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EFFECTIVE DEHAZING WITH CONCEPTUAL REGULARIZATION USING SURF FOR HAZE IMAGE

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ABSTRACT

Image matching plays a crucial role in many remote sensing applications such as change detection, cartography using imagery with reduced overlapping, fusion of images taken with different sensors. In the early remote sensing systems, this task required substantial human involvement by manually selecting some feature points of significant landmarks. Nowadays, due to the significant progress of local feature point's detectors and descriptors, the tasks of matching and registration can be done in most of the cases automatically. We Propose a new process of contrast enhancement aims to increase the perceptibility of the objects in the image such as auto-contrast, gamma correction, linear mapping, histogram stretching. We start from the global operator that enhances the contrast of the luminance 'L' based on the hue 'H' and saturation 'S'. Our strategy is designed to preserve most of the local features and details in the enhanced version, the local contrast preservation is crucial in the process of matching by feature points. In its final stage, the well-known Scale Invariant Feature Transform (SIFT) operator filters out all the features with low local contrast. The enhanced hazy image optimizes the contrast by constraining the degradation of the finest details and gradients to minimum.

Keywords: Dehazing, SURF, SIFT, Airlight, Lumiance.

INTRODUCTION

Outdoor images are often suffered by suspended atmospheric particles such as haze, fog, smoke and mist that reduce the quality of the images taken in the scene. Visibility, contrast, and vividness of the scene are drastically degraded, which makes it difficult to distinguish objects. Enhancing the images acquired in poor weather conditions is called de-weathering and has been a very critical issue in Applications such as aerial photography, driving assistance and visual surveillance. Defogging is a representative deweathering problem especially for removing the weather effect caused by suspended aerosol and water drops. The goal of defogging is to improve the contrast of the foggy images and restores the visibility of the scene.

According to atmospheric scattering model the physical degradation process of foggy image as a linear combination of two components: attenuated scene reflectance and intensified atmospheric luminance The transmission medium is the suspended particles that influence the transmission of scene reflectance and atmospheric luminance. The scene reflectance is the albedo of the scene reflected by atmospheric luminance and is attenuated by the transmission medium. The atmospheric luminance is scattered by suspended particles intensified by the transmission medium and received by the observer as ambient air light. The two components are additive due to the linear characteristic of light propagation. This physical process results in the degradation of both visibilities and contrast.

Two critical factors affect the attenuation and intensification. The first is the atmospheric scattering coefficient of the transmission media that is deemed to the polarization characteristics of the particles and is usually assumed to be a constant in a static scene. The second factor is the distance between the scene and the observer. Longer distance induces more attenuation and intensification. While the depth is deeper, the effect is stronger and the foggy image loses more visibility and contrast. The two factors are combined into a single term called depth map in this paper. Estimating the depth map and air light is therefore very crucial for the restoration of the scene reflectance.

RELATED WORKS

L. Caraffa et al. [1], they show how fog reduces contrast and thus the visibility of vehicles and obstacles for drivers. Each year, this causes traffic accidents. Fog is caused by a high concentration of very fine water droplets in the air. When light hits these droplets, it is scattered and this results in a dense white background, called the atmospheric veil. As

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pointed in [1], Advanced Driver Assistance Systems (ADAS) based on the display of defogged images from a camera may help the driver by improving objects visibility in the image and thus may lead to a decrease of fatality and injury rates.

M. Joshi et al. [8] In their paper, they propose a model-based approach for the multiresolution fusion of satellite images. Given the high-spatial-resolution panchromatic (Pan) image and the low-spatial- and high-spectral-resolution multispectral (MS) image acquired over the same geographical area, the problem is to generate a high-spatial- and high-spectral-resolution MS image. This is clearly an ill-posed problem, and hence, we need a proper regularization. We model each of the low-spatial-resolution MS images as the aliased and noisy version of their corresponding high spatial resolution, i.e., fused (to be estimated) MSimages. A proper aliasing matrix is assumed to take care of the undersampling process.

