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Contrast and SURF based Dehazing for Robust Image Matching

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Abstract

Image matches are always played an important function in numerous remote sensing applications like, change discovery, cartography, combination of images taken with different sensors. In the early remote sensing systems, this task required a lot more human involvement in manually finding and selecting feature points of important landmarks. In the present day, due to the progress of local feature point detectors and descriptors, the tasks of matching and registration can be done in most of the cases automatically. Thus, besides the geometric and photometric variations, outdoor and images taken from the air that need to be matched are often decomposed and decomposed by the haze, an atmospheric phenomenon. The haze is dependent on the unknown depth information.. The current method of Dark channel priorities, for single image haze removal, dark channel prioritization is based on the stats of haze-free images. Some pixels have very lesser intensity in at least one color (RGB) channel. In the method we have proposed, process of contrast enhancement increases the perceptibility of the objects in the image like auto-contrast, histogram stretching, gamma correction, linear mapping. We begin with the global operator that improves and helps in the enhancement of the contrast of the luminance ‘L’ based on hue ‘H’ and saturation ‘S’. Our strategy is thus 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.

Keywords: RGB, Dehazing, SIFT, Speeded Up Robust Features.

Introduction

Haze removal or Dehazing is an important function in both consumer photography applications as well as for scientific research. Removing hazy artifacts can thus significantly increase the clarity of the picture and change the color shifting which happens with the air light [15]. The image free of haze is thus a much clearer version of the original image and is very pleasing to the human eye [8] [11]. Most CV algorithms, lesser-level image analysis of high-level feature recognition, assumes that the inputted image is the radiance of the given scene. Hence Haze removal is a difficult problem because the haze is greatly related to the depth information which is unknown to the software. The problem doesn’t have enough constraints if the input is only a single haze image. Thus, numerous processes have been proposed by an utilizing an array of images or extra information.

Methodology

BLOCK DIAGRAM:

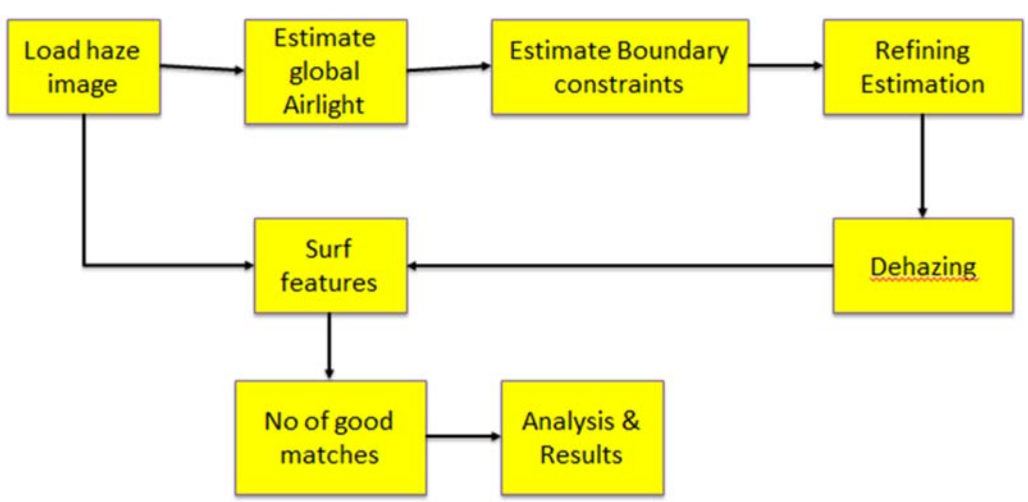

Fig 1

Image Conversion

Here the Haze images are loaded & converted to a different class. The different classes include uint8, double, logical etc. Based on requirement for further processing any one of the class types may be used.

Contrast Enhancement

The process of contrast enhancement aims to increase the perceptibility of the objects. In the image. To solve this problem, we define a contrast technique with several parameters that are optimized for a given image. Our strategy is derived from the global mapping operator used previously also for the decolorization problem. We start from the global operator that enhances the contrast of the luminance L based on the hue H and saturation S (the mapping is processed in the HSL color space) [14]. In contrast, we express the variation of the hue by the flickering equation with the parameters that are adaptively optimized for a given image. Depth image is used here to stretch the contrast of haze images based on the coarse depth layers of scenes.

We start from the global operator that enhances the contrast of the luminance L based on the highland saturation S (the mapping is processed in the HSL color space)

$LE = L\,(1 + SF\,(H))$ (1)

Where are the enhanced contrast and the f can be modeled as a trigonometric polynomial function. This global operator can be also related with the lightness predictor of Nayatani used to model the influence of chromatic components on the perceptual lightness of an isolated color.

