A Weighted Logarithmic Model based Enhancement of Weather Degraded Images

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Abstract

The lack of information content in the images captured under bad weather dominates the reason of poor visibility more, than due to the overall contrast or other. This paper presents a novel method for enhancement of weather degraded images. The proposed enhancement method is based upon the logarithmic image processing (LIP) framework and human visual system (HVS). The proposed method uses multiple images of the same scene in order to increase the information content and produce a visibly enhanced resultant image. A region based contrast measure called the logarithmic region contrast measure (LRCM) for finding the optimal value of location based parameters of the proposed method and its comparison with other traditional contrast measures has been presented here in this paper. The experimental results on two data sets of weather degraded images are included here in this correspondence.

Keywords: Logarithmic image processing (LIP), Image enhancement, contrast measure, human visual system

1. Introduction

The information content of the images captured in misty and scattering media such as fog, haze, and smoke are low and hence suffers from degradation in visibility. In such media, the radiance and transmittance from a scene point radically gets diffused and modulated. Enhancement of such images formed by transmitted light [1] or the human visual system (HVS) [2], may not comply with the classical linear image processing (CLIP) techniques [3, 4, 5]. These images acquired under murky atmosphere results in the information content loss which increases with increase in distance [6]. Retrieving or improving the visual information in poor visibility is significant for various machine vision and user-assisted applications such as aircraft traffic, mapping, surveillance, navigation, and on-road visibility. There is, thus, a growing interest in the analysis and enhancing the visibility of weather degraded images [6, 7, 8, 9].

Several methods have been proposed to restore good visibility. Nayar *et al.*, [7] illustrates that the bad weather effects depends more strongly on the depth of the scenes than the overall contrast. Thus, the traditional enhancement techniques e.g. histogram equalization does not befit here. They conferred on various types of weather conditions and their formation processes and summarized two models of atmospheric scattering – attenuation and airlight-that are most pertinent to a HVS.

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Using these models they recovered the depth map of the scenes for enhancing the scene. Satherley *et al.*, [10] proposed a method for reversing contrast loss in diffuse daylight illumination conditions based on the principle of scattering that required a priori information about the scene geometry. Kopieka and Yitzhaky [11] restore image contrast for a single image that required a priori knowledge of the blur function. Petterson *et al.*, [12] proposed a method for a single image using linear combination of the direct transmission and the airlight.

Models based on the human visual system (HVS) have also been used for image enhancement [13]. Some of these methods attempts to discriminate the edge and non-edge pixels by extracting the edge information of an image [14, 15]. A few HVS based image enhancement model segments an image based upon background intensity and gradient [16], [17].

Thus, due to the deficiency of a broad-spectrum hypothesis of image enhancement, the enhancement task of images is complicated. A successful automatic image enhancement requires an objective criterion for enhancement and an external evaluation of quality [18], [19].

In this paper, we propose a novel method to image enhancement of weather degraded images on the basis of logarithmic image processing model with the inclusion of location parameters pertaining to on road weather degraded images. The proposed method utilizes multiple images to form a single image that is more visually pleasing. The parameters are chosen by performing enhancement with all practical values and then analyzing each output image using the proposed logarithmic region contrast measure and compared with other traditional measures.

This paper is organized as follows. Section 2 presents the necessary background information including the logarithmic image processing (LIP) model operator primitives and a review of contrast measures. Section 3 describes the proposed method for enhancement of weather degraded images and a new logarithmic region contrast measure, for obtaining the optimal parameters. Section 4 presents the computational complexity analysis, Section 5 presents the results of computer simulations for the enhancement of two sets of experimental data of weather degraded images. Section 6 presents concluding remarks.

2. Background

In this section the initial motivation of the LIP model and a review of contrast measures are included.