K. He, J. et al. [3] In this paper, we propose a simple but effective image prior - dark channel prior to remove haze from asingle input image. The dark channel prior is a kind of statistics of the haze-free outdoor images. It is based on a key observation - most local patches in haze-free outdoor images contain some pixels which have very low intensities in at least one color channel. Using this prior with the haze imagingmodel, we can directly estimate the thickness of the haze and recover a high quality haze-free image. Results on a variety of outdoor haze images demonstrate the power of the proposed prior. Moreover, a high quality depth map can also be obtained as a by-product of haze removal.

R. Szeliski *et al.*, [12] Among the most exciting advances in early vision has been the development of efficient energy minimization algorithms for pixel-labeling tasks such as depth or texture computation. It has been known for decades that such problems can be elegantly expressed as Markov random fields, yet the resulting energy minimization problems have been widely viewed as intractable. Algorithms such as graph cuts and loopy belief propagation (LBP) have proven to be very powerful: For example, suchmethods form the basis for almost all the top-performing stereo methods. However, the trade-offs among different energy minimization algorithms are still not well understood. In this paper, we describe a set of energy minimization benchmarks and use them to compare the solution quality and runtime of several common energy minimization algorithms. We investigate three promising methods-graph cuts, LBP, and tree-reweighted message passing-in addition to the well-known older iterated conditional mode (ICM) algorithm. Our benchmark problems are drawn from published energy functions used for stereo, image stitching, interactive segmentation, and denoising. We also provide a general-purpose software interface that allows vision researchers to easily switch between optimization methods.

V. Lempitsky, et al. [14] they propose a new approach to the optimization of multi-labeled MRFs. Similarly to a-expansion it is based on iterative application of binary graph cut. However, the number of binary graph cuts required to compute a labelling grows only logarithmically with the size of label space, instead of linearly. We demonstrate that for applications such as optical flow, image restoration, and high resolution stereo, this gives an order of magnitude speed-up, for comparable energies. Iterations are performed by "fusion" of solutions, done with QPBO which is related to graph cut but can deal with non- submodularity. At convergence, the method achieves optima on a par with the best competitors, and sometimes even exceeds them.

A. Jalobeanu, et al. [19] The deconvolution of blurred and noisy satellite images is an ill-posed inverse problem, which can be regularized within a Bayesian context by using an a priori model of the reconstructed solution. Since real satellite data show spatially variant characteristics, we propose here to use an inhomogeneousmodel. We use the maximum likelihood estimator (MLE) to estimate its parameters and we show that the MLE computed on the corrupted image is not suitable for image deconvolution because it is not robust to noise. We then show that the estimation is correct only if it is made from the original image. Since this image is unknown, we need to compute an approximation of sufficiently good quality to provide useful estimation results. Such an approximation is provided by a wavelet-based deconvolution algorithm. Thus, a hybrid method is first used to estimate the space-variant parameters from this imageand then to compute the regularized solution. The obtained results on high resolution satellite imagessimultaneously exhibit sharp edges, correctly restored textures, and a high SNR in homogeneous areas, since the proposed technique adapts to the local characteristics of the data.

J. P. Oakley et al. [15] This paper is concerned with the mitigation of simple contrast loss due to added lightness in an image. This added lightness has been referred to as "airlight" in the literature since it is often caused by optical scattering due to fog or mist. A statistical model for scene content is formulated that gives a way of detecting the presence of airlight in an arbitrary image. An algorithm is described for

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estimating the level of this airlight given the assumption that it is constant throughout the image. This algorithm is based on finding the minimum of a global cost function and is applicable to both monochrome and color images. The method is robust and insensitive to scaling. Once an estimate of airlight is achieved, then imagecorrection is straightforward.

