Image Defogging by Multiscale Depth Fusion and Hybrid Scattering Model

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ABSTRACT
The season affecting the imaging of the hill station highly and all other reasons moreover time to time. The fog in image is significantly affecting weather issue. This paper compares the hybrid scattering model and multiscale fusion method. For the single scattering of light dominated pixels the single scattering physics model is used in the hybrid model and for the remaining pixels the multiple scattering physics model (MSPM) is used. The optical thickness is the basic parameter for this pixel identification. The fusion method is as an energy minimization based method that depends on spatial Markov model. The multiscale depth fusion method (ILMRF) embeds the fusion scheme into adaptive Markov regularization to achieve better estimation of depth map. The result of the multiscale fusion is better as compared to the hybrid methodology.

Keywords
Image Fusion, Image Defogging, Scattering model, single image defogging

1. INTRODUCTION
There are lot of factors that affect the indoor image but the outdoor image gets much more affect by the environmental factors. In 2009 Chen et al. [1] employed the very much interesting technique of dark channel prior an iterative algorithm for the adjustment of distorted color in the case of higher saturation. This method deals with the problem as defogging in term of similarity-to-atmospheric-light objects.

In December 2009 Yao et al. [2] developed a method to compute the defogging ratio with edge intensity. The edge halation is restrained by virtual airlight defogging technique using the depth information of neighboring pixel's [2]. It provides the halation restraining in the resultant image. For the real time imaging in 2010, Ji et al. [3] worked for the contiguous frame similarity histogram in video data. The equalization of histogram is improved to enrich the image quality. The algorithm based on median filter is applied to abolish the noise [3]. A fast approach for defogging is developed through a single image scene using a fast bilateral filtering method [4]. It uses a linear function containing various number of image pixels and allows a fast implementation. It provides good restoration for color fidelity and contrast. Yoon et al. [5] provides an adaptive selection of light of undesired cloud or fog in dark channel prior corresponding to the image edges and produce a map through the atmospheric light. It adaptively eliminates fog with the help of projected transmission map and uses the tone mapping with gradient of image. It eliminates the local color distortion problem [5]. Yu et al. [6] presents a method for defogging using a scene based single image of a model based on atmospheric scattering. It used the coarser estimate to refine an edge-preserving tactic. Yoon et al. [7] present a color correction based image defogging process in the HSV color space for video processing. It creates transmission map based image segmentation through multi-level set of intensity (V) values. It basically estimates the atmospheric light of intensity. The reparation of color distortion in successive frames is done using temporal alteration ratio of the HSV color channels. Gibson et al. [8] used the assets of color ellipsoids attached to depth cues in the image. The Gaussian mixture model is used to account for manifold blends that provide the intuition such as observations at depth discontinuity in single image defogging. Zhen et al. [9] combined the bilateral filter and the adaptive median filter for clear dark channel on image edges. The physical model of algorithm for foggy images is to estimate transmission. It provides the reliability for outdoor visual systems in foggy climate [9]. In 2013 Caraffa et al. [10] worked on the MRF model for single image defogging method on road side images using planar constraint [10]. In Sept. 2013, Mutimbu et al. [11] presented a method to improve albedo and the depth in a single image. It uses the atmospheric vision model scattering theory in dehazing and defogging. The relaxed factorial Markov random field (FMRF) of the albedo and the depth layers in image. It leads to construction of the layers in the FMRF. The sparse representation is used for the involvement of graph Hessian and Laplacian. It then implies the global minima for each layer via sparse Cholesky factorisation systems [11]. Veeramani et al. [12] restored the foggy motion-blurred images using the depth cues derived from the fog itself. It elaborates road scene of foggy images that are segmented into road, right, left and sky planes, and all the planes deblurred individually. Wang et al. [13] proposed a multi values depth fusion (MDF) for recovery of fog using local Markov regularization via single foggy image. The fog priors are fused in the inhomogeneous Laplacian IL-MRF adaptively from multiscale filtering. The depth map estimation is a reiterative process with optimization of two variables in adaptive truncated Laplacian (ATL) potential: a base potential variable to regularize smoothness and a line field variable for adaptive control. In 2014 Kawarabuki et al. [14] presented the snowfall estimation from falling snow grains measurement quality that extracted the difference in present defogged image and image background produced by the median. It recognizes the degree of snowfall automatically even in the low visibility by fog. The basic image processing and the application to the image enhancement is studied by more literature [15-27] . In 2015 Zhao et al. [15] removed the fog by Image defogging (IDF) method that influences from the fogs in an image to improve its quality. For the single scattering of light dominated pixels the single scattering physics model is used in the hybrid model and for the remaining pixels the multiple scattering physics model (MSPM) is used. The rest of the paper is organised as follows. The second section provides the methodology on hybrid image defogging algorithm and the Depth fusion based defogging algorithm. The third section shows the result analysis and fourth section covering future scope with in conclusion.

