A Hybrid Approach of Guided Filters and Deep Learning for Effective Defogging in Multimedia Data Analysis

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ABSTRACT - The visibility of multimedia data is affected by many atmospheric interferences that degrade the quality of the image and video content. The multimedia information is also affected by climatic events such as rain, fog and other details. The low visibility degrades the performance of subsequent video analysis or processing applied in computer vision techniques. This undesirable situation degrades the performance of several computer vision applications. Several computer vision techniques that employ feature information, such as object identification, tracking, segmentation, and recognition, will be harmed by these disturbances. Even if only a little portion of the object is obscured, the object cannot be accurately tracked. The attribute of a rain scene is that an image pixel is never completely covered by rain throughout the data. The dynamic adverse weather model is researched for restoration resolution. Rain is the most important component of the dynamic poor weather system. Rain-formed intensities have a strong spatial structure and are strongly influenced by background brightness. When light passes through, it is refracted and reflected, making them brighter than the surrounding area. When it falls at a high rate, though, the motion blurs. The intensity of the rain streak is thus determined by the brightness of the drop, the radiances of the background scene, and the camera's integration time. Rain and snow particles are more difficult to analyses. Rain-like spatial and temporal occurrences can be produced by some scene dynamics. In this work, we can implement the framework to analyse the degraded pixels and classify that pixel using guided filter and deep learning algorithm.

KEYWORDS:Multimedia data, Haze removal, Guided filtering, Spatial and temporal features, Dehazed multimedia data

1. INTRODUCTION

In outdoor imaging, captured images are easily affected by particles in the atmospheric that absorb and scatter light as it travels from the scene to the camera. Such degraded photographs often lack visual vividness, and provide poor visibility of the contents of the scene. This effect may be uncomfortable during driving, as well as for commercial and artistic photographers. In almost every practical scenario the light reflected from a surface is scattered in the atmosphere before it reaches the camera. This is due to the presence of aerosols such as dust, mist, and fumes which deflect light from its original course of propagation. In long distance photography or foggy scenes, this process has a substantial effect on the image in which contrasts are reduced and surface colors become faint. Such degraded photographs often lack visual vividness and appeal, and moreover, they offer a poor visibility of the scene contents. This effect may be an annoyance to amateur, commercial, and artistic photographers as well as undermine the quality of underwater and aerial photography. This may also be the case for satellite imaging which is used for many purposes including cartography and web mapping, land-use planning, archeology, and environmental studies. The quality of image taken under bad visibility is always degraded by the presence of fog, haze, smog or mist. Since the atmosphere was affected the contrast of the image is greatly reduced. Haze removal1 (or dehazing) is highly desired in both consumer/computational photography and computer vision applications. First, removing haze can significantly increase the visibility of the scene and correct the color shift caused by the airlight. In general, the haze-free image is more visually pleasing. Second, most computer vision algorithms, from low-level image analysis to high-level object recognition, usually assume that the input image (after radiometric calibration) is the scene radiance. The performance of vision algorithms (e.g., feature detection, filtering, and photometric analysis) will inevitably suffer from the biased, low contrast scene radiance. Last, the haze removal can produce depth information and benefit many vision algorithms and advanced image editing. Haze or fog can be a useful depth clue for scene understanding. The bad haze image can be put to good use. However, haze removal is a challenging problem because the haze is dependent on the unknown depth information. The problem is under-constrained if the input is only a single haze image. Dehazing is the process of removing haze from a captured image.

2. RELATED WORK

Sixiangchen, et.al,…[1]propose a novel real-time transformer to tackle a new task: depth estimation and haze removal from varicolored haze scenes. Moreover, we present a semi-supervised contrastive learning paradigm for the domain gap problem to achieve domain adaptation in real-world haze scenes. To maintain depth estimation performance in clean scenes, we propose domain consistency learning to simultaneously enforce network learns from hazy and clean domains. Extensive experiments on synthetic and natural varicolored haze data demonstrate the superiority of our DEHRFormer. This work focuses on a novel and practical task: varicolored image dehazing and depth estimation. Compared with prior arts which only consider common haze removal (grayish haze scenes) or depth estimation from clean scenes, we are the first to joint consider dehazing and estimating depth maps from varicolored haze scenes in a unified way. We propose a real-time transformer for depth estimation and haze removal, which unifies the challenging varicolored haze removal and depth estimation to a sequence-to-sequence translation task with learnable queries, significantly easing the task pipeline. A semi-supervised learning paradigm is proposed to boost the generalization of DEHRFormer in the real haze domain. Furthermore, we considered the domain consistency of depth estimation over the haze and clean domains.

