Image Segmentation and Adaptive Contrast Enhancement for Haze Removal

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***Abstract* — With a view to restoring image details of heavily hazy images, we propose an adaptive contrast enhancement algorithm specifically for haze removal. It is composed of 3 parts. The first part is to segment the input image into flat background of air space and foreground which is the rest of the image. A specific gradient matrix is defined to generate a gradient feature value to identify the pixels of very weak signals with the presence of noise of similar amplitude. In the second part, a CLAHE-based method is developed and applied to the foreground to provide a stronger enhancement to weaker signal variations while the background is protected from noise enhancement. A specifically designed filter is then applied to remove noise caused by the discontinuity between the foreground and background areas, while preserving the enhanced image details. The proposed algorithm has been tested and its effectiveness has been proven by the test results.**

***Key words*— adaptive contrast enhancement, CLAHE, image segmentation, gradient matrix, haze removal.**

I. INTRODUCTION

The quality of outdoor images can be severely degraded by haze due to smog, dust, and other environmental or climactic issues. Haze-removal became important part in processing images of outdoor scenes, and the results of haze-removal can affect the quality of the succeeding processing.

Images of hazy scenes have poor contrast. Haze-removal is, in most cases, to improve the image contrast and to reveal haze-veiled image details. In general, adaptive histogram equalization (HE), such as CLAHE [1], is designed to enhance local image contrast and thus is effective for haze removal. However, if the input images have very poor contrast, such as the very heavily hazy scene shown in Fig. 1 (a), and if the clip limit is chosen to avoid noise amplification in flat areas, the enhancement in heavily hazy areas may not be sufficient to reveal image details, as shown in Fig. 1 (b). However a strong enhancement causes visible noise in the background, as shown in Fig. 1 (c). The method reported by Boschetti et al. is to make the clip limit to vary with image data variations [2]. As the data variations in hazy areas are similar as those in flat background, enhancing the contrast in these areas also causes noise in background, as shown in Fig. 1 (d). It is thus a challenging task to enhance very weak signal of image details without generating visible noise in flat areas.

The dark channel approach [3] can also be used for image haze-removal. Similar to the methods based on histogram equalization, it was not designed specifically to aim at restoring heavily hazed images.

The objective of the work presented in this paper is to develop an algorithm to restore heavily hazed outdoor images. It involves an effective image segmentation and a new version of CLAHE with adaptive clip limit, with a view to applying a strong contrast enhancement without generating visible image noise. A new gradient matrix is proposed to detect very weak signal variations with the presence of noise gradients of similar magnitudes. The algorithm has been applied to a good number of heavily hazed images, and its effectiveness has been demonstrated by the test results.

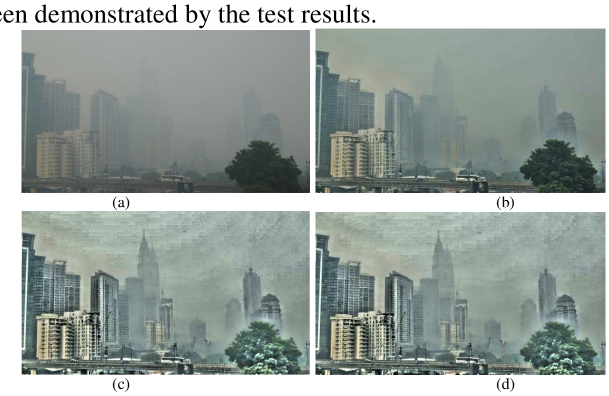


Fig. 1 (a) Example of heavily hazed outdoor image. (b) Result by CLAHE with moderate enhancement. (c) Result by CLAHE with strong enhancement. (d) Result by the method of variable clip limit [2].

II. DESCRIPTION OF THE ALGORITHM

As mentioned previously, the proposed algorithm aims at a good restoration of heavily hazy outdoor images. The key point in it is to make the contrast enhancement local-signal-dependent in such a way that the weaker the signal variations due to thicker haze, the stronger the enhancement to reveal more image details. However, this enhancement approach may cause a noise amplification in flat areas, such as part of sky in outdoor images. Hence, this algorithm comprises a stage of segmentation to identify the areas of objects and the areas of background, and a CLAHE-based enhancement method is proposed and applied only to the areas of objects. The block diagram of the processing is shown in Fig. 1. The details of the processing are presented in the following subsections.

