International Journal on Advanced Science Engineering Information Technology

Vol.6 (2016) No. 6
ISSN: 2088-5334

A Study of Atmospheric Particles Removal in A Low Visibility Outdoor Single Image

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***Abstract*— Maximum limit of human visibility without the assistance of equipment is 1000 m based on International Commission on Illumination. The use of a camera in the outdoor for the purpose of navigation, monitoring, remote sensing and robotic movement sometimes may yield images that are interrupted by haze, fog, smoke, steam and water drops. Fog is the random movement of water drops in the air that normally exists in the early morning. This disorder causes a differential image observed experiences low contrast, obscure, and difficult to identify targets. Analysis of the interference image can restore damaged image as a result of obstacles from atmospheric particles or drops of water during image observation. Generally, images with atmospheric particles contain a homogeneous texture like brightness and a heterogeneous texture which is the object that exists in the atmosphere. A pre-processing method based on the dark channel prior statistical measure of contrast vision and prior knowledge still produces good image quality but less effective to overcome Halo problem or ring light, and strong lighting. This study aims to propel the development of machine vision industry aimed at navigation or monitoring for ground transportation, air or sea.**

***Keywords*— atmospheric particles removal; single image; haze removal; fog removal; image enhancement**

I. INTRODUCTION

Atmospheric particles consist of haze, fog, mist, smoke, dust and non-drip water [1]. These atmospheric particles can be divided into two classes, static and dynamic. Fig. 1 refers to the division contained in the static and dynamic class [2], [3], [4], [5]. One of the major problems in atmospheric particles is haze [6]. The content of hazardous particles in the haze is very harmful to health because the dangerous chemicals can reduce lung and human blood ability. Haze is caused by daily human activities such as open burning and industrial smoke departure [7]. Repeal of existing image scattered with atmospheric particles needs to be analysed to restore damaged images due to obstacles during the atmospheric particles observation [8]. This degraded image contains higher noise, more blurring, lower contrast and colour decay [3], [4], [5]. Meanwhile, these atmospheric particles always disturb vision application such as environmental monitoring, objects tracking, autonomous robot navigation, and reconnaissance. This is important to eliminate the bad factor to enhance the image quality for visualization and analysis as well as recovering useful information from degraded images [2], [9].

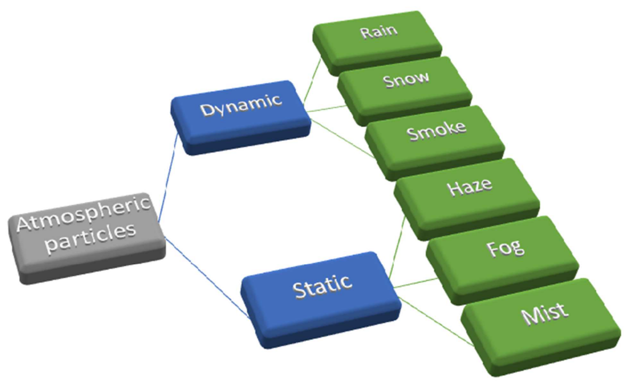

Fig. 1 Classes of atmospheric particles

A number of methods have been proposed for atmospheric particles removal from images. Computer vision and digital image processing methods can extract useful information from images such as scene depth, contrast, and colour channels (chromaticity). But, atmospheric particles removal is a difficult problem due to the inherent ambiguity between the atmospheric particles and the underlying scene [10], [11], [12], [13], [14], [15], [16], [17]. This study is about scattered image and still has not established a complete theoretical system yet. Currently, this study is lack of systematic summary of research work. This study is necessary to summarise and review the development of image of atmospheric particles removal in the recent decade. Fig. 2 refers to the input of degraded image and output after atmospheric particles removal according to He, Tarel, and Tan methods [11], [17], [18].

