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# Removal of Fog and Noise in Ocean Images by using the method of Illumination Decomposition

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**ABSTRACT:** Image Defogging and Image Denoising are the two well addressed and challenging problems in the area of image processing. Fog and noise are two different factors which adversely affect the images and both creates a lot of problems in the area of image processing. Fog is a thick cloud of tiny water droplets suspended in the atmosphere and noise is a random variation of brightness or color information in the images captured. The images acquired by a visual system are degraded due to the scattering of atmospheric particles under foggy weather conditions. Similarly the images captured by camera are degraded by noise, which leads to reduction in many parts of image information and visual image quality.

The image degradation can affect the detection, tracking and recognition of objects, image analysis and limit the efficiency of the system. There were a lot of research papers addresses both these Image Defogging and Image Denoising independently ie. either to remove the noise or to remove fog in the image. In the present work, it is trying to implement both image defogging and image denoising on a single ocean images is examined. The fog hampers visual maritime surveillance, which is often deployed as part of law enforcement and environment protection for littoral nations.

## I. INTRODUCTION

The quality of images is very important in long range imaging system, where the presence of fog and noise directly influence the screen visibility by reducing its contrast. Fogs are caused by atmospheric aerosols. While the fogged images do depend on the scene depth, most often the aerosol particles are shown to have more influence on illumination in a fogged scene. The noise may be came from various sources like image capturing devices, faulty memory location or may be introduced due to imperfection or inaccuracy in the image capturing device like camera, lenses etc. All the image enhancement techniques developed yet have neglected the techniques to remove noise in the foggy image. The goal of present work is to find an image defogging method applied for ocean images which consider noise present in the image.

## II. LITERATURE SURVEY

The published literature is rich with a lot of papers addressing the problem of Image Defogging and Image denoising. Following are some of the related works in Single Image Defogging based on prior –based approach.

### 1. Dark Channel Prior model by He *et al.*[2]

Dark channel prior (DCP) model is originally proposed by He *et al.*[2]. The Key idea is, based on certain statistics of haze-free outdoor images – outdoor objects in clear whether have at least one colour channel that is significantly dark. The algorithm used is based on Gaussian based dark channel.

### 2. Colour attenuation prior model by Zhu *et al.*[3]

Colour attenuation prior (CAP) model is proposed by Zhu *et al* [3]. It constructs a linear relationship between the scene depth and the hazy image, with parameters of the model learned by a supervised learning method. The authors have used the removal algorithm.

### 3. An Improved Image Denoising Model Based on Nonlocal Means Filter by Yan Jin *et al* [9]

NLM filter takes the mean of all pixels in the image, weighted by how similar these pixels to the target pixel. Here similar pixel neighbourhood give larger weights.

### 4. Image Denoising Model based on NLM Filter by A.Buades *et al*[4]

The original non local means method replaces a noisy pixel by the weighted average of pixels with related

neighbourhoods, In this paper new filters are introduced that eliminate unrelated neighbourhoods from the weighted average.

### III. DESIGN OF THE PROPOSED SYSTEM

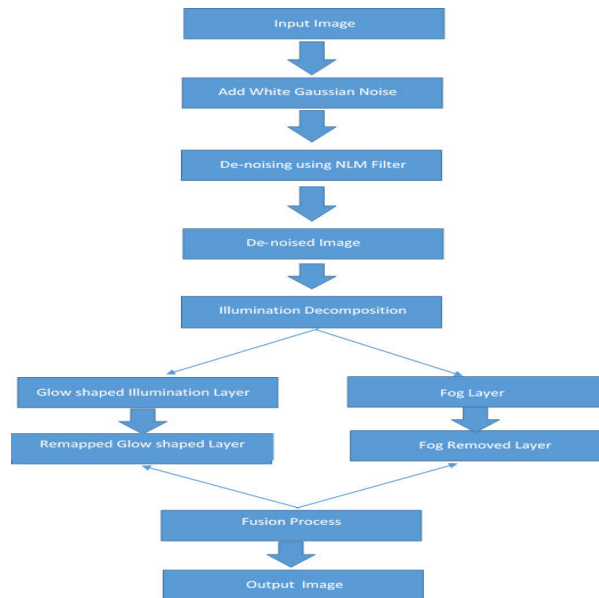


Figure 3.1. Architecture of the Proposed System

#### 3.1 Architecture of the Proposed System.

The architecture of the proposed system is given in Fig.3.1. Removal of fog and noise process consists of the following steps

1. A Comprehensive Scattering Model is created to formulate the fog image with glow shaped illumination
2. Addition of Gaussian noise to the fogged image.
3. Removal of noise using NLM filtering algorithm.
4. Apply Illumination Decomposition algorithm to the resultant image .
5. Estimation of transmission map to obtain the defogged image using non local haze line prior method .
6. Fusion of fog removed image and remapped illumination component to obtain the final result.

