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Enhancement of low visibility aerial images using histogram truncation and an explicit Retinex representation for balancing contrast and color consistency

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ABSTRACT

This paper presents an improved multi-scale Retinex (MSR) based enhancement for ariel images under low visibility. For traditional multi-scale Retinex, three scales are commonly employed, which limits its application scenarios. We extend our research to a general purpose enhanced method, and design an MSR with more than three scales. Based on the mathematical analysis and deductions, an explicit multi-scale representation is proposed that balances image contrast and color consistency. In addition, a histogram truncation technique is introduced as a post-processing strategy to remap the multi-scale Retinex output to the dynamic range of the display. Analysis of experimental results and comparisons with existing algorithms demonstrate the effectiveness and generality of the proposed method. Results on image quality assessment proves the accuracy of the proposed method with respect to both objective and subjective criteria.

1. Introduction

Approach and landing under low visibility are critical issues for aviation security. Although advanced airborne equipment can improve safety during approach and landing, low visibility remains a leading threat that can cause CFIT (Controlled Flight into Terrain) and runway intrusion. Thus, improving a pilot's visual perception of the surroundings prior to landing has been a subject of great interest in recent years.

The aim of enhancement is to improve the visual appearance of digital images, or to provide a better cue for future processing, such as feature extraction, feature matching, and recognition. Current image enhancement techniques can be divided into two broad categories (Ekstrom, 2012): spatial domain image enhancement (Han et al., 2011; Sadeghi et al., 2011; Zuo et al., 2013) and frequency domain image enhancement (Schettini and Corchs, 2010; Demirel and Anbarjafari, 2011; Bhutada et al., 2011). Unfortunately, the effects of adverse weather increase exponentially with the distances of 3D scene points from the sensor. As a result, the space invariant image processing techniques mentioned above are not sufficient to remove weather effects from images.

Normally, bad weather such as fog, haze, smog, blizzard, sand storm, cloud (Shen et al., 2014; Wu et al., 2016) can significantly degrade the visibility of a scene. Among these conditions haze or fog is a common phenomenon in metropolises. Researchers have analyzed physics-based decay models and prior scene structures to remove weather effects. He et al. (2011) derived the statistics of outdoor haze-free images. Based on a haze image model they proposed a dark channel image prior to recover a high-quality haze free images. Several other researchers (Wang and Wu, 2010; Xu et al., 2012; Wei and Long, 2013) have studied the computation of atmospheric light and scattering function, and improved the speed and accuracy of dark channel prior based image dehazing. Dou et al. (2015) introduced Beltrami regularization and color image manifold theory to reconstruct haze-free images. All of these methods perform well for haze removal in non-sky regions. Unfortunately, they cause color distortions in sky regions. Except for that, due to the influence of the weather, images acquired from remote sensors are often contaminated by clouds, especially in the humid tropical areas.

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Narasimhan and Nayar (2003) presented a physics-based method to restore contrast of a scene under a wider range of weather conditions such as mist, haze, fog and other aerosols. They assumed that the weather condition does not change spatially in the field of view. However, multiple input images of a scene are required. Tan (2008) introduced an automated method that only requires a single input image. He developed a cost function following the framework of Markov Random Fields to enhance the contrast of an input image for improved visibility. Note that the method is not intended to fully recover the original colors of a scene (Tan, 2008). Thus, there are probable color differences between input and output images. Land and McCann (1971) conceived the Retinex theory as a model of the lightness and color perception of human vision. Land improved the concept especially considering the computational process (Land, 1983; Land, 1986). Jobson et al. (1997b) defined a practical implementation of the Retinex theory and defined a single-scale Retinex (SSR). SSR can either provide dynamic range compression with a small scale, or tonal rendition with a large scale. In the following years, they proposed the multi-scale Retinex with color restoration (MSRCR) (Jobson et al., 1997a) which combines the dynamic range compression of the small-scale Retinex with the tonal rendition of the large scale. Subsequently (Rahman et al., 2002; Rahman et al., 2004) used MSRCR as a platform for digital image enhancement by synthesizing local contrast improvement, color constancy and lightness/color rendition. In the last decade, researchers (Hines et al., 2004; Tsutsui et al., 2010; Kyung et al., 2011; Okuhata et al., 2013) focused on algorithm optimization to achieve real-time processing. The Retinex model emulates human color perception, which makes Retinex widely used in RGBW and OLED (Organic Light Emitting Diode) displays (Kwon and Kim, 2012; Nam et al., 2014). Recently, NASA Langley Research Center has been involved in vision enhancement for general aviation, with the goal of developing an inexpensive, enhanced vision system to aid pilots flying under poor visibility. To achieve this objective, they have developed an improved MSRCR + Autolevels algorithm and parallel implementation on a graphics processing unit (GPU) (Jiang et al., 2014). Retinex theory assumes that the human visual system has three independent ways to perceive short, medium, and long wavelengths in the visible light spectrum. Therefore, three scales are generally accepted in the literature we reviewed. How to devise multiple scales that can be broadly used in a variety of applications is an important consideration in this paper.