(a)

(b)

(c)

(d)

Fig. 2 Input (a), He method (b), Tan method (c) and Tarel method (d) [11], [17], [18]

II. Material and Method

The accurate nature of scattering is complex due to atmospheric particles contain in image and characteristic of the existing light [2], [3], [4], [5]. The equation in Koschmieder is define as following (1) [19]:

$$L(x, y) = L_0(x, y)e^{-kd(x,y)} + Ls(1 - e^{-kd(x,y)}) \qquad (1)$$

Where L(x, y) is the apparent luminance at pixel (x, y), d(x, y) is the distance of the corresponding object with intrinsic luminance $L_0(x, y)$, L_s is the luminance of the sky and k denotes the extinction coefficient of the atmosphere. This model is directly extended to a color image by applying the same model to each RGB component, assuming a camera with a linear response. The first effect of the fog is an exponential decay $e^{-kd(x,y)}$ of the intrinsic luminance $L_0(x, y)$ and of the intrinsic colors. Thus, the contrast of the object is reduced and thus its visibility in the scene. The second effect is the addition of a white atmospheric veil $L_s(1 - e^{-kd(x,y)})$ which is an increasing function of the object distance d(x, y) [14].

In the early theory of image scattered with atmospheric particles was first explored by Schechner in the year 2001 [2]. Followed by Narashimhan, in which degraded image were caused by the weather destruction and poor visibility in images [3,4,5]. They proposed the mathematical theory [2,3,4,5] to calculate the degradation of the image using the equation suggested by Koschmieder in the year of 1934 [19]. The equation relating the apparent contrast, C_d of an object against a sky background, at a given distance of observation d, to the inherent contrast C_0 and to the atmospheric transmissivity T, which is assumed to be uniform as in equation (2):

$$C_d = C_0 \cdot T^{\frac{d}{d_0}} \qquad (2)$$

where d_o is the length specified for the definition of T.

This equation can be simplified and understood into equation (3):

$$Image_{degrade} = Image_{clear} \cdot Transmision_{depth} \qquad (3)$$

where $Image_{clear}$ is the image with clear scene, $Image_{degrade}$ is the image scattered with atmospheric particles and $Transmision_{depth}$ is the transmission depth map.

Previous works occurred as an effort to achieve clear image in recent camera application. These methods can be categorised into three main approaches, they are user interaction and additional information approach, multi-image approach, and single image approach. The first approach insists on user interaction and additional information such as scene depth, and geometrical model. This approach is less practical in many computer vision applications [2], [11], [14], [16], [17], [20]. The second approach requires to calculate and compare two or more images of the same scene. However, camera position and angle maybe destructive on account of human factors [3], [4], [5]. For the third approach, it is rather more practical and applicable to discover the potential information to the convenience, adaptive, and reasonable results [10], [14], [16], [17]. Fig. 3 refer to this approach.

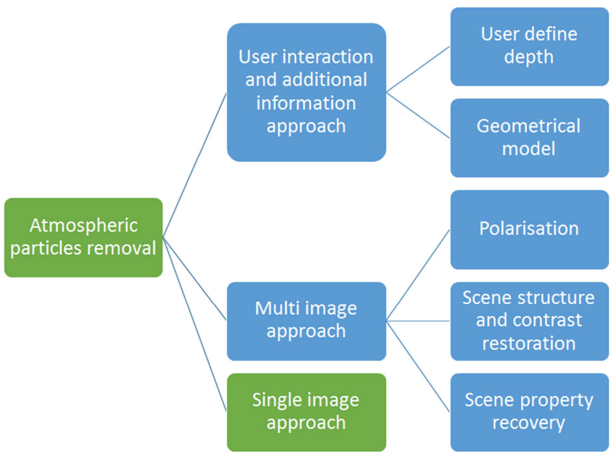

Fig. 3 Atmospheric particles removal approach class

This study focusing on a single image due to the more practical method to solve the problem occurred in recent camera application [10], [14], [16], [19]. Atmospheric particles in an image removal method can be divided into 3 categories: prior knowledge based, contrast recovery based and blur and noise removal. Fig. 4 refer to this category class.

