WAVELENGTH-ADAPTIVE IMAGE FORMATION MODEL AND GEOMETRIC CLASSIFICATION FOR DEFOGGING UNMANNED AERIAL VEHICLE IMAGES

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ABSTRACT

In this paper, we present an image enhancement algorithm based on the wavelength-adaptive image formation model and geometric classification for defogging UAV images. We first generate a labeled image using geometric class-based segmentation. We then generate a modified transmission map based on the wavelength-adaptive image formation model with scattering coefficients in the labeled image. We also estimate the atmospheric light from the modified transmission map instead of simply choosing the brightest pixel. The proposed method can significantly enhance the visibility of foggy UAV images compared with existing monochrome model-based defogging method. The proposed algorithm can enhance the visibility by removing atmospheric degradation factor in airborne images acquired by aerial platforms such as satellite, airplane, and UAV under critical weather conditions such as haze, fog, and smoke.

***Index Terms*—** Image enhancement, image defogging, unmanned aerial vehicle

1. INTRODUCTION

Image enhancement algorithms are designed to improve human visual perception and interpretation of images by removing various types of image degradation. In this paper we address the problem of removing atmospheric degradation, such as fog, smoke, which degrade the quality of an image capture by an unmanned aerial vehicle (UAV). It is well-known that it is hard to identify the original color and visibility when the image is corrupted by atmospheric these degradations.

Various methods have been a growing interest in the analysis of single image for removing for or defogging. To the best of our knowledge, Fattal [1] has first developed a single-image defogging method, which uses a local window-based operation and a graphical model. However, it attempts to separate uncorrelated fields, namely, the object shading and the particle attenuation. He [2] observed that most local regions of a fog-free image have a set of pixels with very low intensity, and used the dark channel prior to remove fog. Kratz [3] used factorial Markov random field to model the haze image, takes scene albedo and depth as two statistically independent components, and removes the haze by factorizing the image into scene albedo and depth. In spite of the implementational simplicity, the existing single image-based defogging methods are prone to halo effect and color distortion problem.

Ji [4] has combined the histogram equalization algorithm with a median filter, and enhanced both contrast and noise implemented in the FPGA level. It is difficult to restore the original color of the object. Xie [5] used the dark channel prior to estimate the atmospheric light, and then calculates a universal transmission map of the intensity component in the background image using a series of multiscale retinex, parameter adjustment, bilateral filtering, and total variation denoising filtering. This algorithm can generate real-time and has good defogging performance at the cost of blurring effects in some edges in the processed image because of degraded the quality of the transmission map.

In order to solve the above mentioned problems, we present a single UAV image-based defogging algorithm. The proposed algorithm first generates a labeled image using the geometric classes-based segmentation method. The modified transmission map is then generated using the wavelength-adaptive image formation model with scattering coefficients in the labeled image. The atmospheric light is estimated in the modified transmission map. Based on the estimated the atmospheric light and the modified transmission map, foggy component is removed in the spatially adaptive manner. Consequently, the proposed defogging method can significantly increase the visual quality of an atmospherically degraded image in the sense of preserving color and sharp details.

2. THEORETICAL BACKGROUND

In most practical images the light reflected from a surface is scattered by various atmospheric particles before it reaches the camera. Therefore, the original color of an object is changed according to the property of atmospheric particles and varying degrees of light attenuation for different wavelengths. Fig. 1 shows the image degradation model for foggy images acquired by an UAV platform.

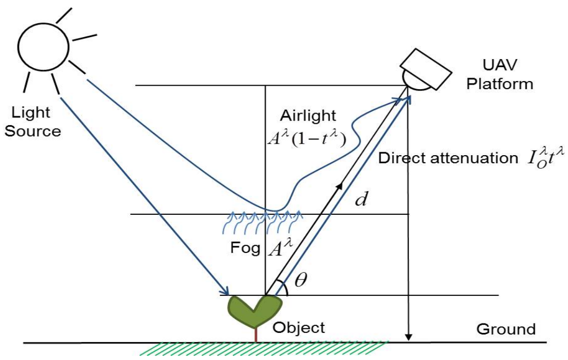


Fig. 1. The proposed wavelength-adaptive image formation model for foggy images acquired by an UAV platform.