#### 3.1.1 Comprehensive Scattering Model.

Before going to the fog removal process, first we have to specify what is mean by glow shaped illumination? The uneven distribution of illumination caused by multiple scattering effect is called glow shaped illumination. ie. the spatial variance of illumination from multiple scattering effect.

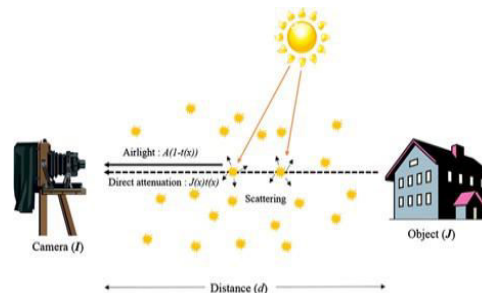


Figure-3.2 a. Conventional Scattering Model [1]



Figure-3.2 b. Multiple Scattering Effect [1 ]

Fig 3.2 a shows the conventional scattering model [1 ] and Fig 3.2 b shows the principles of multiple scattering effect [1] defined in comprehensive scattering model used in the proposed method. When the presence of particles in the atmosphere is substantial, the images captured that generate a glow. The comprehensive scattering model [7] includes airlight, transmission and glow term is described in Fig.3.3.

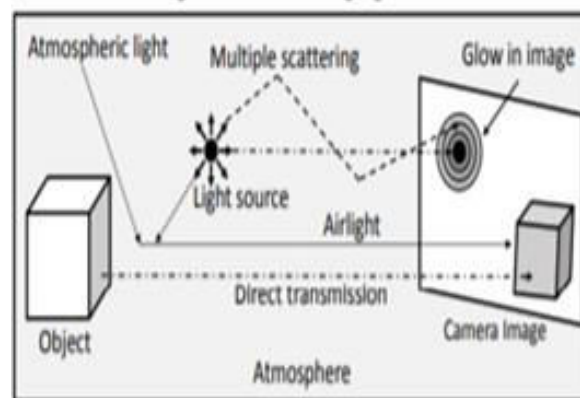


Figure-3.3. Comprehensive Scattering Model [7]

In the Defogging process of ocean images, first we have to analyse the scattering properties and features of ocean images. The physical characteristics of ocean images is different from that of land images. The atmospheric particle effect on illumination and gradient sparsity properties of ocean images are discussed below.

**1) 1. Atmospheric particle effect on Illumination**

The sky illumination is constant in a fog scene. The properties of particle model such as size  $r$ , forward scattering ability  $q$  and scattering coefficient  $\beta$  can affect the illumination in a fog scene. The table 3.1 [1] shows the properties of particle model under different weather conditions.

Parameter P	Air	Small aerosol	Haze	Fog
$r(\text{Gm})$	$10^{-4}$	$10^{-3} - 10^{-2}$	$10^{-2} - 1$	1-10
$B(\text{km}^{-1})$	0.01-0.39	0.39-0.95	0.96-1.96	1.96-10.0
$q$	0.0-0.2	0.2-0.7	0.7-0.8	0.8-0.9

Table-3.1. Scattering Properties of Atmospheric Particles [1]

The irradiance function of scattering light from a particle is defined by particle scattering function  $G(\theta)$ , radial distance  $T$  of atmosphere. The function  $G(\theta)$  in equation 3.1 [1] describes the angular distribution of light scattered by a particle in the space.

$$G(\theta) = (1 - 2\cos(\theta) + q^2)^2 \quad 3.1 [1]$$

Theta denotes the angle between direction of incident light and scattering light from a particle. The difference of  $G(\theta)$  lead to different distribution of scattered light in atmosphere which gets scattered multiple times. It is seen that particles in fog has larger  $q$ , scatters more close to forward direction.

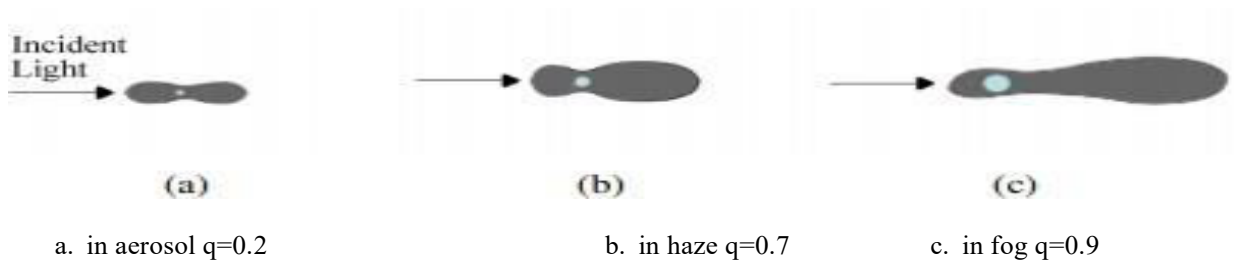


Figure-3.4.  $G(\theta)$  of particles in different weathers [1]

