High Dynamic Range Image Compression by Fast Integrated Surround Retinex Model

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Abstract

Proposed method

- Compressing HDR image based on fast integrated surround Retinex model

- Two novelties
  - Integrating multiscale surround images to a single surround field
    - Simplifying the complicated computational steps in conventional multiscale Retinex
    - Reduction of “banding artifact” in normal SSR
  - Gaussian pyramid method
    - Cutting computation time for generating a large-scale surround
Introduction

- Necessity of HDR image compression
  - Human vision
    - Capable of seeing five orders in magnitude simultaneously
    - Adapting gradually to scenes with high dynamic ranges
  - Current display devices
    - Cannot capture the dynamic range more than 100:1
    - Necessity of compressing high dynamic range scene to low dynamic range of the device
Classifying HDR image compression

- Spatially-invariant tone reproduction curve (TRC)
  - Based on the global adaptation of human vision
- Spatially-variant tone reproduction operator (TRO)
  - Using spatial structure of the image data and attempts to preserve local image contrast
- This paper
  - Following the method of TRO
  - Presenting a new idea based on the Retinex theory
- Multiscale Retinex (MSR)
  - The most popular algorithm
  - Generated by the weighted sum of multiple single-scale Retinex (SSR)
  - Conventional MSR
    - Difficulty of optimization of weights
      - Equal weights to all scales of SSR
    - Not always give a satisfactory image
  - An adaptive scale-gain MSR by Kotera
    - Improvement of the color appearance in conventional MSR
    - Complication of selection of scales and weights
    - Large computation cost
Retinex model

- Image captured by camera

\[ I = R \times L \]

\[ R \approx I / L \]

Where \( I \) is captured image by camera
\( R \) is reflectance
\( L \) is illuminant distribution

- Center/surround model

  - Estimation of the luminance \( L \) around a pixel in consideration by averaging the image \( I \) with Gaussian filter

\[ R = C / S \]

Where \( R(x,y) \) is reflectance image
\( C(x,y) \) is center
\( S(x,y) \) is surround = \( L(x,y) \) is spatial distribution of illumination
Representative C/S MSR model of NASA

\[ R_{MSR}^i(x, y) = \sum_{m=1}^{M} w_m R_{SSR}^i(x, y, \sigma_m); i = R, G, B \]  \hspace{1cm} (1)

where \( w \) is weighting

\[ R_{SSR}^i(x, y, \sigma_m) = \log \left( \frac{I_i(x, y)}{I_i(x, y) \otimes G_m(x, y)} \right); i = R, G, B \]  \hspace{1cm} (2)

where \( C = I_i(x, y) \)

\[ G_m(x, y) = K_m \exp\left\{ -\frac{x^2 + y^2}{\sigma_m^2} \right\}, \quad \int \int G_m(x, y) dx dy = 1 \]  \hspace{1cm} (3)

where \( G_m \) is Gaussian averaging filter with scale \( m \) and standard deviation \( \sigma_m \)
\( \otimes \) is convolution
• MSR model by Jobson
  – Integrating multiple SSRs with different $\sigma_m$ and appropriate $w_m$
  – Unclear optimization process of $\sigma_m$ and $w_m$
  – Logarithmic conversion $\Rightarrow$ accentuating the dark noise level

• An adaptive scale-gain MSR model by Kotera
  – Stable and excellent color reproduction
  – Linear space without using logarithmic conversion
  – Automatic setting method for weights adapted to the scale gain
  – Computation
    » Requiring computation for weights
    » Taking much time with increasing Gaussian kernel size
Integrated-surround retinex model

- Proposed a concise new Retinex model
  - Based on the work of Kotera’s method
    - Adopting linear space without logarithmic conversion
    - Using the luminance channel to form the surround for each color channel in order to keep color balance
  - Difference from Kotera’s method
    - Integrated-Surround Retinex Algorithm
    - Gaussian pyramid
Integrated-Surround Retinex Algorithm

- Integrating surround images $S_m$ into a single surround image $S_{sum}$ with adaptive weight parameters $w(\sigma_m)$

Fig. 1. Proposed Retinex model using integrated surround
– Ratio of the center pixel $I_i$ to integrated luminance surround $S_{sum}$

$$SSR_{sum}(x, y, \sigma_m) = A \frac{I_i(x, y)}{S_{sum}(x, y, \sigma_m)}; \quad i = R, G, B, A: \text{gain coefficient}$$  \hfill (4)

$$S_{sum}(x, y, \sigma_m) = \sum_{m=1}^{M} w(\sigma_m) S_m(x, y, \sigma_m)$$  \hfill (5)

$$S_m(x, y, \sigma_m) = \langle G_m(x, y) \otimes Y(x, y) \rangle; \quad \sigma_m = 2^m, Y(x, y): \text{luminance channel}$$  \hfill (6)

$$\sum_{m=1}^{M} w(\sigma_m) = 1$$  \hfill (7)
– Comparison with conventional methods