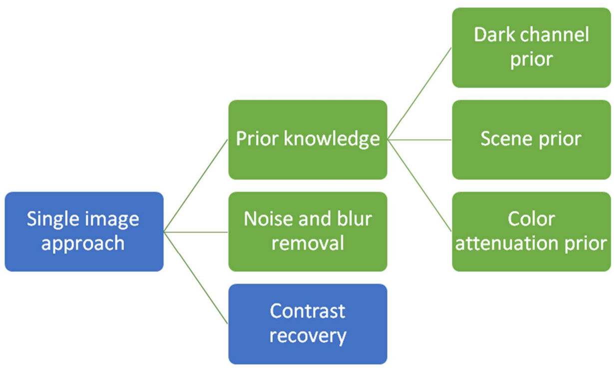

Fig. 4 Single image approach class

For the prior knowledge based is refer to the research made by He that proposed the dark channel prior as the main characteristic to estimate the transmission depth in the image. He suggested that when the intensity of the dark channel is low and close to zero in $Image_{clear}$, the depth of the scene in equation (2) can be obtained as follow this equation in (4) and (5):

$$Transmision_{depth} = e^{-kd} \tag{4}$$

$$Transmision_{depth} = \frac{Image_{degrade}}{Image_{clear}} \tag{5}$$

Where k is the scattering coefficient of the atmosphere and d is the scene depth.

To raise $Image_{clear}$ with dark channel prior this equation (6) would be followed.

$$Image_{dark} = min_{\in\Omega}(min_{c\in\{r,g,b\}} Image_{clear}) \tag{6}$$

The result can occur with less atmospheric particles but this method will use much time processing to calculate transmission map, distort the colour and dependent of model accuracy and image light [17].

For the contrast recovery, the main idea for this methods is to recover the transmission and the surface shading is locally uncorrelated. This approach recover colour and visibility by maximising the contrast level in the image [10], [11], [14], [16].

For the removal of the noise and blur approach, this method use the gauss filtering as a kernel filtering to remove atmospheric particles as a noise. However, this method will make an image loss information and distort colour [52], [53], [54].

According to Tarel and Hautierre (2009) [14], atmospheric particles removal for use in decision making should be a very short processing time and good image quality [61], [62], [63]. So that this study will focus on contrast recovery approach.

This approach is a part of single image to deal with the layer of the contrast level to be removed. This contrast recovery based can be split into two approaches, which are image enhancement and physical model. Fig. 5 refer to this approach.

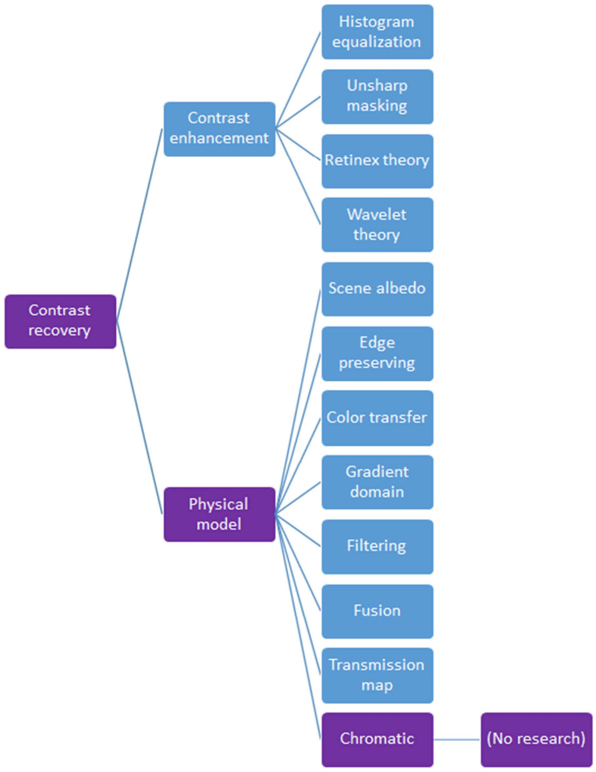

Fig. 5 Contrast recovery class

This approach is algorithm recoveries image based on the workflow that includes a sequence of step such as building image degradation model, estimating image information and improving image quality. For the physical model based on a scattered image model is shown in Fig. 6.