The mathematical expression of the image degradation model in RGB wavelengths is given as

$$I_F^{\lambda}(x,y) = I_O^{\lambda}(x,y)t^{\lambda}(x,y) + A^{\lambda}(1 - t^{\lambda}(x,y)), \quad \text{for } \lambda \in \{\text{red, green, blue}\}, \tag{1}$$

where $I_F^{\lambda}(x,y)$ represents the foggy image acquired by the UAV platform in the color of wavelength $\lambda \in \{\text{red, green, blue}\}$, $I_O^{\lambda}(x,y)$ the original fog-free image, A^{λ} the global atmospheric light, and $t^{\lambda}(x,y)$ the transmission map. The first term $I_O^{\lambda}(x,y)t^{\lambda}(x,y)$ is called direct attenuation, and the second term $A^{\lambda}(1 - t^{\lambda}(x,y))$ is called airlight. The direct attenuation term describes the decayed version of $I_O^{\lambda}(x,y)$ in the medium or space, while the airlight term results from scattering by fog and color shifts. Therefore the goal of the defogging algorithm is to recover $I_F^{\lambda}(x,y)$, A^{λ}, and $t^{\lambda}(x,y)$, given $I_O^{\lambda}(x,y)$. Also, we can estimate direct attenuation and airlight uisng atmospheric light A^{λ} and transmission map $t^{\lambda}(x,y)$. Equation (1) is a wavelengths-extended version of the original foggy image formation model proposed in [2].

3. THE PROPOSED SINGLE IMAGE-BASED DEFOGGING APPROACH

The proposed algorithm consists of image segmentation and labeling, modified transmission map generation, atmospheric light estimation, and image defogging, as shown in Fig. 2.

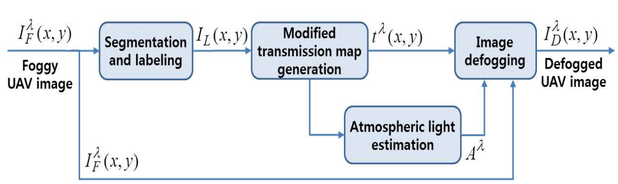
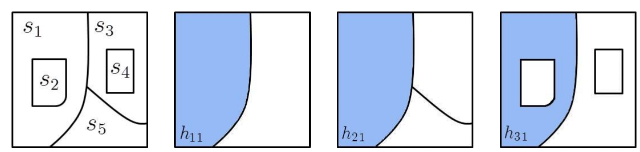


Fig. 2. The proposed single image-based defogging algorithm for enhancing UAV images.

3.1. Image Segmentation based on Geometric Classes

Existing methods for estimating atmospheric light and transmission map exhibit various undesired artifacts, such as color distortion, incompletely removed fog, and unnatural contrast enhancement, to name a few. In order to overcome the above mentioned limitations in existing methods, we pre-segment the foggy UAV image for three-dimensional (3D) context-adaptive processing. The proposed segmentation method has been inspired by the geometric context estimation method proposed in [7, 8], which proved that the coarse geometric properties can be estimated by learning appearance-based models of geometric classes. Although Hoiem et al. defined a complete set of geometrical classes for segmenting a general scene in their original works, we present a modified version by selecting only three classes, {sky, vertical, ground} for efficiently representing the UAV images. In order to explain the concept of the proposed segmentation method, we use a simple example as shown in Fig. 3.



(a) 5 superpixels (b) 1^{st} segment (c) 2^{nd} segment (d) 3^{rd} segment

Fig. 3. An example of the proposed labeling method for $i = 1$; (a) five superpixels of an input image and (b-d) three multiple segmentation results, where $h_{j1,\ j=1,2,3}$, represents the region containing superpixel s_1 for the j^{th} hypothesis.

