LOW LIGHT IMAGE ENHANCEMENT BASED ON TWO-STEP NOISE SUPPRESSION

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ABSTRACT

In low light condition, the signal-to-noise ratio (SNR) is low and thus the captured images are seriously degraded by noise. Since low light images contain much noise in flat and dark regions, contrast enhancement without considering noise characteristics causes serious noise amplification. In this paper, we propose low light image enhancement based on two-step noise suppression. First, we perform noise aware contrast enhancement using noise level function (NLF). NLF is used to get a noise aware histogram which prevents noise amplification, and we use the noise aware histogram in contrast enhancement. However, the increase of intensity by contrast enhancement reduces the visibility threshold, which makes noise visible by human eyes. Second, we utilize a just noticeable difference (JND) model from luminance adaptation to suppress noise based on human visual perception. Experimental results show that the proposed method successfully enhances contrast in low light images while minimizing noise amplification.

Index Terms— Contrast enhancement, image enhancement, just noticeable difference, low light, noise level function, noise reduction

1. INTRODUCTION

Images captured in low light condition have low dynamic range and are seriously degraded by noise. Many attempts have been made to enhance the contrast of low light images. However, most of traditional contrast enhancement techniques [1][2][3] do not consider noise characteristics, thus leading to noise amplification while improving contrast. Therefore, some contrast enhancement and denoising methods have been proposed in recent years. Malm et al.[4] proposed structure-adaptive anisotropic image filtering to reduce noise while preserving structure. Then, tone mapping was introduced to enhance image contrast. Loza et al.[5] designed non-linear luminance enhancement and simultaneous noise reduction based on local dispersion of wavelet coefficients and a shrinkage function. Sun et al.[6] also achieved contrast enhancement and noise reduction in the wavelet domain. The contrast enhancement was performed by limited adaptive histogram equalization (CLAHE) in the low pass layer, while the noise reduction was conducted by a nonlinear transform in the high pass layer. Although three methods reduced some noise, they still amplified noise in contrast enhancement, especially for low light images. Rivera et al. [7] acquired 256 transformation function by content-aware histogram equalization which considered edge-contrast pairs. Edge-contrast pairs have the intensity difference between neighboring pixels larger than a threshold. They enhanced images by mapping curves by simulating the human visual system (HVS). However, this method cannot provide insufficient enhancement in contrast and luminance for low light images. Lim et al.[8] first performed contrast enhancement on noise-free pixels, and then interpolated the missed noisy pixels by low rank matrix completion. However, this method leads to severe degradation of texture and details due to the removal of noise pixels.

In this paper, we propose low light image enhancement based on two-step noise suppression. We adopt NLF and JND model in contrast enhancement for noise suppression. First, we perform noise aware contrast enhancement by equalizing a noise aware histogram considering both local contrast and noise level. The noise level is the standard deviation of noise in a local region, which is estimated by NLF. Noise aware contrast enhancement prevents contrast overstretching in flat and dark regions. However, contrast enhancement increases intensity and thus reduces the visibility threshold for human visual perception, which makes noise visible. We estimate the visibility threshold using a JND model which represents the minimum intensity difference which can be perceived by human visual system (HVS), i.e. luminance adaptation. Second, we perform perceptual noise reduction in the detail layer based on the JND model. Fig. 1 illustrates the flowchart of the proposed method.

2. NOISE AWARE CONTRAST ENHANCEMENT

Histogram-based contrast enhancement of low light images often causes severe noise amplification and over-enhancement without considering noise characteristics. Two reasons leads to this problem as follows: 1) Low light images often have

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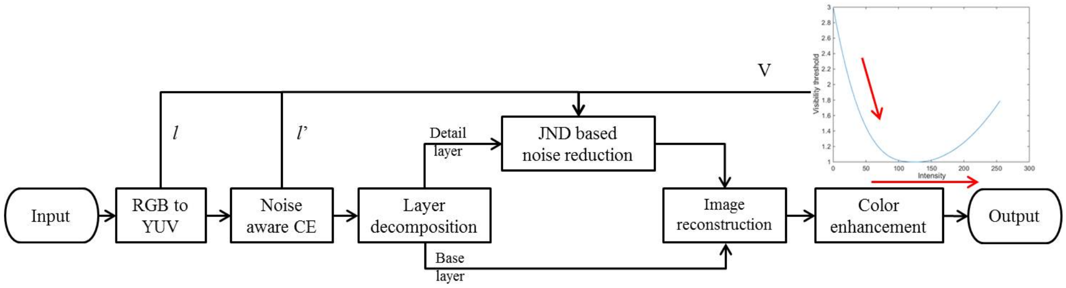


Fig. 1. Flowchart of the proposed method. V is visibility threshold by JND. l and l' are intensities in the original image and its enhanced image, respectively. CE is contrast enhancement.

