An adaptive approach for visibility enhancement in aerial imagery

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ABSTRACT

A novel spatial domain image enhancement algorithm, in which dynamic range of the scene illumination is compressed from the human visual perspective to improve the visual quality and visibility in digital images captured under degraded visual conditions, is proposed. The proposed algorithm employs an adaptive approach so that local image statistics, namely the local standard deviation and the local mean in the image are modified simultaneously utilizing an intensity transform based on a “S” shape curve, the curvature parameter of which is determined adaptively followed by a local contrast enhancement process. The performance of the algorithm is evaluated by a statistical visual measure, along with visual comparisons of the proposed method with state-of-the-art enhancement algorithms are given.

Keywords: Adaptive image enhancement, local image statistics, visibility enhancement.

1. INTRODUCTION

Real world scenes usually comprise high dynamic ranges of light that cause poor visibility when captured by an imaging system. The captured images differ from direct observation of those scenes, since human visual system has some mechanisms that tackle with the high dynamic range of observed scenes. Turbid imaging conditions, such as fog, heavy rain, etc. under which acquired images and the direct observation resembles each other is an exception to this instance. The extreme narrow dynamic range of such scenes leads to extreme low contrast not only in the acquired images but also for the human visual system. Aerial images generally lack clarity that visibility in such images may decrease drastically and sometimes the conditions at which the images are taken may only lead to near zero visibility even for the human eyes. Image processing algorithms can be employed to extract useful information which cannot be perceived by the naked eye for improving the visibility in those images taken under such poor imaging conditions.

Local contrast and lightness in an image determine the perceived visual quality [1] hence developing algorithms to improve both of them has always been a hot area of interest for image processing community. Among these algorithms, global histogram modification techniques cannot provide sufficient local contrast enhancement for the whole image at the same time, especially when the image scene possesses non-uniform illumination which commonly happens in real world scenes. Advanced spatial domain image enhancement techniques may be classified in two main groups: 1. Histogram Equalization based algorithms, 2. Retinex based algorithms. Adaptive Histogram Equalization (AHE) [2]-[4], contrast-limiting AHE (CLAHE) [5] and Multi-Scale AHE (MAHE) [6] are examples that are developed for contrast enhancement based on global Histogram equalization (HE). Those advanced HE variations generally have very strong contrast enhancement, which is especially useful in feature extraction applications like medical imaging for diagnosis. They are not commonly used in processing color images probably because their strong contrast enhancement may lead to excessive noise or artifacts and cause the image to look unnatural.

Retinex based algorithms based on E. Land’s theory [7] model the human visual perception of lightness and color. In Retinex based algorithms, the average of surface reflectance relative to the surrounding surface reflectance, so called lightness values are computed in each of three distinct spectral bands for computation of the color of a pixel. This yields three distinct lightness values that give an invariant description of the surface-spectral-reflectance function at each wavelength implying it provides color constancy under some assumptions of image formation [8]. Modifications of the Retinex are proposed mainly to lessen the computational burden of the original algorithm. MSRCR (Mutiscale Retinex with Color Restoration) [9]-[12], employs the concept of Retinex to synthesize local contrast enhancement, color constancy, and lightness/color rendition for color image enhancement. Although MSRCR performs well for a very large variety of natural images, processing in three spectral channels for at least three scales makes the algorithm hard to

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implement for real-time applications on contemporary PC platforms. In addition, optimal performance is not always obtained with default parameter setting, especially when images that have a dark subject with a very bright background are being processed; MSRCR seems to have difficulty providing sufficient luminance enhancement for the subject. Besides, MSRCR with default parameters cannot handle the images with a very narrow dynamic range, such as images taken under turbid imaging condition without post-enhancement treatment. Moreover, there is a trade-off between using white-balance or not in MSRCR processing. If white-balance is turned off, the uniform bright regions in the original image turn to gray in the enhanced image, but local contrast is improved even for the brightest regions. When white-balance is turned on this drawback is overcome, however, the enhancement of only dark regions can be achieved. Finally, the “halo effect” appearing at the boundaries with a large luminance change between the large uniform regions even though reduced, is not totally removed.

In this paper, a novel spatial domain image enhancement algorithm is proposed for the enhancement of aerial imagery, in which the limited dynamic range of the scene illumination caused by the atmospheric effects is decompressed from the human visual perspective to improve the visual quality and visibility in digital images captured under degraded visual conditions. The enhancement algorithm employs an adaptive approach in which local image statistics, namely the local standard deviation and the local mean in the image are enhanced simultaneously using an intensity transform via an “S” shape curve whose curvature parameter is determined adaptively and locally based on the local mean followed by a local contrast enhancement process. The image under consideration is first split into overlapped sub-regions and in each tile discarding the diffused illumination caused by the atmospheric veil, the transform is decomposed so that the brightness and contrast in that region become greater than predefined values which are indicators of high visual quality [1]. Pixel values are determined by weighted averaging the calculated values in the overlapped tiles, in which the weights are determined based on distances of pixel locations from sub-region borders to provide a smooth transition. Finally, the color of the enhanced image is restored by simply multiplying the values of each color channel in the original image with the ratios calculated between the enhanced and original intensity image. Thus, local image contrast is enhanced via adaptive local operations mimicking the human visual system (HVS). The results of the proposed algorithm exhibit its superiority over MSRCR and CLAHE algorithms in terms of rendition and statistical visual quality measure [13].