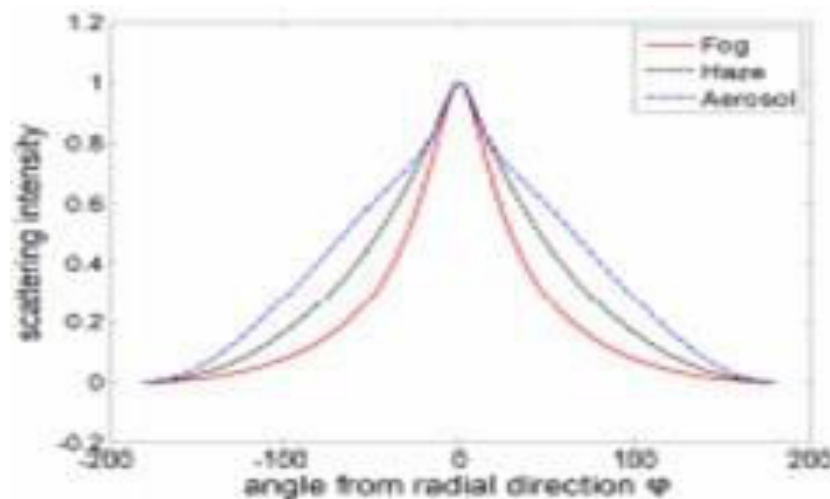


Figure-3.5 Attenuation curves of multiple scattering light at weather conditions [1]

The Fig.3.5[1] shows the attenuation curve of multiple scattering light[1] at different directions with respect to the incident direction in a scene under different weathers. The scattering light intensity with a larger  $q$  in fog weather attenuates more in different directions. Due to the glow shaped illumination the windows at infinite distance have different luminance.

## 2) Characteristics of fog images in ocean

The fog layer seen in the sea has larger thickness and condensation module such as sea salt is more in sea than that in land. The fog images in ocean scene has heavy fog and large smooth area. The conventional scattering model is not suitable here. The fog images in ocean have less texture and light colour than land images. Moreover the gradient curve of ocean images delivers sharper. So considering the properties of sea fog and ocean scene, a comprehensive scattering model is proposed in the proposed method.

### 3.1.2 Image Degradation Model.

Before going to defogging process, first adding some random noise to the fogged image and then remove the noise using NLM filtering technique. Different algorithms are used to denoise the images depending on the noise model. The noise in digital images is either additive or multiplicative in nature. Most of the natural images are assumed to have additive random noise which is modeled as a Gaussian. Principal sources of Gaussian noise in digital images are sensor noise caused by poor illumination and/or high temperature, and/or transmission.

Eqn.3.2 shows the image degradation model in which  $I(x)$  is an original fogged image,  $K(x)$  is the observed image and  $N(x)$  is the additive Gaussian noise. The objective of the denoising scheme is to recover the original image from the observed image, while preserving the important features of image such as edges and textures.

$$K(x) = I(x) + N(x) \tag{3.2}$$

### 3) Gaussian Noise

Gaussian noise, is a statistical noise having a probability density function (PDF) equal to that of the normal distribution, The probability density function of a Gaussian random variable is given in Eqn 3.3:

$$PG(z) = \frac{1}{\sigma\sqrt{2\pi}e} \exp\left(-\frac{(x-\mu)^2}{2\sigma^2}\right) \tag{3.3}$$

where  $\sigma$  is the standard deviation and  $\mu$  is the mean.

#### 3.1.3 NLM filtering Algorithm

Image denoising techniques are classified into two categories: spatial and transform domain. Spatial domain algorithms perform operations directly on the pixels. The spatial and transform domain methods can also be further classified as local and Non-local methods. Most of the spatial domain image denoising filters are mean, median, and Gaussian, and wiener filters. The methods that estimate pixel intensity based on the information from the whole image and thereby exploiting the presence of similar patterns and features in an image are referred as Non-local methods. Image denoising methods like Non-Local Means (NLM) filtering takes the advantage of redundancy present in an image to reduce the noise effectively. Non-Local Means (NLM) method which uses the neighbourhood similarity for reduction of noise [4] and redundant information of the image in pixel to reduce the noise effectively.

The assumption is that every small neighbourhood in a natural image have many similar copies in the same image. Basically, the non-local means filter estimates a noise free pixel intensity as a weighted average of all the pixel intensities in the image, and the weights are proportional to the similarity between the local neighbourhood of the pixel being processed and local neighbourhood of surrounding pixels. Let  $I(x)$  is the input image and  $N(x)$  is the noise induced in it. Then the observed image is represented as  $K(x)$ , where  $x$  is the pixel index. It is assumed that the original image is corrupted by independent and identically distributed Gaussian noise  $N(x)$  with mean zero and standard deviation.