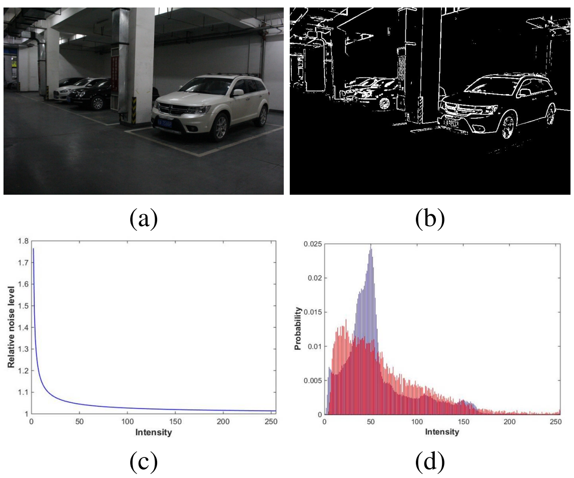


Fig. 2. High contrast map in *Car* and its histograms. (a) Original image. (b) High contrast map. (c) Noise level according to intensity by (2). (d) Original histogram (blue) for (a) and noise aware histogram (red) for (b).

large flat regions with narrow dynamic range and invisible noise. In Fig. 2(a), image *Car* contains large flat regions in ground and wall which has the highest probability in the original histogram (blue) in Fig. 2(d). The highest probability causes histogram over-stretching in these region, which results in over-enhancement of contrast and noise; 2) Noise level becomes larger in low intensity (0-10), and decreases rapidly as intensity increases as shown in Fig. 2(c). That is, noise affects low intensity more severely than high one. Thus, low intensity should be enhanced small to prevent serious noise amplification.

To overcome the two problems, we consider image content and noise level in the noise aware histogram which extracts high contrast pixels with larger local contrast than noise level . First, we estimate local contrast c in a region as follows [9]:

$$c(x,y) = \sqrt{\frac{(g_\sigma * l^2)(x,y)}{(g_\sigma * l)^2(x,y)}} \tag{1}$$

where l is the original image pixel; and g_σ is a Gaussian kernel with the standard deviation σ. We define the noise level $n(I)$ as follows:

$$n(I) = \frac{I + \sigma(I)}{I} \tag{2}$$

where $\sigma(I)$ is the standard deviation of noise by NLF; and the noise level $n(I)$ represents the relative noise ratio. Fig. 2(c) shows the noise level varying with intensity. In general, noise in low light images is signal dependent, which is represented by the generalized signal dependent noise model and Poisson-Gaussian noise model[10][11]. In this work, we use the generalized signal dependent noise model which represents most of camera noise including Poisson noise[11]. NLF for the generalized signal dependent noise model is expressed as follows:

$$\sigma(I) = \sqrt{I^{2\gamma} \cdot \sigma_u^2 + \sigma_w^2} \tag{3}$$

where γ is the exponential parameter which controls the dependence on the signal, u and w are zero-mean Gaussian distributions with variances σ_u^2 and σ_w^2. The parameters are estimated in [11]. Above all, the histogram of high contrast pixels is obtained as follows:

$$p(I) = \frac{\sum_{(x,y)\in B_I} l(x,y)}{\sum_{(x,y)\in S} l(x,y)} \tag{4}$$

where

$$S = \{(x,y) : c(x,y) > n(x,y)\} \tag{5}$$

$$B_I = \{(x,y) \in S : I = 0, 1, ..., 255\} \tag{6}$$

where S is the set of high contrast pixels whose local contrast is higher than the noise level; B_I is the subset of S which contains the pixels whose intensity is I; and $n(x,y)$ is the noise level calculated by (2). Fig. 2(b) shows high contrast map in *Car* by (5) where white pixels mean pixels with high contrast. High contrast map is composed of high contrast pixels obtained by (5). Fig. 2(d) shows the noise aware histogram (red) obtained by (4)-(6) which removes severe noise in dark regions while preventing histogram spikes which causes over-enhancement. In this work, we adopt AGCWD[3] for contrast enhancement which minimizes overstretching of the histogram in large flat regions. We perform AGCWD from the

(a) (b) (c) (d)

Fig. 3. Contrast enhancement results in *Classroom* by AGCWD[3]. (a) Original image. (b) Enhancement by the original histogram. (c) Enhancement by the noise aware histogram. (d) Mapping curve by the original histogram (blue) and the noise aware histogram (red).

noise aware histogram, and show the contrast enhancement results in Fig. 3. As shown in the figure, noise is successfully removed in dark and large flat regions even after contrast enhancement.