In section 2, the implementation steps of the proposed algorithm are explained in detail. Section 3 presents the experimental results with discussions, and the conclusions is given in section 4.

2. ALGORITHM

Three main steps of the proposed algorithm are as follows:

1. Local reflectance estimation from the image histogram to minimize the effects caused by the illuminant variations.
2. Adaptive intensity transform based on a “S” shape curve, followed by an adaptive contrast enhancement process to perform the dynamic range compression preserving/enhancing the local contrast.

The scheme of the proposed algorithm is shown in Fig.1.

2.1 Reflectance Estimation

The sensor signal $S(x, y)$ incident upon an imaging system is given by

$$S(x,y) = L(x,y)R(x,y)$$  \hspace{1cm} (1)

where $R(x,y)$ is the reflectance and $L(x,y)$ is the illuminance at each point $(x,y)$ [8],[14]. The sensors and filters used in cameras have logarithmic responses to light intensity incident upon the photoreceptors. This fact implies that Eq.(1) can be decomposed by the transformation $I(x,y)=$log $S(x,y)$:

$$I(x,y) = \log L(x,y) + \log R(x,y)$$  \hspace{1cm} (2)

where $I(x,y)$ is the intensity of the image at pixel location $(x,y)$. Eq.(2) suggests that illumination has an shift effect on the image histogram. This shift, intrinsically, is not same in distinct spectral bands, e.g. atmospheric scattering of the direct light flux, so-called airlight, which dominates the illumination will be different for different wavelength components of
the incident light. The illumination is also assumed to be locally constant and determined from the histogram of the sub-region.

Another assumption of the lightness algorithms is the gray-world assumption stating the average surface reflectance of each scene in each wavelength band is the same: gray [8]. From an image processing point of view, this assumption indicates that images of the natural scenes should contain pixels having almost equal average gray levels in each spectral band. Based on the gray world assumption along with Eq.(2) and assuming that the atmosphere forms a veil that shifts the local intensities in each spectral channel, reflectance is estimation is realized as [15]:

1. The shift is estimated from the lower tail of the histogram of the intensity channel that is equal to a gray level corresponding a predefined ratio (a typical value would be 0.003) of the total number of pixels in each sub-region.
2. The shift is subtracted from each pixel value in each spectral channel.
3. Intensity transform as described in Section 2.2 is then applied on the histogram modified image.

![Fig. 1 The proposed algorithm](Image)

### 2.2 Intensity Transform via S-shape curve

Intensity transform is realized on the value component of HSV color space. For input color images, the intensity image $I(x,y)$ can be obtained with the following equation:

$$I(x,y) = \max[I_i(x,y)]$$

(3)

where $I_i(x,y)$’s are the RGB components of the color image in RGB color space. The enhancement algorithm is applied on this intensity image.
A raised hyperbolic sine function given in Eq.(4) is employed for the intensity transform [15]. The input normalized range [0,1] of the local intensities are mapped to the same range achieving dynamic range compression

\[
I'_n = \frac{\sinh(4.6248J_n - 2.3124) + 5}{10} 
\]

where \( I_n \) represent the normalized pixel intensities and \( r \) is the curvature parameter and is equal to local mean image intensity. The output of the transform for different \( r \) values is shown in Fig.2. According to the figure the transform is capable of boosting image intensities in underexposed regions and pulling down the intensities in overexposed areas.

The output intensities in each sub-region, obtained by applying Eq.(4) still lacks contrast since the high end and low end values approach to middle gray with the transform. A contrast enhancement procedure is utilized as

\[
I''_n = \begin{cases} 
I'_{n} & \text{for } I_n \leq r \\
\frac{I'_n}{r} & \text{for } I_n > r 
\end{cases} 
\]

Eq.(5) restores the local contrast mimicking human visual system where reflectance ratios with respect to surroundings are evaluated to determine the triplet values of the scene reflectance for discounting the illumination variations. The output intensities in the sub-image are then scaled to span the full range.

