loss of image details. AHE can alter the brightness information over an image and sometimes over-enhance the bright regions of an image which is overcome by the Contrast enhancement using brightness preserving bi-histogram equalization [8] which produced images retaining their brightness with better-improved contrast. Histogram equalization divides the histogram into equal halves for dark and bright pixels. Each half is processed separately to plot the frequency of pixel intensities in the image. This technique maintains natural brightness levels while enhancing contrast and visibility, revealing features previously obscured by fog.

Then Dynamic Histogram Equalization method [9] is used in images with non-uniform intensity distribution or multiple intensity peaks. It removes the image histogram's dominance of higher histogram components over lower histogram components and improves contrast effectively without causing negative side effects or unwanted artifacts. It also improves the contrast to view the objects hidden by fog. A retinex-based method [10] was suggested that offers colour constancy, dynamic range compression, and lightness rendition. Image decomposition separates images into components, such as reflectance and illumination. Local adaptation enhances reflectance by comparing the brightness of each pixel to its local surroundings. Global adaptation corrects for lighting variations by comparing the image's brightness to a reference image with known lighting conditions. By combining these techniques, images can be enhanced and corrected for optimal clarity and visibility.

It is very suitable for foggy images with low intensity but fails to enhance the image with inhomogeneous fog. The multi-Scale Retinex method [11] was then introduced which provides clear images in case of high levels of noise and low contrast, it also has an adaptive scale selection making it more robust to various lighting conditions. The scale-space method for image enhancement, based on Retinex, divides an image into various scales and processes each scale separately. By highlighting details previously obscured by fog or haze, this technique improves image clarity. However, it can also generate halos around edges with high contrast, which should be considered during the image-defogging process. A technique called wavelet transform [12] was then proposed which separates the image into different frequency components by passing it through the low-pass and high-pass filters, allowing for a more targeted manipulation of specific frequency ranges. It provides a sharp and accurate image compared to the retinex method. Image decomposition into different frequency bands and enhancement of high-frequency components can remove fog or haze and highlight local details and edges. By improving these features, the image becomes more visually appealing and easier to interpret. Fattal [13] then proposed a method to estimate the optical transmission in hazy scenes using a single input image. By estimating the transmission, the scattered light can be removed to enhance scene visibility and recover haze-free scene contrasts. The method uses a sophisticated image formation model that considers surface shading in addition to the transmission function to resolve data ambiguity. The resulting shading and transmission functions are locally statistically uncorrelated, and the method also estimates the colour of the haze. The results show that the proposed method can remove the haze layer and provide a reliable transmission estimate which provides high image visibility under inhomogeneous or thin fog but fails in thick fog conditions and when the image has a low signal-to-noise ratio. Then a good contrast image was produced as an output using [14]. This method is based on two observations: first, clear-day images have higher contrast than images with bad weather, and second, the variation of air light in an image mainly depends on the distance of objects to the viewer and tends to be smooth. These observations have been used by the authors to describe a cost function that can be optimised efficiently through techniques like graph cuts or belief propagation in Markov random fields. The method offers a solution to the problem of image defogging, in situations where multiple input images are not available or hard to obtain.

In Single image haze removal using a dark channel prior [6] minimum filtering technique is used which provides a correct transmission map, but fails in direct light and halos are produced because of the dark channel. The DCP method works by identifying the pixels in the image with the lowest intensity in each colour channel, which is assumed to be part of the atmospheric light. By taking the minimum value of these pixels across all colour channels, an estimate of the haze-free transmission is obtained. When the sunshine is exceptionally strong, the constant-air light assumption might not be appropriate. It has difficulty in handling scenes with non-uniform haze and producing artifacts in certain situations. Then an Improved Dark Channel Prior (IDCP) Method [15] was proposed which estimated the atmospheric light perfectly and produce clear images in place of bright sky regions. The IDCP method uses a patch-based processing approach to refine the estimated transmission map. This involves dividing the image into small patches and using the DCP to estimate the transmission for each patch. Then, the transmission values are filtered to remove outliers and smooth the transmission map. This method may still result in some colour distortion in bright areas such as the sky or white objects where dark prior is not established. It provides lesser artifacts when compared to the DCP method. The proposed Median Channel based Image Restoration Method (MCIR) method will reduce the halos and artifacts produced in the image using the median channel technique and develop a model to provide clear visibility for autonomous cars and surveillance cameras during bad weather conditions.

A technique called wavelet transform [12] was then proposed which separates the image into different frequency components by passing it through the low-pass and high-pass filters, allowing for a more targeted manipulation of specific frequency ranges. It provides a sharp and accurate image compared to the retinex method. Image decomposition into different frequency bands and enhancement of high-frequency components can remove fog or haze and highlight local details and edges. By improving these features, the image becomes more visually appealing and easier to interpret. Fattal [13] then proposed a method to estimate the optical transmission in hazy scenes using a single input image. By estimating the transmission, the scattered light can be removed to enhance scene visibility and recover haze-free scene contrasts. The method uses a sophisticated image formation model that considers surface shading in addition to the transmission function to resolve data ambiguity. The resulting shading and transmission functions are locally statistically uncorrelated, and the method also estimates the colour of the haze. The results show that the proposed method can remove the haze layer and provide a reliable transmission estimate which provides high image visibility under inhomogeneous or thin fog but fails in thick fog conditions and when the image has a low signal-to-noise ratio. Then a good contrast image was produced as an output using [14]. This method is based on two observations: first, clear-day images have higher contrast than images with bad weather, and second, the variation of air light in an image mainly depends on the distance of objects to the viewer and tends to be smooth. These observations have been used by the authors to describe a cost function that can be optimised efficiently through techniques like graph cuts or belief propagation in Markov random fields. The method offers a solution to the problem of image defogging, in situations where multiple input images are not available or hard to obtain.