2.1 Logarithmic Image Processing (LIP)

In the LIP framework, the images are represented by mappings, called gray tone functions (f) [20, 21] that are defined on the spatial domain and valued in the positive real number set $[0, M)$, called the gray tone range. The transmittance of f at point (x, y) is given by:

$$N_f(x, y) = \frac{\xi_s(x, y)}{\xi_e(x, y)} \quad (1)$$

Where, $\xi_s(x, y)$ is the incoming flux,

$\xi_e(x, y)$ is the outgoing flux,

In this perspective, the gray tone function f is defined by:

$$f(x, y) = M(1 - N_f(x, y))$$ (2)

Eq. (1) and (2) illustrates the physical rationale and its consistency with the transmittance image formation model. The linear space constituted by the set of these gray tone functions ordered with a vector addition denoted $\oplus$ and a scalar multiplication, denoted $\otimes$ are defined in [20]. A mathematical meaning to the opposite and difference between two gray tone functions f and g is given [20] by:

$$\Theta f = \frac{-Mf}{M - f}$$ (3)

$$f \Theta g = M \frac{f - g}{M - g}$$ (4)

2.2 Contrast Measure

A light that is observed by human eye may be expressed in differential form i.e. either as slightly brighter or much brighter than another light, but it is tough to allocate numerical values to such observations. It is however, expected to evaluate a contrast measure indirectly in terms of the minimum change in illumination which can be distinguished as a change in brightness.

If L is the uniform background luminance observed by a human eye, and ΔL is the increase or decrease in that luminance, then the measure of the contrast defined [22] by:

$$C_w = \frac{\Delta L}{L}$$ (5)

is considered a measure of the perceptive power of the eye. This description of the relation between the discriminable threshold ΔL and the original luminance L is known as the Weber-Fechner law.

For simple patterns, the Michelson contrast measure [23] is used to measure the contrast of a periodic pattern such as a sinusoidal grating and is defined as:

$$C_M = \frac{L_{max} - L_{min}}{L_{max} + L_{min}}$$ (6)

Eqs. (7) and (8) depicts the variability and deviation from a common ground. Fixed measurement of contrast using Eq. (8) is not appropriate because a pair of points of extreme brightness or darkness can determine the contrast of the whole image. For example, if a single over illuminated point or an especially under illuminated point is added to an average contrast image, the value of the Michelson contrast would increase significantly, but the apparent contrast may be reduced [22].

The definition of a local band limited contrast in the frequency domain defined in [22] provides a local contrast measure for every band that depends not only on the local energy at that band but also on the local background luminance as it varies from place to place in the image:

$$C(x, y) = \frac{a(x, y)}{l(x, y)}$$ (7)

Where, $a(x,y)$ - Filtered image

$l(x,y)$ - Luminance mean image.

Eq. (7) is applicable to complex images and finds the contrast in the frequency domain.

Weber's law based contrast measure is defined in [26], for an image I, divided into $k_1 \times k_2$ blocks with center (k,l) of size $M_1 \times M_2$:

$$EME_{k_1,k_2}(\Phi) = \frac{1}{k_1 k_2} \sum_{l=1}^{k1} \sum_{k=1}^{k2} 20 \ln \frac{I^{w}_{\max;k,l}(\Phi, par)}{I^{w}_{\min;k,l}(\Phi, par) + c} \qquad (8)$$

where, Φ is a given transform, $I^{w}_{\max;k,l}$, $I^{w}_{\min;k,l}$ are the maximum and minimum luminance values in a block of the image, and c is a small constant equal to 0.0001 to avoid dividing by 0. This measure of enhancement is used to find the average ratio of maximum to minimum intensities in decibels. Another method of enhancement defined is based upon the concept of entropy [26]

$$EMEE_{k_1,k_2}(\Phi) = \frac{1}{k_1 k_2} \sum_{l=1}^{k1} \sum_{k=1}^{k2} \mu \left(\frac{I^{w}_{\max;k,l}(\Phi, par)}{I^{w}_{\min;k,l}(\Phi, par) + c} \right) \times \ln \frac{I^{w}_{\max;k,l}(\Phi, par)}{I^{w}_{\min;k,l}(\Phi, par) + c} \qquad (9)$$

This is known as the measure of enhancement by entropy, or EME using entropy. The measures that are based on the Michelson contrast (Eq. (6)) are AME and AMEE defined in [27]. These gives the relationship between the spread and the sum of the two luminance values found in a small block.

