Illuminant and Gamma Comprehensive Normalisation in log RGB Space

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Abstract

- A non-iterative comprehensive normalization
  - Using logarithms of RGB images
  - Considering lighting geometry and illuminant color
    - Leading to invariance with two simple projection operators in log color space
  - The efficacy of new normalization procedures

Introduction

- Approaching methods to deal with illumination dependencies
  - Color constancy algorithms
    - approximating surface reflectance
    - Finding some correlate of surface reflectance that we known
    - Being insufficient to render color a stable enough cue for object recognition

– Color invariant approach

- Finding functions of proximate image pixels which cancel out lighting dependencies
- Removing the intensity from an RGB response vector
- Removing lighting geometry
  - Chromaticity function and the grey-world normalization

  → Insufficient

◆ Comprehensive normalization

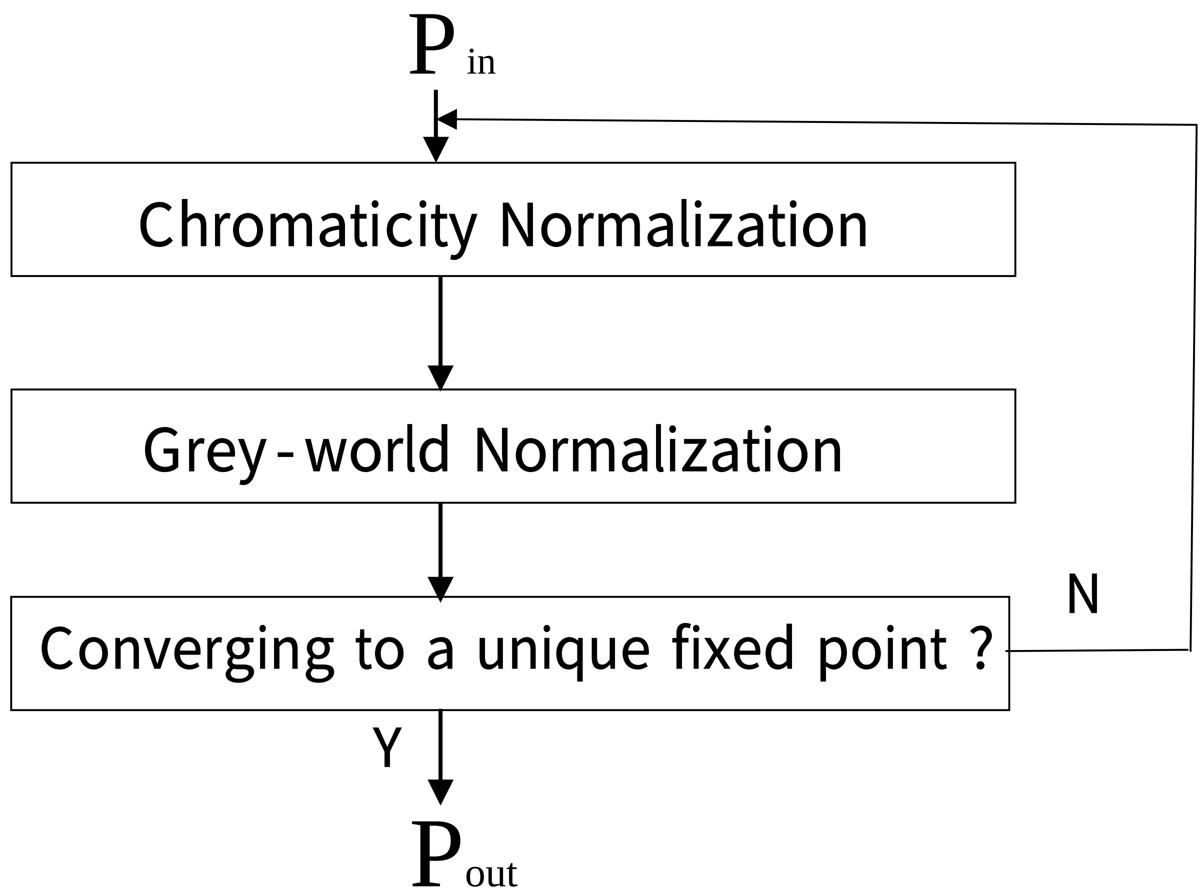

Fig.1. Flowchart of CN

◆ Non-iterative comprehensive normalization

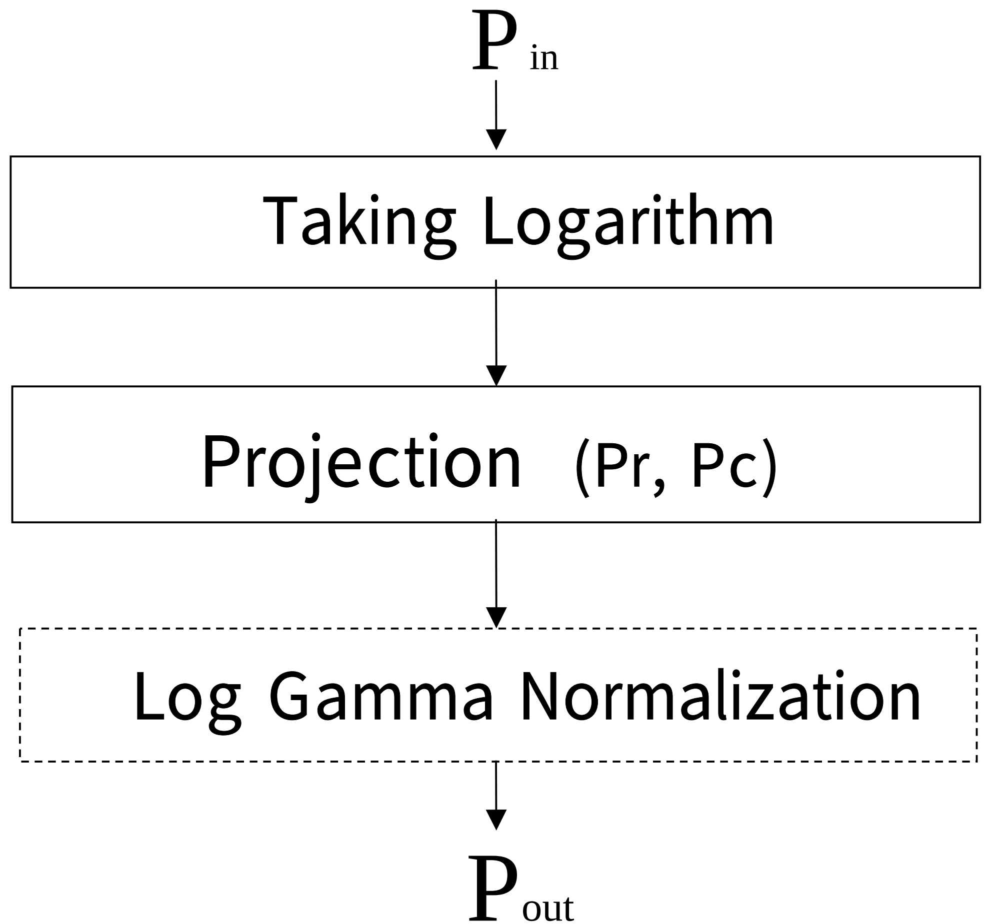

Fig. 2. Flowchart of NCN

Background

- Assumption that imaging device is linear
  – With respect to the incident light

$$\begin{pmatrix} R_i \\ G_i \\ B_i \end{pmatrix} \rightarrow \begin{pmatrix} \rho_i R_i \\ \rho_i G_i \\ \rho_i B_i \end{pmatrix} \qquad (1)$$

where ρ_i : A simple scalar
i : Indication of each pixel

– Lambert law

- The power of the light striking a surface is proportional to the scalar $\underline{n} \cdot \underline{e}$

where $\underline{n}$: Surface normal
$\underline{e}$: Lighting direction

◆ The mathematical model of the RGB value

– A change in illumination

$$\begin{pmatrix} R_i \\ G_i \\ B_i \end{pmatrix} \rightarrow \begin{pmatrix} a & 0 & 0 \\ 0 & b & 0 \\ 0 & 0 & c \end{pmatrix} \begin{pmatrix} R_i \\ G_i \\ B_i \end{pmatrix} \qquad (2)$$