The estimated pixel values can be derived as the weighted average of all values within the whole image  $I$ . Estimated value is the weighted average of all pixels in the image. The family of weights depend on the similarity between the pixels. In other wards similar pixel neighbourhood give larger weights. Every image has an area that have similarities between them. The filtering operation is explained in Eqn 3.4

$$\frac{1}{INLM} = Z \sum_{q \in I} G\sigma(N_p - N_q) f(q) \tag{3.4}$$

The equation averages pixels that have similar neighbourhoods. If neighbourhood of  $p$  looks similar to neighbourhood of  $q$ , then give higher weight. The weight depends on difference in intensities

Thus we obtained the noise free image from the input image by using NLM filtering technique. Next step in our design phase is to defog the resulting image using illumination decomposition method. Here the output from the denoised stage is given as input to the defogging method. Thus we have to assign the value INLM to  $I$ , which is the input to the defogging process.

**4) Image Defogging Model.[6]**

The image degradation model [6] in the presence of fog is shown in Equation 3.7 [6]. The model assumes that scattered light in the atmosphere is a linear combination of direct transmission and airlight.

$$I(x) = J(x)t(x) + A(1 - t(x)) \quad (3.7)$$

where  $I$  is the observed image intensity after removing noise using NLM filtering,  $J$  is the scene radiance,  $A$  is the global atmospheric light and  $t$  is the medium transmission describing the portion of light that reaches the camera.

The main goal of fog removal is to recover  $A, J$ , and  $t$  from the image  $I$ . The steps used to achieve this goal is, first to estimate the uniform atmospheric light  $A$  and transmission  $t$ . From these two parameters we have to estimate the scene radiance  $J$ .

The comprehensive scattering model [7] used to represent the fog image with glow shaped illumination is shown in Equation 3.8 [1]. In equation 3.8 [1],  $x$  denotes the position of the pixel within an image,  $y$  denotes the distance between the atmospheric light source and the observer,  $d(x)$  denotes the distance of the scene at pixel  $x$ ,  $\beta$  is the scattering coefficient and it is the ratio of light scattered by particle in the direction of observer,  $e^{-\beta d(x)}$  denotes the transmission of incident light to the observer. Here a variable  $I_s(x, y)$  is used as the atmospheric light intensity instead of using constant atmospheric light  $A$ , as in Equation 3.7 [1]

The first term,  $J(x)e^{-\beta d(x)}$  in Equation 3.8 denotes the irradiance produced by observed objects and, in the second term,  $I_s(x, y)\beta e^{-\beta y} dy$  denotes the irradiance produced by a particle as a source of light in distance  $y$ . For simplicity Equation 3.3 [1] can be rewritten as

$$I(x) = F(x) + G(x) \quad [1] \quad (3.9)$$

Where the vector  $F(x)$  in equation 3.9 [1] represents the underlying fog layer and  $G(x)$  denotes the part of the radiance of airlight caused by the glow effect

**3.1.4 Illumination Decomposition Algorithm [1].**

The next step in our design phase is to separate glow layer  $G$  and Fog layer  $F$  from input image. For this Illumination Decomposition algorithm [1] is used. According to Wang [9] an image is the summation of reflect lightness

and ambience illumination. The illumination decomposition algorithm in the proposed method is based on some constraints to obtain  $G$  and  $F$ .

- The gradient of  $F$  in ocean scene should be sparse.
- The curve of the scattering light in a fog scene is bell - shaped curve and illumination in a fog scene should be spatial smooth.
- $G$  is positively related to transmission and illumination. The transmission has negative correlation with the gradient of  $F$ .

Based on the above constraints, a penalty function can be defined as follows in Equation 3.10 [1]

$$P(F, G) = \|\nabla F\|_1 + \alpha \|\nabla G\|^2 + \beta \|\mathbf{F} * \mathbf{f}_1\|^2, s.t. 0 \leq F \leq I, G^r = G^s = G^b \quad [1]$$

Where  $\nabla$  is the Laplacian gradient operator,  $\alpha, \beta$  are free positive parameters,  $*$  is the convolution operator.  $\|\cdot\|_1$  is the vector norm operator and  $\mathbf{f}_1$  is a  $10 \times 10$  Gaussian filter, in which the variance equals 3.  $L_1$  norm is used to keep within limits the gradient of  $F$  in  $\|\nabla F\|_1$ , which can limit outliers and preserve edges of decomposed fog layer  $\|\nabla G\|^2$  is used to enforce spatial smoothness. The term  $\beta \|\mathbf{F} * \mathbf{f}_1\|^2$  restrains the background brightness of  $F$  in the high brightness regions.

