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SHORT NOTE

Visual enhancement based on salient region detection and layered difference representation

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Abstract We propose a novel image enhancement method based on salient region detection and a layered difference representation of 2D histograms. We first obtain the visual salient region corresponding to maximal human attention using saliency filters. Then, we obtain a difference vector for the visual salient region by solving a constrained optimization problem of the layered difference representation at a specified layer. Finally, the new difference vector and the difference vector of the original image are aggregated to enhance the salient region and protect other regions from overstretching or brightness shift. Experimental results including comparisons with other methods show that our proposed algorithm produces more suitable enhanced images compared with the results of existing algorithms.

Keywords Image enhancement · Salient region detection · Layered difference representation · Image contrast

1 Introduction

Image enhancement techniques are commonly used to yield high contrast ratios and bring out hidden details. One of the classical image enhancement techniques is histogram equalization (HE), which derives a single global transformation function using the input intensity histogram and maps the input intensities to the output image with the transformation function. However, without any constraints, HE introduces unwanted visual effects such as over-enhancement, artifacts, and mean brightness shift [1–4]. Many variations of HE have been developed to alleviate these problems. Plateau histogram equalization (PHE) [5] and double plateau histogram equalization (DPHE) [6] were proposed to reduce tinny gray values coalition by replacing some histogram terms with plateau thresholds. The neighborhood of each pixel is used to obtain a local mapping function to moderate over-enhancement and enhance the local contrast in a method called local histogram equalization and modified contrast limited adaptive histogram equalization (MCLAHE) [7]. In [8], a method based on probability distribution gamma correction, which smoothes the fluctuating distribution function, was proposed to reduce over-enhancement and other artifacts. Several sectional histogram equalization algorithms such as bi-histogram equalization [3], dualistic sub-image histogram equalization [2], and minimum mean brightness error bi-histogram equalization [4] have been proposed to preserve mean brightness. Recently, a layered difference representation (LDR) of 2D histograms was constructed to obtain a unified transformation function from 255 difference vectors in a typical 8-bit imaging system [1]. This method attempts to amplify gray-level differences that frequently occur in the input image to enhance the contrast and overcome image over-enhancement. However, LDR may produce unwanted artifacts because it ignores the dependencies between each intra-layer and simply amplifies gray-level differences over the entire input image [1].

Saliency filtering has been used for salient region detection [9] and contrast enhancement [10]. Contrast and

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saliency estimations can be formulated using high-dimensional Gaussian filters [9]. An image enhancement framework consisting of bilateral tone adjustment and saliency-weighted contrast enhancement was presented in [10]. The regions that humans pay more attention to are subject to greater enhancement [10]. In our work, we develop a new image enhancement algorithm based on salient region detection and layered difference representation. After the salient region of an input image is detected using saliency filters, we calculate the 2D histogram for each input pixel in the detected salient region. A new difference vector generated from the linear system solver and the original difference vector are combined to protect other regions from overstretching or noise amplification while enhancing the contrast in the salient region. Experimental results show that our novel method can effectively enhance the contrast in the salient region with fewer unwanted artifacts, thereby producing more suitable enhanced images than existing methods.

The remainder of this paper is organized as follows. The details of the proposed algorithm are provided in Sect. 2. Section 3 discusses the performance evaluation of our algorithm. Section 4 concludes this paper.

2 Algorithm details

We begin by briefly introducing LDR. LDR uses statistical information on the gray-level differences between neighboring pixels in the input image to obtain 2D histograms h_k^l. These gray-level differences are then represented in a tree-like layered structure, as shown in Fig. 1. The difference variable d_k^l is defined as:

$$d_k^l = x_{k+l} - x_k \quad 0 \le k \le 255 - l \tag{1}$$

where x_k, a member of the transformation function, is the gray level in the output image for the gray level of k in the input image. The gray-level difference between the gray-level values l and $k + l$ from the input image is mapped to the output gray-level difference d_k^l. Then, gray-level differences have the following relationship with 2D histograms because the LDR amplifies gray-level differences occurring frequently in the input image [1]:

$$d_k^l = \alpha_l \times h_k^l \quad 0 \le k \le 255 - l \tag{2}$$

Equations (3), (4), and (5) formulate a constrained optimization problem to obtain the difference vector for each layer, where $\mathbf{A}_l \in \mathbb{R}^{(256-l)\times 255}$ is a binary matrix, $\mathbf{d}_l = [d_0^1, d_1^1, \ldots, d_{254}^1]$ is the difference vector to be determined, α_l is a normalizing constant at layer l, and $\mathbf{h}_l$ is the column vector from the input histogram at layer l. The inter-layer aggregation combines the difference vectors at all of the layers into a united difference vector, thereby generating a transformation function.