R. T. Tan, et al. [13] Bad weather, such as fog and haze, can significantly degrade the visibility of a scene. Optically, this is due to the substantial presence of particles in the atmosphere that absorb and scatter light. In computer vision, the absorption and scattering processes are commonly modeled by a linear combination of the direct attenuation and the airlight. Based on this model, a few methods have been proposed, and most of them require multiple input images of a scene, which have either different degrees of polarization or different atmospheric conditions. This requirement is the main drawback of these methods, since in many situations, it is difficult to be fulfilled. To resolve the problem, we introduce an automated method that only requires a single input image.

P. P. Gajjar et al. [6] In this paper, they propose a new learning-based approach for super-resolving an image captured at low spatial resolution. Given the low spatial resolution test image and a database consisting of low and high spatial resolution images, we obtain super-resolution for the test image. We first obtain an initial high-resolution (HR) estimate by learning the high-frequency details from the available database. A newdiscrete wavelet transform (DWT) based approach is proposed for learning that uses a set of low-resolution (LR) images and their corresponding HR versions. Since the super-resolution is an ill-posed problem, we obtain the final solution using a regularization framework.

DEHAZING WITH CONCEPTUAL REGULARIZATION

A physical degradation process known as the atmospheric scattering model has been widely applied in many dehaze works. In this manner we propose the Contextual Regularization based image dahaze. We present a new method for recovering a haze-free image given a single photograph as an input. This techniques restore the hazy images based on the estimated transmission (depth) map. Our method benefits from three main contributions. The first is a new constraint on the scene transmission. This simple constraint, which has a clear geometric interpretation, shows to be surprisingly effective to image dehazing. Our second contribution is a new contextual regularization that enables us to incorporate a filter bank into image dehazing. These filters help in attenuating the image noises and enhancing some interesting image structures, such as jump edges and corners. Our final contribution is an efficient optimization scheme, which enable us to quickly dehaze images of large sizes.

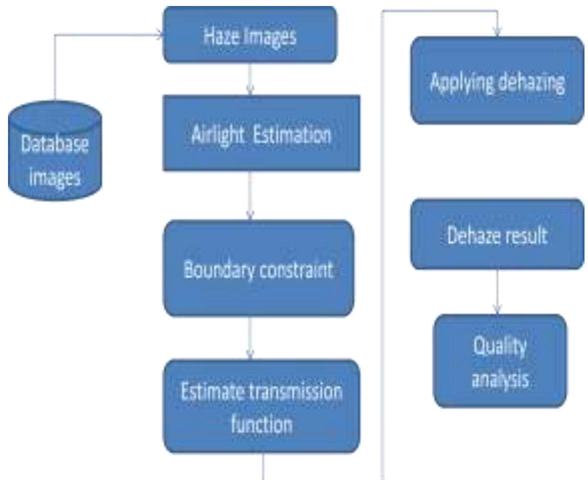

Fig 1 : System Architecture

In the proposed system we are using global airlight estimation for perfect analysis for the presence of fog,smoke or dust in the image . Boundary constraint is used inorder to increase the conceptual regularization . dehazing is done in order to remove the presence of fog,smoke or dust in the image.quality analysis is done to increase the originality of the image and to increase the quality of the image.

A. Global airlight estimation:

The airlight function is the multiplication of two factors: atmospheric luminance and the inverse of depth map. We can assume that a portion of the image contains pixels infinitely far away.The image points corresponding to scene points at infinity are regarded as the set of representative color vectors of atmospheric luminance and an average operation is applied to estimate the expected color vector of atmospheric luminance.White pixels that have the highest intensity values in the fog image are considered as atmospheric luminance, since these pixels may represent the scene points with no reflection, assuming to be at infinite distant .

The following linear interpolation model is widely used to explain the formation of a haze image,

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

where,

$I(x)$ is the observed image,

$J(x)$ is the scene radiance,

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A is the global atmospheric light, and

$t(x)$ is the scene transmission .

The transmission function $t(x)$ $(0 \leq t(x) \leq 1)$ is correlated with the scene depth.
Where,

$$t(x) = e - \beta d(x) \qquad (2)$$

β is the medium extinction coefficient
$d(x)$ is the scene depth.