$$AME = \left(\frac{1}{k_1 k_2} \sum_{l=1}^{k_1} \sum_{k=1}^{k_2} 20 \ln \frac{I^{w}_{\max;k,l} - I^{w}_{\min;k,l}}{I^{w}_{\max;k,l} + I^{w}_{\min;k,l} + c} \right) \qquad (10)$$

$$AMEE = \frac{1}{k_1 k_2} \sum_{l=1}^{k_1} \sum_{k=1}^{k_2} \mu \left[\frac{I^{w}_{\max;k,l} - I^{w}_{\min;k,l}}{I^{w}_{\max;k,l} + I^{w}_{\min;k,l} + c} \right]^{\mu} \times \ln \frac{I^{w}_{\max;k,l} - I^{w}_{\min;k,l}}{I^{w}_{\max;k,l} + I^{w}_{\min;k,l} + c}^{\mu} \qquad (11)$$

Next section describes the proposed method and a region based logarithmic contrast measure (LRCM) for finding the optimal parameters of the proposed method.

3. Proposed Enhancement Method

The following approach pertains at the outset to images obtained in the perspective of transmittance image formation LIP model:

Let G be a set of weather degraded images:

$$G = \{D_1, D_2, ...D_n\} \qquad (12)$$

Where,

D_n - Weather degraded images/frame as captured from the silicon sensor based digital camera [25] at a time instant t and location l as depicted in Fig. 1.
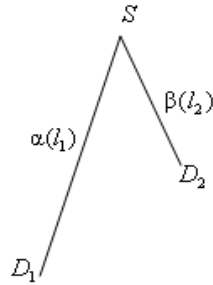
Figure 1. Illustration of location parameters and capture points, of the degraded images (D_1, D_2) **with respect to a scene point** (S)

The sensitivity curve for human and silicon sensors as shown in Fig. 2 [24] evidently depicts a very low strength of silicon sensors sensitivity [25] in the human visual range as compared to human sensitivity, whereas beyond the range of human sensitivity, silicon sensitivity has significant strength.
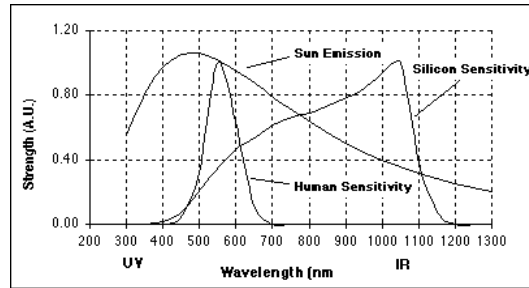

Figure 2. Sensitivity Curve

We attempt to define a spatial domain transformation function (T) as a function of gray tones of degraded images and their respective location parameters to enhance and increase the information content of the weather degraded image captured from a silicon sensor based digital camera. This corresponds to the findings that the transmittance of a scene point gets modulated and it increases with increase in distance [6], [25]. T is defined as:

$$T = F\left\{\alpha(l_1), \beta(l_2), D_n\right\} \tag{13}$$

For a set of two images and location parameters $\alpha(l_1)$ and $\beta(l_2)$ using both the conventional operators $+, \times$ and LIP primitives $\oplus, \otimes$, T_s and T_L are defined as:

$$D_s = T_s\left\{(\alpha(l_1), \beta(l_2), D_1, D_2)\right\} = \alpha(l_1) \times D_1 + \beta(l_2) \times D_2 - \alpha(l_1)\beta(l_2) \times \frac{D_1 D_2}{M} \tag{14}$$

$$D_L = T_L\left\{(\alpha(l_1), \beta(l_2), D_1, D_2)\right\} = \alpha(l_1) \otimes D_1 + \beta(l_2) \otimes D_2 - \alpha(l_1)\beta(l_2) \otimes \frac{D_1 D_2}{M} \tag{15}$$

Where, D_s and D_L are spatial domain transform images having distance information of the gray tone functions of both D_1 and D_2 .