$$\text{minimize} \quad ||\mathbf{A}_l\mathbf{d}_l - \alpha_l\mathbf{h}_l||^2 \tag{3}$$

$$\text{subject to} \quad 1.\mathbf{d}_l \succeq \mathbf{0} \tag{4}$$

$$2.\mathbf{1}^T\mathbf{d}_l = 255 \tag{5}$$

According to perceptual studies, the human visual system is sensitive to gray-level differences between neighboring pixels. Thus, emphasizing these differences can achieve a perceptual contrast enhancement. However, in most cases, the region of interest is only the salient region that corresponds to the majority of human attention, rather than the entire image [1, 9]. Without any constrains on the region of interest, LDR may not output a perceptually pleasing image. We develop a new method for image enhancement based on this observation and related analysis. Figure 2 shows an overview of the proposed algorithm. The five main steps involved in the proposed method are described is the following subsections.

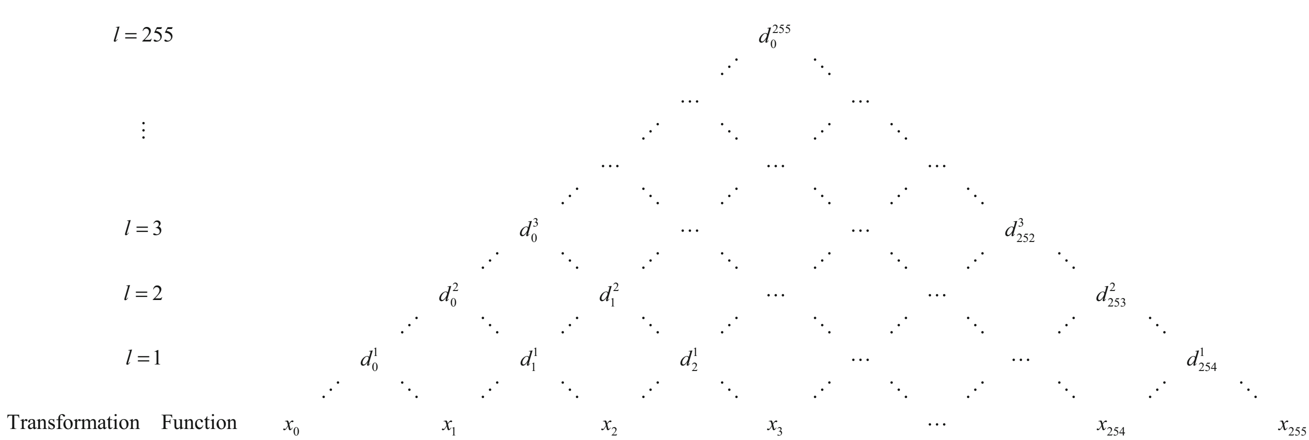

Fig. 1 Layered difference representation (LDR)