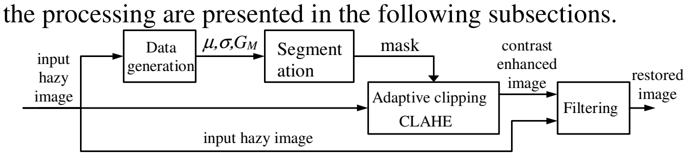


Fig. 2 Block diagram of the proposed algorithm for contrast enhancement.

A. *Image segmentation*

The input image is segmented into background and foreground areas. The background is specifically atmospheric, i.e., air space, and all the other parts in the input image, such as buildings, trees or vehicles, belong to the foreground. Thus, the foreground comprises areas of signals and the gray level variations will be significantly enhanced, whereas the areas of atmospheric background is expect to receive a very light enhancement to avoid noise enhancement.

Gradient-based image segmentation has been used in haze removal operations [4]. In a normal case, as the foreground has more significant gray level variations, with respect to the flat background, simple gray level gradients can be used to differentiate foreground segments from the background ones. However, in images of severely hazy outdoor scenes, as the example shown in Fig. 1(a), the gray level variations of distant buildings are in the same level as that of the noise in the background. Thus, one needs to find other feature data to distinguish the foreground from the background.

To differentiate the signal gradients and noise ones, we propose to get 3 kinds of image data at each pixel position.

- average gray level $\mu(i,j)$ of the neighborhood,
- signal variation measured by the standard deviation $\sigma(i,j)$,
- gradient matrix $G_\Sigma(i,j) = [g_{1\Sigma}(i,j), g_{2\Sigma}(i,j), \ldots g_{k\Sigma}(i,j)]$ and its gradient feature value $G_M(i,j)$.

Each of the above data is generated in a neighborhood centered at (i,j) and sized $(2n+1)^2$ pixels.

The gradient matrix G_Σ is proposed for this image segmentation. Let us use the following example to explain how the elements of $G_\Sigma(i,j)$ are defined.

If we consider the signal gradients in 4 directions ($k = 4$), e.g., (0º, 45º, 90º, 135º) or (180º, 180º+45º, -90º, 180º+135º), $G_\Sigma(i,j)$ will has 4 elements calculated in 2 steps. In the first step, we use a set of 4 high-pass filtering kernels to generate 4 gradient maps, representing the gradients in the 4 directions, respectively, and each gradient component in these maps is a signed value. In the second step, in a neighborhood of $(2n+1)^2$ pixels, the $(2n+1)^2$ signed values of the gradient components in the same map are summed up algebraically to generate the element of that gradient direction. For example, $g_{3\Sigma}$ is the algebraic sum of the $(2n+1)^2$ signed values of the gradient components in the 3^{rd} direction (±90º). Hence, each element in G_Σ represents the gradient components of the neighborhood in a specified direction, and the algebraic summation of the signed gradient values helps to eliminate some gradient components produced by noise.

The gradient feature value G_M is defined as $G_M = \max(g_{1\Sigma}, g_{2\Sigma}, \ldots g_{k\Sigma})$, the maximum value of the elements of G_Σ, if the input is a gray-scale image. In case of color image of RGB maps, there will be three G_Σ matrices, namely $G_{\Sigma R}(i,j)$, $G_{\Sigma G}(i,j)$ and $G_{\Sigma B}(i,j)$. The feature value G_M can be defined in different way. We propose the following three options.

- Option 1: $G_M = G_{M1}$, the maximum value of all the 3k elements of the three matrices.
- Option 2 is to let G_M to be the arithmetical or algebraic sum of G_{M1} and the 2 elements in the same gradient direction. For example, if $G_{M1} = |g_{2\Sigma R}|$, $G_M = |g_{2\Sigma R} + g_{2\Sigma G} + g_{2\Sigma B}|$ or $G_M = |g_{2\Sigma R}| + |g_{2\Sigma G}| + |g_{2\Sigma B}|$.
- Option 3: Instead of a simple summation of the three elements in Option 2, in Option 3, G_M is the square root of the sum of their squared values.

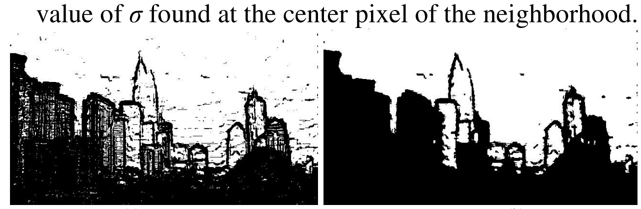
As G_M is based on the maximum value of the elements in the G_Σ matrix, it carries information of the dominant gray level variations In the neighborhood.