In our implementation, each sub-region is rectangular and overlaps one half of the total number of pixels in its neighboring sub-regions, thus each pixel is covered by four adjacent sub-regions having four different intensity values based on the curvature parameter, i.e. the local mean of the related region. Therefore, for a given pixel location, a weighted average of those four distinct values is required to determine the pixel intensity. The weights \( W_k \) given in Eq.(6) are inversely proportional the distances between the pixel location \((x_0, y_0)\) in hand and center locations of the corresponding \( k \)th neighboring sub-region.
\[ wx_1 = 1 - \frac{x_0 - 1}{0.5m - 1} \quad wy_1 = 1 - \frac{y_0 - 1}{0.5n - 1} \quad wx_2 = 1 - \frac{x_0 - 1}{0.5m - 1} \quad wy_2 = \frac{y_0 - 1}{0.5n - 1} \]
\[ wx_3 = \frac{x_0 - 1}{0.5m - 1} \quad wy_3 = 1 - \frac{y_0 - 1}{0.5n - 1} \quad wx_4 = 1 - \frac{x_0 - 1}{0.5m - 1} \quad wy_4 = \frac{y_0 - 1}{0.5n - 1} \]
\[ W_k = wx_k wy_k \quad \{k = 1,2,3,4\} \]

where \( m \) and \( n \) are row and column numbers of each sub-region, respectively.

### 2.3 Color Restoration

A linear color restoration process is carried out to obtain the final color image. The ratio between the original and enhanced intensity image along with the original image colors are employed for determining the RGB values \( I_{enh}(x, y) \) of the enhanced color image.

\[
I_{enh,i}(x, y) = \frac{I_{enh}(x, y)}{I(x, y)} I_i(x, y) \quad i = r, g, b
\]

where \( I(x,y) \) is the pixel value of the input intensity image at \((x,y)\) and is determined by Eq.(3); \( I_i(x, y) \) are the RGB values of the input color image at the corresponding pixel location and \( I_{enh}(x, y) \) is the resulting enhanced intensity value for the same location.

### 3. RESULTS AND DISCUSSION

The proposed algorithm has been applied to a set of aerial images with different degree of turbidity, which is depicted in Fig.3. The results show improved clarity for images captured in diverse flight conditions providing increased visibility distance. Some examples for such conditions are shown in Fig.4. In Fig.4 left column depicts the original images and right column shows the enhanced results. The first example shows a scene with mild haze, proposed algorithm completely removes the haze resulting in sharper image with saturated colors. The scene in the second row suffers from moderate fog with some clouds causing thicker turbidity. Good clarity is achieved and the colors of the scene content are restored in the enhanced image. The last row is an example of a scene with thick fog causing near zero visibility. The enhanced image achieves a high level of improvement to feature visibility removing the severe turbidity.

In Fig.5 a comparison of the proposed algorithm with MSRCR and CLAHE is presented. MSRCR belongs to Retinex based algorithms family and CLAHE is a member of HE based enhancement algorithms class and both are broadly used enhancement techniques. MSRCR enhanced images are obtained using PhotoFlair® with default “high contrast mode” settings but the white balance turned off and CLAHE results are produced using the routine in the Image Processing Toolbox of MATLAB® with default settings. From Fig.2 and from the experiments conducted with many other images, it can be inferred that the proposed algorithm outperforms these two algorithms, providing better visibility enhancement and rendition simultaneously.
For evaluation of the proposed technique, Visual Contrast Measure introduced in [13] is used. The VCM is a stand-alone external metric that can be used to determine visual quality. Computationally, the VCM is given by

\[ VCM = 100 \frac{R_v}{R_t} \]  

where \( R_v \) is the number of regions in an arbitrary image that exceed a specific threshold for regional signal standard deviation, and \( R_t \) is the total number of regions into which the image has been divided. The regions are rectangular and non-overlapping each other.

In table 1 VCM scores for the original and enhanced images are illustrated, showing far better VCM scores for all of the aerial images used in the experiments.

4. CONCLUSIONS

An adaptive image enhancement algorithm for enhancement of aerial images which lacks contrast especially when they are taken under poor weather conditions is proposed. The aim is to improve the visibility in aerial images so that one would able to see some features beyond the atmospheric veil, even under near zero visibility conditions. The proposed algorithm provides far better results in terms of visual contrast measure score. The results obtained enhancing a set of aerial images that exhibit different levels of turbidity showed its superiority over two widely used image enhancement algorithms. The enhanced results from a wide diversity of aerial images exhibit high visual quality and improved visibility inferring the proposed algorithm possesses a promising use in aerial imagery during poor visibility flight conditions.

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Fig. 4 The enhancement results for different types of turbidity. Left column: original images, right column: enhanced images.
Fig 5. Comparison of different contrast enhancement techniques. Upper left: original, upper right: MSRCR enhanced, Bottom left, CLAHE enhanced, bottom right: proposed method.

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<th>CLAHE</th>
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