ADVANCED IMAGE HAZE REMOVAL USING DENOISING AND DEHAZING ALGORITHM WITH COMPRESSION

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ABSTRACT:

Single image haze removal has been a demanding problem due to its ill-posed nature. Images captured in hazy weather environment often suffer from poor illumination conditions that will create a lot of impact on the outer Computer vision systems, such as video surveillance, intelligent traffic assistance system, remote sensing and space cameras soon. In proposed system, two methods for removing both haze and noise from a single image is used. The first approach is to de noise the image prior to de hazing. This serial approach essentially treats haze and noise separately, and so a second approach is proposed to simultaneously de noise and de haze using an iterative, adaptive, non-parametric regression method. Our findings show that when the noise level is precisely known a priori, simply de noising prior to de hazing performs well. When the noise level is not given, underlying errors from either low level denoising or high noising can be intensified, and in this situation, the repetitious approach can yield superior results.

KEYWORDS – Wiener filter, Denoising, Depth restoration Dehazing, Scene radiance recovery,

1. Introduction

Made outdoor shooting in bad weather usually lose contrast and infidelity, of the fact that light resulting absorbed through the turbid medium and scattered as particles and water droplets in the atmosphere during the process of propagation. And there are many automated systems, the strongly on the definition of the input images, fail, usually caused by the deteriorated images. Therefore, improving the technology of image haze removal will fit many image understanding and computer vision applications such as aerial photographs, image classification image / video retrieval, remote sensing and video analysis and recognition animals. Since concentration is the mist be seen from place to place and it is difficult, in a hazy image, the image dehazing is therefore a challenging
task. Early researchers use the traditional techniques of image processing to remove the haze of a single image. However, dehazing effect is limited because only a hazy picture hardly much information. Later, researchers are trying with multiple images to improve dehazing performance. Polarization for dehazing with multiple images with different degrees of polarization, based methods. In this paper we propose a new color damping front for frame dehazing. This simple and powerful front can help to create a linear model for the scene depth of blurred image. By learning the parameters of the linear model with a supervised learning method, the bridge between the blurred image and the corresponding depth map will be built effectively. With the obtained depth information, we can easily remove the haze from a hazy image.

Significant advances in the single image haze removal has been made in recent years. Tan 10 made the observation that a fog-free image has higher contrast than a hazy image, and was able to get good results by maximizing the contrast in local regions of the input image. However, the final results obtained by this method are not on a physical model and are often unnatural search due to supersaturation. Fattal 11 was capable of good results on the assumption that transmission and surface shading to obtain locally uncorrelated. This assumption, he receives the transmission map by independent component analysis. This is a physically sensible approach, but this method has problems with very hazy regions where the different components are difficult to solve. Finally, by He et al simple but powerful approach. 4 used dark pixels in the local window to get a rough estimate of the transmission map, followed by a refinement step using a screen mat technology. Their method obtains results on a par with or exceeding other state-of-the-art algorithms and is even more successful with very hazy scenes. Even if the turbidity level is known, noise may be a big problem in restoring hazy images. Largely avoid the above work the problem, usually by adopting a noise-free image or dehazing images to a point where noise is negligible. Noise Reduction before dehazing and noise reduction during dehazing: existing literature that has addressed noise, has taken two basic approaches. Recently Joshi and Cohen 1 has the first approach, addressing noise with image fusion. By multiple images of the same scene and cloudy with weighted averaging, they receive a sharp, low-noise gloomy picture she then dehaze using a variation of the dark channel approach. Schechner and Averbuch 2 use a polarization-based method to estimate turbidity, and the address of noise by adding a local detention term proportional to the transfer value as regularization in
scene radiance recreation. Since the regularization is relatively simple, cloudy regions are substantially blurred, while non-turbid areas sharp left. A more sophisticated variant on this theme is proposed by Kaftory and Schechner, who uses a total variation methods based on Beltrami flow for regularization. Although effective, the use of complicated PDE method, requires the minimization of the entire image, is a great disadvantage. In addition, each of the said work was based on multiple images. This article deals with the problem of recovering the underlying scene radiance of a single noisy hazy image, with the most significant contributions as follows. First, prior to an investigation into the effect of noise on the estimate haze with dark channel. Continue beating and compare two different methods of scene radiance recovery once a haze estimate we obtained is. The first method is to be suppressed the image with a state-of-the-art noise reduction algorithm before dehazing, which can be interpreted as a single image adjustment Joshi and Cohen. The second method is to simultaneously and dehaze and denoise using an approach that nonparametric iterative regression.