In Single image haze removal using a dark channel prior [6] minimum filtering technique is used which provides a correct transmission map, but fails in direct light and halos are produced because of the dark channel. The DCP method works by identifying the pixels in the image with the lowest intensity in each colour channel, which is assumed to be part of the atmospheric light. By taking the minimum value of these pixels across all colour channels, an estimate of the haze-free transmission is obtained. When the sunshine is exceptionally strong, the constant-air light assumption might not be appropriate. It has difficulty in handling scenes with non-uniform haze and producing artifacts in certain situations. Then an Improved Dark Channel Prior (IDCP) Method [15] was proposed which estimated the atmospheric light perfectly and produce clear images in place of bright sky regions. The IDCP method uses a patch-based processing approach to refine the estimated transmission map. This involves dividing the image into small patches and using the DCP to estimate the transmission for each patch. Then, the transmission values are filtered to remove outliers and smooth the transmission map. This method may still result in some colour distortion in bright areas such as the sky or white objects where dark prior is not established. It provides lesser artifacts when compared to the DCP method. The proposed Median Channel based Image Restoration Method (MCIR) method will reduce the halos and artifacts produced in the image using the median channel technique and develop a model to provide clear visibility for autonomous cars and surveillance cameras during bad weather conditions.

3. Proposed Work

The proposed MCIR method obtains a foggy image as input and first estimates the intensity of light present in the surrounding by choosing the top 0.1% brightest pixels and then estimates the depth i.e., the amount of light that is incident directly on the camera's surface without being scattered which is described as the transmission map. Both this estimation is done using the median channel technique and the static patching method. Then the obtained atmospheric light from the environment and the estimated transmission map is used to calculate the scene radiance, which in turn provides the output defogged image.

3.1. Visibility Restoration Model

The image de-weathering is done using the restoration model of Narasimhan and Nayar [16] and is shown in (1)

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

where I(x, y) is the input foggy image, J (x, y) is the defogged image, t(x, y) is the transmission map, and A(x, y) is the atmospheric light. Using the (1), the defogged image can be obtained. The aim of the visibility restoration model is to estimate the clear image J(x, y) from the hazy image I(x, y) by estimating the transmission map t(x, y) and the atmospheric light A(x, y). The MCIR technique works with the help of the median channel technique and static patching. This step is involved in both the atmospheric and transmission map estimation. The flowchart of the proposed system is shown in Fig. 1.

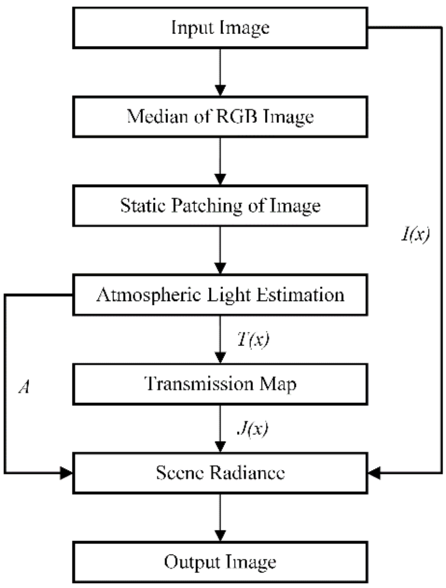

Fig. 1. Flowchart of the MCIR technique

3.2. Atmospheric Light Estimation using Median Channel Technique with Static Patch

The atmospheric light scattering model estimates atmospheric light and recovers fog-free scenes. Atmospheric light estimation is a crucial step in many image-defogging algorithms. It involves determining the amount of light that has been scattered and absorbed by the atmosphere before it reaches the camera lens. This information is used to correct the intensity of pixels in the foggy image and restore its original brightness. In the image, pixel intensity is used to determine atmospheric light using a static patch.

3.2.1 Median Channel Technique

The median value, or an average of the list's centre values, is known as a median. The median filter is effective at reducing noise in an image while preserving edges and other important image features. It uses statistics-based nonlinear signal processing. The original value will be replaced by the median value of this group, which is stored. They could characterize it using [17] as stated in (2)

$$J(x,y) = med\big(I(x-i,y)\big) \quad i \in W \tag{2}$$

where W is a mask and J(x, y) and I(x, y) are de-noised and noisy pictures, respectively. The equation computes the median value of each colour channel separately in a local neighborhood around each pixel x, and then computes the median of the resulting median values in the patch to obtain the final output pixel value. A median value is used rather than the smallest number of pixels because an image's content will typically be hidden in the middle of the image as stated in (3)

$$I^{median}(x) = \text{median}_{x\in W(x)}\left(\underset{x\in W(x)}{\text{median}}\left(I^{c}(\text{x})\right)\right) \tag{3}$$

The halo effect shown in Fig. 2 is brought on by the white region's edge darkening, which results in undesirable pixel intensity and an incorrect pixel value. The halos can be eliminated when the pixel median is used.