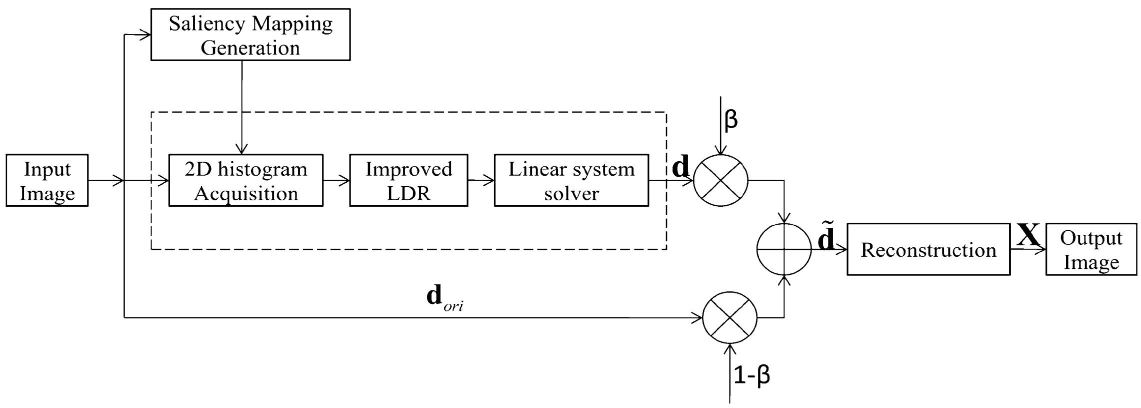

Fig. 2 Overview of the proposed algorithm

2.1 Saliency remapping

We obtain a salient region using saliency filters, thereby producing a pixel-accurate saliency map that uniformly covers the objects of interest and consistently separates the fore- and background [9]. Saliency filtering consists of four basic parts: abstraction, element uniqueness, element distribution, and saliency assignment. U_i and D_i form the normalization result of element uniqueness and element distribution for each element, respectively. The saliency value for each element is calculated as follows:

$$S_i = U_i \cdot \exp(-K \cdot D_i) \tag{6}$$

The final saliency value S_i^* is defined as a weighted linear combination of the saliency S_i of its surrounding image elements.

$$S_i^* = \sum_{j=1}^{N} w_{ij} S_j \tag{7}$$

w_{ij} is the Gaussian weight of the up-sampling process. Then, the salient region (Fig. 3c) is determined as:

$$\tilde{S}(i) = \begin{cases} S_i^*(i) & S_i^*(i) > \mathrm{th} \\ 0 & else \end{cases} \tag{8}$$

where th is the saliency threshold. This threshold can be calculated from $\Theta\mathrm{th} = \alpha$, where Θ is the cumulative histogram of the non-zero values in S_i^* and α is in [0,1]. Inspired by [11], we set the default value of α to 0.7.

2.2 Layered difference representation of 2D histogram for salient region

The LDR is obtained using the 2D histogram for the salient region. In [1], the intra-layer dependencies are ignored and the final difference vector is obtained by aggregating 255 different vectors. We propose an improved LDR to consider these dependencies. The difference variables at each layer are related to the transformation function in the output image; we can thus describe the relationship between the difference variables of each layer and a fixed basic layer. A more reliable 2D histogram is obtained with a smaller basic layer. A larger basic layer results in information loss in the 2D histogram. Considering the 2D histogram and difference vector of the original image, we choose $l = 2$ as a basic layer. For example, the elements of the difference variables at layer 5 and 6 can be rewritten as:

$$\begin{aligned} d_2^5 &= x_7 - x_2 = x_7 - x_5 + x_5 - x_3 + x_3 - x_2 \\ &= d_5^2 + d_3^2 + d_2^1 \end{aligned} \tag{9}$$

$$\begin{aligned} d_2^6 &= x_8 - x_2 = x_8 - x_6 + x_6 - x_4 + x_4 - x_2 \\ &= d_6^2 + d_4^2 + d_2^2 \end{aligned} \tag{10}$$

The relationship between the difference variables of each layer and layer $l = 2$ is:

$$d_k^l = x_{k+l} - x_k = \begin{cases} \sum_{i=0}^{l/2-1} d_{2*i+k}^2 & l = 2, 4, \ldots, 254 \\ \sum_{i=0}^{l/2-1} d_{2*i+k}^2 + d_k^1 & l = 3, 5, \ldots, 255 \end{cases} \tag{11}$$

Then, the corresponding 2D histogram term at layer a higher than two can be decomposed (the difference variables at layer 1 are disregarded):

$$h_{2*i+k}^2 = \frac{\alpha_l}{l/2} h_k^l \quad i = 0, \ldots, l/2 - 1; \quad 0 \le l \le 255 \tag{12}$$

2.3 Difference vector d calculation for $l = 2$

After calculating the 2D histogram for $l = 2$, we can obtain a difference vector **d** through a linear system solver. The equalization is given by (13), $\mathbf{A}^2 \in \mathbb{R}^{254 \times 255}$. Solving a constrained optimization problem (Eqs. 13, 4, 5), we obtain a new difference vector **d** for the salient region.