The resultant enhanced images $E_{s,D1}$, $E_{L,D1}$ with respect to D_s and D_L is obtained by spatially transforming the degraded image D_1 (corresponding to location l_1) using:

$$E_{s,D1} = T_s\{(D_s, D_1)\} \tag{16}$$

$$E_{L,D1} = T_L\{(D_L, D_1)\} \tag{17}$$

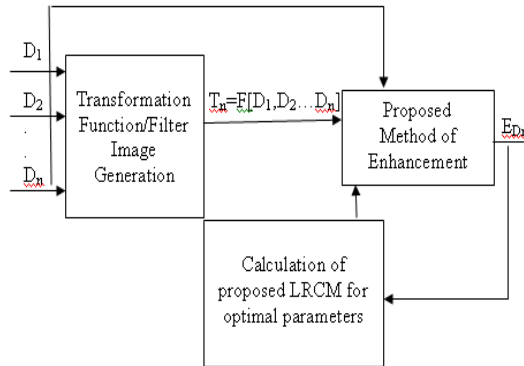Figure 3 shows the block diagram of the proposed method.

Figure 3. Block diagram of the proposed enhancement method

For finding the optimal location parameters $\alpha(l_1)$ and $\beta(l_2)$ a region based logarithmic contrast measure (LRCM) is presented. The defined measure is comprised of logarithmic subtraction and summation. It computes the contrast measure for a smallest discrete region (spatial domain) within the image, as compared to previously defined measures that calculate the same for each block of a divided image. The presented measure does not posses the disadvantage of range dependence while the contrast measures defined in Eqs. (8)-(11) are range dependent that change itself based on the maximum and minimum range [22].

$$LRCM = 20\ln\left\{\sum_m \sum_n \left(\frac{I(m,n)\Theta}{\frac{1}{4} \oplus \sum_{i,j=0}^{1} I(m \pm i, n \pm j)}\right)\right\} \tag{18}$$

Next sections include an analysis of the computational complexity and results of computer simulation performed on two sets of experimental data of on road weather degraded images.

4. Computational Complexity Analysis

The evident implementation details of each conventional image enhancement method are currently unavailable. We provide a computational analysis on our proposed method. This calculates the spatial domain transformation function that computes one addition, one subtraction, two multiplications, one division and three LIP multiplications for each gray tone. Thus, the order of finding the transformation function is $O(n)$. Similarly the order of obtaining the enhanced image is also $O(n)$. For computing location parameters it uses one

LIP subtractions and four LIP additions which results into a total of 6 subtractions, 4 additions, one multiplication, and one division, which must be calculated for every pixel of the resultant image. Thus, the complexity for the overall method for a set of two degraded images would be $O(3n) \rightarrow O(n)$.

5. Results

In this section, we present the results of computer simulations of the proposed image enhancement method on two sets of experimental image data set of on road weather degraded images. We compare the results of the proposed method using the basic LIP model, method using conventional multiplicative parameters and the result of the method using logarithmic multiplicative parameters. We also compare the enhancement results of the proposed method with the result of histogram equalization.

For finding the optimum parameters; we use the presented measure LRCM and compare the same with those found using AMEE. Figure 4 and Figure 5 shows the results for two sets of experimental data of on road weather degraded images and their LRCM values. Table 1-2 compares the values of the contrast measures while increasing the location parameter $\alpha(l_1)$ for image data set of distant vehicle and letter board.

Table 1. Comparison of measures for increasing $\alpha(l_1)$ and $\beta(l_2) > 1$ Distant vehicle image data set

Distant Vehicle					
Alpha	AME	AMEE	EME	EMEE	LRCM
0.2	0.1057	0.1435	0.2089	10.5041	10.2748
0.3	0.1064	0.1478	0.209	10.5491	10.8162
0.4	0.1017	0.1562	0.2092	10.5691	10.8383
0.5	0.1101	0.1718	0.2095	10.6038	10.7129
0.6	0.1124	0.1886	0.2098	10.6463	10.8212
0.7	0.1147	0.2069	0.2101	10.6996	11.0472

It evidently indicates that measure value increases with increase in $\alpha(l_1)$ (corresponding to degraded image D_1). Tables 3-4 compares the values of the measures while decreasing the location parameter $\beta(l_2)$ (corresponding to degraded image D_2) for distant vehicle and letter board.

The values shown in Table 3 and 4 indicate a decrease in measure values with decrease in the value of location parameter $\beta(l_2)$.