The main contributions of our paper are:

(1) A mathematically explicit representation of multiple scales in MSRCR is proposed. This representation, considering more than 3 scales, performs well in enhancing images degraded under low visibility conditions.
(2) A histogram truncation method is introduced to remap MSRCR output to the dynamic range of the display.

The two contributions listed above are what makes our approaches substantially different from the literature Jiang et al. (2014).

The remainder of the paper is organized as follows. Section 2 gives a brief overview of the usual MSRCR method. An improved MSRCR enhancement algorithm is presented in Section 3, including analysis of parameters, mathematically explicit representation of multiple scales and the histogram truncation method for displaying the MSRCR output. Experimental results and comparison with existing methods are outlined in Section 4. Finally, we conclude and discuss some directions for future research in Section 5.

2. Multi-scale Retinex with color restoration

The Multi-scale Retinex (MSR) (Jobson et al., 1997a) can be described by:

$$I_i^{\mathrm{MSR}}(x,y) = \sum_{n=1}^{s} \omega_n \frac{\log(I_i(x,y)+1.0)}{\log(I_i(x,y)+1.0) * F_n(x,y)} \tag{1}$$

where $I_i^{\mathrm{MSR}}(x,y)$ is MSR output, $I_i(x,y)$ is the image distribution in the i-th spectral band (for color image, i = 1, 2, 3 represents the red, green and blue channels respectively), ω_n is the weight associated with the n-th scale, "$*$" denotes the convolution operation and $F_n(x,y)$ is the surround function:

$$F_n(x,y) = \kappa_n e^{-\frac{(x+y)^2}{\sigma_n^2}} \tag{2}$$

where σ_n is the Gaussian surround space constant, and κ_n is selected such that:

$$\iint F_n(x,y)dxdy = 1 \tag{3}$$

In order to eliminate color distortion, a color restoration scheme is expressed as:

$$I_i^{\mathrm{MSRCR}}(x,y) = C_i(x,y) I_i^{\mathrm{MSR}}(x,y) \tag{4}$$

where $C_i(x,y)$ is the i-th band of the color restoration function in the RGB color space and is given by:

$$C_i(x,y) = \log\left(\eta \frac{I_i(x,y)+1.0}{\sum_{i=1}^{3}(I_i(x,y)+1.0)}\right) \tag{5}$$

where η controls the strength of the non-linearity.

Compared to traditional MSRCR, we skip the linear stretch transformation of the MSRCR output. Hence, we call the above manipulation reduced MSRCR. Experimental results in Section 4 show that this is a valid approach.

3. Improved MSRCR enhancement algorithm

Eqs. (1), (2), (4) and (5) constitute the reduced MSRCR enhancement algorithm where parameters $\omega_n, s, \sigma_n, \eta$ are determined as follows.

3.1. Value of ω_n, s and σ_n (explicit mathematical representation for multiple scales)

Considering $\omega_n = \frac{1.0}{s}$, Eq. (1) can be simplified to:

$$I_i^{\mathrm{MSR}}(x,y) = \log(I_i(x,y)+1.0) - \sum_{n=1}^{s} \omega_n \log(I_i(x,y)+1.0) * F_n(x,y) \tag{6}$$

Majority of MSRCR applications use $s = 3$ (Rahman et al., 2004; Livingston et al., 2011; Patil et al., 2013), with σ = 5, 20, 240, denoting the small, medium and large scale, respectively.

Multiple trials conclude that in Eq. (2) the smaller σ_n is, the sharper the output images look. However, smaller σ_n inherently induces greater halo artifacts. Likewise, the bigger σ_n is, the smoother the output images are. At the same time, the color of the output image coincides with the original one, at the cost of sacrificing high contrast. Experimental results show that more scales can help in improving the quality of enhancement. Therefore, how to balance the contrast and color consistency is an important issue to consider. We propose a strategy to construct multiple scales to address this concern.