(a) Input              (b) SSR (σ=32)        (c) SSR (σ=128)

(d) NASA MSR     (e) Our previous MSR   (f) Proposed Retinex

(σ=8, 32, 128, weight=1/3)

Fig. 2. Sample by proposed Retinex model in comparison with conventional methods
Optimum Parameters

- Making target image

Fig. 3. Synthesis of target image visually matched to real scene
– Color differences between the visual target image and the processed images

\[ \Delta E_{ab}^* = (\Delta L^*{}^2 + \Delta a^*{}^2 + \Delta b^*{}^2)^{1/2} \]  
\[ \Delta L^* = L_R^* - L_V^*, \quad \Delta a^* = a_R^* - a_V^*, \quad \Delta b^* = b_R^* - b_V^* \]

where \( L^*, a^*, \text{ and } b^* \) are tristimulus values of CIELAB color space

\( R \) represents the results of proposed method

\( V \) represents target image

\[ L^* = 116 \times f\left(\frac{Y}{Y_n}\right) - 16, \]

\[ a^* = 500 \times \left\{ f\left(\frac{X}{X_n}\right) - f\left(\frac{Y}{Y_n}\right) \right\}, \quad b^* = 200 \times \left\{ f\left(\frac{Y}{Y_n}\right) - f\left(\frac{Z}{Z_n}\right) \right\}, \]

\[ f(t) = \begin{cases} t^{1/3} & \text{for } t > 0.008856 \\ 7.787t + 16/116 & \text{for } t \leq 0.008856 \end{cases} \]

where \( X, Y, \text{ and } Z \) are CIEXYZ tristimulus values

\( X_n, Y_n, \text{ and } Z_n \) are the CIEXYZ tristimulus values of the reference white point
Producing a MSR image from a small number of SSRs

- Need at least three SSR images
  - Producing a MSR image without banding artifact
- Using three scales
  - Small ($\sigma_1 = 2$), middle ($\sigma_2 = 16$), and large ($\sigma_3 = 128$)
  - Adjusting the weights $w_m$ to minimize the color difference
  - Smallest color difference $\Delta E_{ab}^* = 8.6$
    
    $A = 0.8, w(\sigma_1) = 0.3, w(\sigma_2) = 0.1, w(\sigma_3) = 0.6

Fig. 4. Color reproducibility by proposed model with three-scale sets ($\sigma_m = 2, 16, 128$)
– Other scales

Fig. 5. Color reproducibility by proposed model with two-scale sets \( (\sigma_m = 2, 128) \)

Smallest color difference
\[ \Delta E_{ab}^* = 8.54 \]
\[ A = 0.8, \ w(\sigma_1) = 0.4, \ w(\sigma_3) = 0.6 \]

Fig. 6. Color reproducibility by proposed model with three-scale sets \( (\sigma_m = 8, 32, 128) \)

Smallest color difference
\[ A = 0.8, \]
\[ w(\sigma_1) = 0.2, \ w(\sigma_2) = 0.1, \ w(\sigma_3) = 0.7 \]
Color reproducibility by the proposed model

Fig. 7. Color reproducibility results by the proposed model in comparison with conventional methods.
Conventional Retinex algorithm

- Large computation time
  - Convolution between the original image and Gaussian filters
  - An example
    - Image size $1280 \times 960$, $\sigma = 128$
    - Taking more than one hour
Fast computation method

\[ g_k = \text{Reduce}(g_{k-1}) = \text{Downsample}_{1/2}\{\text{Lowpass}(g_{k-1})\} \]

\[ \text{Lowpass}(g_{k-1}) = m \otimes g_{k-1}; \otimes \text{ means convolution} \]

\[ m = [m_{ij}] = [w_i \cdot w_j]; i, j = 1, 2, ..., 5 \]

\[ w = [w_i] = [0.05, 0.25, 0.5, 0.25, 0.05]: \text{lowpass filter coefficients} \]

\[ S_K = g_K \otimes G_m(x, y, \sigma_K), \]

\[ S_{k-1} = \text{Expand}(s_k) = \text{Upsample}_{2}\{\text{Interpolate}(s_k)\}; \]

\[ k = K, K - 1, ..., 1. \]

Fig. 8. Fast computation method for surround by Gaussian pyramid.
Table I. Reduction in process time by Gaussian pyramid.

