Non-Linear Mapping for Image Enhancement

Shouxin Liu*, Lei He*, Yanyan Li[+] and Wei Long*

** [+]Sichuan University, No.24 South Section 1, Yihuan Road, Chengdu 610065, China*
{2019223029160, 2019223020007}@stu.scu.edu.cn {liyanyan, long_wei}@scu.edu.cn

The existing low-light image enhancement methods may cause under enhancement, unbalance brightness and blurry, to address this shortage we proposed the non-linear mapping method based on Retinex theory (NMMR). We use the improved traditional gamma function to estimate the reflectance, and we proposed the maximum brightness channel to estimate the illumination. The main idea can be descripted as following steps: firstly, we convert the image from RGB (Red, Green, Blue) color space to HSV (Hue, Saturation, Value) color space and the V channel is processed to estimate the reflectance and illumination. Then we use the piecewise function to stretch the gray level dynamic range to achieve the contrast enhancement. Finally, we use the fast pixelwise method to correct the color saturation and convert the image to RGB color space. The experimental results show that the proposed method has lower computational complexity, the enhanced image has better objective and subjective evaluation results than other state-of-the-art methods.

Improved gamma correction

The improved gamma function is expressed as $g(x,y) = (1-(v(x,y)-1)^2)^\gamma$

Mathematical proofs:

We use x to replace the term $v(x,y)$ to simplify the inequation. When x falls within the range (0,1) and we get

$$1 > (x-1)^2 > 0$$

Then

$$0 < 1-(x-1)^2 < 1$$

We also need to prove the value of the improved gamma function is larger than that of the traditional gamma function when x falls within the range (0,1), so we let

$$1-(x-1)^2 - x = 0$$

And

$$1-(x-1)^2 > x$$

Therefore, we can prove that

$$(1-(v(x,y)-1)^2)^\gamma > v(x,y)^\gamma$$

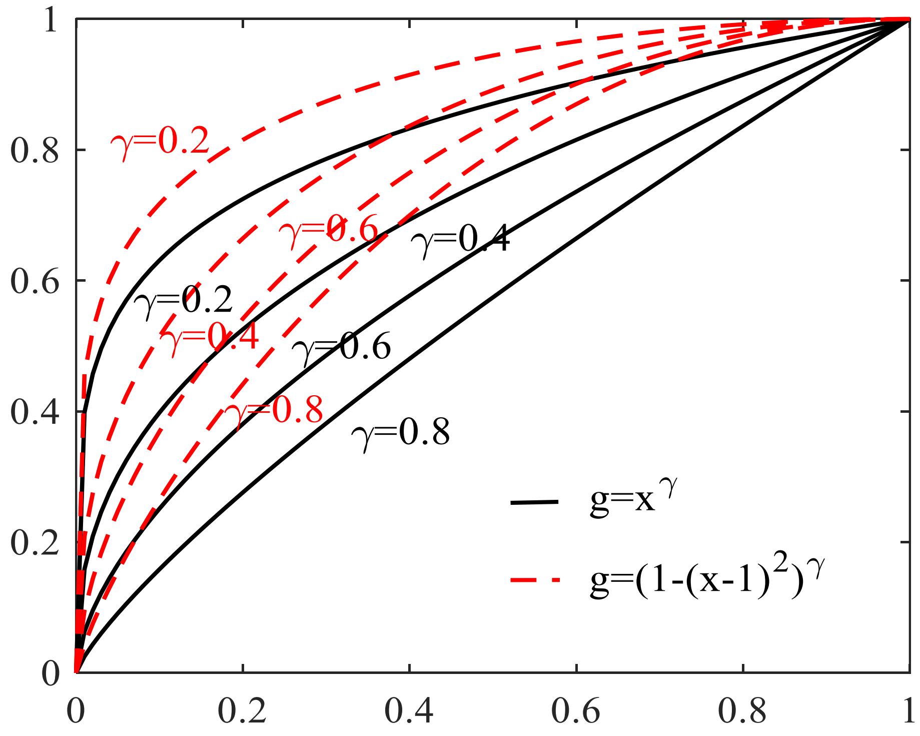


Fig 1: The shape of gamma function with different γ value

The Maximum Brightness Channel

We assume that the reason for insufficient brightness of low-light image is low illumination, the sum of the low illumination and high illumination is 1, and it can be expressed as follows

$$V + Vi = 1$$

where the V denotes the low illumination, Vi denotes the high illumination. Then we can infer that the expression about Vi