SIFT

SIFT can robustly identify objects, even among untidy collection and under partial resistance, because the SIFT feature descriptor is invariant to uniform scaling, orientation, and partially invariant towards distortion and illumination changes. It summarizes laser object recognition methods and mentions a few competing techniques available for object recognition under untidy collection and partial resistance.

SURF

SURF (Speeded Up Robust Features) first presented by Herbert Bay *et al*. ECCV 9th in International Conference on CV held in Austria in May 2006is a robust local feature detector, that can be used in CV tasks like object recognition or 3D reconstruction. It is partly inspired by the SIFT descriptor. The standard version of SURF is several times faster than SIFT and claimed by its authors to be more robust against different image transformations than SIFT. SURF is based on sums of 2D Haar wavelet responses and makes an efficient use of integral images [19].

Estimating the Global Airlight

1) The airlight function is the multiplication of two factors: atmospheric luminance and the in-erseof depth map.
2) 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.
3) 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.

Calculating the Boundary constraints

Dehazing an image by requires to estimate an appropriate transmission function and the global atmospheric light at. To estimate the atmospheric light, We propose a method based on the image's dark channel. They first pick up the top 0.1% brightest pixels in the dark channel, and then select the one with the highest intensity as the estimate of A [8].

HSL and HSV color model

HSL (hue-saturation-lightness) and HSV (hue-saturation-value) are the two most common cylindrical-coordinate representations of points in an RGB color model. Developed in the 1970s for computer graphics applications, HSL and HSV are used today in color pickers, in image editing software, and less commonly in image analysis and CV.

4. Implementation

Software: MATLAB-Dark channel Prior

The dark channel prior is based on the follessering observationon haze-free outdoor images: in most of the non-sky patches, at least one color channel has very lesser intensity at some pixels. In other words, the minimum intensity in such a patch should has a very lesser value.

SURF (Speeded Up Robust Features)

The SURF algorithm is based on the similar principles and steps off SIFT, but it uses a different scheme and should provide better results: it works much faster. In order to detect characteristic points on a scale invariably SIFT approach it uses cascaded filters, where the difference Gaussian, DOG, is calculated on rescaled images progressively. The SURF descriptor is based on the similar properties of SIFT, with a complexity stripped down even further.

RGB color code

The RGB color model is an additive color model in which red, green, and blue light are added together in various ways to reproduce a broad array of colors. The name of the model comes from the initials of the three additive primary colors, red, green, and blue.

Simulation Results

Image Matching

Local feature points (keypoints) are used for matching images due to their impressive robustness
and invariance to different transformations. The matching process based on key points shown to be more effective than matching techniques based on extracting edges and contours. Typically, the framework of matching images based on local keypoints consists on three main steps.

The hazy images are converted to dehazed image by using the software MATLAB and further matched, both dehazed and hazy image and their matching sections are shown in figure below.

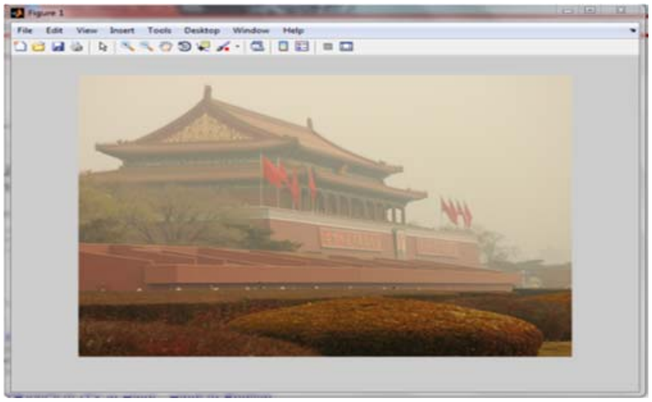

Fig 17: Hazy image: Original hazy image with fog,snow and dust which is shown above

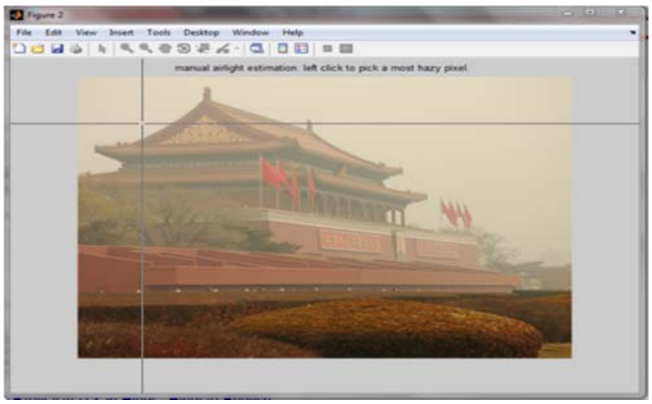

Fig 18: Manual airlight estimation: Estimation of the most hazy part of the image which is done manually clicking the most hazy pixel.