2. HYBRID IMAGE DEFOGGING ALGORITHM

The hybrid algorithm is not the simplified combination of the methods it covers the main beneficial features from different techniques [13]. The Single foggy image, captures in either thin fog or heavy fog weather conditions, contains two types of pixels, i.e. single scattering dominating pixels and multiple scattering dominating pixels. Neither SSPM nor MSPM can simultaneously deal with two types of pixels. To address this issue, a hybrid image defogging method for single image (HIDF) is used. The HIDF combines both SSPM and MSPM together as a whole.

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

The first term is direct attenuation and the second term represents the air light.

$$I(T,\mu) = \sum_{m=0} (g_m(T) + g_{m+1}(T))L_m(\mu) \quad (2)$$

where I denotes the observed image intensity, T = βd represents the radial optical thickness, μ the cosine of inclination from the radial direction, and Lm is m^{th} order Legendre polynomial which explains the angular spread of the brightness. In particular, HIDF applies SSPM (1) for pixels where single scattering dominates; otherwise, HIDF employs MSPM (2). The first problem is how HIDF distinguishes these two types of pixels.

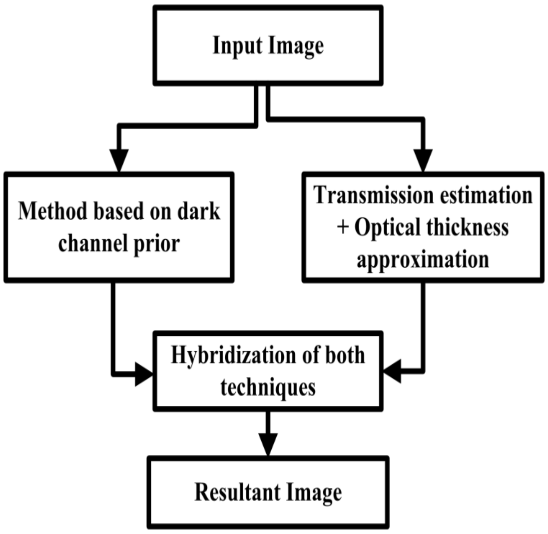

Fig 1 flowchart of the hybrid method

Figure 1 shows the flowchart of the hybrid methodology of the image defogging. Through feature analysis [28] of the two types of pixels, it utilizes the optical thickness of corresponding pixels. If the optical thickness is smaller than one, the threshold which determines whether the single scattering or the multiple scattering dominates, the pixels are dominated by single scattering, and the pixels are multiple scattering dominating otherwise. Based on this fact and according to parts-based methods [29][30][31], HIDF applies SSPM for pixels whose optical thickness is smaller than one, and HIDF utilizes MSPM otherwise.

3. DEPTH FUSION METHOD

Various filtering techniques are used in image processing for the removal of unwanted elements in the images. The selected form of the non-linear and its subordinates in the appropriate intense manner are used for the suitable fusion method [15]. The flowchart of the depth fusion based method is illustrated in figure 2 with a clear flowchart. The inhomogeneous Laplacian-Markov random field (ILMRF) applies the nonlinear filtering is usually applied to obtain a good bound on scene depth at each pixel from the corresponding observed RGB color values, because each pixel contains three measurements, the three channels of the observed foggy image that may contribute to the depth estimation. The nonlinear filtering is a function over I (x) defined as follows:

p(x) = f (I (x)) (3)

where f (·) can be a maximum or minimum operator and p(x) is called a prior map. The nonlinear operator can work on chromatic tristimulus and neighborhood pixels of I (x). [32] adopts a maximum way channel-wise and pixel-wise because the farthest possible depth at each pixel is lower than the foggy intensity:

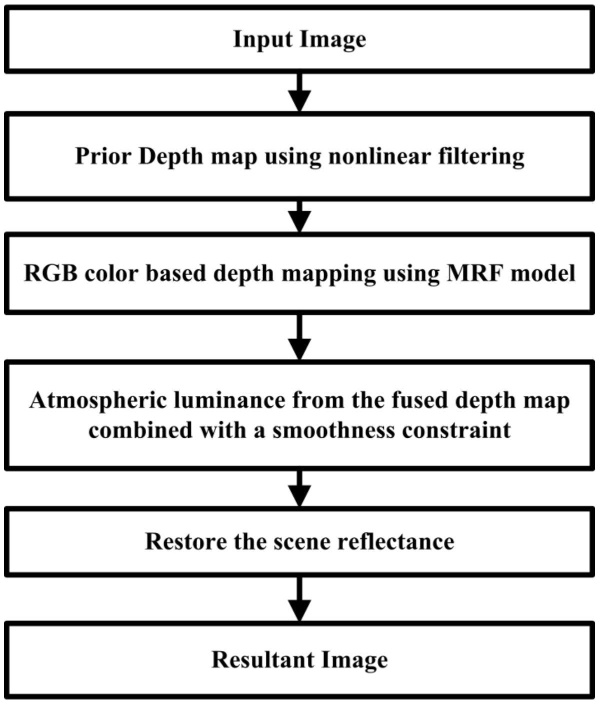

Fig 2 flowchart of the multiscale depth fusion method

D(x) = (1/I0)(I (x) − A(x)) < I (x) − A(x) < I (x) < max c I c(x) = p(x), where c ∈ {R, G, B} denotes color channel. The prior map becomes an upper bound of the depth map. The dark channel observation [33] says that the minimum intensity of an outdoor haze-free image is low and tends to be zero. A minimum operator is employed to obtain the prior map channel-wise and block-wise:

$$p(x) = \min_{c} \min_{x' \varepsilon\, \Omega(x)} I^c(x') > \max_{x' \varepsilon\, \Omega(x)} D(x') \quad (4)$$

3.1 Defog Algorithm

A defog algorithm employing energy minimization to find the fused depth map and then restoring foggy images is presented in this section.

A. Energy Minimization

The introduced ATL potential enables us to compute the regularized depth map $\tilde{D}$ by minimizing the following function:

$$\tilde{D} = \arg\max_{D,b} E(D,b)$$

Where $$E(D,b) = \sum_i \sigma_i^2 (p_i - D)^T (p_i - D) + \lambda \sum_{x\varepsilon S} \{b_H \varphi_H + b_v \varphi_v\} \tag{5}$$

And b is a dummy variable representing both horizontal and vertical line fields. The minimization process has to simultaneously estimate both D and b, which is a very difficult task and computationally demanding. An important characteristic of the edge-preserving regularization is that the computation involves the minimization of nonconvex energy functions, in contrast to the minimization of a quadratic potential function that a simple gradient method can quickly find the minimum [34], [35]. Hence it needs costly optimization methods such as simulated annealing [36], [37] and Markov chain Monte Carlo [38], [39].

3.2 The Algorithm

The MDF method automatically restores a foggy image is summarized as follows. First, it uses an existing nonlinear filtering method to estimate the depth maps with different scales.

(a)

(b)

(c)

Fig 3 defogging result by (a) Foggy Image of garden with house (b) Multiple Hybrid Scattering Model, (c) Multiscale Depth Fusion method

The depth maps obtained this way are not sufficiently accurate to solve the defog problem and are called prior maps. It applies the prior maps to the proposed ILMRF and minimize the energy function (5) by the alternate optimization to get the regularized result that is the major contribution of this paper and is given in the second and third steps of the algorithm. Atmospheric luminance is then computed from the fused depth map combined with a smoothness constraint. Finally the inverse of the atmospheric scattering model is utilized to restore the scene reflectance.

4. RESULT ANALYSIS

The results of the methods are described through the following as in figure 3 and figure 4. The result obtained by the hybrid method has some halo effect around the clear object. This halo effect can be overcome in the depth fusion method. The significance of the depth fusion method is to improve the removal of fog from the highly affected fog region. The objects are showing the very clear effect in the image. The quantitative result analysis is done by using the structure similarity index (SSIM0 and the peak signal to noise ratio (PSNR) in the table 1.

(a)

(b)

(c)

Fig 4 defogging result by (a) Foggy Image of city (b) Multiple Hybrid Scattering Model, (c) Multiscale Depth Fusion method

Table 1 SSIM and PSNR comparison for Multiple Hybrid Scattering Model and Multiscale Depth Fusion method

Method	**Multiple Hybrid Scattering Model**		**Multiscale Depth Fusion method**	
Images	SSIM	PSNR	SSIM	PSNR
House with Garden Image	0.74	18.75	0.82	22.48
City Image	0.72	17.42	0.76	21.57

5. CONCLUSION

This paper compares the hybrid scattering model and multiscale fusion method. For the single scattering of light dominated pixels the single scattering physics model is used in the hybrid model and for the remaining pixels the multiple scattering physics model (MSPM) is used. The optical thickness is the basic parameter for this pixel identification. The fusion method is as an energy minimization based method that depends on spatial Markov model. The multiscale depth fusion method (ILMRF) embeds the fusion scheme into adaptive Markov regularization to achieve better estimation of depth map. The result of the multiscale fusion is better as compared to the hybrid methodology. The future work may be the alternatives of the fusion and the hybridization.

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