A NEW FAST METHOD FOR FOGGY IMAGE ENHANCEMENT

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***Abstract*— Images captured in bad weather condition suffer from the adverse effects of atmosphere. In these conditions the light going through the atmosphere is dimmed, which results in the decrease in the quality of the images. Although the traditional methods address the problem of poor visibility, they can not reach to an acceptable result in terms of quality and complexity. In this paper, a new method is proposed in order to enhance the contrast in foggy images. The proposed method developes an image atmospheric model which is based on the Koschmieder's theory of the atmospheric vision. Morphological operators is used to achieve an outline of strength of the fog in the different areas. Quantitative analysis and qualitative judgment illustrate that the proposed method has reached to the same or even better results than other ones. In addition, low complexity gives us the opportunity to use it in real-time applications.**

Keywords— Fog removal, image enhancement, defogging algorithm

I. INTRODUCTION

Nowadays, Computer Vision technology plays a very significant role in modern life in most countries. The performance and reliability of the Computer Vision devices are directly affected by the quality of the images which can be influenced by a number of different factors. Fog is a factor which can considerably decrease the resolution of the images. As a result, removing the fog from images can be perceived as one of the most important topics in image restoration.

Many methods have been proposed in an attempt to remove the fog from images. These methods can be divided into two main categories. The first type of approaches uses multiple images captured by a camera of a foggy scene in order to remove the fog from the images [3,9,10,11]. Despite the fact that these methods can effectively remove the fog from images, they are not widely used in practical applications. It is mainly because the speed of these algorithms are constrained by the rate of changes happening in the atmosphere. In [9] the foggy images of a scene were explained by a physical model. Variation in intensities of the scene under different weather conditions imposes serious constraints on the detection of discontinuities in depth.

The second type of approaches [1,4,7,12] uses a single image as the only source of information. The procedures of second type algorithms are sometimes significantly different from one another. In [4] the hazy image was broken down into many regions with the assumption that each region has a constant reflectance. Each region was expressed in terms of shading and transmission which are locally uncorrelated. The performance of this method is greatly affected by the statistics of the input data such as the color information and the significance variation. Moreover, heavy haze can significantly decrease the performance of the algorithm which is mainly because most of the fundamental assumptions are violated in this situation.

Another method was introduced in [1] which tried to calculate the depth map and the air light constant. The proposed algorithm estimated the air light in the first step by searching the regions with the highest value of intensity. Then a robust optimization framework was introduced based on graphical Markov Random Field (MRF) to estimate the depth. When the intensity of air light was close to that of the objects in the scene, the reliability of the estimation of depth would reduce.

He [6] introduced an algorithm by using Dark Channel Prior. It is based on the idea that the thickness of haze can be estimated using a kind of statistics called Dark Channel Prior. Dark pixels are the pixels which have a very low intensity in at least one color channel (RGB). The transmission map can be created using these dark pixels. Then, the high quality fog-free image can be recovered by using the model proposed in this paper.

Tarel [12] used a modification of a common physical model. The issue of depth estimation is not considered in this model which can lead to decreasing the complexity of the proposed algorithm. However, too many parameters should be adjusted which can lead to the limited application of this method. In [2], two versions of the original image were used as the inputs weighted by specific maps. Three weight maps (luminance, chromatic and saliency) were used as weighting components. The basic idea in this fusion-based method was to combine these input images into a single one. The proposed method is very fast and easy to implement. As a consequence, it can be widely used in real-time applications.

The basic assumption of the proposed algorithm in [8] was that each image is created by reference and characteristic intensity levels. The first one shows the background intensity level and can be calculated by applying a lowpass filter while the other one can be obtained by subtracting the reference intensity level from the original intensity level. To summarize, the proposed method can be expressed in three major steps. At first, reference intensity level should be obtained by applying lowpass filter. Secondly, target intensity model should be obtained by using a logarithmic function. Finally, the turbid image is degraded by using a proposed transformation. In [13] a method was proposed for defogging which was mainly based on Dark Channel Prior. One transmission map is generated based on a single point pixel and another one is generated based on patches. The atmospheric veil will be created by using the fusion of these maps. The main advantage of this algorithm is that it is fast which is due to its simplicity. The complexity of the algorithm can be expressed as a linear function of the number of pixels of the input image.

A new defogging method is introduced in this paper which is mainly based on a modified version of Koschmieder's model. In our method, a rough estimation of atmospheric veil is calculated using Dark Channel Prior in the first place. Then, an exponential transformation is applied on the estimation of atmospheric veil. This transformation improves the accuracy of the estimation because we assume that variations in the luminance of light can be expressed as an exponential function of depth. Finally, a fog-free image can be recovered using the proposed model. Achieving a high quality fog-free image in a short time can be regarded as the main advantage of the proposed algorithm. One can evaluate the usefulness of the present paper by observing the quality and quantity of the performance of this method.

The organization of the rest of this paper is as follows. The proposed method is described in three subsections which are introduced in the section 2. The results of the proposed method and many other algorithms are shown in the section 3. Finally, section 4 presents the conclusions of our analyses regarding the performance of the proposed method.