2. RELATED WORK
2.1 Bilateral Filtering for Gray and Color Images
In this paper, we propose a noniterative scheme for edge preserving smoothing that is noniterative and simple. Although we claims no correlation with neurophysiological observations, we point out that our scheme could be implemented by a single layer of neuron-like devices that perform their operation once per image. Furthermore, our scheme allows explicit enforcement of any desired notion of photometric distance. This is particularly important for filtering color images. If the three bands of color images are filtered separately from one another, colors are corrupted close to image edges. In fact, different bands have different levels of contrast, and they are smoothed differently. Separate smoothing perturbs the balance of colors, and unexpected color combinations appear. Bilateral filters, on the other hand, can operate on the three bands at once, and can be told explicitly, so to speak, which colors are similar and which are not. Only perceptually similar colors are then averaged together, and the artifacts mentioned above disappear.

2.2 Investigating Haze-relevant Features in A Learning Framework for Image Dehazing
In this paper, we systematically investigated a variety of haze-relevant features in a regression framework based on 1 Random Forest. In order to learn the regression model, we need to collect haze-free outdoor images with accurate scene depth maps as ground truth, which,
unfortunately, are hard to obtain. Instead, we synthesize hazy patches from clean image patches randomly sampled from high quality, haze-free images (not necessarily outdoor images). Surprisingly, such synthetic data turns out to be effective in training the dehazing model. This offers our model the flexibility to learn adaptive models for specific situations, such as heavy haze cases, light haze cases, landscape images, scenery images, and so on.

2.3 An Improved Single Image Haze Removal Algorithm Based on Dark Channel Prior and Histogram Specification

The research of using physical model of haze as prior knowledge has made significant progresses. Researchers devote to studying the physical characteristics of haze such as how does the light pass through the haze so as to find deep information of the haze image. Tan et al. observe that compared with haze image, the haze-free image must have higher contrast, so, based on Markov Random Field, a novel approach combined maximization of local contrast is proposed to remove haze [3]. Tan’s approach improves the contrast of the image well, but also easily lead to over-enhanced in practice. Fattal et al. find a prior knowledge that the transmission and surface shading are locally uncorrelated. Based on this prior, Fattal gets haze-free image by estimating the albedo of the scene, and then deduces the color of the whole image by MRF [4]. This method produces an impressive result in general haze image while losing effectiveness when dealing with thick haze that is lack of too much color information. In order to remove the haze drastically, Kaiming He et al. do a massive experiments of the haze-free image and propose a novel prior knowledge - dark channel prior. He points that in most of the local regions which do not cover the sky, it is very often that some pixels have very low intensity in at least one color (RGB) channel. Utilizing this prior, He builds the distribution of haze thickness, and then eliminates the haze from the haze image. DCP approach is concision and graceful, and it achieves obviously dehazing result for almost all kinds of the haze images. But we observe that the contrast and intensity of haze image after DCP approach will unavoidably tend to lower than those of the real scene. We will elaborate the reason why DCP method has defects on the intensity and contrast of image in the next section. During experiment, we find that in the situation of large background (such as sky, clouds, or just thick haze) area and low contrast in the image, DCP result makes the background darker obviously, which drive the whole image to dim. In order to improve the defect of DCP method, we propose a method combining the dark channel prior and histogram specification. First, we do a research on the image ith large background
area and low contrast, and build the histogram of this kind of haze images together with their haze removal result. Then we find that compared with original haze image, the histogram of haze removal image has a tendency of left-shifting and narrow, and some sharp points occurs in the high intensity region. This kind of change on histogram intimate that the contrast and the intensity of the whole image will get lower, and the noise on the background appears. Next, we rebuild the histogram of haze removal image by expand the low intensity area of the histogram and eliminate the sharp point at the high intensity area. We do a lot of experiment and the result demonstrate that for the haze image with much background area and low contrast, our approach achieve a much better result than DCP. Figure 1 shows the example of our work. Furthermore, in order to make our method more universality, we modify our method to fit the general haze image, which makes the haze removal result more close to the real.