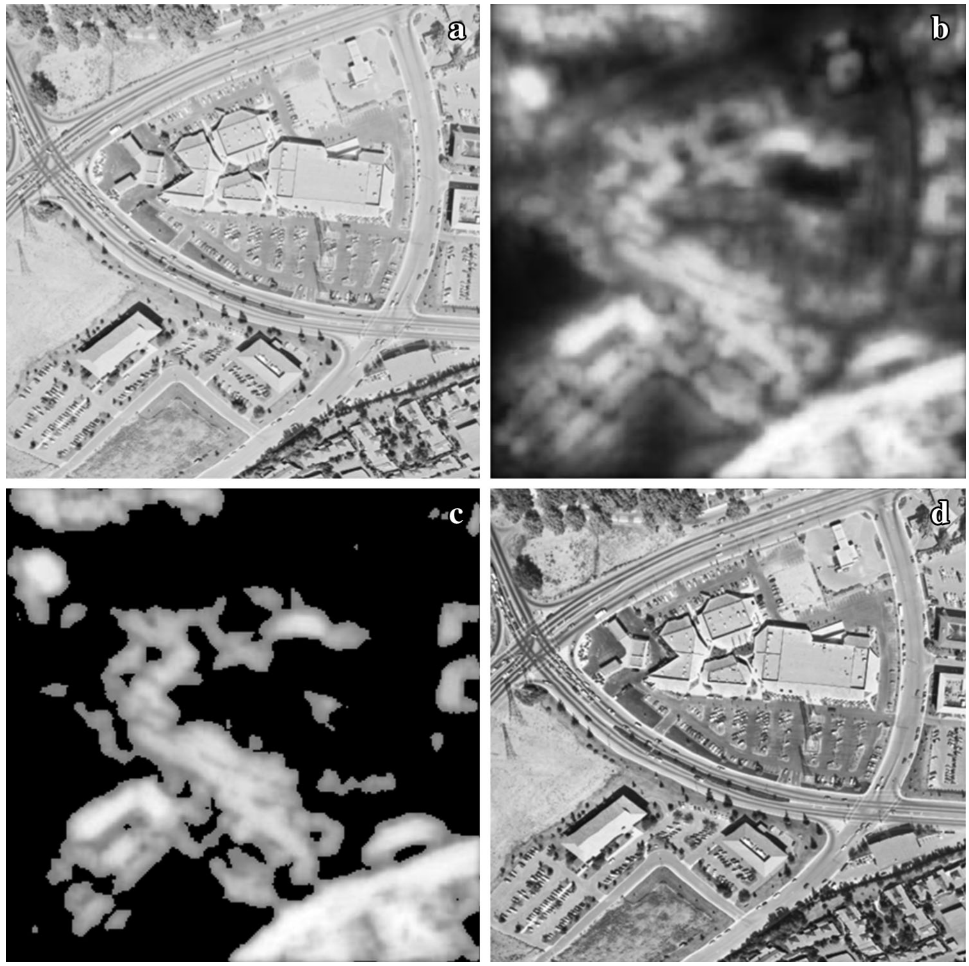

Fig. 3 Example of the results of different steps of our algorithm: **a** original image, **b** salient image after saliency filtering, **c** salient image after th, and **d** enhanced image output by our proposed algorithm

$$\begin{bmatrix} 1 & 1 & 0 & \cdots & 0 & 0 & 0 \\ 0 & 1 & 1 & \cdots & 0 & 0 & 0 \\ 0 & 0 & 1 & \cdots & 0 & 0 & 0 \\ \vdots & \vdots & \vdots & \ddots & \vdots & \vdots & \vdots \\ 0 & 0 & 0 & \cdots & 1 & 1 & 0 \\ 0 & 0 & 0 & \cdots & 0 & 1 & 1 \end{bmatrix} \begin{bmatrix} d_0^1 \\ d_1^1 \\ d_2^1 \\ \vdots \\ d_{253}^1 \\ d_{254}^1 \end{bmatrix} = k \begin{bmatrix} h_0^2 \\ h_1^2 \\ h_2^2 \\ \vdots \\ h_{252}^2 \\ h_{253}^2 \end{bmatrix} \tag{13}$$