Table 2. Comparison of measures for increasing $\alpha(l_1)$ and $\beta(l_2) > 1$ Letter board image data set

Letter Board					
Alpha	AME	AMEE	EME	EMEE	LRCM
0.2	0.0946	0.0909	0.208	6.9267	10.7181
0.3	0.0976	0.1032	0.2082	6.9795	10.7668
0.4	0.1012	0.1196	0.2085	7.0484	10.8848
0.5	0.1043	0.1359	0.2088	7.1165	11.0242
0.6	0.1072	0.1529	0.2091	7.189	11.2057
0.7	0.1097	0.1691	0.2094	7.2665	11.2055

Table 3. Comparison of measures for decreasing $\beta(l_2)$ and $\alpha(l_1) < 1$ Distant vehicle image data set

Distant Vehicle					
Beta	AME	AMEE	EME	EMEE	LRCM
1.5	0.1147	0.2069	0.2101	10.7023	11.0472
1.4	0.1133	0.1954	0.2099	10.6703	10.9047
1.3	0.112	0.1855	0.2097	10.6388	10.8632
1.2	0.1102	0.1724	0.2095	10.6125	10.8006
1.1	0.1086	0.1617	0.2093	10.587	10.5732
1	0.1071	0.1522	0.2091	10.5639	10.3789

Figure 6(b) and 6(c) shows the results of enhancement of distant vehicle image data set with certain randomly chosen parameter values and with optimal parameter values respectively.

Table 4. Comparison of measures for decreasing $\beta(l_2)$ and $\alpha(l_1) < 1$ Letter board image data set

Letter Board					
Beta	AME	AMEE	EME	EMEE	LRCM
1.5	0.1097	0.1691	0.2094	7.2665	11.2055
1.4	0.1091	0.1652	0.2093	7.2458	11.2553
1.3	0.1082	0.159	0.2092	7.2158	11.2425
1.2	0.1072	0.1526	0.2091	7.1875	11.0915
1.1	0.1057	0.1439	0.2089	7.15	10.9561
1	0.1049	0.1392	0.2088	7.1303	10.8452

It is clearly evident that the image enhanced with the optimal parameters is visually better than the other. Figure 7(b) and Figure 7(c) show the results of letter board data set with similar outcome. Figure 6(d), Figure 7(d) shows the plot between LRCM and parameters for

the purpose of choosing an optimal value as their local maxima. The optimal values are then compared with the values obtained from the plot between AMEE and parameters; Figure 6(e), Figure 7(f). Figure 7(e) shows the result of the proposed enhancement method with the parameters found as the local maxima of Figure 7(f). It is thus illustrated that we obtained similar optimal values for the distant vehicle data set when using both LRCM as well as AMEE measure, while the values found from both the measures differ for the letter board data set.

The original degraded images in Figure 4(a), (e) and Figure 5(a), (e) are images that are captured by a conventional silicon sensor camera (Sony DSC-W210).

Figure 4. (a) Degraded Image D1 (LRCM=10.6295) (b) Result of method using basic LIP model (LRCM=9.6831) (c) Result of method using conventional multiplicative parameters (LRCM=10.9504) (d) Result of method using optimal