The set of data $\sigma(i,j)$, $\mu(i,j)$, and $G_M(i,j)$ represents the image feature information of the gray level distribution and the dominant edge orientation in the neighborhood surrounding the pixel position (i,j). In the proposed algorithm, the data of the input image is processed to generate σ-map, μ-map, and G_M-map. These maps are then used to segment the input image into the regions of the foreground and those of the background.

The segmentation is a process of 2 identifications. The first is to check G_M of all the pixels and those having higher values, normalized with the gray level at the location, are identified as foreground pixels. The remaining pixels will get the second identification and it is based on μ and σ, the data of local gray level distribution. A pixel will be identified as a foreground pixel, if its neighbors have higher σ values, with respect to its μ value.

The proposed segmentation has been applied to a number of heavily hazy images. In this application, G_M is calculated with Option 3 and then normalized by $x(i,j)$, the gray level of the location. A pixel satisfying one of the two conditions is identified as foreground pixel:

1. Its $G_M(i,j)/x(i,j)$ value is higher than a given threshold, or
2. its ratio of $(\Sigma\sigma)^4/\mu(i,j)$ is higher than a certain value, where $(\Sigma\sigma)$ is the sum of the $[(2n+1)^2 - 1]$ values of σ in the neighborhood of $(2n+1)^2$ pixels, excluding $\sigma(i,j)$, the value of σ found at the center pixel of the neighborhood.



(a) (b)

Fig. 3 (a) Binary image in which the black pixels have higher G_M values than white ones. (b) Binary mask generated by the stage of segmentation.

The image shown in Fig. 3(a) is produced by applying the first identification, based on G_M, to the image shown in Fig. 1(a). After the two identifications, a very simple morphological operation is performed to remove small spots, as those shown in Fig. 3(a) in the background. The mask generated at the end of the segmentation is shown in Fig. 3(b). One can see that

1. the outlines of very distant buildings are included in the foreground, indicating that, by means of the gradient feature value G_M, the proposed segmentation method is effective in identifying the foreground pixels from the background though their gray level variations are in a similar level, and
2. the pixels of smaller flat areas, such as brighter parts in the buildings located in the very left-hand side of the image shown in Fig. 1(a), are also included in the foreground, by means of the ratio of $(\Sigma\sigma)^4/\mu(i,j)$, with a view to a good enhancement in the following stage.

This image segmentation has also been applied to other hazed images to identify the foreground and background pixels, and similar results have been obtained, and the binary masks generated will be effectively used in the stage of the adaptive contrast enhancement.

B. Adaptive contrast enhancement and filtering

As mentioned previously, a good contrast enhancement is a key issue in haze-removal operations. CLAHE is likely the best adaptive histogram equalization method for contrast enhancement, and its clip limit can be used to adjust the dose of the enhancement. Using the mask generated in the image segmentation, one can apply a lightly dosed enhancement to the background areas without risk of noise enhancement. For the enhancement in the foreground areas, we propose an adaptive clip-limit CLAHE to make the contrast gain better adapt the local signals. In this particular CLAHE, the clip limit α is made to be signal-dependent, defined as

$$\alpha = (1 + 0.4\mu_{k,l}/\sigma_{k,l}^{1.2})\ (2n_t+1)^2/256$$

where $(2n_t+1)^2$ is the number of pixels in each tile, (k,l) is the coordinates of the tile, $\mu_{k,l}$ and $\sigma_{k,l}$ are the average level and the standard deviation of the input pixel signals, respectively, in the tile. The clip limit is made to be inversely related to the variations. In this way, the more signal degradation by thicker haze, the smaller signal variations, the higher clip limit, and the stronger enhancement.

It should be noted that the above-described adaptive clip limit is different from that presented in [2]. In that algorithm, to avoid noise enhancement in flat areas, the clip limit was made to decrease with the signal variance. The clip limit in this work adapts to the local signal in the opposite direction, as there is no concern of noise enhancement in the flat background.

As mentioned previously, the input image can be a gray-scale or color image. If it is composed of RGB maps, like the one shown in Fig. 2(a), one can convert it to a gray-scale image, and then apply the proposed enhancement to the gray-scale image. The image shown in Fig. 4(a) is the contrast enhanced gray-scale image, produced by the proposed enhancement. Many image details that were veiled by haze in the original input appear in the enhanced image. However, one can also notice some noise, mostly due to the discontinuity between the foreground and the background areas. A filtering stage is designed to remove it.