– Non-linearity (Power function transformation)

$$\begin{pmatrix} R_i \\ G_i \\ B_i \end{pmatrix} \rightarrow \begin{pmatrix} R_i^{\gamma} \\ G_i^{\gamma} \\ B_i^{\gamma} \end{pmatrix} \qquad (3)$$

– Combining Eqs. (1)-(3)

$$\begin{pmatrix} R_i \\ G_i \\ B_i \end{pmatrix} \rightarrow \begin{pmatrix} [a\rho_i R_i]^{\gamma} \\ [b\rho_i G_i]^{\gamma} \\ [c\rho_i B_i]^{\gamma} \end{pmatrix} \qquad (4)$$

– Simplifying Eq. (4)

$$\begin{pmatrix} R_i \\ G_i \\ B_i \end{pmatrix} \rightarrow \begin{pmatrix} a'\rho_i' R_i^{\gamma} \\ b'\rho_i' G_i^{\gamma} \\ c'\rho_i' B_i^{\gamma} \end{pmatrix} \qquad (5)$$

◆ Chromaticity normalization

$$r_i = \frac{\rho_i R_i}{\rho_i R_i + \rho_i G_i + \rho_i B_i},$$

$$g_i = \frac{\rho_i G_i}{\rho_i R_i + \rho_i G_i + \rho_i B_i}, \quad (6)$$

$$b_i = \frac{\rho_i B_i}{\rho_i R_i + \rho_i G_i + \rho_i B_i}$$

where r, g and b : The new co-ordinates and independent of ρ_i

– Denoted this procedure C( )

◆ Grey-world normalization

$$\mu(R) = \frac{\sum_{i=1}^{N} R_i}{N} \tag{7}$$

$$\mu(R)' = \frac{\sum_{i=1}^{N} aR_i}{N} = a\mu(R) \tag{8}$$

$$R_i' = \frac{aR_i}{a\mu(R)}, \quad G_i' = \frac{bG_i}{b\mu(G)}, \quad B_i' = \frac{cB_i}{c\mu(B)} \tag{9}$$

where N : The number of pixels in the image

– Denoted this procedure $G(\ )$

◆ Comprehensive normalization

– Appling successively and repeatedly until the resulting image converges to a fixed point

- Initialization

$$I_0 = I$$

- Iteration step

$$I_{i+1} = G(C(I_i)) \tag{10}$$

- Termination condition

$$I_{i+1} = I_i$$

– Denoted this procedure $CN(\ )$

Non-iterative comprehensive normalization in log-space

◆ Taking logarithms from Eq. (5)

$$\begin{bmatrix} \log(R_i) \\ \log(G_i) \\ \log(B_i) \end{bmatrix} \rightarrow \begin{bmatrix} a'' + \rho_i'' + \gamma \log(R_i) \\ b'' + \rho_i'' + \gamma \log(G_i) \\ c'' + \rho_i'' + \gamma \log(B_i) \end{bmatrix} \qquad (11)$$

$$\begin{pmatrix} R_i' \\ G_i' \\ B_i' \end{pmatrix} \rightarrow \begin{pmatrix} a'' \\ b'' \\ c'' \end{pmatrix} + \rho_i'' \begin{pmatrix} 1 \\ 1 \\ 1 \end{pmatrix} + \begin{pmatrix} \gamma R_i' \\ \gamma G_i' \\ \gamma B_i' \end{pmatrix} \qquad (12)$$

where $a'' = \log a'$, $b'' = \log b'$, $c'' = \log c'$, $\rho_i'' = \log \rho_i'$