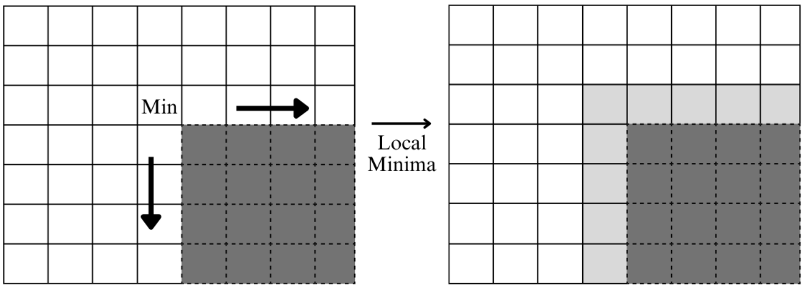

Fig. 2. Halo Effect

3.2.2 Patch Size

Patching in an image refers to the process of filling in or repairing a specific area of an image to remove inconsistencies, reduce noise or remove blemishes. The patching chosen here is static i.e., the size of the patch can be chosen by the user. Depending on the patch size chosen, the quality of the image changes, and also the evaluation metrics of an image such as PSNR, MSE, and SSIM also change. The W parameter chosen above is the patch size value or mask value. The recovered image varies depending on the patch size chosen and the patch size can be chosen depending on the user application. The detailed analysis is discussed in Section 4.

3.2.3 Atmospheric Light Estimation

The challenge of determining the unknown parameter "A" in de-haze techniques is difficult. In most current techniques, the most haze-opaque pixel is used to assess atmospheric light, as shown in Fig. 3. One such technique is the median channel technique, which is based on the observation that the atmospheric light in an image is dominated by the brightest pixels. To determine atmospheric light, the technique selects the top 0.1% of the median channel's brightest intensity pixels in the blurry image, calculates their indices, and compares them to other brighter values in the three channels. Finally, the highest intensity value in the input frame is used to obtain atmospheric light for the RGB channels. Determining atmospheric light accurately is important for the effective de-hazing of images.

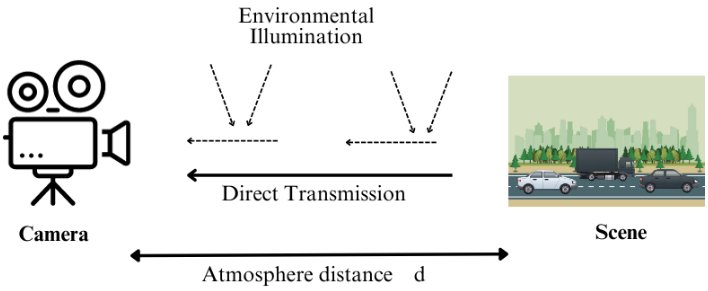

Fig. 3. Scattering of light by Atmospheric Particles

3.3. Transmission Map Estimation

An inaccurate transmission map is produced when the dark channel [17] is used. Consequently, a transmission map should be separated from the dark channel to avoid refinement of the transmission map. The goal of this approach is to estimate the clear image by removing the effects of atmospheric haze or fog in the image. The transmission map *t*(x, y) is typically a function of two variables and is stated as in (4). The way to derive it is as follows.

$$t(x, y) = e^{-\alpha\, dis(x,y)} \tag{4}$$

where *dis*(*x*, *y*) represents the depth of the scene and *α* the scattering coefficient [18]. The MCIR for an image *J* is given as shown in (5)

$$J^{median}(x, y) = \mathrm{med}_{c\in(r,g,b)}\left(\underset{y\in\Omega}{\mathrm{med}}\left(J^{C}(x, y)\right)\right) \tag{5}$$

The equation is then standardized using the Atmospheric light, *A* and is applied to all three colour channels separately as in (6)

$$\frac{I^{c}(x)}{A^{c}} = t(x)\frac{J^{c}(x)}{A^{c}} + 1 - t(x) \tag{6}$$

The atmospheric scattering model provides a physical basis for this optimization problem by modelling the observed hazy image as a combination of the clear image and the atmospheric scattering due to the haze. Then, the median channel is applied on both sides of (6) to get (7).

$$\mathrm{med}_{c\,\in\,\Omega(x)}\left[\underset{c\,\in\,(r,g,b)}{\mathrm{med}}\left(\frac{I^{c}(x)}{A^{c}}\right)\right] = t(x)\underset{c\,\in\,\Omega(x)}{\mathrm{med}}\left[\underset{c\,\in\,(r,g,b)}{\mathrm{med}}\left(\frac{J^{c}(x)}{A^{c}}\right)\right] + 1 - t(x) \tag{7}$$

In this equation, there are two unknowns and a single equation to solve. The equation (8) represents the median of the median colour channel intensities of the image *J* at all pixel locations y in a local window centered at pixel location *x*. Here, $J^c(y)$ represents the intensity value of colour channel *c* (*c*=r, g, or b) at pixel location *y* in the image *J*(y), and med denotes the median operation. So, an assumption is made as shown in (8) in order to eliminate one variable and find the transmission map alone.

$$J^{median}(x) = \underset{y\,\in\,\Omega(x)}{\mathrm{median}}\left[\underset{c\,\in\,(r,g,b)}{\mathrm{median}}\left(J^{c}(y)\right)\right] = 0 \tag{8}$$

From the above assumption, the transmission map can be estimated using (9)

$$t(x, y) = 1 - w\, med\, \left[\underset{y\,\in\,\Omega(x)}{\mathrm{median}}\left(\frac{I^{c}(y)}{A^{c}}\right)\right] \tag{9}$$

The acquired image is very far away from the observer when *dis*(x, y) goes to infinity, and there is no transmission map because it tends to zero at the same time. Image de-hazing depends on the transmission map in this ambiguous scenario, another observation is that if *t*(x,y) goes to infinity, no image exists. Consequently, it is necessary to estimate an accurate transmission map

3.4. Scene Radiance

The scene radiance J (x,y) can be calculated as in (10) once the transmission *t*(x,y) and air-light (*A*) are known

$$J^{c}(x, y) = \left[\frac{I^{c}(x,y) - A^{c}(x,y)}{max(T(x,y), t_0)}\right] + A^{c}(x, y) \tag{10}$$

where the control parameter is t_0. The image appears under exposed after the haze has been removed because the scene radiance is typically not as brilliant as ambient light. So, by changing t_0, we enhance *J*(x, y) exposure for display. So, in summary, the proposed method estimates the atmospheric light and transmission map using median channel technique and static patching. Then the scene radiance is calculated with the help of the input image, atmospheric light and the transmission map.