Equation (3.10) can be rewritten as follows to obtain optimised result by introducing an auxiliary variable  $w$  and replacing  $G$  by  $I - F$ . Where  $\alpha, \beta$  are free positive parameters,  $*$  is the convolution operator.  $\|\cdot\|_1$  is the vector norm operator and  $\mathbf{f}_1$  is a  $10 \times 10$  Gaussian filter, in which the variance equals 3.  $L_1$  norm is used to keep within limits the gradient of  $F$  in  $\|\nabla F\|_1$ , which can limit outliers and preserve edges of decomposed fog layer is used to

enforce spatial smoothness. The term restrains the background brightness of  $F$  in the high brightness regions. Equation 3.10 can be rewritten as follows to obtain optimised result by introducing an auxiliary variable  $w$  and replacing  $G$  by  $I - F$ .

### 3.1.5 Fog Removal by Non-local haze-line prior method [1].

In the illumination decomposition process, the glow effect due to illumination can be reduced, when the noise become less. The haze-line prior method is used to estimate the transmission map of the fog layer. The pixels scattering over the global image  $I$  can form a haze line in the RGB color space and the transmission value of the pixels can be obtained by the relative position in the haze line, The assumption is called non-local haze-line prior[8].

The aim of non-local haze -line prior method used here is to remove the fog from the fog layer  $F$  and obtain the fog free layer ( $J$ ). For this we have to estimate the atmospheric light intensity  $L(A)$  and transmission  $t$ . The definition of  $F$  can be changed into equation 3.16[1].

$$F(x) - A = t(x).[J(x) - A][1] \tag{3.16}$$

$$t(x) = \frac{\|F(x) - A\|}{\max_{x \in H} \|F(x) - A\|} [1] \tag{3.17}$$

The per-pixel estimation of transmission  $t$  can be obtained by using the equation 3.17[1]. Noting that  $x$ , pixels are clustered into a haze-line  $H$ . Here the transmission  $t$  is done per haze-line  $H$  and  $\|\cdot\|$  is the Euclidean distance operator in RGB space. Accordingly, the results of pixels clustering in  $F$  will be more accurate while  $G$  is stripped out. And from this we have to obtain the for removal layer by using equation 3.18[1].

$$J(x) = \{F(x) - [1 - t(x)]A\} / t(x)[1] \tag{3.18}$$

### 3.1.6 Luminance Compensation Algorithm [1]

After using non-local haze line prior, we have to obtain the fog removal layer  $J$ , which contains the texture information recovered and  $G$  represents the natural illumination information of input image. In the Luminance compensation method [1], a fusion process is proposed by combining the fog removal layer  $J$  and  $G$  to recover the illumination information and contrast in the defogged image as follows,

$$J_e(x) = J(x) + G_m(x)[1] \tag{3.19}$$

For avoid veiling the texture in  $J$ ,  $G$  is remapped into  $G_m$  by multiplying a coefficient vector  $R$ , which is the contrast and chromatic of pixels in  $J$ .  $R$  is the ratio of pixel value to background brightness in  $J$ , given by

$$R^c(x) = \{J^c(x) / Guide[J_{back}(x), I]\}^{g(x)} [1]$$

$G_m$  required in Eqn.3.13 [1] can be calculated as

$$G_m^c(x) = G^c(x).R^c(x)[1] \tag{3.20}$$

Finally,

$$J_{back}(x) = \max(\max(J^c(y))), c \in r, g, b [1]$$

Here  $\Omega(x)$  is a local patch,  $J_{back}$  is the background brightness of  $J$ . A guided image filter can be used to preserve edges in  $G_m(x)$ , and to refine  $J_{back}$  use  $I$  as the guide image.

The algorithm of the proposed method, can be summarised as given below:

1. **Input:** The fog image  $I, \alpha, \beta, \lambda$  for cost function in eqn. (3.11), filtering window size  $r$  and parameter of guided filter for obtaining  $J_{back}$  in eqn. 3.21 and similarity window size  $f$ , neighbourhood window size  $N$ , standard deviation for Gaussian filter  $G\sigma$  for NLM filtering in equation in 3.4
2. Add randomwhite noise with a standard deviation  $G\sigma$  and mean zero.
3. Denoise Image  $I$  using equation in 3.4 and obtain the result  $I_{NLM}$
4. Assign  $I = I_{NLM}$ , which is the input image of image defogging.
5. Repeat the steps upto 5.5 to perform Image defogging



**Initialize :**  $k=1$  ,  $K^0=I$ ,  $w^0=\nabla I$   
**Output:** The defogged result  $J_e$  1: **While** not converge **do**  
 At the  $k$ th iteration:  
 Update  $w^k$  and  $F^k$  using Equation 3.13 [1 ] and 3.14 [1 ]

**5) End while.**

Obtain  $G$  and  $F$

2: Estimate the atmospheric light  $L$

3: Cluster the pixels into each – haze line  $H$  by hue of  $L-F$ . calculate the transmission  $t$  for each pixels using Equation 3.18

4: Obtain the fog removal result  $J$  using Equation 3.19 [1 ]

5: Obtain the coefficient  $R$  and calculate  $G_m$  using Equation 3.21 [1 ]. Compensate the luminance for  $J$ . obtain  $J_e$  using Equation 3.20 [1 ]

**IV. RESULT AND ANALYSIS**

**4.1 Results**

The qualitative output of proposed image defogging method after noise removal for ocean images is evaluated here. The system is tested with the images available in the data set “<https://github.com/yeyekurong/defogging-for-sea-fog-images.git>”. The following subsections also provide the intermediate results after each operation specified in the design.