Vladimir frants, et.al,…[2]adverse weather conditions (haze, snow, rain, fog) are among the most prevalent reasons for the limited use of automatic video surveillance, crowd counting, accident detection, person re-identification, computational photography, and other computer vision tasks. Consequently, a preprocessing step is necessary to limit the impact of weather conditions on the rest of the image analysis system. In real-world applications mentioned above, image de-raining is highly desirable due to the facts that a) rainy weather often causes poor visibility, contrast reduction, and color modification, b) the removal of rain-streaks typically produces over-smoothed images and leads to lost image details, c) the lack of robust prior-models of both rainstreaks and background, and d) the image rain removal is a highly ill-posed problem. Image de-raining aims to create a sharp, clean image from a rainy image. Therefore, it is essential to develop algorithms that automatically remove these artifacts and not degrade the rest of the image's contents. Current deraining efforts can be grouped into model-based and data-driven approaches. Images captured in real-world applications in remote sensing, image or video retrieval, and outdoor surveillance suffer degraded quality introduced by poor weather conditions. Conditions such as rain and mist, introduce artifacts that make visual analysis challenging and limit the performance of high-level computer vision methods. For time-critical applications where a rapid response is necessary, it becomes crucial to develop algorithms that automatically remove rain, without diminishing the quality of the image contents. This article aims to develop a novel quaternion multi-stage multiscale neural network with a self-attention module called QSAM-Net to remove rain streaks. The novelty of this algorithm is that it requires significantly fewer parameters by a factor of 3.98, over prior methods, while improving visual quality. This is demonstrated by the extensive evaluation and benchmarking on synthetic and real-world rainy images. This feature of QSAM-Net makes the network suitable for implementation on edge devices and applications requiring near real-time performance. The experiments demonstrate that by improving the visual quality of images. In addition, object detection accuracy and training speed are also improved.

Yuanyangzou, et.al,...[3] implementedto remove haze of hazy images, a combining algorithm is introduced. In the algorithm, ambient illumination is predicted by logarithmic guide filtering. Then, to obtain the value of the transmission t(x), first, a multi-channel prior method is proposed, which contains two models with two parameters and the values of the two parameters can be self-adaptively calculated. Then, a weight factor self-adaptively calculated is presented in the equation, which is employed to reckon the transmission t(x). At last, a well-quality dehazing image is obtained. In the experiment section, which is executed in four types(light haze outdoor/ indoor, heavy haze outdoor/indoor), it is obtained that (1) Experiments on the selected 20 testing images (divided into four types: light haze outdoor images; light haze indoor images; heavy haze outdoor images; heavy haze indoor images) show that our method can outperform the others both in the subjective and objective evaluations; (2) PSNR, RMS, DE, and AG values on 500 randomly selected testing images demonstrate that the performance and capability of our method have better robustness; (3) The average running time of the presented method is acceptable by analyzing the performance of computational time.

Haoranwei, et.al,..[4]proposes a novel Non-Homogeneous Haze Removal Network (NHRN). Instead of following the bivariate estimation based atmospheric scattering model, our NHRN considers the poor visibility of haze as inappropriate exposure and attempts to correct it via joint artificial multi-exposure fusion and non-local filtering, which are achieved by the proposed artificial scene prior and bidimensional graph reasoning modules. To the best of our knowledge, this is the first exploration to remove non-homogeneous haze via the graph reasoning based framework. By means of the enriched artificial scene priors and comprehensive contextual information utilization, the proposed method efficiently overcomes the error accumulation and haze residue issues when a single image is available. These proposed two modules are cost efficient for coping with diverse images with significant content changes. However, when a video is fed to the dehazing system, the high correlation between neighboring frames would significantly increase the computational redundancy for our artificial shot generation and graph construction. In our future work, we would explore more flexible parameter reuse strategies for artificial shot and graph reasoning in the video dehazing task. Meanwhile, we will also attempt to extend the graph reasoning based non-local information propagation from the spatial domain to the temporal domain in the video dehazing.