logarithmic multiplicative parameters (LRCM=11.0153) (e) Degraded Image D2 (LRCM=10.6536) (f) Result of Histogram Equalization (LRCM=11.0074)
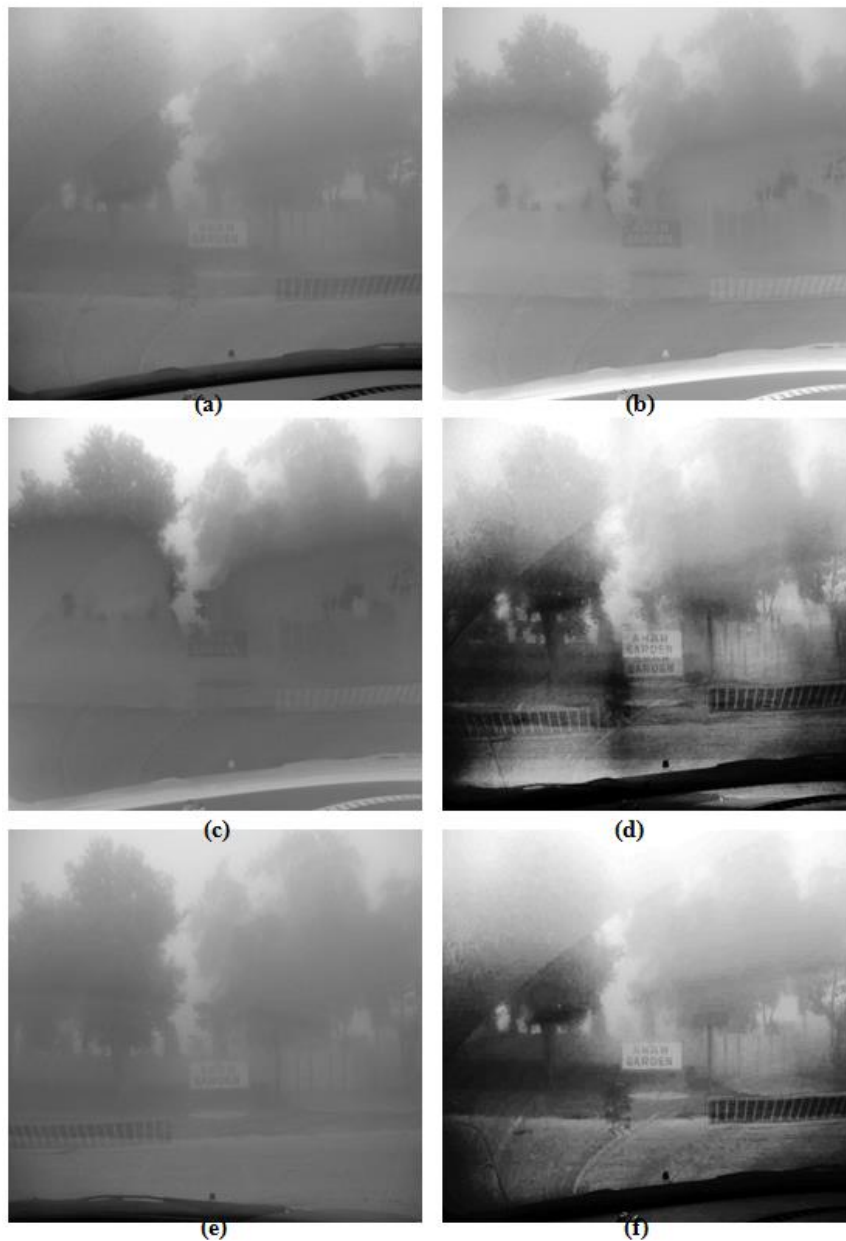