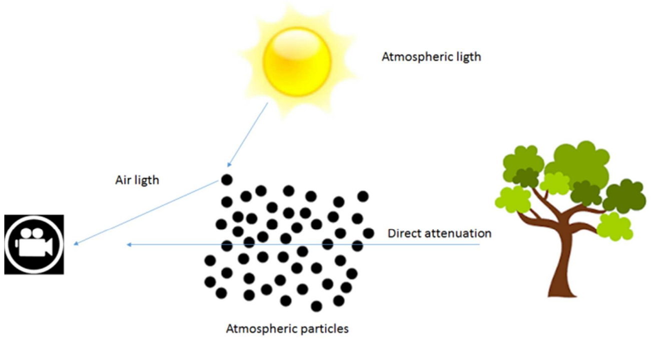

Fig. 6 Scattering atmospheric particles model

The first method is due to the inherent bilinearity between scene albedo and depth as make explicit in this method. As in any other ill-posed computer vision problem encounter, previous work has focused on imposing additional constraints to resolve the ambiguity. In particular, recent work focuses on estimating the scene albedo by significantly constraining their values to maximize contrast or to be decorrelated from depth-induced effects (transmission) within constant albedo regions. In this work, the scene depth is rather a by-product that can be computed once the scene albedo is estimated using a physically based scattering image model. Due to the formulation, this method resulted in over contrast stretched images and inaccurate restoration of the colour or depth. A recent independent work leverages an empirical observation, that within local regions the scene albedo values are very small in at least one colour channel, to constrain the depth variation. The method still suffers from the ambiguity between colour and depth leading to inaccurate restoration [15].

The second method is an edge preserving method that the decomposition model proposed in the previous section. The global atmospheric light is first empirically determined by using a hierarchical searching method based on the quad-tree subdivision. However, this method estimation of atmospheric particles level is not accurate [21].

The third method is based on the digital TV filter with colour transfer (DTVFCT). Inferring the atmosphere veil, we use the digital TV filter to refine the minimal component image for preserving the edges and gradients of images. Adopting the obtained atmospheric veil, the clear image can be recovered by the scattering model. Since the recovered image may cause higher dynamic than the original one, the colour transfer model is applied to atmospheric particles removal image by utilizing combined colour information of the Multiple-Source Retinex with Colour Restoration (MSRCR) resulting image and the original image. However, the speed of processing time is a bit slow and inconstant. In addition, the result of the image after processed is quite dim and dark [8], [22].

The fourth method is based on the fact that the smaller the value of the transmission, the worse the gradient that needs to be multiplied by the larger coefficient to enhance the visibility. The proposed approach makes the following changes to avoid the drawback caused by the compromises in previous approaches. An enhancement function is defined instead of the inverse of the transmission. Then secondly, the approach is processed in the gradient domain. Furthermore, the multi-scale method is used to restore visibility in regions with very small transmission and maintain the contrast in close range regions. However, manipulating the gradient easily turns low-dynamic range image into high dynamic range, which causes the restored image become dark or over exposure. This method uses a simple linear dynamic range compression to avoid problems, but sometimes will slightly blur part of the details. Another drawback is the expensive computation complexity. Moreover, although the results are artefacts free, the colour cast phenomenon cannot be ignored. As this method does not depend on the physical atmospheric particles imaging model, its colour compensation may fail when colour cast appears in the original atmospheric particulate image. The transmission of the sky region is underestimated, so the colour of this region is overcompensated and colour cast is more obvious [23], [24].

The fifth method uses filtering method where the observation that was used as an estimate for veiling contains significant noise and needs refinement. This noise is due to many factors. Although statistically supported natural scenes, the assumption that at least one colour component of a radiant object is zero is not necessarily valid. An example is when a bright coloured paved road appears to be the same colour as the horizon [58], [59], [60]. There is ambiguity in distinguishing the range of the road with respect to the horizon. Another factor that contributes to the noise component is the texture of the scene. Expecting the veiling to be representative of the scene depth, the depth variation in scenes is typically piece-wise smooth and void of any texture components. The texture is not desired and needs to be removed to have an accurate veiling estimation. Otherwise, false colours are introduced when enhancing with histogram equalisation [8], [25], [26], [27], [28], [29], [30].

III. RESULTS AND DISCUSSION

This study used the data set from Fog Road Image Database (FRIDA). The database comes up with two series namely FRIDA and FRIDA2. This database has numerical synthetic images easily usable to evaluate in a systematic way the performance of visibility and contrast restoration algorithms. Fig. 7 is a sample data set that has been used in this study for evaluation. This dataset is widely used among researchers to evaluate their performance with the benchmark data set [14], [18], [31], [32]. Others, the data set from the real images are used to make a comparison to the real cases. Fig. 8 is the sample of images that had been used in this study.