3.5. Input Images

Various input foggy images of different dimensions as shown in Fig.4 are chosen to perform the MCIR method on it and obtain the defogged image. The input image as shown in Fig.4 (a) [19] is of the dimensions 436×639 and has the three colour channels R, G and B. The input image as shown in Fig.4 (b) [20] is of the dimensions 680×1200. The dimensions of Fig.4(c) [21] are 576×800. The input image as shown in Fig.4 (d) [22] is of the dimensions 298×561. The dimensions of Fig.4 (e) [23] are 321×593.

(a) (b) (c)

(d) (e)

Fig. 4. Input Images (a) 436×639 dimension [19] (b) 680×1200 dimension [20] (c) 576×800 dimension [21] (d) 298×561 dimension [22] (e) 321×593 dimensions [23]

3.6 Recovered Images

Recovered images of the input foggy images shown in Table 1 obtained using the Proposed MCIR method and the existing DCP method [6] for varying patch sizes.

3.7. Qualitative Analysis

Image artifacts are unintended and undesirable distortions or changes that occur during image processing, compression, or transmission. Blurring, ringing, blockiness, noise, and halos are all examples of artifacts. They can have a significant impact on the image's perceived quality and interpretability. Halos are image artifacts that appear as bright or dark rings around the boundaries of objects. Sharpening or enhancement filters that increase the contrast between adjacent pixels are commonly the reason for the appearance of halos.

Qualitatively, the output images obtained using the DCP method [6] undergo the halos effect which is strengthen if the patch size is too large and the halos and artifacts are removed if it is a small patch size. Artifacts such as blockiness are produced in the sky region when using the DCP method [6]. But the artifacts produced near the sky regions reduce with the increase in patch size because the probability that a patch contains a dark pixel increases with patch size. The output images obtained using the MCIR method are not affected by halos as the median filter is less sensitive to outliers and tends to preserve the edges in the image nu not smoothing them excessively. The median filter is an effective method for preserving the edges as well as removing noise which makes it produce more visually appealing images than the ones obtained using the DCP method.

4. Results and Discussion

4.1 PSNR

Peak signal-to-noise ratio (PSNR) is a term that denotes the relationship between a signal's greatest achievable strength and the power of corrupting noise that degrades the accuracy of its representation and is calculated using (11). This ratio is frequently used to assess the quality between the source and final images. The quality of the produced image will be better when a higher PSNR value is achieved.

$$PSNR = 10\log_{10}\left(\frac{L^2}{MSE}\right) = 20\log_{10}\left(\frac{L}{RMSE}\right) \tag{11}$$

where L is the maximum pixel value, MSE is the Mean Square Error Value and RMSE is the Root Mean Square Value. The graph analysis for various input foggy images of different dimensions is shown in Fig.5. From Fig.5 it is observed that the MCIR method has higher PSNR values across various patch sizes when compared to the DCP method. It can be noticed that when the patch size is reduced, a higher PSNR value is produced as fewer pixels are replaced by the median value and the noise value is also less in that patch. The values are almost consistent among different patch sizes but slightly decrease for larger patch sizes as the MCIR method smoothes out the details and increases noise by replacing the pixel values in a patch with the median value. This smoothing effect is more pronounced with larger patch sizes, resulting in a lower PSNR value.

Table 1. Recovered images with 3×3 patch size using DCP method and MCIR method

Dimension	**Using DCP method [6]**	**Using MCIR Method**
436 × 639		
680 × 1200		
576 × 800		
298 × 561		
321 × 593		

For the DCP method [3], the PSNR values are exponentially increasing as the pixel values in a patch are replaced with minimum values by getting rid of the noise-affected values i.e., the high-intensity pixels. In small patch sizes, fewer pixels are replaced by minimum values but in large patch sizes, more pixels are replaced by minimum values which leads to small PSNR and larger PSNR values respectively. As a result, the image is smoother and has less noise, which can lead to a higher PSNR value but a lot of image details are lost which is why the PSNR values obtained for the DCP method are less than those obtained using the MCIR method. The proposed MCIR method provides, a 31.70% of improvement in PSNR for the patch size of 3 × 3 and it is reduced to 14.30 % for the patch size of 30 × 30 for Fig. 5.

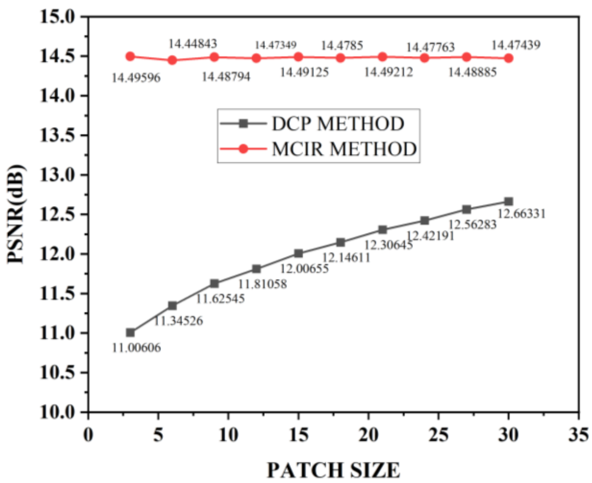

Fig. 5. PSNR value for the input image 436 × 639 dimensions with different patches using DCP method and MCIR method

4.2. MSE

The MSE value is the average difference between pixels over the whole picture. A bigger disparity between the original picture and the processed image is indicated by a higher MSE score. MSE is calculated by using (12)

$$MSE = \frac{1}{mn}\sum_{i=0}^{m-1}\sum_{j=0}^{n-1}[O(i,j) - D(i,j)]^2 \tag{12}$$

where m is the number of rows, n is the number of columns, O(i, j) is the original input foggy image and D(i,j) is the defogged image. The graph analysis of the different input foggy images is shown in Fig.6.