(a) (b)

Fig. 4 (a) Contrast-enhanced image before the filtering.
(b) Contrast-enhanced and filtered image.

C. Adaptive filtering

The inputs of the filtering stage are the gray-scale hazy image x, and the contrast-enhanced image x_E. From x-map and x_E-map, one can generate E-map, i.e., the map of the enhancement coefficients with $E(i,j) = x_E(i,j)/x(i,j)$. From the data of the E-map and the x-map, the variance $var(x)$, the covariance $cov(x,E)$ and the ratio of $cov(x,E)/var(x)$ in neighborhoods of $(2n_v+1)^2$ pixels are calculated. The filtering coefficient $f(i,j)$ is calculated as follows:

$$f(i,j) = \mu_{Cov/var}(i,j)\ [(x(i,j) - \mu_X(i,j)] + \mu_E(i,j)$$

where $x(i,j)$ is the pixel value at (i,j) in the x-map, $\mu_X(i,j)$, $\mu_{Cov/var}(i,j)$ and $\mu_E(i,j)$ are the average values of x, $cov(x,a)/var(x)$, and E, within a window of $(2n_m+1)^2$ pixels, in their respective maps.

This filtering is local signal-adaptive. In flat areas, $f(i,j) \approx \mu_E(i,j)$, and in the other areas, $f(i,j)$ is adjusted bi-directionally around $\mu_E(i,j)$ by $\mu_{Cov/var}(i,j)[(x(i,j) - \mu_X(i,j)]$ to remove strong discontinuity while preserving the original enhancement $E(i,j)$. The filtering coefficient $f(i,j)$ is applied to the input image to produce a new contrast-enhanced image. Fig. 4(b) illustrates the filtered gray-scale image produced from the image shown in Fig. 4(a). The quality of the image is evidently improved by this filtering.

D. Color information and color restoration

In case of color hazy image, the color information is used, as described in II.A, to produce G_M that is used in the segmentation. In the stage of the CLAHE-based enhancement, the local histogram is established with the pixels of all the 3 tiles from the 3 color maps, it is then clipped to generate the cumulative distribution function (cdf) that is applied to the gray-scaled image x, converted from the color input, to produce a gray-scale enhanced image x_E. The filtering coefficient map (f-map), produced based on the data of the x-map and x_E-map, is applied to each of the 3 original input RGB maps to produce a color image.

III. TEST RESULTS

The proposed algorithm for haze removal has been implemented and tested with a good number of color images of heavily, modestly, and lightly hazy outdoor scenes.

In the stage of the image segmentation, the gradient components in the 4 directions, i.e., (0º, 45º, 90º, 135º) are calculated. As each image has RGB maps, three gradient matrices, each having 4 gradient elements, are generated at each pixel position. The neighborhood size to calculate the elements is 5x5 pixels. The feature value G_M is calculated with Option 3 described in Section II.A.

For the CLAHE-based adaptive contrast enhancement, the tile size is 25x25 pixels. For the filtering, the neighborhood size for the calculation of $\mu_X(i,j)$ and $cov(x,a)$, $\mu_{Cov}(i,j)$, $\mu_X(i,j)$ and $\mu_A(i,j)$ is 27x27 pixels.

The test results are compared with those resulting from Dark Channel Prior (DCP) [3]. Though a good number of algorithms based on DCP have been reported more recently but it is not evident to see significant improvement in overall performance from them.

Figs. 5 illustrates 2 examples of outdoor scenes covered with heavy haze and the results of haze-removal with DCP and the proposed algorithm. In terms of restoring severely degraded image details, the proposed algorithm has evidently better performance. It has resulted in significantly better enhancement without noise amplification in the background thanks to the effective protection of the mask.

The scenes shown in Fig. 6 are less hazy, but of higher dynamic range, compared to those in Fig. 5. In these cases, the CLAHE-based adaptive local enhancement has the advantage to produce better contrast in different image locations, without concern of noise generation in flat background areas.

Though the proposed algorithm is designed to remove heavy haze. It can also be used to process lightly hazy images as shown in Fig. 7, to recover image details.