**6) Intermediate Results**

**4.1.1 Denoising Result**

The intermediate result obtained after the denoising operation using NLM filtering is shown in figure 4.1.1. Here first column represents the input image, second column represents the input image after the addition of random noise and third column represents the denoised fogged image after applying NLM Filtering.

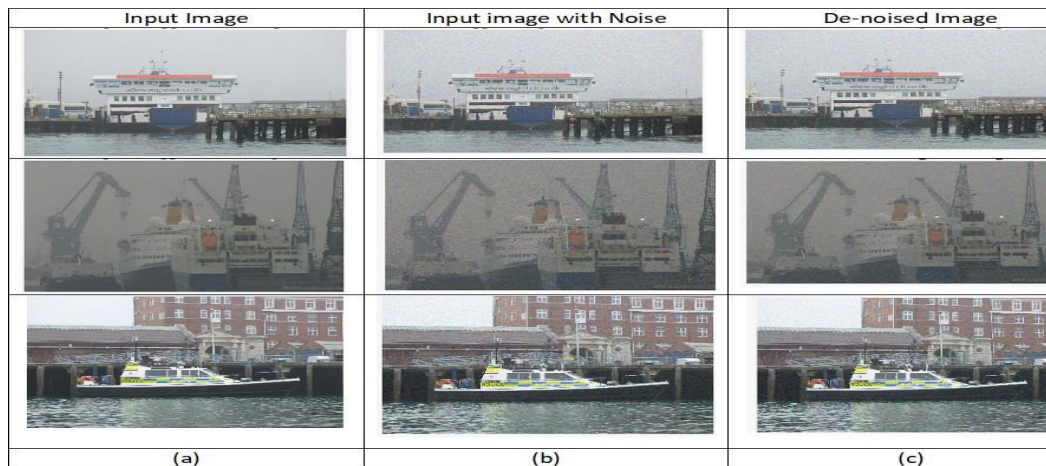


Figure.4.1.1 Denoising Result

**4.1.2 Decomposition Result**

The denoised image is then pass through the decomposition phase to separate the glow effect from the denoised image and obtain an illumination component such as glow shaped illumination layer and reflectance component such as Fog Layer (F) as shown in figure 4.1.2. Here column (a) represents the denoised image ,column (b) represents the illumination layer (G) and Fog Layer (F) is represented in column (c).

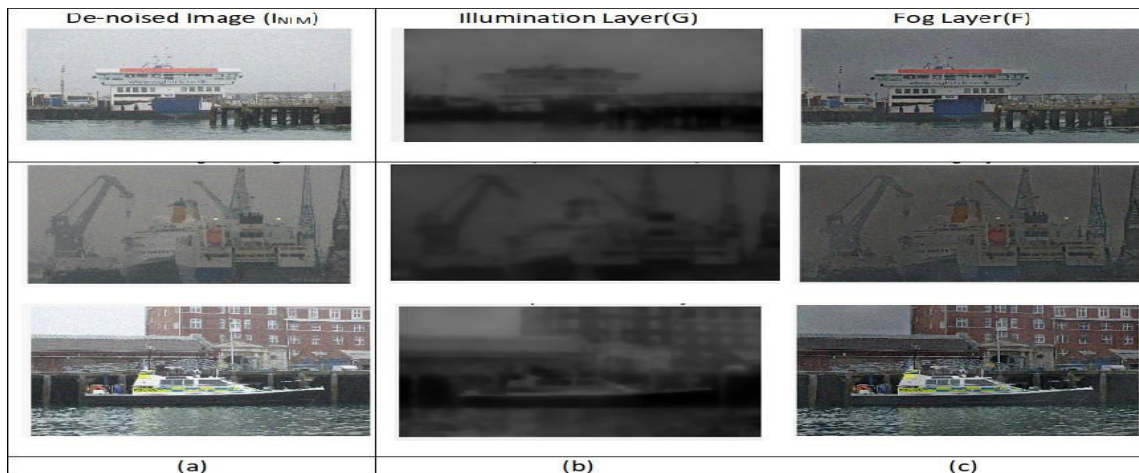


Figure.4.1.2 Decomposition Result

#### 4.1.3 Fog Removal Result

The fog layer obtained from decomposition process can then processed using non-local haze line prior method to calculate the transmission map and then by estimating the fog removed layer. The first column (a) represents the fog layer(F), second column(b) represents the Transmission Map (t) and third column (c) represents the fog removed Layer (J).

