

Histogram Equalisation

Contrast is difference in color that makes an object distinguishable from other objects within some field of view
i.e. detailing better observable

Brightness increases whitening in image i.e. increasing avg. pixel value

E.g.

Intensity
value

3	4	5	5
4	4	4	3
0	0	2	1
4	5	6	2

original



3	5	7	7
5	5	5	3
1	1	2	1
5	7	7	2

Hist Equalized

Highest Intensity = 6 (i.e.) 110 (i.e.) 111 (i.e.) 7 max intensity

gray levels	freq	PMF	CM	$7 \times \text{PMF}$	Round off
0	2	0.125	0.125	0.875	1
1	1	0.0625	0.1875	1.3125	1
2	2	2
3	2	3
4	5
5	3
6	1
7	0	0	1	7	7
sum = 16					

fill this

$$\text{Probability Mass } f^n = \frac{\text{no. of } g}{\text{sum}}$$

$$\text{Max Intensity} \times \text{CM}$$

Histogram is graphical representation of intensity distribution of an image i.e. it represents no. of pixels for each intensity value.

- It spreads most frequent intensity values, i.e. stretching out intensity range of image.

Gray Level

'gray' level or 'gray' value indicates brightness of a pixel

gray scale \Rightarrow 8 bit images (0-255) [Dark-light]

16 bit + 32 bit \Rightarrow RGB [with more bits no. of color increases]

Kernel

Kernel is a 2-D matrix of numbers.

It can range in dimension

New Exposure Fusion Network

In outdoor scene, cameras don't make well exposed since dynamic range is limited

We use fusion of over exposed & underexposed image.

The best exposure ratio is found so that synthetic image is well exposed in region where original image is underexposed.

Exposure Ratio k

- First we enclose well exposed pixels and image is globally under-exposed.

$$Q = \{P(x) | T(x) < 0.5\}$$

Q consist of low illuminated pixel

- The brightness of image under different exposure changes significantly while color is same. So, consider only brightness for k .

Brightness component $B = \sqrt[3]{Q_r \cdot Q_g \cdot Q_b}$ → red blue green channels of i/p image.

for each pixel weight matrix is

$$w_d(x) = \frac{1}{|\sum_{y \in w(x)} \nabla_d L(y)| + \epsilon}, \quad d \in \{h, v\}$$

$|x| \rightarrow$ absolute value operator

$w(x) \rightarrow$ local window centered pixel x

$\epsilon \rightarrow$ very small constant to avoid zero denominator

$\nabla_d \approx \nabla_{h(\text{horizontal})}$ & $\nabla_{v(\text{vertical})}$

$$\min_T \sum_x \left((T(x) - L(x))^2 + \lambda \sum_{d \in \{h, v\}} \frac{w_d(x) (\nabla_d T(x))^2}{|\nabla_d L(x)| + \epsilon} \right),$$

λ is balance factor

To prevent exposure ratio becoming infinite when illumination tends to zero, lower bound:

$$K(x) = \frac{1}{\max(T(x), \epsilon)}$$

Finally based on our camera response model & estimated exposure ratio map, we can enhance each pixel $P(x)$ of low-light input image

$$P'_c(x) = e^{b(1-K(x))} P_c(x)^{K(x)}$$

camera parameters

$$\lambda = 1, \epsilon = 0.001$$

$$w(x) = 5$$

Color Distortion

ΔE = color difference. Euclidean distance b/w two colors in CIE color space

$$\Delta E = \sqrt{(L_1 - L_2)^2 + (a_1 - a_2)^2 + (b_1 - b_2)^2}$$

- Calculate average RGB value in each color patch of enhanced image then matching them to CIE Lab space colors & calculate ΔE difference with standard color.

MSR

Retinex mainly consist mainly

1 Illumination & Reflectance

$$f(x, y) = I(x, y) * R(x, y)$$

Illumination is amount of light falling on the scene and dependent on external condition.

Reflectance is amount of light reflected by obj & is affected by object's property.

To compensate for non illumination aim is to remove illumination as it depends on external lighting & keep only reflectance

Illumination varies slowly across image as compared to brightness

$$\text{Product} = \log(I(x, y)) + \log(R(x, y))$$

2 Gamma Correction

Gamma correction is a grey level non linear transformation to replace each pixel with intensity I in the image with I^γ ✓

$$0 \leq \gamma \leq 1 \quad \text{or} \quad \log(I) \quad \text{if} \quad \gamma = 0$$

- It increases dynamic range of image
- scale of output image from 0 to 255.

e.g. $\gamma = 0.5$

pixel from 0-50 mapped to

pixel from 200-255 are "

range 0-155
" 230-255

- Thus γ corr has effect of enhancing image in dark regions while compressing it in bright regions. dynamic range of

Difference of Gaussian Filtering

γ corr or other contrast normalization algorithm does not remove overall effects of intensity gradients like shading effects.

It is not possible to distinguish between illumination gradient and one caused by shading effect of surface structure since illumination is also modelled as low frequency phenomenon.

- High pass filtering is required for it.

- DOG filter is a way to perform Bandpass filtering operation which removes shading and illumination components in the image and also reduces the noise.

- DOG filter approximates a Laplacian of Gaussian filter, which is used for edge detection.

Output is edge intensity image.

Gaussians are characterized by mean and variance / std deviation (σ)

- large σ → blur out fine details / edge while low pass filtering
so use small σ is used which will only eliminate the noise.
- second Gaussian has large σ - removes high frequency details in image & retain only low " component.
- Now we subtract this low frequency image from original low pass filtered image, thereby obtaining a high frequency edge image.
- Typically 1:2 ratio between two Gaussian provides good result. In present implementation the σ is chosen as 3 and 7 for Gaussians.

Contrast Equalization

Final step of our preprocessing chain is contrast equalization which globally rescales the image intensities to standardise a robust measure of overall contrast or intensity variation.

Since DOG approximate Gradient, there are Bound to be extreme value produced by highlights, shadows and noise data.

$$I = \frac{I}{(\text{mean}(I^\alpha))^{\frac{1}{\alpha}}} = \frac{I}{(\text{mean}(\min(T, I^\alpha)))^{\frac{1}{\alpha}}} \\ = T \times \tan\left(\frac{I}{T}\right)$$

- output of eqn is image with pixel intensity in ranges $(-T, T)$
- To get a integer output, we normalize values between 0 to 255.
- diff of gaussian
- contrast stretching
- tanh normalization
- integer value normalization