<table>
<thead>
<tr>
<th></th>
<th>Scale</th>
<th>Image size</th>
<th>256 x 192 (process time (s))</th>
<th>256 x 192 (64 x 48) (process time (s))</th>
</tr>
</thead>
<tbody>
<tr>
<td>(a)</td>
<td>$n$</td>
<td>$\sigma_m$</td>
<td>Normal</td>
<td>Pyramid</td>
</tr>
<tr>
<td></td>
<td>3</td>
<td>8</td>
<td>0.29</td>
<td>0.24</td>
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<tr>
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<td>4</td>
<td>16</td>
<td>0.75</td>
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<td>0.90</td>
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<td></td>
<td>7</td>
<td>128</td>
<td>166.3</td>
<td>10.65</td>
</tr>
<tr>
<td>(b)</td>
<td>$n'$</td>
<td>$\sigma_{m'}$</td>
<td>1280 x 960 (process time (s))</td>
<td>1280 x 960 (80 x 60) (process time (s))</td>
</tr>
<tr>
<td></td>
<td>5</td>
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<td>59.10</td>
<td>5.13</td>
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<tr>
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<td></td>
<td>7</td>
<td>128</td>
<td>4118</td>
<td>9.29</td>
</tr>
</tbody>
</table>
– Color difference

Fig. 9. Color reproducibility by proposed pyramid with three-scale sets ($\sigma_m = 2, 16, 128$)

The smallest color difference

$$\Delta E_{ab}^* = 8.54$$
$$A = 0.65, \ w(\sigma_m) = 0.1, 0.1, 0.8$$

Fig. 10. Color reproducibility by proposed pyramid with two-scale sets ($\sigma_m = 2, 128$)

The smallest color difference

$$\Delta E_{ab}^* = 8.5$$
$$A = 0.6, \ w(\sigma_m) = 0.1, 0.9$$
– Comparison with proposed model and proposed pyramid

Fig. 6. Color reproducibility by proposed model with three-scale sets ($\sigma_m = 8, 32, 128$)

Fig. 11. Color reproducibility by proposed pyramid with three-scale sets ($\sigma_m = 8, 32, 128$)
Fig. 12. Samples by the proposed model

(a) Pyramid: A=0.5, K=2,
\[ \mu(\sigma_m) = 1/3, \]
\[ \sigma_K = 2,8,32, \sigma_m = \sigma_K \times 2^k \]

(b) Pyramid: A=0.8, K=2,
\[ \mu(\sigma_m) = 0.1,0.1,0.8, \]
\[ \sigma_K = 2,8,32, \sigma_m = \sigma_K \times 2^k \]

(c) Pyramid: A=0.8, K=2,
\[ \mu(\sigma_m) = 0.2,0.1,0.7, \]
\[ \sigma_K = 2,8,32, \sigma_m = \sigma_K \times 2^k \]

(d) Proposed: A=0.5,
\[ \mu(\sigma_m) = 1/3, \]
\[ \sigma_m = 8,32,128 \]

(e) Proposed: A=0.5,
\[ \mu(\sigma_m) = 0.1,0.1,0.8, \]
\[ \sigma_m = 8,32,128 \]

(f) Proposed: A=0.8,
\[ \mu(\sigma_m) = 0.2,0.1,0.7, \]
\[ \sigma_m = 8,32,128 \]

(g) Original image

(h) NASA

(i) Pyramid: A=0.5,
\[ \mu(\sigma_m) = 0.5, \sigma_m = 2,128 \]
Computing the integrated surround Retinex image $Y_R(x, y)$ for HDR luminance channel

$$Y_R(x, y) = \frac{Y(x, y)}{S_{sum}}$$  (14)

Fig. 13. Histogram of luminance image by proposed Retinex of high dynamic range image.
– Dividing histogram of $Y_R$ into two parts
  • [Min-Mean] and [Mean-Max] by the mean value
– Calculation of pixel numbers
  • Num$_1$ less than Mean
  • Num$_2$ larger than Mean
– Ratios of Num$_1$ and Num$_2$ to all pixel numbers
  \[
  ratio_1 = \frac{Num_1}{Num_1 + Num_2} \quad ratio_2 = \frac{Num_2}{Num_1 + Num_2}
  \] (15, 16)
  \[
  bin_1 = 255 \times ratio_1; \quad bin_2 = 255 \times ratio_2
  \] (17)
– Compressed color image
  \[
  I_{di}(x, y) = \left( \frac{I_i(x, y)}{Y(x, y)} \right)^\gamma Y_d(x, y)
  \] (18)
  where $\gamma = 0.5$
◆ Experimental results

(a) Proposed Model           (b) Larson

Fig. 14. Bathroom
(a) by proposed model
(b) by Larson with histogram adjustment

(a) Proposed Model           (b) Larson

Fig. 15. Memorial Church
(a) by proposed model
(b) by Larson with histogram adjustment
◆ Experimental results

(a) Proposed Model                  (b) Larson

Fig. 16. Win office

(a) Proposed Model                  (b) Larson

Fig. 17. Air traffic tower
Conclusions

- A concise and fast Retinex algorithm
  - Integrating multiscale surround images into a single surround
    - Suppressing the banding artifacts obtained by conventional SSR
  - Reducing computation time by introducing the Gaussian pyramid
  - Working nicely in appearance improvement for both normal LDR and HDR images with range compression