Bowen zhang, et.al,…[5] provided the development of the Internet of Things, big data, and cloud computing technologies, video devices are increasingly used in outdoor video surveillance systems. However, hazy weather significantly affects the image quality of the video surveillance systems and the subsequent image processing results, such as image segmentation, target recognition, and other tasks. Numerous haze removal algorithms have been proposed to improve the quality of haze affected images. The HRNSCT algorithm decouples the haze removal and noise suppression of hazy images, minimizing the risk of noise amplification during the haze removal process of traditional algorithms. The transmission map and atmospheric light are estimated accurately by using the low-frequency sub-bands of the hazy image and combining the CAP and the DCP. This approach improves the estimated transmission map and avoids noise interference when estimating the transmission map and atmospheric light. The HRNSCT algorithm allows for dehazing only the low-frequency components of hazy images and provides a new approach for dehazing hazy images with noise. The noise in the dehazed image is suppressed by shrinking the high-frequency sub-bands of the original hazy image, providing a new method for the noise suppression of dehazing algorithms.

3.EXISTING METHODOLOGIES

The quality of a captured image in bad weather is usually degraded by the presence of haze in the atmosphere, since the incident light to a camera is attenuated and the image contrast is reduced. Dehazing is the process to remove haze effects in captured images and reconstruct the original colors of natural scenes. Recently, lots of efforts have been made to develop efficient dehazing algorithms. In general, dehazing algorithms estimate scene depths and compute the thickness of haze accordingly. Recently, single image haze removal has made significant progresses. The success of these methods lies in using a stronger prior or assumption. Then observes that the haze-free image must have higher contrast compared with the input haze image and he removes the haze by maximizing the local contrast of the restored image. The results are visually compelling but may not be physically valid. Since the dark channel prior is a kind of statistic, it may not work for some particular images. When the scene objects are inherently similar to the atmospheric light and no shadow is cast on them, the dark channel prior is invalid. This work also shares the common limitation of most haze removal methods - the haze imaging model may be invalid. More advanced models can be used to describe complicated phenomena, such as the sun's influence on the sky region, and the blueish hue near the horizon. This method may fail in scenes where the airlight is significantly brighter than the scene. In such cases, most pixels will point in the same direction and it will be difficult to detect the haze lines.