The goal of image dehazing is to recover the scene radiance J(x) from I(x) based on Equation.(1). This requires us to estimate the transmission function $t(x)$ and the global atmospheric light A. Once $t(x)$ and A are estimated, the scene radiance can be recovered by:

$$J(x) = I(x) – A / [\max (t(x), e)]\delta + A, \qquad (3)$$

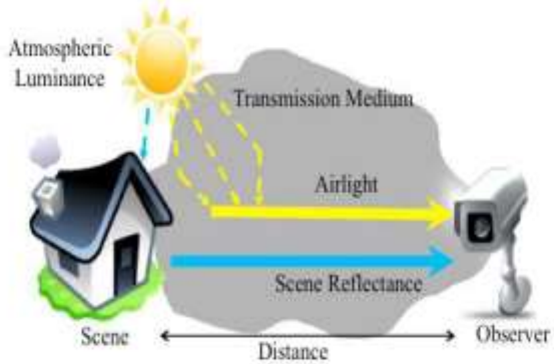

Fig 2 : Airlight Estimation

B. Boundary constraint:

Single image dehazing is essentially an under-constrained problem. The general principle of solving such problems is therefore to explore additional priors or constraints. Following this idea, we begin our study in this paper by deriving an inherent boundary constraint on the scene transmission.This constraint, combined with a weighted based contextual regularization between neighboring pixels,is formalized into an optimization problem to recover the unknown transmission. Our contribution is a new contextual regularization that enables us to incorporate a filter bank into image dehazing.These filters help in attenuating the image noises and enhancing some interesting image structures, such as jump edges and corners.A bank of high-order filters used in our project.It consists of Laplacian operator for preserving image edges and corners.

Boundary Constraint from Radiance Cube:

where $tb(x)$ is the lower bound of $t(x)$, given by

$tb(x) = \min \{\max c\{r,g,b\} (Ac - Ic(x)/Ac - Cc0, Ac - Ic(x)/Ac - Cc1), 1\}$

where Ic, Ac, $Cc0$ and $Cc1$ are the color channels of I, A,C0 and C1, respectively.

Weighted L1-norm based Contextual Regularization:

Generally, pixels in a local image patch will share a similar depth value. Based on this assumption, we have derived a patch-wise transmission from the boundary constraint. However, this contextual assumption often fails to image patches with abrupt depth jumps, leading to significant halo artifacts in the dehazing results.
A trick to address this problem is to introduce a weighting function $W(x, y)$ on the constraints, i.e.,

$$W(x, y)\,(t(y) - t(x)) \approx 0$$

where x and y are two neighboring pixels. The weighting function plays a "*switch*" role of the constraint between x and y. When $W(x, y) = 0$, the corresponding contextual constraint of $t(x)$ between x and y will be canceled. The question now is how to choose a reasonable $W(x, y)$. Obviously, the optimal $W(x, y)$ is closely related to the depth difference between x and y. In another word, $W(x, y)$ must be small if the depth difference between x and y is large, and vice versa. However, since no depth information of each pixel is available in single image dehazing, we cannot construct $W(x, y)$ directly from the depth map.

A beneficial to use the high-order differential operators . This simple extension endows us with more flexibilities in the use of the contextual constraints.A bank of high-order differential filters used in this study. To employ those filters, we have to accordingly revise the computation of the weighting functions as below:

$$Wj(i) = e^{-\sum_{c\in\{r,g,b\}} \| Dj \otimes Ic \| / 2\sigma 2}$$

A bank of high-order filters used in our study. It consists of eight Kirsch operators and a Laplacian operator for preserving image edges and corners.

C. Dehazing:

Our method benefits from three main contributions. The first is a new constraint on the scene transmission. This simple constraint, which has a clear geometric interpretation, shows to be surprisingly effective to image dehazing. Our second

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contribution is a new contextual regularization that enables us to incorporate a filter bank into image dehazing. These filters help in attenuating the image noises and enhancing some interesting image structures, such as jump edges and corners. Our final contribution is an efficient optimization scheme, which enables us to quickly dehaze images of large sizes.