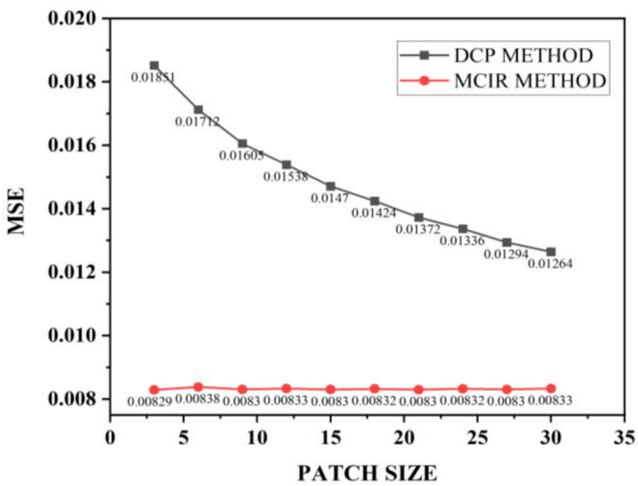

Fig. 6. MSE value for the input image 436 × 639 dimension with different patches using DCP method and MCIR method

It is observed that the MCIR method has lower MSE values across various patch sizes when compared to the DCP method. The values are also consistent for different patch sizes but a slight increase is observed because the noise increases as the patch size increase as a median value replaces the whole patch. In the DCP method, the MSE values are exponentially decreasing as the noise of the image gets decrease because the minimum value replaces the high-intensity noise pixels in that patch thereby reducing the noise but leading to severe loss in image details, the values are also getting decreased from the patch size 3 × 3 to 30 × 30. In Fig. 6 the proposed method has a 55.22 % rate of decrease in MSE obtained for the patch size of 3 × 3 and 34.09 % for the patch size of 30 × 30. The efficiency percentage is obtained in negative which indicates the rate of decrease i.e., how much the error is decreased in the MCIR method when compared to the DCP method [3].

4.3. SSIM

The Structural Similarity Index (SSIM) is an experiential metric that assesses the loss in image quality caused by data transmission losses or other processing steps such as data compression. SSIM is calculated using (13)

$$SSIM(x,y)=\frac{(2\mu_x\mu_y+c_1)(2\sigma_{xy}+c_2)}{(\mu_x^2+\mu_y^2+c_1)(\sigma_x^2+\sigma_y^2+c_2)} \tag{13}$$

where μ_x is the mean over a window in Image X, μ_y is the mean over a window in Image Y, σ_x is the standard deviation over a window in Image X, σ_y is the standard deviation over a window in Image Y, σ_{xy} is the co-variance over a window in the Image X and Image Y respectively and c_1 and c_2 are constants.

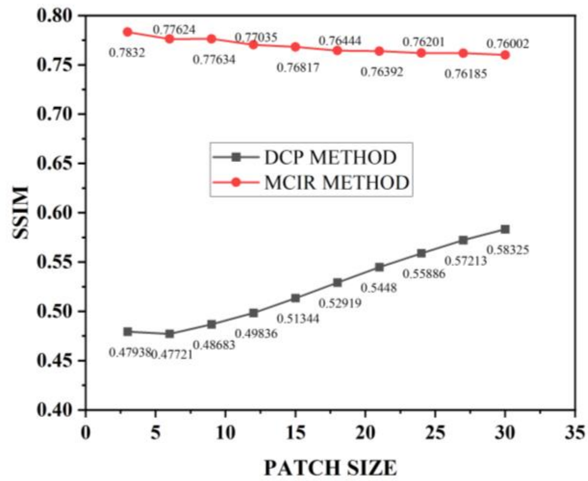

Fig. 7. SSIM value for the input image 436 × 639 dimension with different patches using DCP method and MCIR Method

From Fig. 7, it is observed that the MCIR method has higher SSIM values across various patch sizes when compared to the DCP method. When the patch size is increased, more pixels are replaced with the median value, resulting in a higher degree of smoothing. This smoothing effect can cause a loss of fine details and edges in the image, leading to a lower SSIM value, which causes the processed image to be less similar to the input image so, the values keep decreasing for larger patches, while for smaller patches the original signal information will be retained to a greater extent, thus producing higher SSIM value. In the DCP method [3], the SSIM values are exponentially increasing as it reduces noise by replacing high-intensity pixels which are associated with noise with low-intensity pixels, which results in a higher degree of similarity. But still, the degree of similarity obtained is less than the MCIR method. In Fig. 7 the proposed method has a 39.80458371 % of improvement in SSIM obtained for the patch size of 3 × 3 and it is reduced to 18.59294792 % for the patch size of 30 × 30.