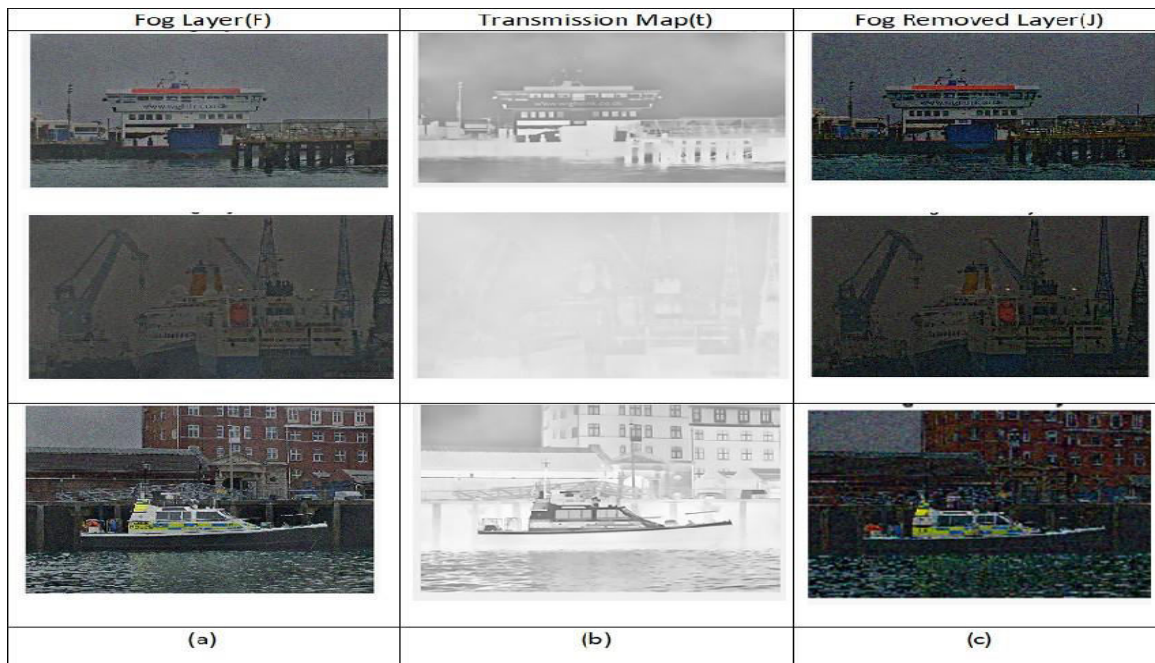


Figure.4.1.3. Transmisison Map Estimation and Fog Removal Process

#### 4.1.4 Luminance Compensation Result

The defogging result via the fusion process is shown in figure 4.1.4. The glow shaped layer (G) is remapped to Remapped glow shaped Layer( $G_m$ ) for getting the texture feature is shown in the first column (a) and combine this layer with removed fog layer (J) to obtain the defogged image ( $J_e$ ) is shown in second column(b).

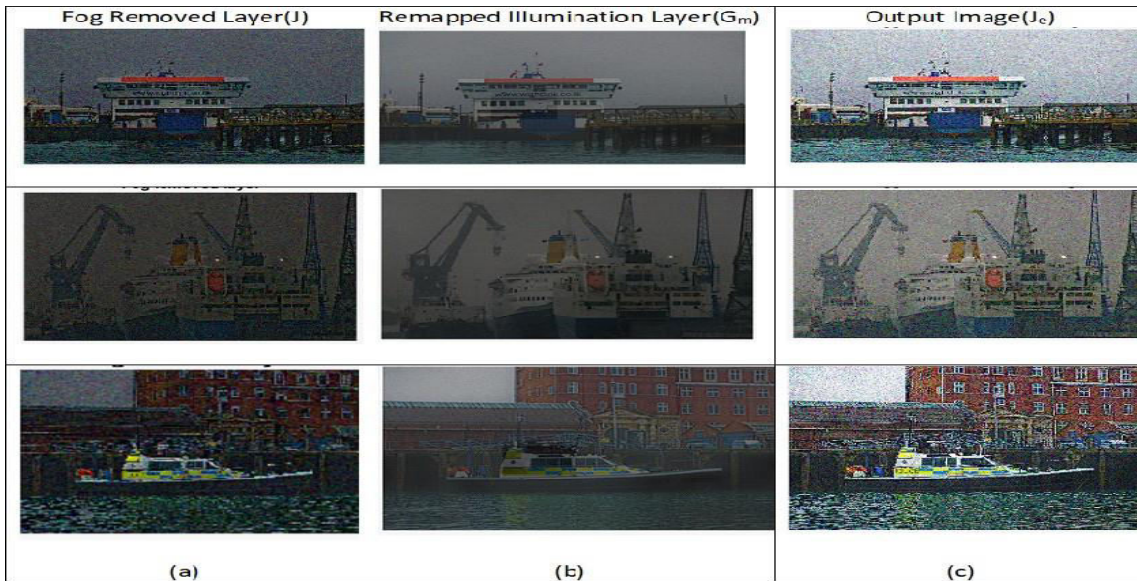


Figure.4.1.4. Luminance Compensation Result

#### 4.1.5 Final Result

The final output of proposed method (b) with corresponding input image (a) is shown in figure 4.1.5.