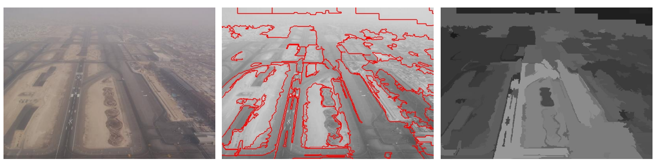
Fig. 3(a) shows that the input image is divided by five superpixels, $s_{i,\ i=1,....,5}$. In order to assign one of three labels $v \in \{(S)ky, (V)ertical, (G)round\}$ to each s_i, we perform three segmentations using different hypotheses as shown in Figs. 3(b-d), where h_{ji} represents the region containing s_i for the j^{th} hypothesis or in the j^{th} segmentation result. Let b_i and $\tilde{b}_{ji} \in \{S, V, G\}$ respectively represent labels of s_i and h_{ji}, then the most suitable label for the i^{th} superpixel is determined by maximizing the confidence value defined as

$$C(b_i = v|I_F) = \sum_{j=1}^{N_h=3} P(h_{ji}|I_F)P(\tilde{b}_{ji} = v|h_{ji}, I_F), \tag{2}$$

where h_{ji} represents the region containing the i^{th} superpixel s_i for the j^{th} hypothesis, and N_h the number of multiple hypotheses. $P(h_{ji}|I_F)$ represents the homogeneity likelihood, and $P(\tilde{b}_{ji} = v|h_{ji}, I_F)$ the label likelihood.

The first step in generating the labeled image is to estimate super-pixels from small, nearly-uniform regions in the image. More specifically, the proposed method starts from a single-pixel region, and keeps merging two adjacent regions if the minimum intensity difference across the boundary is greater than the maximum difference within the regions, possibly with a bias toward larger regions. The next step compute multiple segmentations based on simple features (e.g. color, texture, and shape). We generate multiple segmentations of the normalized foggy image, with different numbers n_s of regions. We determine the most suitable class to each region using the estimated probability that all super-pixels have the same label, which is the confidence in each geometric class.

Fig. 4(a) show an original foggy UAV image. The last step is classifier-based segmentation that groups each segment into larger continuous segments as shown in Fig. 4(b). We can estimate labeled image $I_L(x, y)$ using the same segment samples of the image as shown in Fig. 4(c).



(a) (b) (c)

Fig. 4. (a) A foggy UAV image, (b) the segmentation result, and (c) the labeled image of (b).

3.2. Adaptive Generation of Modified Transmission Map

We note that existing transmission maps exhibit a halo effect and color distortion since the intensity discontinuity across edges is not considered in the reconstruction process. To solve this problem, we generate a modified transmission map using the wavelength-adaptive image formation model with scattering coefficient and the proposed context-adaptive segmentation method described in the previous section.

The amount of transmission through the air depends on the depth $d(x, y)$ between the object and the UAV platform. Atmospheric scattering also depends on the wavelengths $\lambda \in \{\text{red}, \text{green}, \text{blue}\}$ and angle θ between the object and the UAV platform as shown in Fig. 1. The modified transmission map has been described as an exponential term

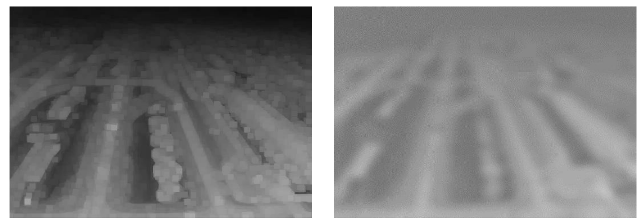
$$t_\lambda(x, y) = e^{-\beta\lambda^{-\alpha d(x,y)}},\ for\ \lambda \in \{red,\ green,\ blue\}, \quad (3)$$

where β represents the scattering coefficient of the atmosphere, λ the wavelength in red ($700\mu m$), green ($520\mu m$), and blue ($440\mu m$), $d(x, y)$ the depth, and α the wavelength exponent. Because the foggy image is segmented using the three classes of sky, vertical, and ground, we are able to assume that the segmented information includes the depth of the image. Consequentially, the is blurred labeled image using guided filter [9] and $\alpha = 1.3$.