4.4. Duration

The time taken to process the input foggy image and produce the de-weathered image varies for different images depending on the image dimensions, the patch size chosen for the atmospheric and transmission map estimation, and for different methods such as the DCP method and the MCIR method. From Fig. 8, it is observed that the MCIR method takes higher computation time to process the fogged image and produce a defogged image across various patch sizes when compared to the DCP method [6]. When the MCIR method is applied to larger patches it requires more resources to compute the median of a patch and produce a defogged image. In the DCP method, the duration is almost consistent and also less than the MCIR method for different patch sizes as the resource needed by it is less to compute the minimum of a patch. The duration taken by the MCIR method increases from the patch size 3 × 3 to 30 × 30.

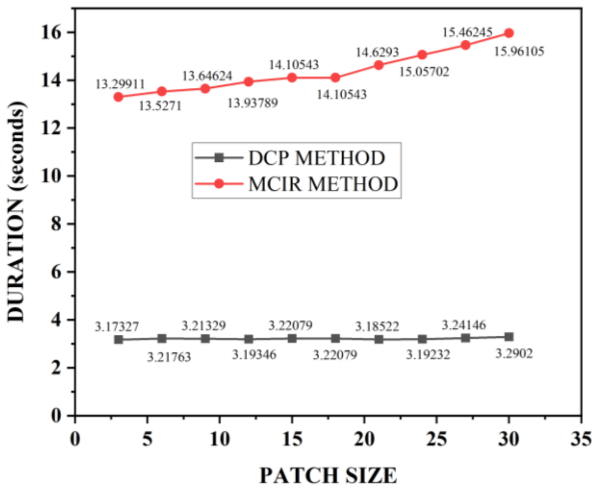

Fig. 8. Duration for the input image 436 × 639 dimension with different patches using DCP method and MCIR method

4.5. *Comparative Analysis*

The comparative analysis for the different values of the evaluation metrics such as PSNR, SSIM, and MSE values obtained using the DCP method and MCIR method is shown in Table 2-6. Quantitatively, the MCIR method produces a recovered image with higher PSNR and SSIM values, and lower MSE values compared to the DCP method. The higher PSNR values for the MCIR method are due to the chosen median value for each patch, which replaces the patch values with its median value. This replacement of patch values reduces the noise-affected values (i.e., high-intensity pixels) and leads to a smoother image with less noise, resulting in a higher PSNR value. On the other hand, the DCP method uses the minimum value to replace patch values, effectively reducing noise by replacing high-intensity pixels with low-intensity pixels. However, the minimum filter can result in a loss of detail by replacing high-intensity pixels with low-intensity pixels that are not part of the image's actual structure, resulting in a lower PSNR value than the median. Therefore, the MCIR method produces a higher PSNR value than the DCP method.

Table 2. Comparative Analysis of PSNR, MSE, SSIM and Computation Time using DCP Method [6] and MCIR Method for 436 × 639 dimension

Patch Size	Parameters Analysed							
	PSNR		MSE		SSIM		Duration	
	DCP Method	MCIR Method	DCP Method	MCIR Method	DCP Method	MCIR Method	DCP Method	MCIR Method
3 x 3	11.00606	14.495961	0.018513	0.0082888	0.5818074	0.8133935	3.1698219	13.837874
15 x 15	12.006547	14.491248	0.0147040	0.0082978	0.6313128	0.8028170	3.1967964	14.390478
30 x 30	12.663313	14.474390	0.0126404	0.0083301	0.6758789	0.8015447	3.2086246	16.619003

Table 3. Comparative Analysis of PSNR, MSE, SSIM and Computation Time using DCP Method [6] and MCIR Method for 680 × 1200 dimension

Patch Size	Parameters Analysed							
	PSNR		MSE		SSIM		Duration	
	DCP Method	MCIR Method	DCP Method	MCIR Method	DCP Method	MCIR Method	DCP Method	MCIR Method
3 x 3	7.2788126	13.369886	0.0149110	0.0036677	0.4793750	0.7832020	8.9035379	39.141135
15 x 15	8.3605347	13.253842	0.0116234	0.003767	0.5134433	0.7681733	9.0985424	42.122649
30 x 30	9.1861043	13.074002	0.0096112	0.0039263	0.5832518	0.7600227	9.1427741	47.419127

Similarly, the MCIR method produces less MSE when compared to the DCP method as the MCIR method preserves more of the original signal's information and also reduces the effect of outlier pixels. If the fog or haze is removed completely, the image may appear unnatural and the sense of depth may be lost so a 'w' parameter as stated in equation (9) is included which has values between 0 and 1. The 'w' parameter which determines how much amount of fog is to be retained is chosen as 0.85 and not the typical value of 0.95 because of the median channel technique. The purpose of having selected a comparatively lesser value for the parameter 'w' is due to the requirement of acquiring a higher resultant value which supports an output that is less prone to error and less affected by noise. Hence, on observation, the value of 0.85 proves to be compatible to satisfy a suitable reconstruction. The lower the MSE value the better the reconstruction of the image. The MCIR method has higher SSIM values when compared to the DCP method. The MCIR method preserves more of the original signal's information and also reduces the effect of outlier pixels. So, the output image is less affected by noise and the error produced is also less, the SSIM which is the similarity of reconstruction is high than the DCP method.