2.4 Combination of different vectors

To define the difference vector $\mathbf{d}_{\mathrm{ori}}$ of the original image, we formulate the following expression:

$$d_0^1 = d_1^1 = \cdots = d_{254}^1 = 1 \tag{14}$$

Using the difference vector $\mathbf{d}_{\mathrm{ori}}$ allows us to avoid superfluous changes to the gray values of the non-salient region. Then, the final difference vector is a combination of $\mathbf{d}$ and $\mathbf{d}_{\mathrm{ori}}$:

$$\tilde{\mathbf{d}} = \beta \mathbf{d} + (1 - \beta)\mathbf{d}_{\mathrm{ori}} \tag{15}$$

where β is an adjustable coefficients, we set $\beta = 0.5$ in our work.

2.5 Reconstruction

At last, we obtain the transformation function from the difference vector obtained in Sect. 2.4. The algorithm yields the output image (Fig. 3d) by forming a reconstruction with global transformation function $\mathbf{x}$.

$$x_k = \sum_{i=0}^{k-1} \tilde{\mathbf{d}}_i \quad 1 \le k \le 255 \tag{16}$$

3 Evaluation

To illustrate the performance of our proposed algorithm, we compare it to traditional HE, a state-of-the-art method called modified contrast limited adaptive histogram equalization (MCLAHE) [7], and LDR [1]. Figures 4a and 5a are the input images to be enhanced and Figs. 4b and 5b are their corresponding salient images. HE results in over-enhancement and loses detail information in some regions, as shown in Figs. 4c and 5c. Moreover, it yields a visually