3. JND-BASED NOISE REDUCTION

Although noise aware contrast enhancement reduces noise in dark and large flat regions, noise still remains in the results (see Fig. 3). There are two main reasons: 1) Contrast enhancement brightens images but decreases JND threshold calculated by (8), which makes noise more visible (see the top right corner of Fig. 1); 2) Global contrast enhancement provides a coarse adjustment on noise without considering locality, and signal dependent noise becomes serious and is distributed in all intensity. Thus, we perform a fine adjustment for noise reduction based on JND model considering locality. We perform base-detail layer decomposition using anisotropic diffusion-weighted bilateral filtering [9]. Due to the first reason, we reduce noise based on the ratio of JND thresholds before and after contrast enhancement. Due to the second reason, we first analyze the effect of histogram stretching on noise amplification in textural and smooth regions. The histogram stretching in textural regions enhances details, and noise is less visible in the textural regions by contrast masking phenomenon[12]. However, noise amplification in smooth regions is more severe, which results in the degradation of visual quality. Thus, we perform noise reduction differently according to the textureness in a local region. We perform noise reduction in the detail layer as follows:

$$d_{out}(x,y) = e \cdot \frac{V(l'_{(x,y)\in\overline{S}}(x,y))}{V(l_{(x,y)\in\overline{S}}(x,y))} d(x,y) \tag{7}$$

where

$$V(l(x,y)) = \begin{cases} k_1 \cdot (1 - \frac{2l(x,y)}{256})^{\lambda_1} + 1 & l(x,y) \leq 128 \\ k_2 \cdot (\frac{2l(x,y)}{256} - 1)^{\lambda_2} + 1 & otherwise \end{cases} \tag{8}$$

$$\overline{S} = \texttt{Inv}(S)\{(x,y) : c(x,y) \leq n(x,y)\} \tag{9}$$

where $d_{out}(x,y)$ and $d(x,y)$ are outputs of noise reduction and noise aware contrast enhancement in the detail layer, respectively; $l(x,y)$ and $l'(x,y)$ are the original image and its enhanced result by noise aware contrast enhancement, respectively; $V(x,y)$ is the visibility threshold generated by JND model [12][13]; k_1, k_2, λ_1, and λ_2 are constants; $\overline{S}$ is the inverse of S; and e is the control parameter of noise reduction degree. We perform noise reduction in the region where the local contrast is the same as or smaller than the noise level, i.e. smooth and textural regions. We segment the original image into smooth and textural regions by the statistical property of textureness[11]. Fig. 4 shows the JND-based noise reduction result in *Car*. Finally, we enhance colors of the image as follows[14]:

$$M_e(x,y) = M_o(x,y) \cdot (\frac{l_e(x,y)}{l(x,y)})^{\gamma} \tag{10}$$

where $M_e(x,y)$and $M_o(x,y)$ are trichromatic channel value of output color image and original image; $l_e(x,y)$ and $l(x,y)$ are gray images from noise reduction results and original images.

(a) (b)

Fig. 4. JND-based noise reduction result in *Car*. (a) Detail layer after noise aware contrast enhancement. (b) Noise reduction result.

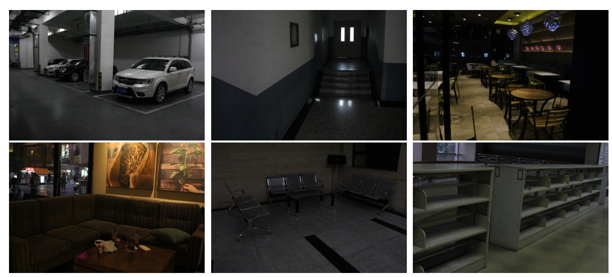
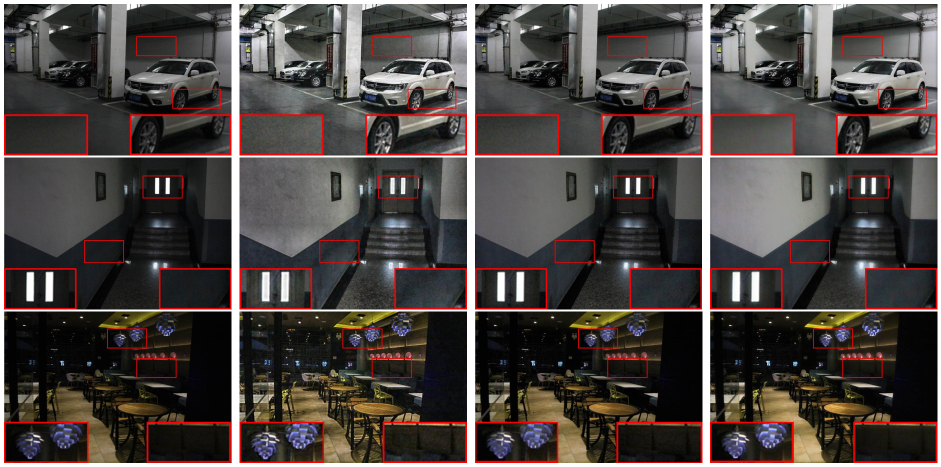