(a)

(b)

(c)

(d)

(e)

Fig. 7 Clear scene (a), Light scattered (b), Moderate scattered (c), Scattered (d), and Heavy scattered (e)

Fig. 8 Sample of an image contain atmospheric particles

Since the human vision has difficulty in evaluating the performance of the variety of results of the atmospheric particles removal method, this study uses several methods to evaluate the performance to indicate contrast to noise ratio and cyclomatic complexity. The rate of the contrast to noise ratio refer to equation (7):

$$C = \frac{|\, S_A - S_B \,|}{\sigma_0} \tag{7}$$

Where S_A and S_B are signal intensities for signal producing structures A and B in the region of interest and σo is the standard deviation of the pure image noise. Contrast-to-noise ratio (CNR) is a measure used to determine image quality. CNR is similar to the metric, signal-to-noise ratio (SNR), but subtracts off a term before taking the ratio. This is important when there is a significant bias in an image, such as from haze. As can be seen in the picture on the right, the intensity is rather high even though the features of the image are washed out by the haze. Thus this image may have a high SNR metric but will have a low CNR metric [33].

For the complexity performance, the use of cyclomatic complexity will measure the level of complexity of the method. Cyclomatic complexity is a software metric (measurement), used to indicate the complexity of a program. It is a quantitative measure of the number of linearly-independent paths through a program. Cyclomatic complexity is computed using the control flow graph of the program, the nodes of the graph correspond to indivisible groups of commands of a program, and a directed edge connects two nodes if the second command might be executed immediately after the first command. Cyclomatic complexity may also be applied to individual functions, modules, methods or classes within a program. The complexity M is defined as equation (8):

$$\mathrm{M} = \mathrm{E} - \mathrm{N} + 2\mathrm{P} \tag{8}$$

Where E is the number of edges of the graph, N is the number of nodes of the graph and P is the number of connected components [34].

TABLE I
COMPARISON OF CONTRAST TO NOISE RATION AND CYCLOMATIC COMPLEXITY AMONG ATMOSPHERIC PARTICLES REMOVAL METHODS

Method	CNSR, C, %	Cyclomatic Complexity, M	Time processing, s
Histogram	48.92	3	8.55
Unsharp masking	32.01	5	1.56
Retinex theory	44.85	9	211.89
Wavelet theory	52.94	4	7.33
Scene albedo	39.65	7	100.23
Edge preserving	34.68	6	20.33
Colour transfer	51.54	3	1.02
Gradient domain	23.86	2	0.88
Filtering	32.56	5	30.45
Fusion	39.34	3	64.95
Transmission map	54.95	5	32.15

Table 1 shows the comparison between atmospheric particles removal methods using contrast to noise ratio and cyclomatic complexity.

There are several methods that are very useful in removing atmospheric particles content in an image. The quite improved image scene vision used the transmission map method but the complexity of processing is high. This is the indication to use the illuminance in chromatic as the estimation of the atmospheric light veil as mentioned by Tarel that the scene is two dimensional while processing with physical model method [14], [18], [31], [32]. The equation (4) is used to estimate the white atmospheric veil using luminance and illuminance [35].

IV. Conclusion

The purpose of this paper is to review the methods regarding the removal of the classification of atmospheric particulate image benchmark. In this paper, various methods of removal of atmospheric particles are classified into three divisions, which are user interactions, multiple images, and single image. In addition, at the top of the image is divided into three categories, namely prior knowledge, the removal of noise and blur, and contrast recovery. In the class of contrast recovery, there are two categories of image enhancement and restoration of the physical model. Several quantitative assessments measure also discussed to estimate the ability of the different methods that are described in this paper. Some of the experiments conducted to show the effects of visualization and efficiency. Exploration of a variety of literature and research project also developed a number of programs to meet some significant of the algorithms. Based on this study on this challenging but capable issue, works about atmospheric particulate image recovery should focus on rapid image segmentation algorithm and process a single image that will be widely used in various fields.

ACKNOWLEDGMENT

This study is a grant and supported by Ministry of Higher Learning Malaysia, National Defence University of Malaysia and the National University of Malaysia.

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