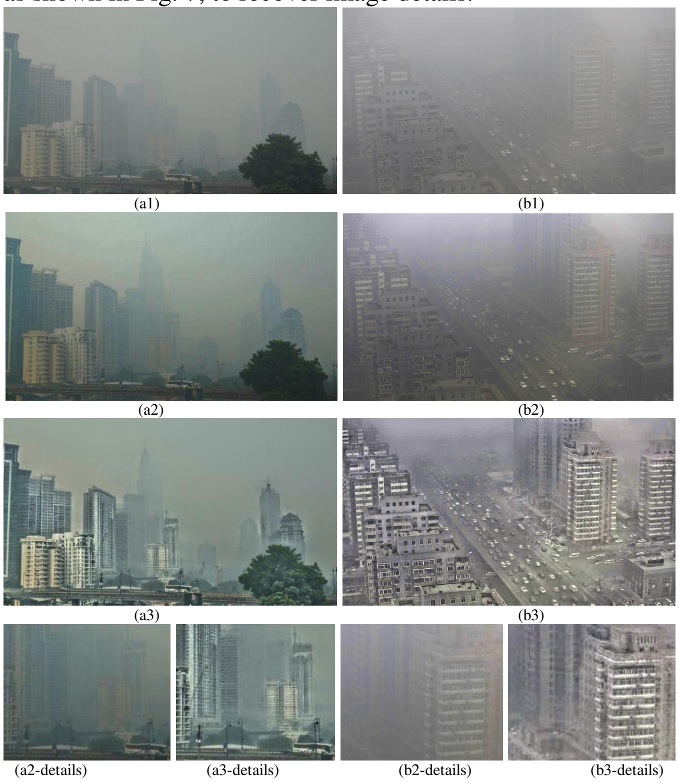


Fig. 5 (a1) (b1) Input images of severely hazy scenes.
(a2) (b2) Haze removed images by DCP [3].
(a3) (b3) Haze removed images by the proposed algorithm.

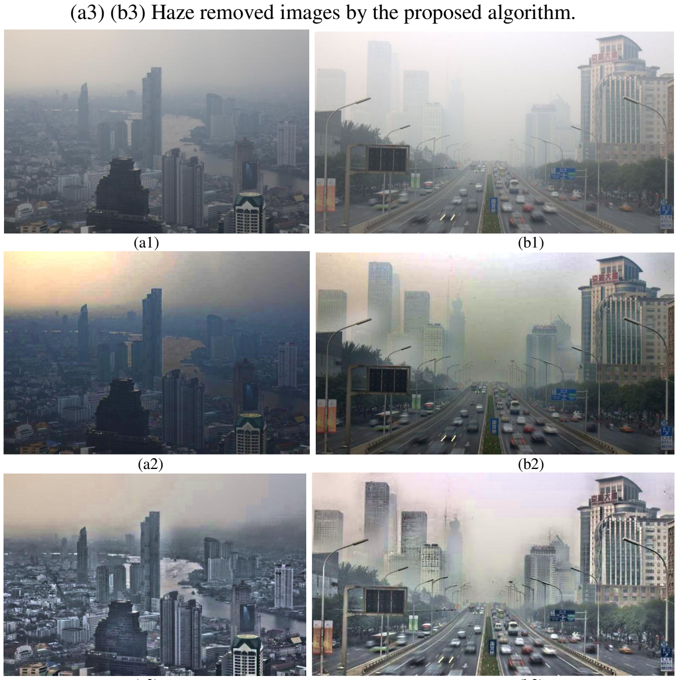


Fig. 6 (a1) (b1) Input images of hazy scenes.
(a2) (b2) Haze removed images by DCP [3].
(a3) (b3) Haze removed images by the proposed algorithm.

Fig. 7 (a1) (b1) Input images of lightly hazy scenes.
(a2) (b2) Haze removed images by DCP [3].
(a3) (b3) Haze removed images by the proposed algorithm.

IV. CONCLUSION

In this paper, an adaptive contrast enhancement algorithms has been proposed to restore signal details from heavily hazy images, where signal variations in the foreground areas are degraded to the level of noise in flat area. The challenge in the design is to apply a strong enhancement to such signals without noise amplification. It has been achieved by three elements. Firstly a specific gradient matrix is defined to generate a gradient feature value used to identify the pixels of very weak signals with the presence of noise of similar amplitude. Together with other signal data, the image is well segmented into the foreground and background areas. Then a CLAHE-based enhancement method is developed and applied in the foreground areas while the background is protected from noise enhancement. Finally an effective filtering operation is performed to improve the visual quality of the restored image, while preserving the enhanced image details. The effectiveness of the proposed algorithms has been demonstrated by the test results. Though the algorithm is designed for haze removal, it can also be applied for other image quality enhancements.

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