The scattering coefficient is the integral of angular scattering coefficient in all directions, for example $\beta = \int \beta(\theta)dw$. However, UAV platform keep the 60 to 80 degrees of the angle θ between object and UAV platform. Therefore, scattering coefficients is defined as follows [10]

$$\beta = \begin{cases} 0.3324 & \text{if}\ \ \lambda = 700\mu\text{m(red)},\ \ \theta = 70^\circ \\ 0.3433 & \text{if}\ \ \lambda = 520\mu\text{m(green)},\ \ \theta = 70^\circ \\ 0.3502 & \text{if}\ \ \lambda = 440\mu\text{m(blue)},\ \ \theta = 70^\circ. \end{cases} \quad (4)$$

Fig. 5(a) and 5(b) respectively show an existing and the proposed modified transmission maps.



(a) (b)

Fig. 5. (a) The existing transmission map and (b) the modified transmission map using proposed method.

3.3. Estimation of Atmospheric Light and Image Defogging

Conventional defogging methods estimate the atmospheric light from the brightest pixel in the foggy UAV image. To the best of our knowledge He [2] was the first to raise the issue of color distortion that occurs when the atmospheric light is incorrectly estimated from an undesired region such as a white car or a white building.

To address this problem we estimate the atmospheric light A^λ from the high intensity value in the transmission map $t^\lambda(x, y)$. This procedure can mitigate the contrast distortion problem occurring in other methods.

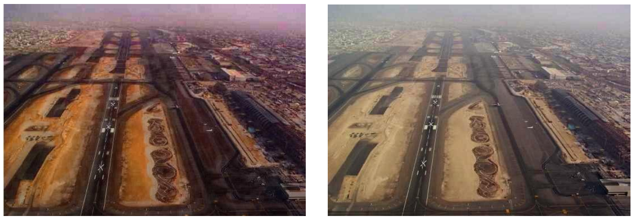
Given the adaptive atmospheric light A^λ and the modified transmission map $t^\lambda(x, y)$, the defogging image can be recovered as

$$I_D^\lambda(x, y) = \frac{I_F^\lambda(x, y) - A^\lambda}{t^\lambda(x, y)} + A^\lambda. \quad (5)$$

Fig. 6(a) and 6(b) show defogged UAV images using the existing transmission map in Fig. 5(a) and the modified transmission map in Fig. 5(b), respectively. As shown in Fig. 6, the defogged image using the proposed method shows significantly improved image quality without color distortion or unnaturally amplified contrast.

4. EXPERIMENTAL RESULTS

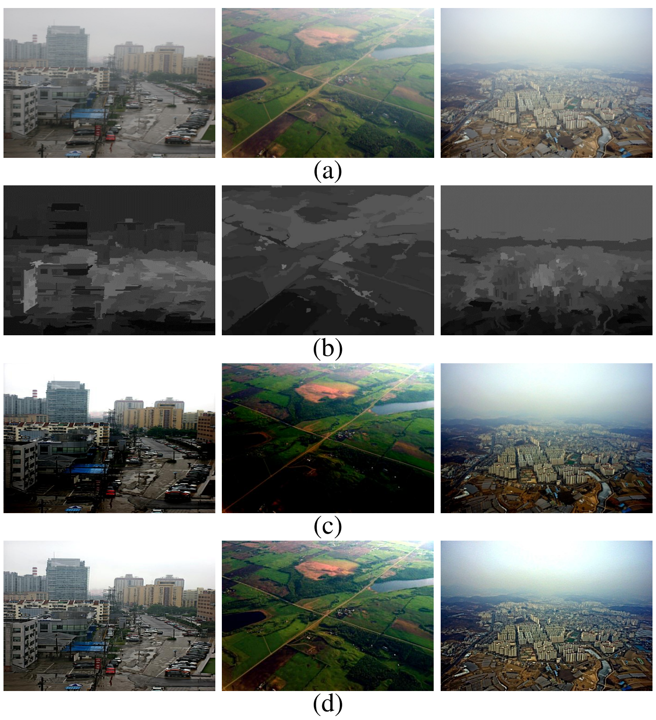
In this section, we demonstrate the performance of the proposed algorithm for enhancing various foggy UAV images. Fig. 7(a) shows three foggy UAV images, and Fig. 7(b) shows the labeled images using the proposed geometric classification method. Fig. 7(c) shows the defogged images using the