II. Proposed Method

A. Atmospheric model

In order to address the problem of poor visibility in foggy images, modeling the atmospheric effects of fog can be considered as the first step. To serve this purpose, the observed image should be expressed in terms of the atmospheric light and fog-free image. The most common model of gray level foggy image was developed by Koschmieder as the following equation [5]:

$$L(x,y) = L_0(x,y)e^{-\beta d(x,y)} + L_\infty\left(1 - e^{-\beta d(x,y)}\right) \qquad (1)$$

Where $L(x,y)$ is the luminance of observed image, $L_0(x,y)$ is the luminance of fog-free image and L_∞ is defined as the luminance of the atmospheric light. In addition, β is the atmospheric extinction coefficient and $d(x,y)$is the distance between the observer and the surface.

The main goal of all defogging methods is to extract the value of luminance of the fog-free image from luminance of the observed image. The accuracy of the estimation of fog-free images is significantly dependent on the accuracy of depth estimation. Depth-Map determines the distance between each pixel of the image and the observer. Therefore, by holding some assumptions on the atmospheric light, the luminance of the fog-free image can be estimated through Equation (1). Since the necessary computation for obtaining depth-map can enormously increase the complexity of the methods, another model is presented in [12], with the assumption that no information is available about the depth of pixels. This model can be obtained by substituting $L_\infty\left(1 - e^{-\beta d(x,y)}\right)$ by the atmospheric veil term $V(x,y)$ in the Equation (1). Hence the modified model can be expressed as follows:

$$L(x,y) = L_0(x,y)\left(1 - \frac{V(x,y)}{L_\infty}\right) + V(x,y) \qquad (2)$$

Since both terms in the right side of Equation (2) are positive, it can be concluded that the value of all pixels in $V(x,y)$ are less than the corresponding pixels in $L(x, y)$. Moreover, the value of $V(x, y)$ is less than L_∞ for all points of the image surface. Separating the observed image into these terms and calculating the value of L_0 for each pixel can be perceived as the main goal of any proposed algorithm.

The modified version of the defined model in Equation (2) is used in this paper which has been shown in Equation (3). As can be seen from this model, the effect of atmospheric veil is controlled by two main parameters. Since the information about depth is not available, the estimation of $V(x,y)$ will not be accurate enough. So, it is more logical to consider a scale of this term in the model as the effect of the atmospheric veil. The parameter α_1 is used as the scale of $V(x,y)$. The value of this factor should be considered to be 1, if the atmospheric veil is accurately estimated based on the information of depth. However, this factor is assumed to be a free parameter in this model and should be considered to have a value between 0 and 1. The main imposed constraint on α_2 is that the value of the first term in Equation (3) should be positive. Since the intensities of some pixels of atmospheric light are nearly 1, the maximum bound for α_2 can be considered as equal to1. Therefore, the value of α_2 should also be considered something between 0 and 1.

$$L(x,y) = L_0(x,y)(1 - \alpha_1 V(x,y)) + \alpha_2 V(x,y) \qquad (3)$$

In order to obtain an equation for calculating the value of pixels in fog-free images, Equation (3) can be rewritten as:

$$L_0(x,y) = \frac{L(x,y) - \alpha_1 V(x,y)}{1 - \alpha_2 V(x,y)} \qquad (4)$$

Equation (4) is defined only for gray level images. In order to extend the proposed model for RGB images, it should be separately applied on each component of the RGB images.

As it was previously mentioned, the proposed model does not include any information about the depth. As a consequence, estimating the value of $V(x,\ y)$ can be sufficient in order to obtain an estimation of the fog-free image. The next section mainly discusses the method for estimating the atmospheric veil.

B. Rough estimation of atmospheric veil

A rough estimation of the atmospheric veil can be made via [6], which is very simple and effective. The basic assumption of this method is that there is at least one color channel with very low level of intensity in most of the non-sky patches. Based on this assumption, a rough estimation of the atmospheric veil can be made through:

$$\hat{V}(x,y) = \min_{c\in(RGB)}\left(\min_{(x_0,y_0)\in\varphi(x,y)} L^c(x_0,y_0)\right) \tag{5}$$

Where L^c is a color channel of L and $\varphi(x,y)$ is defined as a local neighborhood centered at (x,y). Equation (5) shows an initial estimation of the atmospheric veil in one of the components of the RGB images. Since the pixels of the atmospheric veil are white, the R, G and B components of the fog layer are nearly the same. Therefore, the result of Equation (5) can be used for each of the components of the observed image. Based on Equation (5), the estimation of the atmospheric veil contains some block artifacts which can contribute to the halos effect in the recovered image. These blocks add some high-frequency components to the $\hat{V}(x,y)$. In order to remove these components, a lowpass filter can be applied on the $\hat{V}(x,y)$. This filter can be regarded as a weighted average method of the neighbor pixels. Gaussian filter can be used as the lowpass filter in the proposed method. Since the fog layer does not have clear edges in the real image, this process does not have negative effects on the quality of the initial estimation.