Estimate the transmission function using following formula,

$$t(x) = F-1\left(\frac{\frac{\lambda}{\beta}F(t)+\sum_{j\in\omega}F\,(Dj)\,\circ F\,(uj)}{\frac{\lambda}{\beta}+\sum_{j\in\omega}F\,(Dj)^{\circ}\,F\,(Dj)}\right)$$

Finally we get the dehaze image using

$$J(x) = \frac{I(x) - A}{[\max\,(t(x),\varepsilon)]\delta} + A$$

D. Quality analysis

Image enhancement techniques in Image Processing Toolbox enable you to increase the signal-to-noise ratio and accentuate image features by modifying the colors or intensities of an image. You can:

- Perform histogram equalization
- Perform decor relation stretching
- Remap the dynamic range
- Adjust the gamma value
- Perform linear, median, or adaptive filtering

But in this paper we are using SURF method for finding number of good matches between the original image and the dehazed image inorder to get the proper output. .quality analysis is done to increase the originality of the image and to increase the quality of the image. In the previous paper they had used SHIFT in order to find the number of good matches.since SHIFT is slow and not cost effective we are moving to SURF which is cost effective and faster than SHIFT.

Advantages:

- Our method can recover rich details of images with color information in the haze regions.
- hazes in the images are not homogeneous. Our method dehaze successfully in this types of images.
- Moreover, some significant halo artifacts usually appear around the recovered sharp edges (*e.g.*, trees). In comparison, our method can improve the visuality of image structures in very dense haze regions while restoring the faithful colors. The halo artifacts in our results are also quite small.

Result and Discussion

In comparison with the state-of-the-arts, our method can generate quite visually pleasing results with faithful color and finer image details and structures. Image dehazing often suffers from the problem of ambiguity between image color and depth. From a geometric perspective of image dehazing, we have derived a boundary constraint on the transmission from the radiance cube of an image. Although the boundary constraint imposes a much weak constraint on the dehazing process, it proves to be surprisingly effective for the dehazing of most natural images, after combined with the contextual regularization.

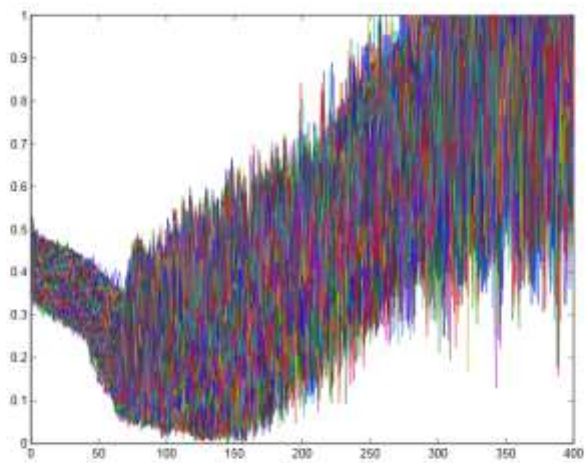

Fig 3: Graphical Result

This ambiguity, revealing the unconstraint nature of single image dehazing, often leads to excessive or inadequate enhancements on the scene objects.

Out output accuracy is about 89% in future using the advanced techniques in matlab we can enhance the output accuracy to 90-95%.

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Conclusion and Future Enhancement

Thus, we have proposed an efficient method to remove hazes from an image. Our method benefits much from an exploration on the inherent boundary constraint on the transmission function. This constraint, together with a weighted $L1$-norm based contextual regularization, is modeled into an optimization problem to recover the unknown transmission. An efficient algorithm using variable splitting is also proposed to solve the optimization problem.

More generally, one can employ a tighter radiance envelop, not limited to a cubic shape, to provide a more accurate constraint on the transmissions. This may help to further reduce the ambiguity between color and depth, and avoid many erroneous enhancements on the image.

This work can be future enhanced in video by converting the video into frames and each frame is dehazed.after dehazing the frames are ordered and again converted into video.

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