Table 4. Comparative Analysis of PSNR, MSE, SSIM and Computation Time using DCP Method [6] and MCIR Method for 576 × 800 dimension

Patch Size	Parameters Analysed							
	PSNR		MSE		SSIM		Duration	
	DCP Method	MCIR Method	DCP Method	MCIR Method	DCP Method	MCIR Method	DCP Method	MCIR Method
3 x 3	11.165714	15.094072	0.0102343	0.0041421	0.6438701	0.8379487	6.4601249	24.785695
15 x 15	12.153493	14.929861	0.0081523	0.0043017	0.6703001	0.8231205	6.5078127	26.26198
30 x 30	12.824076	14.817196	0.00698	0.0044147	0.7116428	0.8165239	6.5009152	29.173346

Table 5. Comparative Analysis of PSNR, MSE, SSIM and Computation Time using DCP Method [6] and MCIR Method for 298 × 561 dimension

Patch Size	Parameters Analysed							
	PSNR		MSE		SSIM		Duration	
	DCP Method	MCIR Method	DCP Method	MCIR Method	DCP Method	MCIR Method	DCP Method	MCIR Method
3 x 3	6.6810403	9.8714526	0.0835212	0.0400641	0.4649697	0.7615314	2.4672029	9.6354095
15 x 15	7.3346166	9.8523919	0.0718521	0.0402403	0.5062195	0.7438758	2.3637568	9.6728582
30 x 30	7.8573555	9.8306374	0.063703	0.0404424	0.5573414	0.7393797	2.368025	11.080372

Table 6. Comparative Analysis of PSNR, MSE, SSIM and Computation Time using DCP Method [6] and MCIR Method for 321 × 593 dimension

Patch Size	Parameters Analysed							
	PSNR		MSE		SSIM		Duration	
	DCP Method	MCIR Method	DCP Method	MCIR Method	DCP Method	MCIR Method	DCP Method	MCIR Method
3 x 3	9.8305089	14.076375	0.021229	0.0079862	0.4840809	0.7615477	4.2962477	16.70940
15 x 15	10.778116	13.992056	0.017067	0.0081428	0.5481858	0.7438897	4.3247272	17.94563
30 x 30	11.446438	13.856553	0.0146331	0.0084009	0.6164708	0.7327267	4.338301	20.657256

5. Conclusion

Autonomous vehicles use a combination of sensors and software to perceive their surroundings and make decisions. In foggy conditions, the primary challenge is reduced visibility, which can make it difficult for sensors to detect and classify objects in the environment. Cameras are the most important sensors for autonomous driving to provide visual information in such conditions. The proposed Median Channel based Image Restoration (MCIR) method is used to remove weather effects from foggy images captured by the camera, by estimating the atmospheric light and transmission map using static patching and applying the MCIR technique to the patches. A comparison is made with the Dark Channel Prior (DCP) method, and the image quality is evaluated using metrics such as PSNR, SSIM, and MSE for different patch sizes. As the patch size increases, the image quality decreases due to the artifacts and halos that appear around the object boundaries. The MCIR method is found to be superior to the DCP method in terms of halo effects. After extensive evaluation, it is found that the MCIR method is most effective for patch size 3x3, producing high PSNR and SSIM values and low MSE values as a smaller patch size restricts the area over which the computed and thus minimizing the smearing effect of the filter. Overall, the MCIR method is a suitable and quality-driven image processing technique for defogging images. The proposed MCIR method does not work well in direct light conditions because it relies on the assumption that the atmospheric haze is uniform across the entire image. However, in direct light conditions, the haze may not be uniform and may be concentrated in certain areas of the image. This concentration of haze can cause the MCIR method to produce incorrect results, leading to the lack of image detail and poor overall image quality. Additionally, direct light can also cause strong shadows and high levels of brightness, which can affect the accuracy of the MCIR method. This can result in over-exposure or loss of detail in certain parts of the image, compromising the overall quality of the reconstructed image. Further, the proposed MCIR method is now applied to defogging images and has shown good results in restoring images affected by fog and haze. It can be applied to video sequences, allowing for the removal of fog and haze from the video footage. This represents a promising area of future work, as it has the potential to improve the visibility of videos captured in hazy conditions.

References

[1] Suliman Gargoum and Karim El-Basyouny, "Automated Extraction of Road Features using LiDAR Data: A Review of LiDAR applications in Transportation", Proceedings of the *4th International Conference on Transportation Information and Safety* (ICTIS) (2017) pp. 563. DOI: 10.1109/ICTIS.2017.8047822.

[2] Pradeep J, Srinivasan E, Himavathi S, "Diagonal based feature extraction for handwritten character recognition system using neural network", *IEEE 3rd International Conference on Electronics Computer Technology*, Vol. 4, pp.364-368 (2011). DOI: 10.1109/ICECTECH.2011.5941921

[3] Jothy N, Anusuyya S, "A secure color image steganography using integer wavelet transform", *IEEE 10th international conference on intelligent systems and control (ISCO)*, pp. 1-4 (2016).

[4] Pradeep J, Srinivasan E, Himavathi S, "Neural network based recognition system integrating feature extraction and classification for english handwritten", *International journal of Engineering*, pp. 99-106 (2012). DOI: 10.5829/idosi.ije.2012.25.02b.03

[5] Chaffin Mitchell, "Self-driving cars 'see' in the rain, snow and fog?" http:// www.abc10.in /, 2021. (Accessed July 7,2022).

[6] Kaiming He, Jian Sun and Xiaoou Tang, "Single image haze removal using dark channel prior", *IEEE Transactions on Pattern Analysis and Machine Intelligence*, Vol. 33, Issue. 12 (2011) pp. 2341-2353. DOI: 10.1109/TPAMI.2010.168.

[7] J. A. Stark, "Adaptive image contrast enhancement using generalizations of histogram equalization", *IEEE Transactions on Image Processing*, Vol. 9, Issue. 5 (2000) pp. 889-896.DOI:10.1109/83.841534.

[8] Yeong-Taeg Kim, "Contrast enhancement using brightness preserving bi-histogram equalization", *IEEE Transactions on Consumer Electronics*, Vol. 43, Issue. 1 (1997) pp. 1-8. DOI: 10.1109/30.580378.