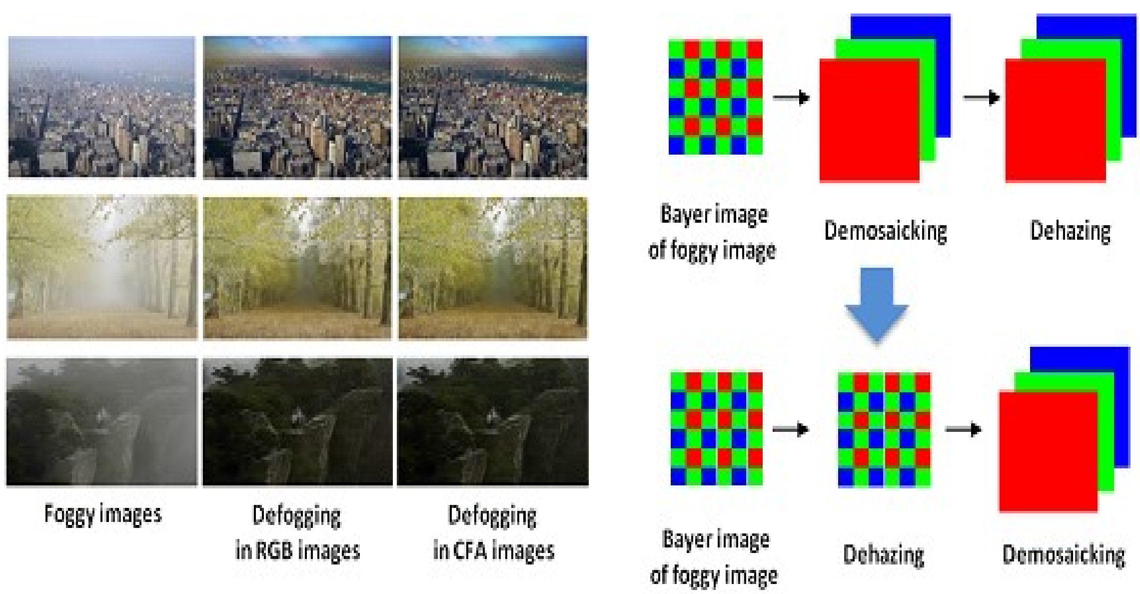


Fig 1: Defogged images

4. PROPOSED METHODOLOGIES

One of the main aims in image processing is to obtain an enhanced image. Outdoor multimedia data are degraded by the atmospheric phenomena like rain, fog, haze etc many applications such as consumer/computational photography and computer vision requires a vision enhanced image. Atmospheric particles absorb and scatter the light as it travels to the observer leads to cause haze, fog. These degraded images lose contrast and air-light shift the color of the image. Haze removal makes the image visually pleasant and corrects the color shift. Here we obtain the haze free image by deep learning method. By the process of deep learning method, the good information from each of the given images is fused together to form a resultant image whose quality is superior to any of the input data. This is achieved by applying laplacian on the input and Gaussian on the weighted inputs. The resultant image is formed by combining such magnified information from the input images into a single image. Aim behind deep learning-based technique is that we derive various layers such as convolutional, pooling and fully connected layer. For blending we require only important features of the images so we go for the weight maps. In this project we propose a new type of explicit image filter, called Gaussian filter. The filtering output is locally a linear transform of the guidance image. This filter has the edge-preserving smoothing property like the bilateral filter, but does not suffer from the gradient reversal artifacts. It is also related to the matting Laplacian matrix, so is a more generic concept and is applicable in other applications beyond the scope of "smoothing". Moreover, the Gaussian filter has an O(N) time (in the number of pixels N) exact algorithm for both gray-scale and color images.

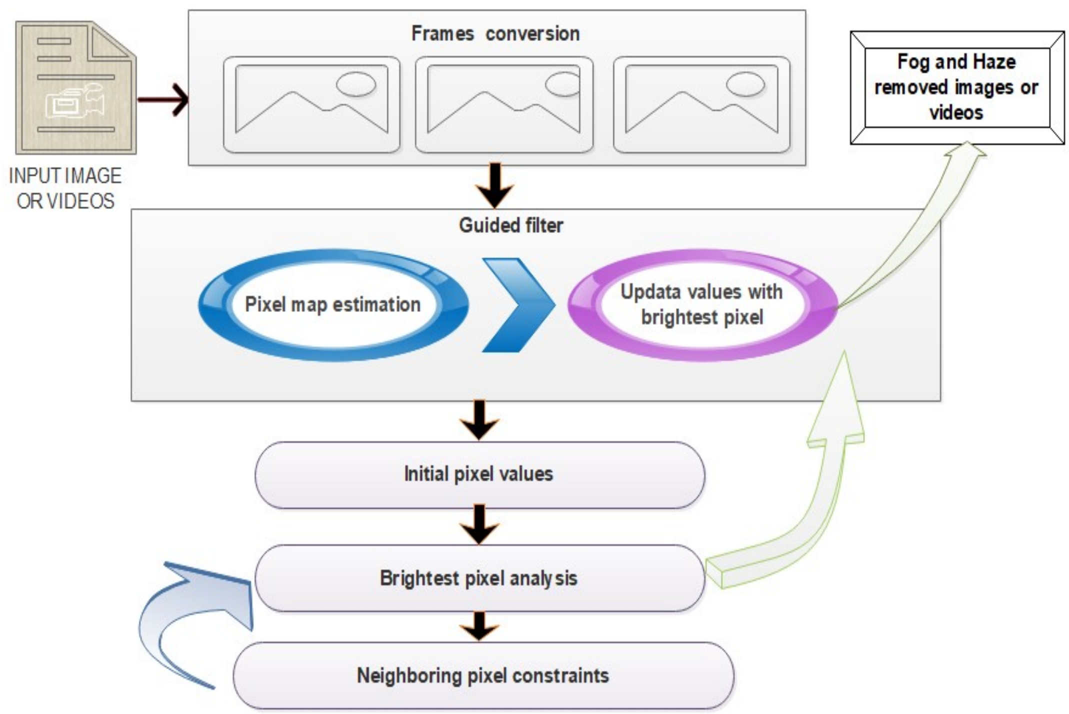


Fig 2: Proposed architecture

Dark Channel Prior Dark channel prior is used for the estimation of atmospheric light in the dehazed image to get the more real result. This method is mostly used for non-sky patches; in one color channel have very low intensity at few pixels. The low intensity in the dark channel is predominant because of three components:

- Colourful items or surfaces
- Shadows (shadows of car, buildings etc)
- Dark items or surfaces (dark tree trunk, stone)

