A Variational Framework for Retinex

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Kimmel R, Elad M, Shaked D, et al. A variational framework for retinex[J]. International Journal of computer vision, 2003, 52(1): 7-23.

- Retinex is made up by Retina and Cortex

- Deal with compensation for illumination effects in images

- The primary goal : to decompose a given image S into two different images
- ----- the reflectance image R

- ----- the illumination image L

- Ill-posed problem

$$S = L \times R$$

Assumptions:

- illumination it's spatial smoothness
- L>=S
- the illumination image is close to the intensity image s
- spatially smooth illumination continues
- smoothly as a constant beyond the image boundaries.

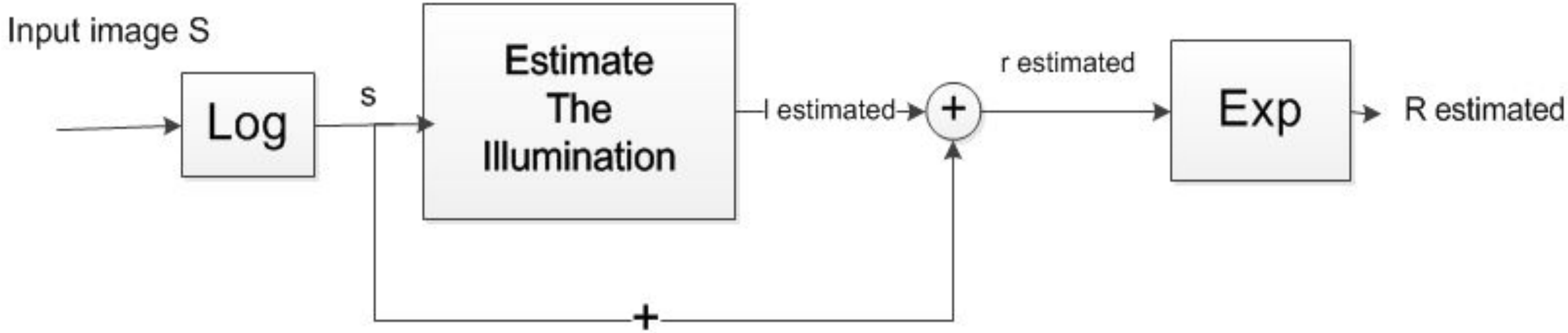


Figure 1. The general flow chart of Retinex algorithms

l = logL ; r = logR

$$Minimize : F[l] = \int_{\Omega} (|\nabla l|^2 + \alpha (l - s)^2 + \beta |\nabla (l - s)|^2) dxdy$$

$$subject \text{ to:} l \geq s, and \left\langle \nabla l, \vec{n} \right\rangle = 0 \text{ on } \partial\Omega$$

Our algorithm

- A modified retinex theory
- Set prior on L,R(upper case)