[9] M. Abdullah-Al-Wadud, M. H. Kabir, M. A. Akber Dewan and O. Chae, "A Dynamic Histogram Equalization for Image Contrast Enhancement", *IEEE Transactions on Consumer Electronics*, Vol. 53, Issue. 2, (2007) pp. 593-600. DOI:10.1109/TCE.2007.381734.

[10] Wang Hao, Ming He, Hui Ge, Cheng-jin Wang, Qing-Wei Gao, "Retinex-Like Method for Image Enhancement in Poor Visibility Conditions", *Procedia Engineering*, Vol. 15, (2011) pp. 2798-2803. DOI: 10.1016/j.proeng.2011.08.527.

[11] Alexander Zotin, "Fast Algorithm of Image Enhancement based on Multi-Scale Retinex", *Procedia Computer Science*, Vol. 131 (2018) pp. 6-14.DOI: 10.1016/j.procs.2018.04.179

[12] Zhu Rong, Wang Li Jun, "Improved wavelet transform algorithm for single image dehazing", Optik, Vol. 125, Issue. 13 (2014) pp. 3064-3066. https://doi.org/10.1016/j.ijleo.2013.12.077.

[13] R. Fattal, "Single image dehazing," ACM Trans. Graph., vol. 27, no. 3, pp. 72:1-10, Aug. 2008. DOI: 10.1145/1360612.1360671

[14] R. T. Tan, "Visibility in bad weather from a single image," in Proc. IEEE Conference on Computer Vision and Pattern Recognition (2008) pp. 1-8. DOI: 10.1109/CVPR.2008.4587643.

[15] Shi L, Cui X, Yang L, Gai Z, Chu S, Shi J, "Image Haze Removal Using Dark Channel Prior and Inverse Image". *MATEC Web of Conferences (2016) 75:30–38*. DOI: 10.1051/matecconf/20167503008.

[16] S. K. Nayar and S. G. Narasimhan, "Vision in bad weather", *Proceedings of the Seventh IEEE International Conference on Computer Vision*, Kerkyra, Greece, vol.2 (1999) pp. 820-827, DOI: 10.1109/ICCV.1999.790306.

[17] Prathap Soma, Ravi Kumar Jatoth, "An efficient and contrast-enhanced video de-hazing based on transmission estimation using HSL colour model", *The Visual Computer (2021) pp. 1-5*. DOI:10.1007/s00371-021-02132-3

[18] Apurva Kumari, Subhendu K. Sahoo, and M. C. Chinnaiah, "Fast and Efficient Visibility Restoration Technique for Single Image Dehazing and Defogging", *Institute of Electrical and Electronics Engineers (2021)* Vol. 9, pp. 48133-48137. DOI: 10.1109/ACCESS.2021.3068446

[19] Benyamin Ghojogh, "Haze Removal Dark Channel Prior", http://github.com/,2020. (Accessed Dec 7, 2022).

[20] ANI, Visibility reduces as a thick layer of fog grips Delhi; Visuals from Yamuna Bank and Akshardham, https://twitter.com/ANI/status/1605399708754927616, 2022.(Accessed Jan 30,2023).

[21] Manas Ranjan Bhui, Delhi's air quality turns 'severe', CAQM asks NCR states to strictly implement anti-pollution curbs, https://www.tribuneindia.com/news/delhi/delhis-air-quality-turns-severe-caqm-asks-ncr-states-to-strictly-implement-anti-pollution-curbs-468905,2023 (Accessed Jan 29, 2023).

[22] Bhubaneshwar wakes up to foggy morning, https://argusnews.in/article/odisha/bhubaneswar-wakes-up-to-foggy-morning, 2023.(Accessed Jan 22,2023).

[23] Caroline Esther D'Souza, As winter sets in, dense fog engulfs many states, https://zeenews.india.com/india/as-winter-sets-in-dense-fog-engulfs-many-states-2331074.html, 2020. (Accessed Jan 23,2023)

Authors' Profiles

P. Raja completed in Bachelor of Engineering with the specialization of Electronics and Communication Engineering at Madras University, Master of Technology with the Speclization of Microelectronics and VLSI Design at IIT Madras and Completed Doctoral Program in Electronics and Communication Engineering at Pondicherry University. He working as a professor in the Department of Electronics and Communication Engineering, Sri Manakula Vinayagar Engineering College, Puducherry, India. He has two decades of teaching experience. His research area is VLSI Design, Signal Processing and Wireless Communication. He is a Professional Membership of the Indian Society for Technical Education and Institute of Electrical and Electronics Engineers, The Institution of Engineers (India) and The Institution of Engineers (India). He also received Excellent Professional Achievement Award (Class1)" from Society of Professional Engineers (India).

Sowmiya. M is a student, Department of Electronics and Communication Engineering, Sri Manakula Vinayagar Engineering College, Madagadipet, Puducherry.

Subathra. V is a student, Department of Electronics and Communication Engineering, Sri Manakula Vinayagar Engineering College, Madagadipet, Puducherry.

Sarah. S is a student, Department of Electronics and Communication Engineering, Sri Manakula Vinayagar Engineering College, Madagadipet, Puducherry.

How to cite this paper: P. Raja, Sowmiya. M, Subathra. V, Sarah. S., "Image De-Weathering Using Median Channel Technique and RGB-based Transmission Map for Autonomous Vehicles", International Journal of Image, Graphics and Signal Processing(IJIGSP), Vol.16, No.5, pp. 91-104, 2024. DOI:10.5815/ijigsp.2024.05.07