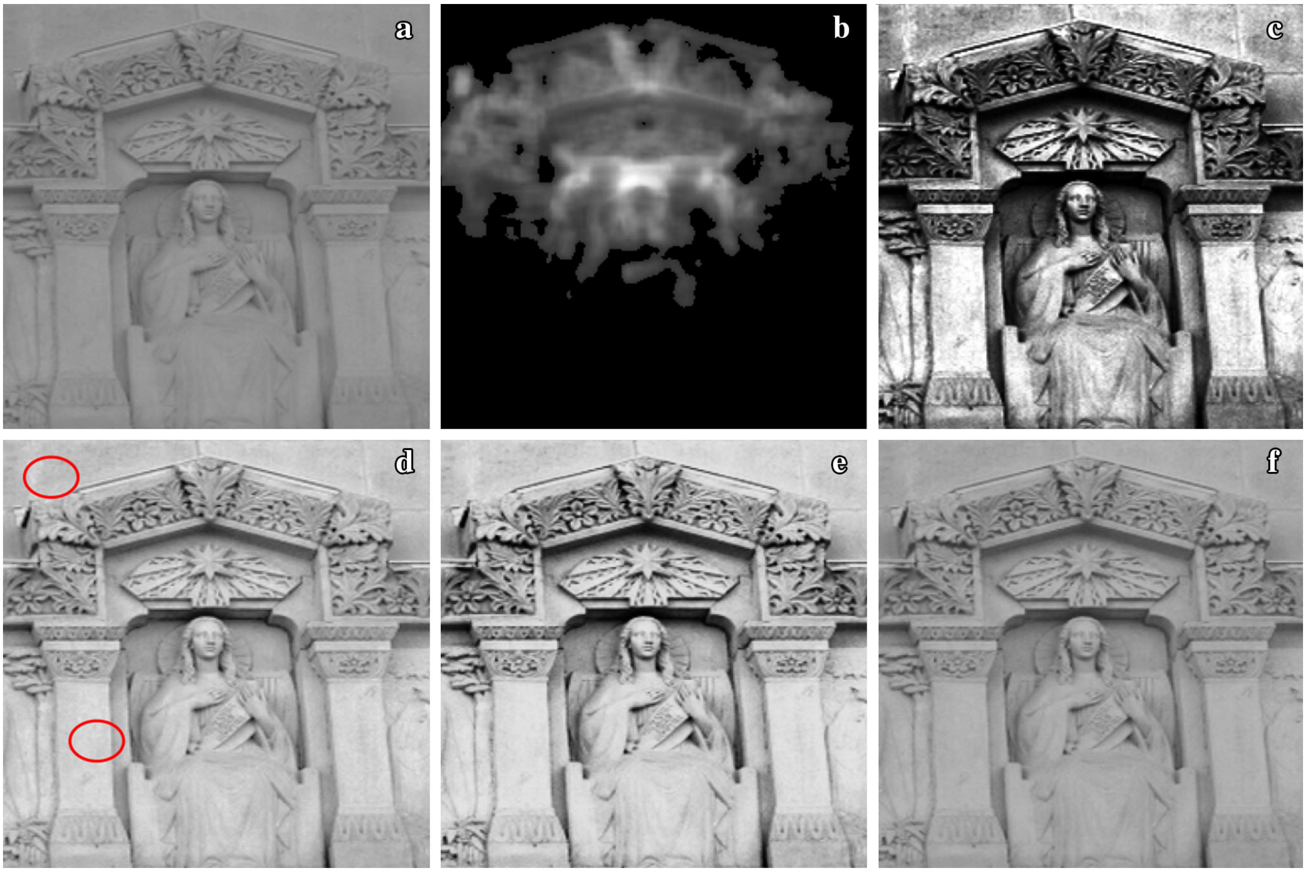

Fig. 4 Enhancement results for image *Statuary*: **a** original image, **b** salient image, **c** HE result, **d** MCLAHE result, **e** LDR result, and **f** proposed algorithm result

displeasing result. Figures 4d and 5d show the enhancement results of MCLAHE. MCLAHE enhances the details and limits the over-enhancement to a great extent, but the smooth region, especially region in the red circle, is still over-enhanced and unwanted details are amplified. The enhancement results of LDR are shown in Figs. 4e and 5e. LDR amplifies the gray-level differences that occur frequently in the input image and the contrast of the entire image is enhanced. However, tinny differences are also amplified in glossy areas and details that occur infrequently in the input image are lost, as shown in the red circle of Fig. 5e. Our proposed algorithm enhances the salient region and protects other regions from over-enhancement or stretching. Figures 4f and 5f demonstrate that the proposed algorithm not only enhances details in the salient region but also retains the uniformity of the non-salient region.

We use three image quality assessment parameters to quantitatively evaluate the performance of the four algorithms. Average absolute mean brightness error (AAMBE) [12] evaluates the ability of the enhancement method to maintain the mean brightness. PSNR [13] denotes the peak signal to noise ratio of the enhancement of the image. Measurement of enhancement by entropy (EME) [14] measures the entropy, or information, in the contrast of the image. A lower AAMBE indicates a smaller mean brightness shift. The quantitative values listed in Table 1 indicate that the proposed algorithm suitably preserves the brightness. PSNR is used to measure the noise ratio of the non-salient region and EME evaluates the local contrast of the salient region. Among the existing methods, our method is superior in keeping the non-salient region uniform (highest PSNR value) and enhancing the salient region with a balanced EME value that is neither over- nor under-enhanced. Both the subjective and quantitative assessments demonstrate that our proposed algorithm yields superior results.

4 Conclusion

We propose a visual enhancement method based on salient region detection and the layered difference representation. We obtain a global transformation function by combining the difference vector for salient region enhancement and the difference vector for preserving details and smooth areas in the non-salient region. Qualitative and quantitative