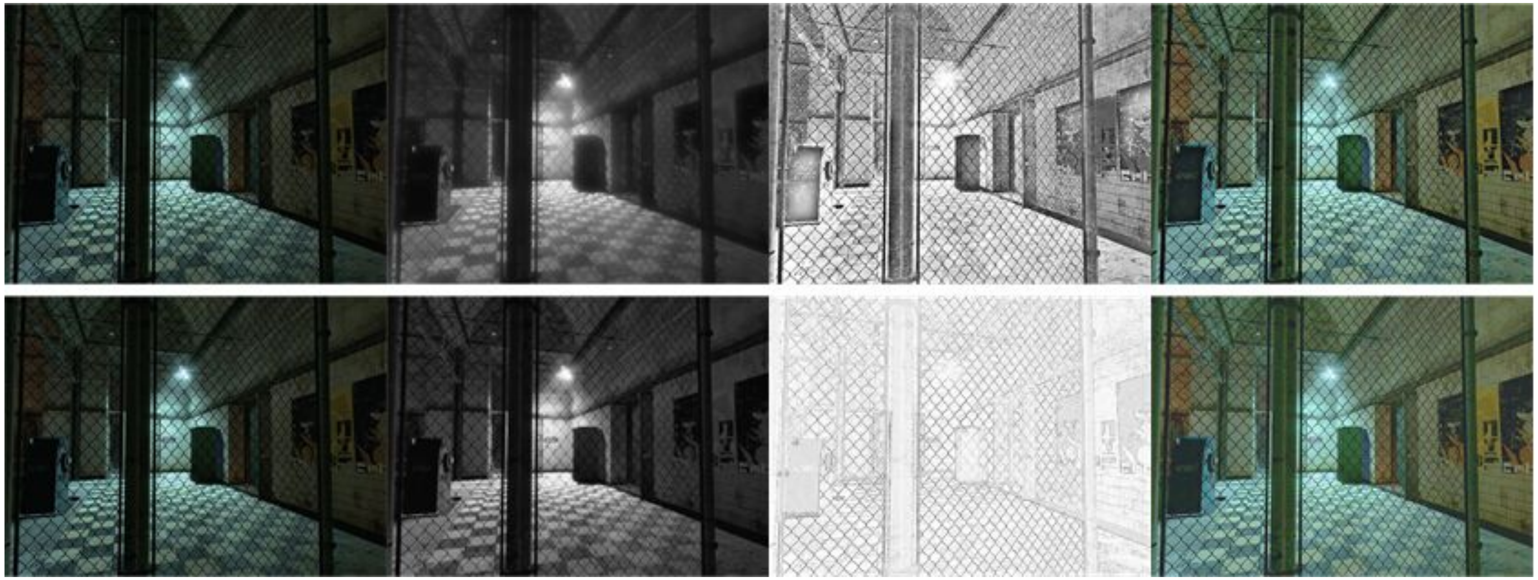
$$Minimize: F[l] = 1/2\left\|l - s\right\|_2^2 + \alpha / 2\left\|\nabla L\right\|_2^2 + \beta / 2\left\|\nabla R\right\|_2^2 \quad (1)$$

$$subject\ to: l \geq s$$

$$Minimize: F[l] = 1/2\left\|l - s\right\|_2^2 + \alpha / 2\left\|L \cdot Dl\right\|_2^2 + \beta / 2\left\|R \cdot Dr\right\|_2^2 \quad (2)$$