$$Vi = 1 - V$$

Finally, we let the maximum pixel at the same location to form the maximum brightness channel. The corresponding mathematic expression is shown as follows

$$Vm = max(V, Vi)$$

where $max(\cdot)$ denotes take the maximum value at the same location between V and Vi. However, when $V(x, y) = 0.5$, we know that $Vm(x, y) = 0.5$, obviously this is not suitable for normal brightness, we have to further enlarge the pixel value. To address this problem, we use the next equation to enlarge the pixel value to obtain the maximum brightness channel

$$Vm' = \sqrt[3]{\frac{\exp(-Vm) - 1}{\exp(-\max(-Vm)) - 1}}$$

The Pixel-wise Method

The relationship between Low-light image and normal-light image

After counting 5600 pairs of low-light images and normal-light images (3150 pairs of images taken by the camera, 2450 pairs of images taken by the mobile phone), we found that the S channel mean value of normal-light images is lower than that of low-light images, and the statistical results are shown in the Table 1 below. All the images come from the R2R dataset[1].

First, we compute the difference of the same pixel location between the V channel and S channel, it can be expressed as

$$V_{S(x,y)} = V(x,y) - S(x,y)$$

Then we compute the single pixel value reduction of S channel, the corresponding expression can be expressed as

$$S1(x,y) = S(x,y) * V_{S(x,y)}$$

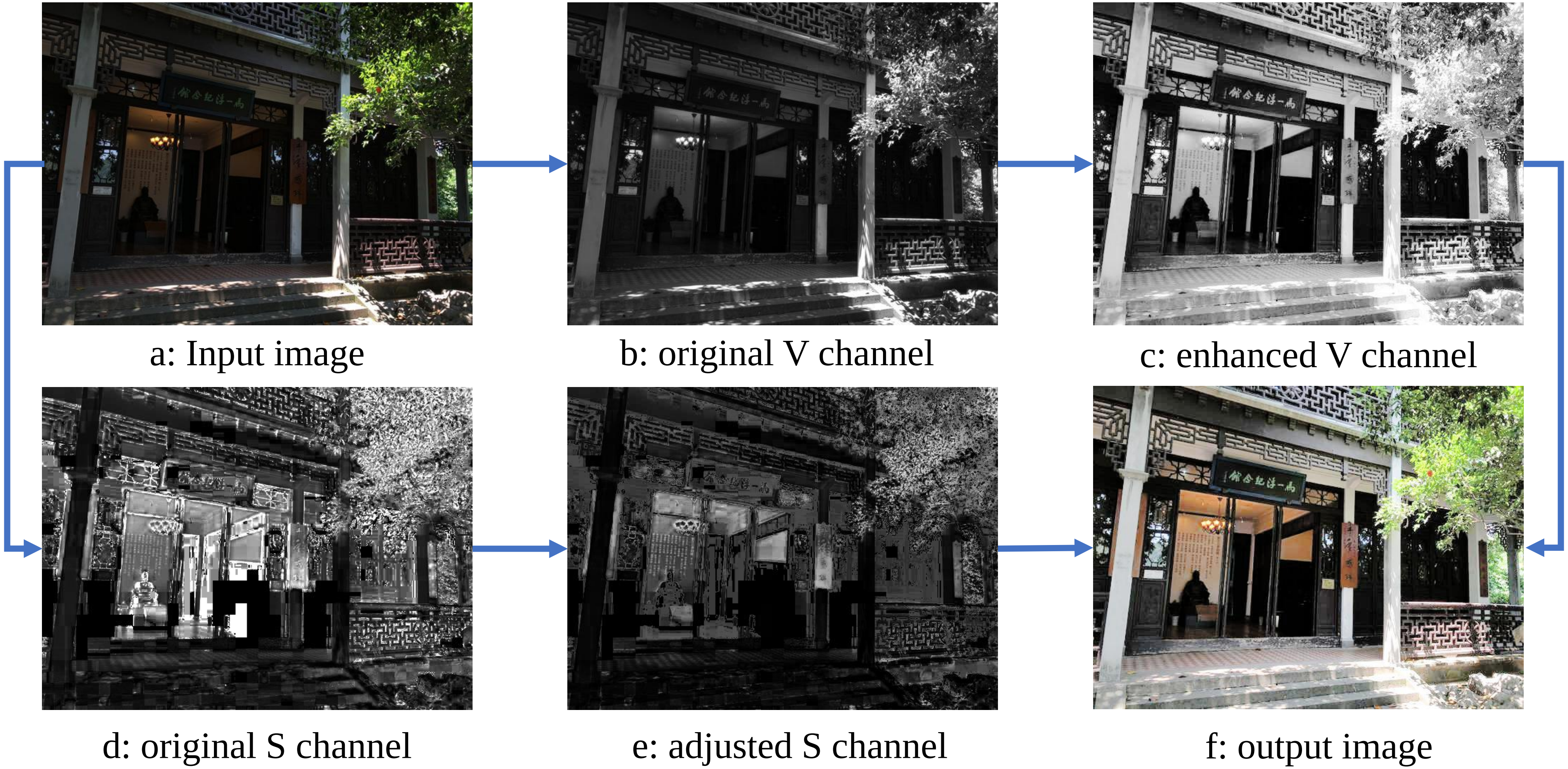
Finally, we use the original S channel to subtract S1 channel to obtain the new S channel named S2. The equation of S2 is shown as