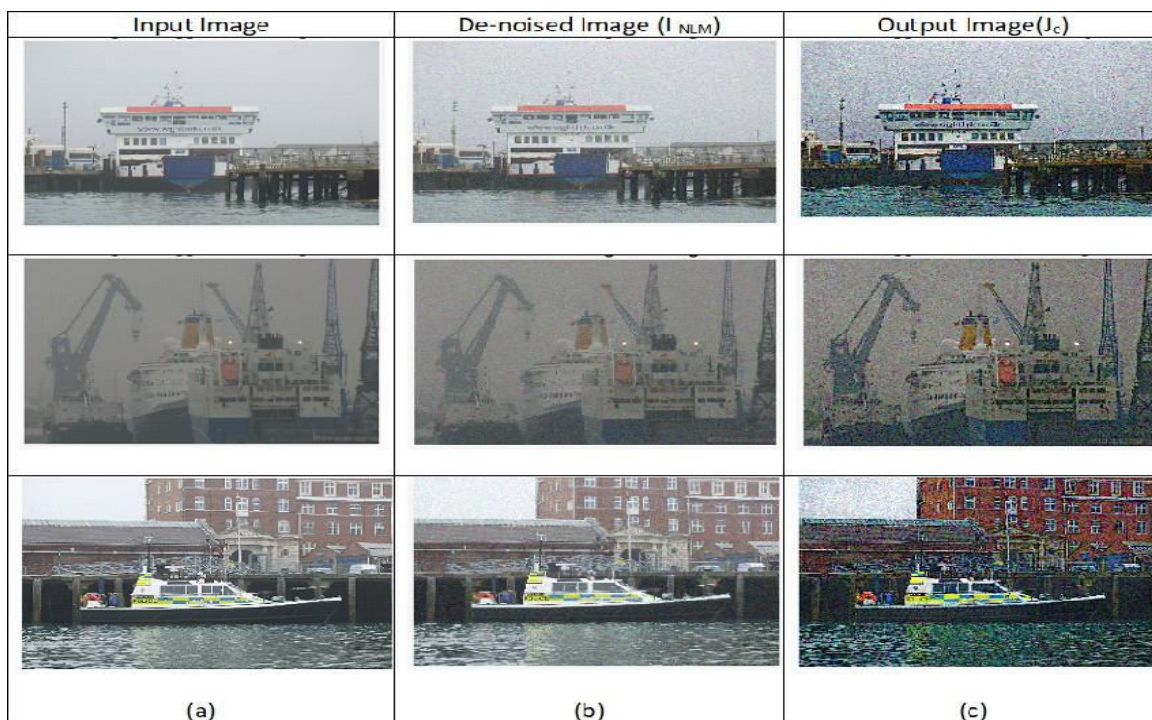


Figure.4.1.5.Final Result of Proposed Method

#### 4.2 Performance Metrics for Image Defogging

There are a lot of image dehazing algorithms are developed. The visual quality of a digital image can be subjective. Due to the lack of reference haze-free images, defogging algorithms are qualitatively analysed. But it is possible to quantitatively analyse the defogging methods based on some metrics. By using same set of test images, we have to conduct evaluation on different algorithms and find out which algorithm is best. The metrics used for quantitative evaluation in the proposed method are.,

1. PSNR
2. MSE

1. Peak Signal to Noise Ratio (PSNR):- PSNR is defined as the ratio between signal variance and reconstruction error variance:- Here: mean squared error (MSE)  $Max1$  is the maximum possible pixel value of the image.  
2. MSE (Mean square Error):- MSE is defined as the some sort of average or sum (or integral) of square of the error between two image. Where  $I$  is the original image  $K$  is the decompressed image and  $m$  and  $n$  is the dimensions of the image.

## V. CONCLUSION

The present chapter out line the Fog removal approach based on

1. A comprehensive scattering model, created to formulate the fog image with glow shaped illumination
2. NLM Filtering algorithm
3. Illumination decomposition algorithm
4. Non-local haze-line prior for fog removal
5. Luminance Compensation algorithm

The algorithm revolves around the key steps, of updating  $w^k$  and  $F^k$  using Equations (3.12,3.13). In order to speed the defogging computation process, which involves convolution, the algorithm uses FFT approach.

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