Figure 5. (a) Degraded Image D1 (LRCM=10.9512) (b) Result of method using basic LIP model (LRCM=10.8415) (c) Result of method using conventional multiplicative enhancement parameters (LRCM=11.4146) (d) Result of method using optimal logarithmic multiplicative location enhancement parameters (LRCM=11.5099) (e) Degraded Image D2 (LRCM=11.0056) (f) Result of Histogram Equalization (LRCM=11.5052)
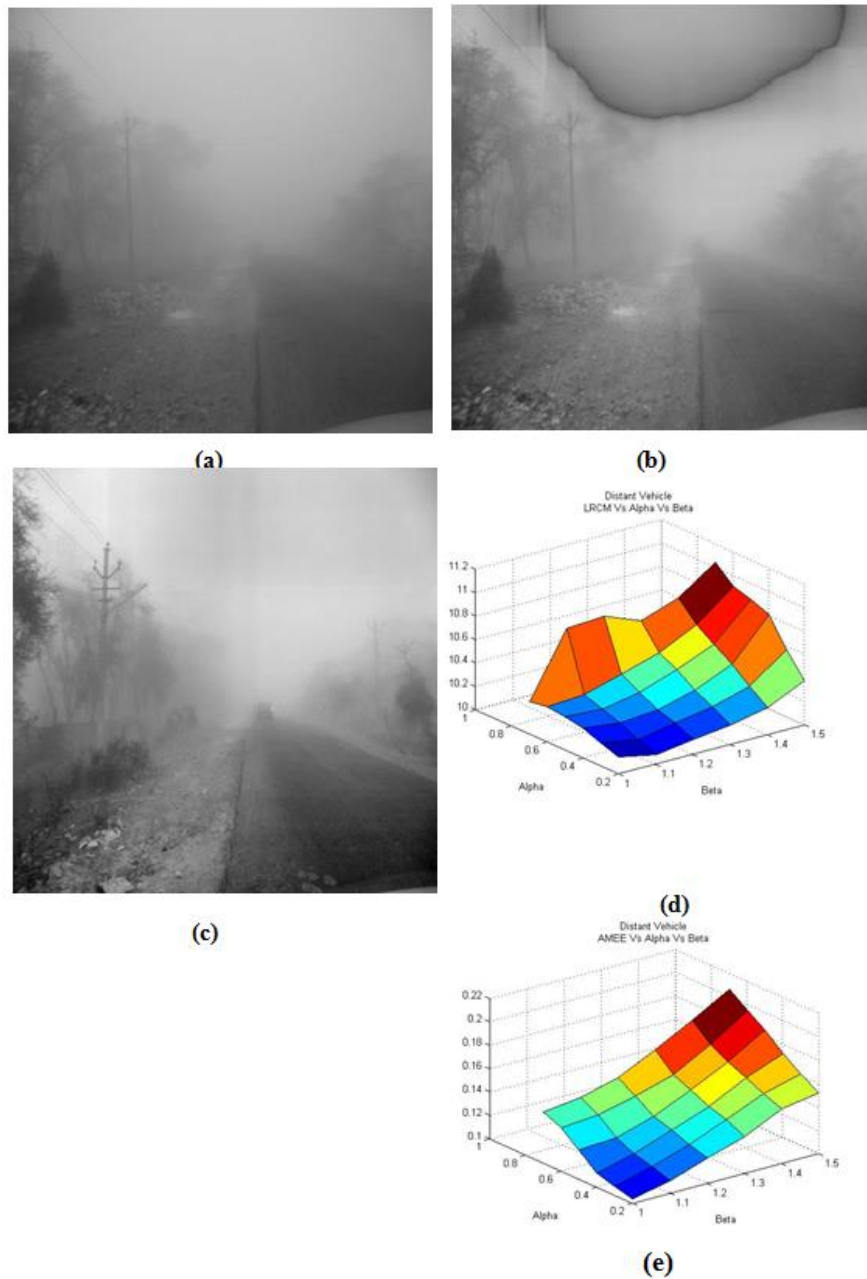
Figure 6. (a) Degraded Image D1 (LRCM=10.6295) (b) Result of enhancement with logarithmic location enhancement parameter $\alpha(l_i,\theta_i)$ **=0.2,** $\beta(l_i,\theta_2)$ **=1.5 (LRCM=10.2748) (c) Result of enhancement with optimal logarithmic location enhancement parameter** $\alpha(l_i,\theta_i)$ **=0.7,** $\beta(l_i,\theta_2)$ **=1.5 (LRCM=11.0153) chosen from local maxima of LRCM Vs Alpha Vs Beta (d) LRCM Vs Alpha Vs Beta (e) AMEE Vs Alpha Vs Beta**
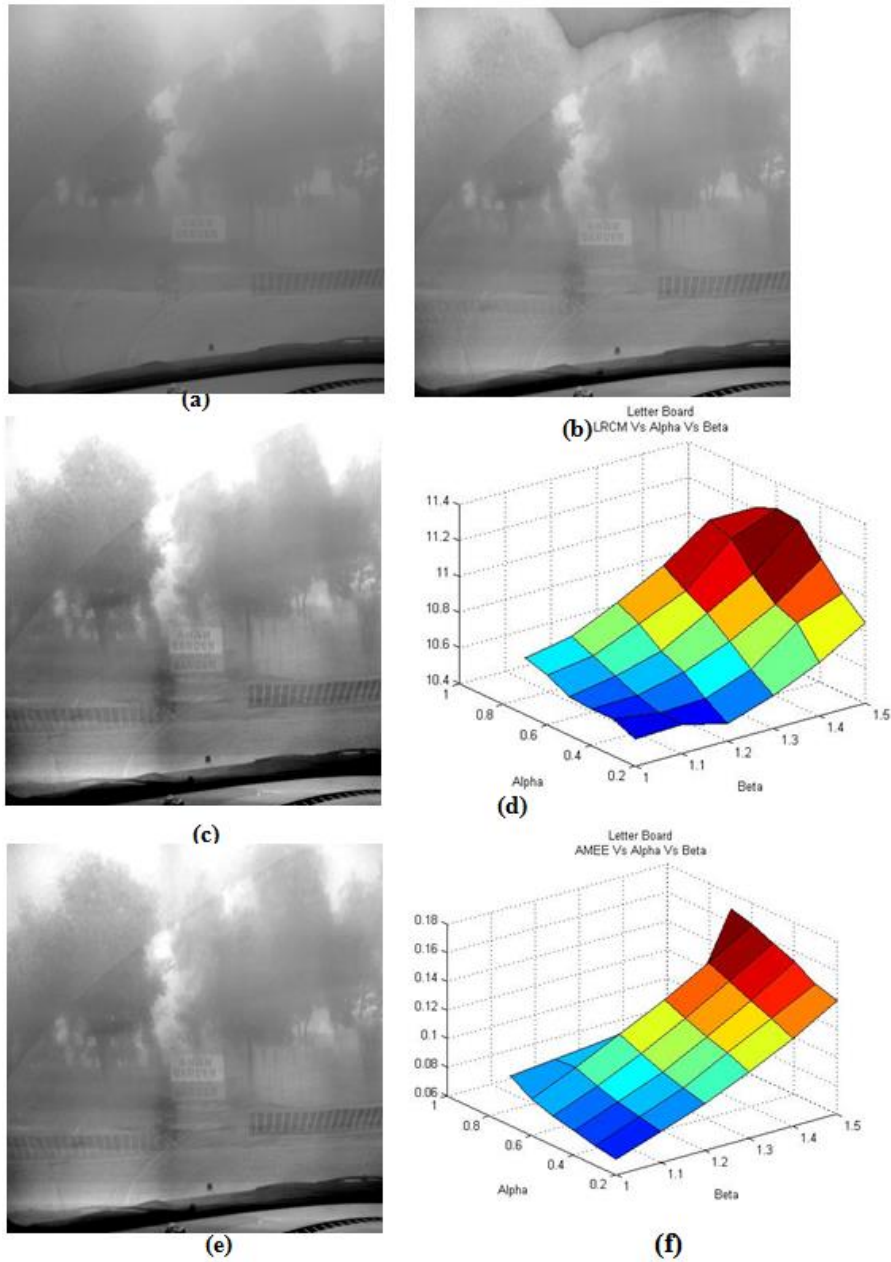
Figure 7. (a) Degraded Image D1 (LRCM=10.9512) (b) Result of enhancement with logarithmic location enhancement parameter $\alpha(l_1)$ =0.3, $\beta(l_2)$ =1.5 (LRCM=10.7668) (c) Result of enhancement with optimal logarithmic location enhancement parameter $\alpha(l_1)$ =0.6, $\beta(l_2)$ =1.4 (LRCM=11.2553) chosen from local maxima of LRCM Vs Alpha Vs Beta (d) LRCM Vs Alpha Vs Beta (e) Result of enhancement with location enhancement parameter $\alpha(l_1)$ =0.7, $\beta(l_2)$ =1.5 (=11.2055) chosen from local maxima of AMEE Vs Alpha Vs Beta (f) AMEE Vs Alpha Vs Beta

6. Conclusion

In this paper, a new weighted LIP model based image enhancement method was presented. Two location based parameters with LIP multiplication are used in the method which produces results that are better than the method without parameters; the method using parameters with conventional multiplication and global histogram equalization. This was illustrated both by observing the enhanced results as well as their contrast measure values. The method that used location based parameters with LIP multiplication provided the maximum value of the contrast measure and hence increased information. A novel region based contrast measure called LRCM was presented and compared with other traditional measures. The presented measure was used for finding the optimum parameters for the proposed method. It was found that the presented measure commensurate with a conventional measure in one case while it outperforms for the other out of the experiments carried out on two data sets.

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