$$S2(x,y) = S(x,y) - |S1(x,y)|$$

Table 1 the mean value of S channel

	Camera		Mobile Phone	
Brightness	Low	High	Low	High
S channel	0.329	0.241	0.289	0.216

Low-light image processing process



Enhanced image comparison

a: Input image

b: LECARM c: JED d: LIME e: SDD

f: AFEM g: MFGC h: RRM i: Proposed

b c d e f g h i

Computation complexity and image quality

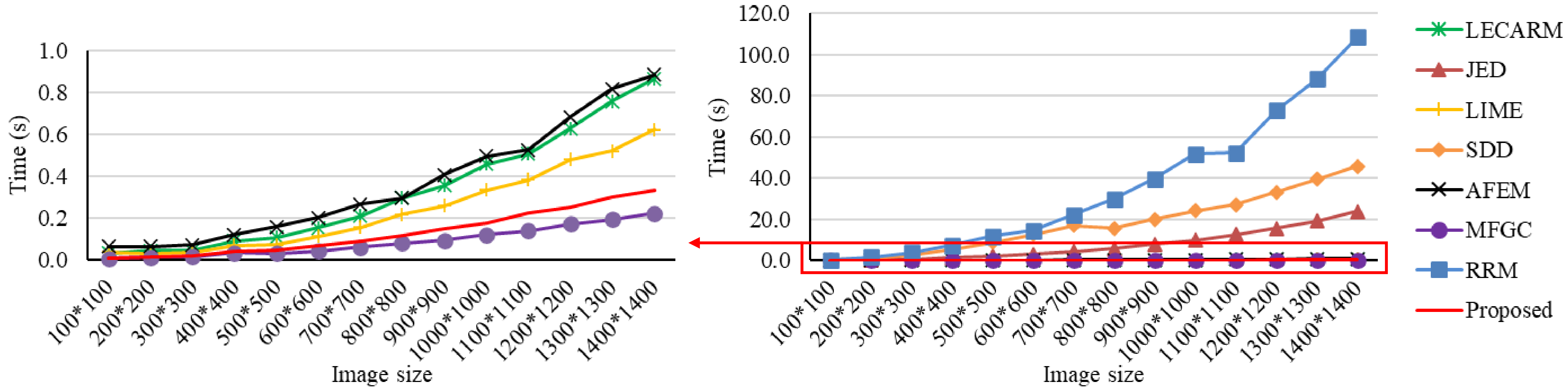


Fig.2: Computation complexity comparison

Table 2 image quality assessment

Datasets	Metrics	LECARM[2]	JED[3]	LIME[4]	SDD[5]	AFEM[6]	MFGC[7]	RRM[8]	Proposed
R2R	LOE	487.470	398.788	642.994	431.168	437.881	**244.164**	403.050	277.757
	SSIM	0.386	0.413	0.304	0.450	0.381	0.322	0.400	**0.501**
	EME	21.681	14.187	24.233	12.888	23.609	13.990	12.411	**28.780**
	PixDist	27.989	21.342	34.083	24.910	25.895	23.802	21.321	32.787
LDSC[9]	LOE	530.832	271.867	671.441	466.097	386.666	150.705	329.252	214.296
	SSIM	0.443	0.508	0.373	0.513	0.491	0.403	0.491	**0.525**
	EME	32.388	23.414	35.284	23.601	34.494	19.791	22.915	**45.644**
	PixDist	34.547	28.370	**41.359**	32.676	30.392	25.620	28.603	40.553

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