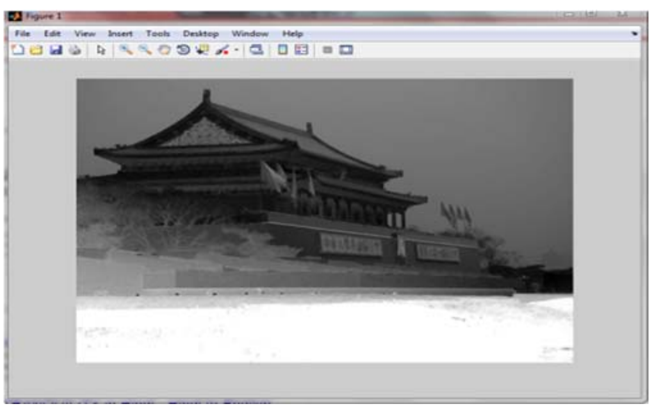

Fig 19: Refining estimation: Refined estimation of the image after selecting the 0.1 % pixel value taken from the image

Fig 20: Depth map

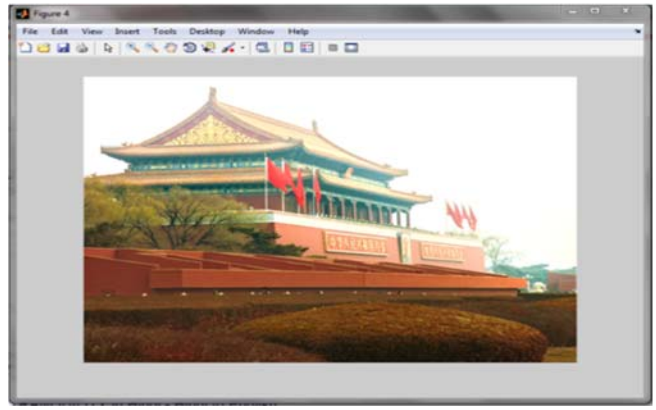

Fig 21: Dehazed image

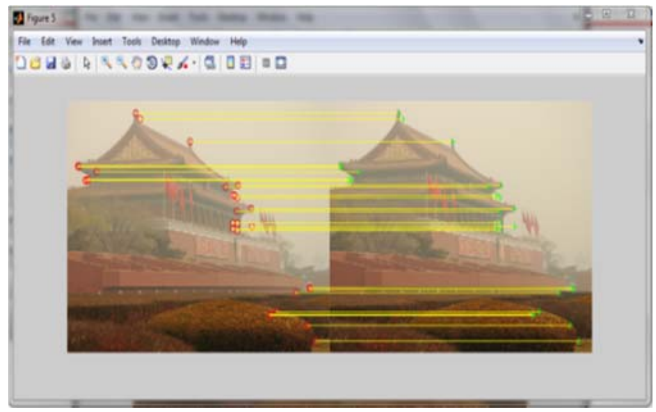

Fig 22: Hazy image matching: Matching hazy images to select the most hazy part of the image and further matched to calculate the matching points

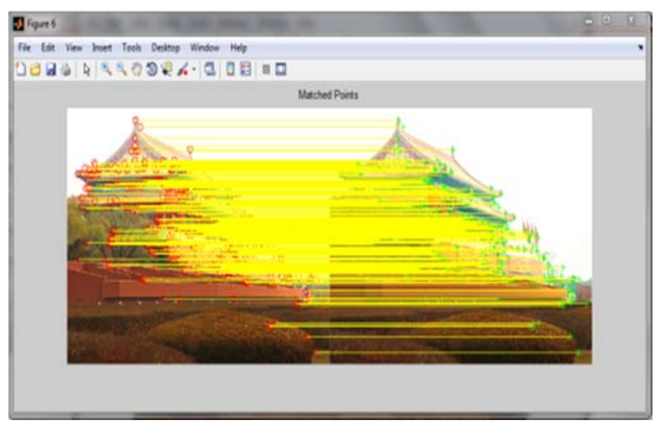

Fig 23: Dehazed image matching: Matching dehazed images to select the most hazy part of the image and further matched to calculate the matching points

Conclusion

Our proposed method, process of contrast enhancement thus increased the perceptibility of the objects in the image like auto-contrast, gamma correction, linear mapping, histogram stretching. We started from the global operator that enhances the contrast of the luminance ‘L’ based on the hue ‘H’ and saturation ‘S’.

Our strategy thus 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, SURF feature filters out all the features with lesser local contrast. The enhanced hazy image optimizes the contrast by the degradation of the finest details to minimum.

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