$$dF/dl = l - s + \alpha(LD)^T \cdot LDL + \beta(RD)^T RD(l - s) \quad (3)$$

Calculation : Gradient descent



a

b

Figure 2:Comparation between ours and Elad's result

c

d

Original L R Final

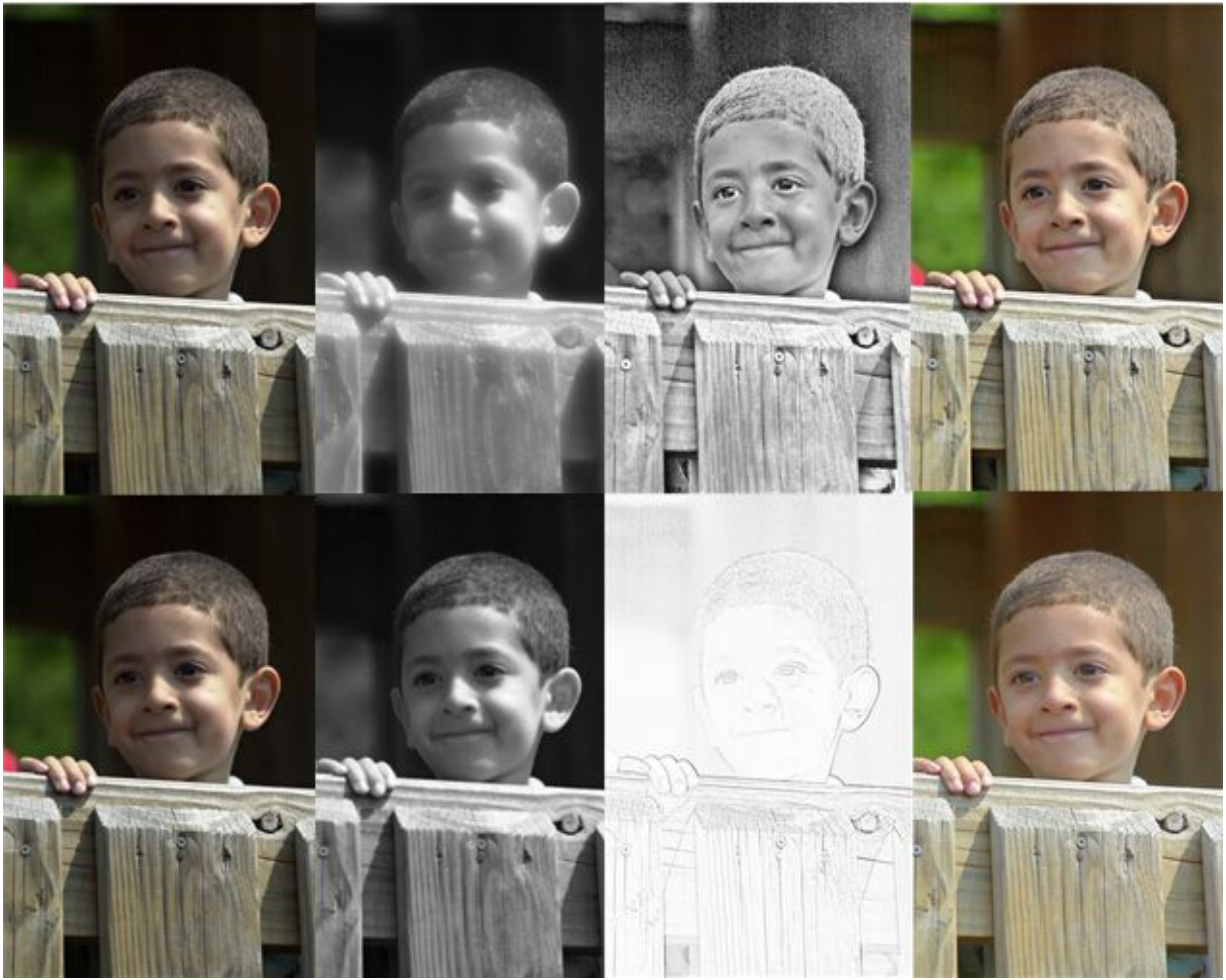
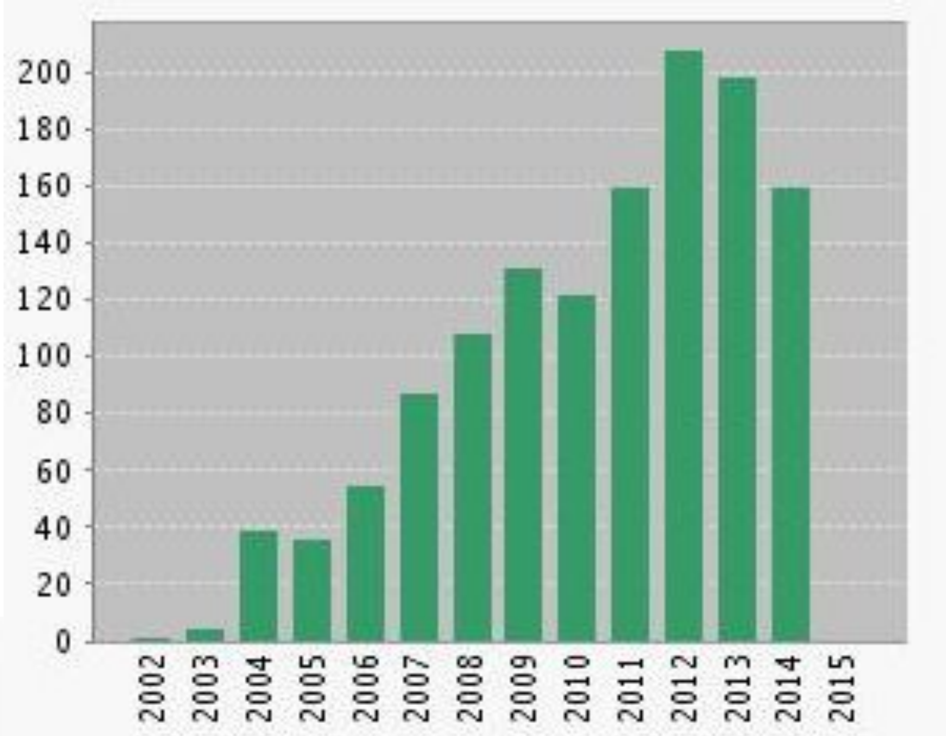
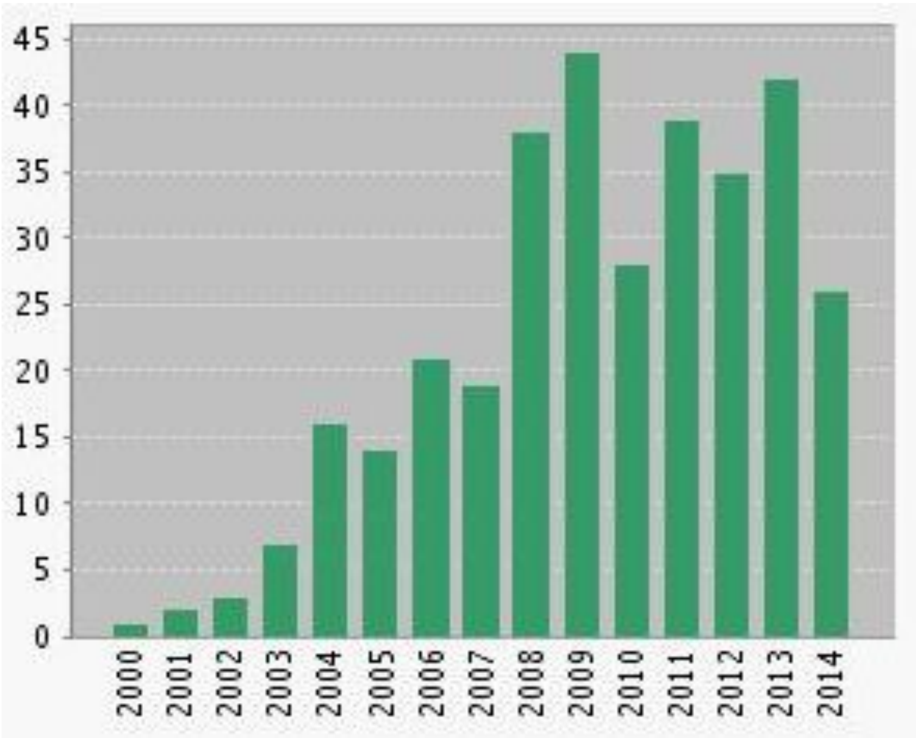