In order to improve the quality of the estimation process, a nonlinear transformation can be applied on the $\hat{V}(x,y)$. This transformation should be able to decrease the values of atmospheric veil which are less than a defined threshold level. Because most of the time the whole image is not degraded by the fog, the intensity of fog-free regions should not change during the reconstruction process. In order to apply this transformation, a nonlinear transformation is used in this paper. This transformation is mainly based on the exponential function which is related to the intrinsic of the fog properties. This transformation is defined as:

$$\hat{V}(x,y) = \begin{cases} e^{(\hat{V}(x,y)-Threshold)}\hat{V}(x,y) & \hat{V}(x,y) \le Threshold \\ \hat{V}(x,y) & otherwise \end{cases} \tag{6}$$

The $Threshold$ level should be determined based on the distribution manner of the fog. It should get a value between 0 and 1.

C. Fog-Free image extraction

As we have shown, the atmospheric veil was estimated in subsection 2.2. In this subsection, a fog-free image can be obtained by using the defined model in Equation (4). According to the previous subsection, Aside from α_1, α_2 the proposed $Threshold$ in subsection 2.2. has a great effect on the brightness of the reconstructed image. Since some regions of the image have not been degraded by the fog layer, this should be considered in the estimation of fog layer. The $Threshold$ parameter which is introduced in the Equation (5) can decrease the amount of values of $V(x,y)$ in the fog-free regions. The main role of this parameter is to hold the values of fog-free regions of images constant during the reconstruction process.

Based on the previous discussions, it can be concluded that the performance of the proposed method is greatly dependent on its parameters such as parameters α_1, α_2 and $Threshold$. The accurate value of these parameters depends on a number of factors, particularly the amount of the fog in the image. As a result, these parameters play a very significant role in the defogging procedure. Finally, the fog-free image can easily be reconstructed through the proposed model in Equation (4). The value of each pixel in the reconstructed image can be calculated by this model. The results of the proposed algorithm are presented in the following section. Moreover, a broad discussion of the results is provided in the next section.

III. Experimental Results

In order to evaluate the performance of the proposed method, we have applied it on a wide range of outdoor foggy images. Some of these images were selected based on their difference in terms of the thickness of the layer of fog. To demonstrate the effectiveness of the proposed method, it was compared to several other algorithms. The results of three foggy images, named City01, Jungle and City02, reconstructed using these algorithms are shown in the figure1. These images can be evaluated in terms of both quantity and quality.

Quality comparison was drawn by comparing visually the resulting images. The brightness of fog-free regions of the foggy images should not significantly change by the defogging algorithms. This can be evaluated by comparing the changes in the color of fog-free regions in the first and third rows of Figure 1. The color of these regions has been considerably changed in the reconstructed images obtained by using [8] and [12]. As it can be seen from the images in the Figure 1, it may conclude that the fog layer has been removed by these methods, but it should be considered that the color of some regions has been significantly changed by using the algorithms. These images can be also visually evaluated by comparing the amount of detail information they have. Since the detail information exists in the edges and corner of images, an effective method should be able to recover the edges more efficiently. The simulation results show the robustness of our proposed method in recovering the details and edges in comparison to the other methods.

Since the original fog-free images are not available, quantity comparison cannot be performed by traditional indicators. We use two parameters in order to evaluate the performance of different algorithms. The indicator e calculates the ratio of visible edges which have been added after the reconstruction process. This indicates the amount of the new visible edges which have been reconstructed by each algorithm. The indicator Σ calculates the ratio of pixels which have become saturated (completely white or black) in the restoration process. The indicators e is related to the extra information which has been obtained from the reconstructed image. Also, the indicator Σ is related to the changes in intensities of pixels through the restoration process. The values of the mentioned indicators for the images of Figure 1 are shown in the Tables 1, 2.

IV. Conclusion

A new method has been introduced in this paper to remove the fog from the images. This method is mainly based on a new version of Koschmieder's model of atmospheric light. In the first step of this algorithm, an estimation of the atmospheric veil is calculated without considering any information about the depth of pixels. Some regions of the image have not degraded by the fog. So, it should consider a small value for the atmospheric veil in these regions. To serve this purpose, a weighted function is applied on this estimation which can greatly decrease the intensity of this layer in the fog-free regions of image. Finally, the fog-free image can be obtained using the proposed version of Koschmieder's model. In addition, a new indicator is proposed to increase the level of accuracy in our evaluations. The complexity of the proposed method can be expressed as a linear function of the number of input pixels. It can make this algorithm more suitable for real-time applications as our experimental results showed.

Table 1. Indicator e for test images defogged by different methods

e	Tarel	Liao	Our Method
City01	0.0053	0.1345	0.1890
Jungle	0.0971	0.1403	0.1128
City02	0.2056	0.0233	0.0961

Table 2. Indicator Σ for test images defogged by different methods

Σ	Tarel	Liao	Our Method
City01	0.0016	0.0001	0.0011
Jungle	0.0062	0.0173	0.0055
City02	0.0028	0.0172	0.0122

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Figure 1. From left to right: the original image, the enhanced image by Tarel [5], Liao [8] and our method.

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