As the outdoor images are usually full of shadows the dark channels of images will be really dark. Due to fog (airlight), a foggy image is brighter than its image without fog. So we can say dark channel of foggy image will have higher intensity in region with higher fog. So, visually the intensity of dark channel is a rough estimation of the thickness of fog. In dark channel prior we use pre and post processing steps for getting good results. In post processing steps we use soft matting or trilateral filtering etc. Let J(x) is input image, I(x) is hazy image, t(x) is the transmission of the medium. The attenuation of the image can be expressed as

$$I_{att}(x) = J(x)t(x)$$

The influence of the fog about airlight effect is expressed as

$$I_{airlight}(x) = A(1 - t(x))$$

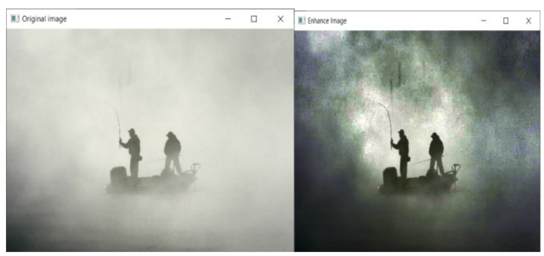
Dark channel for an random image J and expressed as

$$J^{dark}(x) = \frac{min}{y\epsilon\Omega(x)}(minJ^{c}(Y))$$

In this $J^c$is the color image comprising of RGB components, $\Omega(x)$depicts a local patch which has its origin at x. The low intensity of dark channels is because of shadows in images, color objects and dark objects in images. After dark channel prior, we need to estimate transmission t(x) for proceeding further with the solution. After estimating the transmission map depth map is generated. Assume Atmospheric light A is also known.

5. EXPERIMENTAL RESULTS

Peak Signal-to-Noise Ratio (PSNR) is a commonly used metric to evaluate the quality of image dehazing algorithms. PSNR measures the ratio between the maximum possible power of a signal and the power of corrupting noise that affects the fidelity of its representation. In the context of image dehazing, PSNR is used to compare the similarity between the original, hazy image and the dehazed output. Higher PSNR values indicate better quality dehazing results for both images and videos. The proposed PSNR values is 27.827 Db



a) original image b) dehazed image

Fig 3: Dehazed images

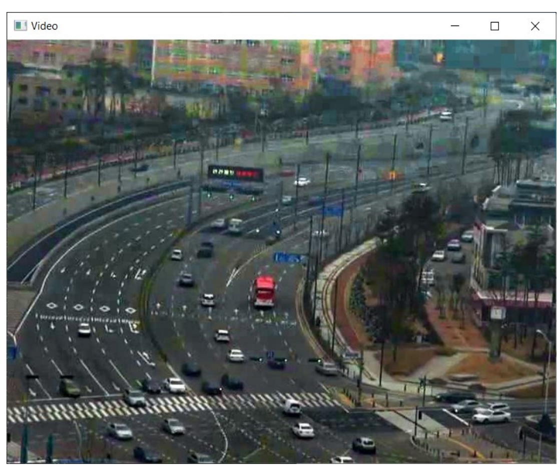


Fig 4: Dehazed video

Fig 3 and 4 shows the results for dehazed images and videos with improved quality.

6. CONCLUSION

Haze due to dust, smoke and other dry particles reduces visibility for distant regions by causing a distinctive gray hue in the captured images. The hazy image is suffers from low contrast and resolution due to poor visibility conditions. One of the central problems in image processing in open air is the presence of cloud, fog or smoke which fades the colors and reduces the contrast of the observed things. Fog or Haze elimination is difficult because the fog is dependent on the indefinite depth information. Weather conditions reduce the operation range of most methods. In this project, a fast and effective method for real-time image and video dehazing is proposed. Using a newly presented image prior - dark channel prior, haze removal for a single image without using any extra information is formulated as a particular filtering problem and an improved filtering scheme is proposed based on guided filter. In the presented algorithm, the airlight and the down-sampled transmission can be estimated and extracted easily. Then using a guided filter, the transmission can be further refined and up-samlped. Results demonstrate the presented method abilities to remove the haze layer and achieve real-time performace. It is believed that many applications, such as outdoor surveillance systems, intelligent vehicle systems, remote sensing systems, graphics editors, etc, could benefit from the proposed method.

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