Figure 3



The published literature per year



Citation number per year

Figure 4

A Closed-Form Solution to Retinex with Nonlocal Texture Constraints

Zhao Q, Tan P, Dai Q, et al. A closed-form solution to retinex with nonlocal texture constraints[J]. Pattern Analysis and Machine Intelligence, IEEE Transactions on, 2012, 34(7): 1437-1444.
Citation:16

Intrinsic image decomposition :

A challenging and greatly underconstrained problem because for each pixel there exist twice as many unknowns (reflectance, shading) as there are measurements.

Contributions :

1. a nonlocal constraint on surface reflectance derived from texture analysis

2. a novel optimization formulation for the intrinsic image decomposition problem which can easily incorporate various proposed cues to separate shading and reflectance.

$$I = S \times R$$

$$I_p = S_p + R_p \qquad (4)$$

formulate the intrinsic image decomposition problem as the minimization of an objective function to model these constraints as follows:

$$\underset{S}{\operatorname{argmin}} \; F(S) = \lambda_l f_l(S) + \lambda_r f_r(S) + \lambda_a f_a(S) \qquad (5)$$

$\lambda_1, \lambda_r, \lambda_a$ ----- all positive weights

f_l ----- a local term to formulate the retinex constraint

f_r ----- global term

f_a ----- absolute value term

Minimize a weighted sum of shading and reflectance differences between neighboring pixels over the whole image.

$$f_l(S) = \sum_{(p,q)\in N} [(S_p - S_q)^2 + \omega_{(p,q)} (R_p - R_q)^2] \qquad (6)$$

$$\omega_{(p,q)} = \begin{cases} 0 & \text{if} \left\| \hat{R}_p - \hat{R}_q \right\|_2 > t \\ 100 & \text{otherwise} \end{cases} \qquad (7)$$

$$f_l(S) = \sum_{(p,q)\in N} [(1+\omega_{(p,q)}) \Delta S_{p,q}^2 \text{ -} 2\omega_{(p,q)} \Delta I_{p,q} \Delta S_{p,q} + \Delta I_{p,q}^2] \qquad (8)$$

$$\Delta S_{p,q} = S_p - S_q ; \Delta I_{p,q} = I_p - I_q$$

Goal:seek to reduce the number of unknowns

2M ------ > M+N (N<<M)

Strategy:

Directly represent the texture at a pixel as a vector of concatenated pixel values from its surrounding neighborhood.

Reasons:theory of Markov Random Fields

Global objective function:

$$f_r(S) = \sum_{G_r^i \in \Gamma_r} \sum_{p,q \in G_r^i} (R_p - R_q)^2$$

$$f_r(S) = \sum_{G_r^i \in \Gamma_r} \sum_{p,q \in G_r^i} (I_p - I_q - S_p + S_q)^2 \qquad (9)$$

Goal : reflectance,require the brightest pixel in the image to have unit shading

$$f_a(S) = \sum_{p \in G_a} (S_p - 1)^2 \quad (10)$$

G_a is a set containing the brightest pixel(s)

Decomposition Algorithm

- **Soft Grouping**

search the chromaticity image for pixels embedded within the same texture configuration.

- **Optimization**

we optimize the overall objective function F(S) to solve for the intrinsic images

Strategy:Groups are formed by iteratively selecting an unmatched pixel and finding all matches in the image with a sum of squared differences (SSD) less than a specified threshold(Window size:3*3)

To alleviate the Inaccuracy problem caused by incorrect grouping, we compute a match weight at each pixel:

$$c_p = m_p \left(1 - \frac{1}{9} SSD\right) \qquad (11)$$

$$f_r(S) = \sum_{G_r^i \in \Gamma_r} \sum_{p,q \in G_r^i} c_p c_q (I_p - I_q - S_p + S_q)^2 \qquad (12)$$

Optimize the objective function F(S):

$$F(S) = \frac{1}{2}s^{T}As - b^{T}s + c \qquad (13)$$

A ----- a symmetric and positive-definite (SPD) matrix

s ----- an M*1 vector obtained by concatenating the shading of all pixels

b ----- another M *1 vector

$$As = b \qquad (14)$$

a b c d e

Figure 5:results of the proposed method without and with the nonlocal texture constraint

a b c d e

Figure 6:Comparasion with User-Assisted Approach

A. Bousseau, S. Paris, and F. Durand, “User-Assisted Intrinsic Images,” ACM Trans. Graphics, vol. 28, no. 5, article 30, 2009.

Thank you!