(a) (b)

Fig. 6. Results of the proposed method; (a) the defogged image using the existing transmission map in Fig. 5(a) and (b) the defogged image using the proposed modified transmission map in Fig. 5(b).

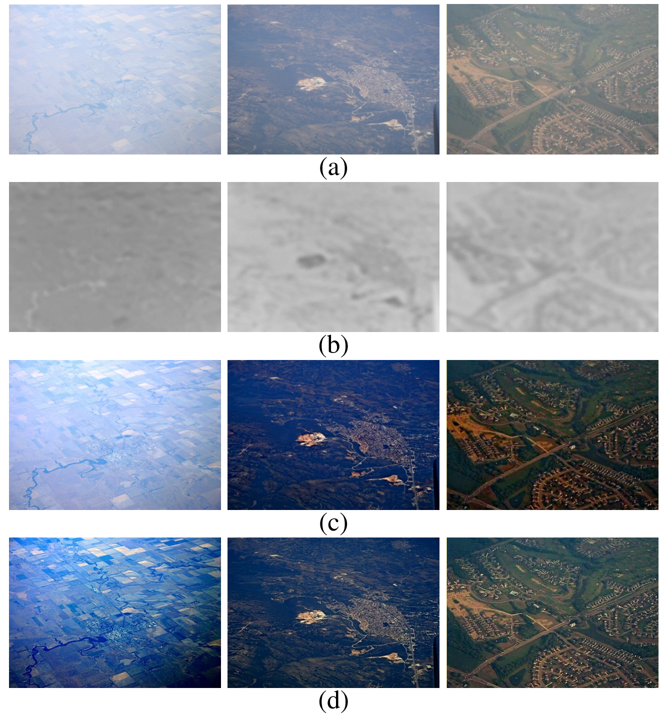
existing method proposed in [4], and Fig. 7(d) shows the defogged images using the proposed method.



(a) (b) (c) (d)

Fig. 7. Experimental results of various defogging method; (a) an input foggy UAV images, (b) the modified transmission map, (c) the defogged image by using the existing method in [4], and (d) the defogged image by using the proposed method.

Based on the experimental results, the proposed defogging method significantly outperforms existing method in the sense of both contrast recovery and color preservation. Fig. 8(a) shows another set of three foggy UAV images, and Fig. 8(b) shows the modified transmission maps generated by the proposed method. Fig. 8(c) shows the defogged images using the existing method proposed in [6], and Fig. 8(d) shows the defogged images using the proposed method.



(a) (b) (c) (d)

Fig. 8. Experimental results of another set of three foggy UAV images; (a) input foggy UAV images, (b) the modified transmission maps, (c) the defogged image by using the existing method in [6], and (d) the defogged images using the proposed method.

5. CONCLUSION

In this paper, we proposed an image defogging algorithm for enhancing the color and visibility in foggy UAV images. The proposed algorithm generates a labeled image using a simplified version of geometric context-adaptive segmentation. We then compute a modified transmission map using the wavelength-adaptive image formation model with scattering coefficients in the labeled image. We also estimated the atmospheric light from the modified transmission map. The defogged image is reconstructed by using the atmospheric light and the modified transmission map. Experimental results demonstrated that the proposed algorithm outperforms the existing algorithm in the sense of preserving the original color and visual contrast.

6. ACKNOWLEDGE

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