Fig. 5. Test images for experiments. Left top to bottom right: *Car*, *Classroom*, *Restaurant*, *Sofa*, *Chair* and *Bookshelf*



(a) (b) (c) (d)

Fig. 6. Experimental results for three test images. Top to bottom: *Car*, *Classroom*, and *Restaurant*. (a) Original images. (b) ACEWC [5]. (c) CADIE[7]. (d) Proposed method.

4. EXPERIMENT RESULTS

For experiments, we use a PC with Intel (R) Core (TM) i5 CPU (2.60GHZ) and 4.00GB RAM running a Windows 7 environment and MATLAB. For quantitative measurements, we evaluate the performance of the proposed method in terms of three measures [7]: Luminance index, contrast index, and structural index. The three measures evaluate luminance enhancement, contrast enhancement, and structural similarity between the original images and their enhanced results, respectively. We set e to 0.3-0.7 for smooth regions, and 0.8-1.2 for textural regions in (7). Also, we set k_1, k_2, λ_1, and λ_2 to 2.0, 0.8, 3.0, 2.0 in (8), respectively. We set γ to 0.6 - 1.0 in (10). We compare the performance of the proposed method with those of ACEWC [5] and CADIE [7], i.e. state-of-the-art methods. As shown in Fig. 5, we use six test images for tests: *Car*, *Classroom*, *Restaurant*, *Sofa*, *Chair* and *Bookshelf*. We capture them in low light condition using a digital camera of Canon EOS 60D. Thus, they have a dark tone with a narrow dynamic range and much noise. Fig. 6 shows contrast enhancement results for three test images. ACEWC[5] provides the best luminance improvement but introduces too much noise in the enhanced results without considering the noise level in Fig. 2(c) (See the second column of Fig. 6). CADIE[7] achieves a good performance in noise reduction but insufficient enhancement in contrast and luminance because CADIE[7] does the content-aware histogram equalization by edge-contrast pairs (See the third column of Fig. 6). However, severe noise in low light condition degrades image edges and transforms edge-contrast pairs into smooth pairs, and thus weakens the degree of contrast enhancement such as white car in *Car*, wall in *Classroom*, and ground in *Restaurant*. The proposed method enhances contrast in low light images considering noise level and HVS, which achieves the least noise amplification as shown in red boxes of Fig. 6. Table I shows average quantitative measurement of three methods on six test images. High values in luminance and contrast indexes mean good luminance and contrast enhancement. Structural index is closer to 1.0, which means the enhanced images is more similar to their original images in structure. It can be observed that the proposed method achieves the best performance in contrast enhancement among three methods while providing equally good results in structural similarity compared with CADIE[7]. Therefore, the proposed method effectively enhances contrast in low light images while successfully suppressing noise.

Table I
PERFORMANCE COMPARISON BETWEEN PROPOSED METHOD, ACEWC[5], AND CADIE[7].

Methods	Luminance	Contrast	Structure
Proposed	1.5873	1.4754	0.9833
CADIE[7]	1.3170	1.1679	0.9875
ACEWC[5]	1.7088	1.2886	0.9164

5. CONCLUSION

In this paper, we have proposed low light image enhancement based on two-step noise suppression. We have used NLF and JND model to consider noise characteristics in low light images. First, we have utilized NLF to obtain the noise aware histogram considering image content and noise level, and performed noise aware contrast enhancement based on the histogram. Second, we have employed the JND model from luminance adaptation to suppress noise based on human visual perception. Experiment results demonstrate that the proposed method successfully enhances contrast in low light images while minimizing noise amplification.

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