2.4 Physics-based fast single image fog removal

We propose a novel VR approach based on the conjunctive utilization of the median filter operation, the adaptive gamma correction technique, the gray world assumption, and the dark channel prior method. The key features of our proposed method are organized into three proposed modules as follows.

1) In order to avoid generation of halo effects and insufficient estimation of the transmission map, the proposed depth estimation (DE) module contains two major procedures that take advantage of the median filter to preserve edge information. The adaptive gamma correction technique is employed to adjust the intensity of the transmission map.

2) Next, the proposed color analysis (CA) module uses the gray world assumption to analyze the color characteristics of input images. The obtained color information can express the variation range of RGB distribution and thereby circumvent color distortion problems.

3) The proposed VR module uses the adjusted transmission map and color-correlated information produced, respectively, by the DE and CA modules to recover a high-quality haze-free image.

3. METHOD

3.1 Haze Estimation

It reveals a weakness in the dark channel prior. Since the dark channel prior relies on sample minima, it is especially sensitive to a separate part of a system. A variety of approaches can be taken to strongly estimate the dark channel, and by extending the conduction map, allowing for the presence of noise. A basic method from the field of
descriptive statistics is to use quantiles, such as the 10th in statistics as an estimate. A more sophisticated approach can be taken by using stochastic approximation to locate local minima, followed by some type of point estimate. However, since other point estimates are needed, a still better approach may be to simply denoise the entire image as a pre-processing step. With the specific denoising algorithm being the color version of BM3D which uses a block matching and collaborative Wiener filtering scheme for denoising is used. As this algorithm is currently among the state-of-the-art, results obtained with it should be about as fine as one could look ahead to from this haze estimation approach. From the denoised hazy image, the dark channel, atmospheric light, and transmission map can be estimated. If noise is ignored, the computed dark channel contains significant errors. However, if the image is first denoised with BM3D, the resulting dark channel is very similar to that of the noise-free case. It shows the dark channel mean squared error for the same example image for a range of noise levels.

3.2 Depth Restoration

Once the transmission and atmospheric light are estimated, the scene radiance can be recovered from the hazy image. Two possible avenues we explore for this final restoration step are denoising and dehazing. The most significant difference between the two approaches is that the first one treats the haze and noise separately, while the other considers haze and noise together. We expect this approach to perform well if the denoising step is very good.

3.3 Denoising with Dehazing

Denoising the hazy image prior to performing the dehazing method is a usual approach to managing the trouble of noise in scene radiance resurgence. It is worth noting to denoising after dehazing was considered. Using the Non-Local Means denoising algorithm, finding that areas of the image is for an image whose intensity values are normalized. By contrast, if we denoise the image previous to dehazing, the noise variance is not spatially varying, and so we should expect a standard denoising algorithm to perform properly. In our refurbishment scheme, denoising as a preprocessing step is especially convenient considering that it is already necessary for estimating the atmospheric light and transmission map. After the hazy image is denoised, the rest of the dehazing process is exactly the same as in the noise-free case.

3.4 Scene Radiance Recovery

For avoiding producing too much noise, we restrict the value of the transmission \( t(x) \) between 0.1 and 0.9. Note that the scattering coefficient \( \beta \), which can be regarded as a constant in homogeneous regions, represents the ability of a unit volume of atmosphere to
scatter light in all directions. In other words, \( \beta \) determines the intensity of dehazing indirectly. We illustrate shows the restored transmission maps with different \( \beta \), and shows the corresponding dehazing results. As can be seen, on the one hand, a small \( \beta \) leads to small transmission, and the corresponding result remains still hazy in the distant regions. On the other hand, a too large \( \beta \) may result in overestimation of the transmission. Therefore, A moderate \( \beta \) is required when dealing with the images with dense-haze regions. In most cases, \( \beta = 1.0 \) is more than enough.