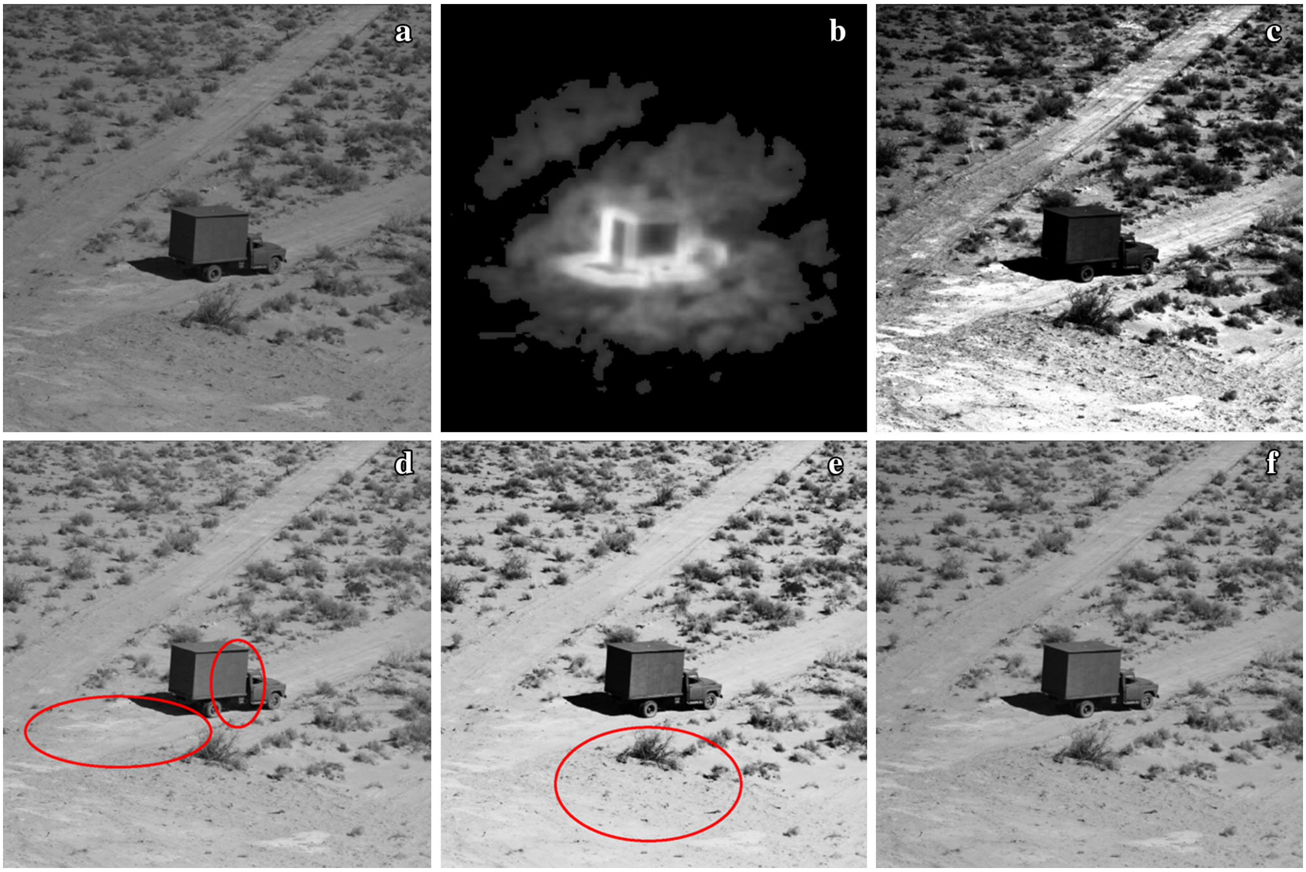

Fig. 5 Enhancement results for image *Van*: **a** original image, **b** salient image, **c** HE result, **d** MCLAHE result, **e** LDR result, and **f** proposed algorithm result

Table 1 Quantitative comparison of different enhancement methods

	HE	MCLAHE	LDR	Proposed
Statuary				
AAMBE	53.9799	40.1111	47.5757	16.6818
PSNR	43.7013	45.7791	41.8796	59.3524
EME	0.1679	0.4257	0.5486	0.2617
Van				
AAMBE	44.8879	42.7939	65.2957	32.9795
PSNR	30.6149	34.7275	37.3824	39.2083
EME	0.1796	0.5351	0.7645	0.4296

assessments demonstrate that our proposed algorithm yields the best performance as compared with existing classic and state-of-the-art enhancement methods.

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