4. IMPLEMENTATION

4.1 Input Image And Preprocess Using Filter

The hazy input image is selected from the collection of images and then it is preprocessed for filtering of images commonly involves in removing low frequency background noise, normalizing the intensity of the individual particles images, removing of enhancing data images prior to computational processing. Generally noise will occur due to malfunctioning pixels in camera sensors, faulty memory location in hardware or error in data transmission.

Wiener Filter : The wiener function is derived from the Wiener filter techniques which is also been a type of linear filter. Apllying the wiener filters in an image adaptively, tailoring itself to the local image variance. It smoothen the image at low variance. Similarly, it also smoothen the image more when the variance high. This filter provides better results compared to the linear filter. It performs well when the noise is constant-power "white" additive noise, such as Gaussian noise.

4.1 Haze Estimation

It reveals a weakness in the dark channel prior. Since the dark channel prior relies on sample minima, it is especially sensitive to outliers. Various approaches can be taken to robustly estimate the dark channel, and by extension the transmission map, considering the presence of noise. A basic method from the field of descriptive statistics is to use quantiles, such as the 10th percentile as an estimate. A more sophisticated approach can be taken by using stochastic approximation to locate local minima, followed by some type of point estimate. However, since other point estimates are needed, a still better approach may be to simply denoise the entire image as a pre-processing step. With the specific denoising algorithm being the color version of BM3D which uses a block matching and collaborative Wiener filtering scheme for denoising is used. As this algorithm is currently among the state-of-the-art, results obtained with it should be about as good as one could expect from this haze estimation strategy. From the denoised hazy image, the dark channel, atmospheric light, and
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Simply denoising the hazy image prior to performing the dehazing process is a natural approach to handling the problem of noise in scene radiance recovery. It is worth noting that denoising after dehazing was considered using the Non-Local Means denoising algorithm, with the authors finding that areas of the image is for an image whose intensity values are normalized. Since they typically treat the noise level as homogeneous throughout the image, and we know that noise in the recovered scene radiance is inversely proportional to the spatially varying transmission. By contrast, if we denoise the image prior to dehazing, the noise variance is not spatially varying, and so we should expect a standard denoising algorithm to perform properly. In our restoration scheme, denoising as a pre-processing step is especially convenient considering that it is already necessary for estimating the atmospheric light and transmission map. In the denoising step, we can treat our image model as: \( Y = I + n \), with the task being only to estimate \( I \), which encapsulates the hazy image. After the hazy image is denoised, the rest of the dehazing process is exactly the same as in the noise-free case.

5. CONCLUSION

We have introduced a new fast dehazing and denoising method based on the variational approach. The proposed method first estimates a transmission map using the windows adaptive method, and then converts the transmission map to a depth map. Using this depth map, we construct an energy functional to seek the final haze- and noise-free image. Therefore, we can conclude that our proposed method can remove haze and noise efficiently and effectively.

Simultaneously dehazing and denoising is still a challenging problem, and there are many open questions that should be studied. Our method is effective, but it also can be improved. First, since our windows adaptive
method is based on the dark channel prior, it also can’t deal with sky regions very reasonably. Till now, there are few suitable models handling sky regions more naturally. The building of models to handle the sky regions will be the aim of our further research. Second, our results are acceptable but some artifacts are still visible. There may be some difficulty in the choice of the parameter \( r \) used for the windows adaptive method. A constant \( r \) may not be suitable for all images. We will extend our research based on some more advanced models. Additionally, as our method is a general framework, it can be extended in many possible ways, such as the application of total generalized variation or tight-frame. We leave this as further works.

6. REFERENCES
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