◆ Projection matrix Pr

$$\square\square \; Pr = U^t (UU^t)^{-1} U = \begin{pmatrix} \frac{1}{3} & \frac{1}{3} & \frac{1}{3} \\ \frac{1}{3} & \frac{1}{3} & \frac{1}{3} \\ \frac{1}{3} & \frac{1}{3} & \frac{1}{3} \end{pmatrix} \tag{13}$$

$$Pr^{\perp} = I - Pr = \begin{pmatrix} \frac{2}{3} & -\frac{1}{3} & -\frac{1}{3} \\ -\frac{1}{3} & \frac{2}{3} & -\frac{1}{3} \\ -\frac{1}{3} & -\frac{1}{3} & \frac{2}{3} \end{pmatrix} \tag{14}$$

where $U = (1,1,1)^t$

◆ Projection of a log RGB onto the orthogonal space

– Multiplying by $Pr^{\perp}$

$$\begin{pmatrix} \frac{2}{3} & -\frac{1}{3} & -\frac{1}{3} \\ -\frac{1}{3} & \frac{2}{3} & -\frac{1}{3} \\ -\frac{1}{3} & -\frac{1}{3} & \frac{2}{3} \end{pmatrix} \begin{pmatrix} R_i' \\ G_i' \\ B_i' \end{pmatrix} = \begin{pmatrix} \frac{2R_i'}{3} - \frac{G_i'}{3} - \frac{B_i'}{3} \\ \frac{2G_i'}{3} - \frac{R_i'}{3} - \frac{B_i'}{3} \\ \frac{2B_i'}{3} - \frac{R_i'}{3} - \frac{G_i'}{3} \end{pmatrix} = \begin{pmatrix} R_i' - \frac{R_i' + G_i' + B_i'}{3} \\ G_i' - \frac{R_i' + G_i' + B_i'}{3} \\ B_i' - \frac{R_i' + G_i' + B_i'}{3} \end{pmatrix} \tag{15}$$

- Removing dependency on lighting geometry by subtracting the mean log response at a pixel (a "brightness" correlate) from each pixel

– Multiplying by $Pc^{\perp}$

$$\begin{pmatrix} a'' + \gamma R_1' \\ a'' + \gamma R_2' \\ \vdots \\ a'' + \gamma R_N' \end{pmatrix} \rightarrow \begin{pmatrix} \gamma R_1' \\ \gamma R_2' \\ \vdots \\ \gamma R_N' \end{pmatrix} + a'' \begin{pmatrix} 1 \\ 1 \\ \vdots \\ 1 \end{pmatrix} \qquad (16)$$

$$Pc = \begin{pmatrix} \frac{1}{N} & \frac{1}{N} & \cdots & \frac{1}{N} \\ \frac{1}{N} & \frac{1}{N} & \cdots & \frac{1}{N} \\ \vdots & \vdots & & \vdots \\ \frac{1}{N} & \frac{1}{N} & \cdots & \frac{1}{N} \end{pmatrix} \qquad (17)$$

$$Pc^{\perp} = I - Pc$$

$$= \begin{pmatrix} \frac{N-1}{N} & -\frac{1}{N} & \cdots & -\frac{1}{N} \\ -\frac{1}{N} & \frac{N-1}{N} & \cdots & -\frac{1}{N} \\ \vdots & \vdots & & \vdots \\ -\frac{1}{N} & -\frac{1}{N} & \cdots & \frac{N-1}{N} \end{pmatrix} \qquad (18)$$

- Operating on the vector of all log red (or green, or blue) responses
- Removing the effect of illuminant color

◆ Explicit equation for the application

– The lighting geometry and light color normalization

$$\gamma Y = (I - Pc)Y\gamma(I - Pr) \qquad (19)$$

– Projection theory

$$(I - Pc)(I - Pc) = (I - Pc)$$

$$(I - Pr)(I - Pr) = (I - Pr) \quad \text{: Idempotent}$$

$$\gamma Y = (I - Pc)(I - Pc)Y\gamma(I - Pr)(I - Pr)$$
$$= (I - Pc)Y\gamma(I - Pr) \qquad (20)$$

- Removing shading or light color completely
- $Y\gamma$: N pixel image as an N x 3 matrix of log RGBs

◆ Gamma normalization

– Second order statistic

$$\sigma^2(\gamma Y) = \frac{\mathrm{trace}((\gamma Y)^t(\gamma Y))}{3N} \tag{21}$$

where trace( ) : The sum of the diagonal elements of a matrix

– Dividing by the standard deviation

$$\frac{\gamma Y}{\sigma(\gamma Y)} = \frac{\gamma Y}{\gamma\sigma(Y)} = \frac{Y}{\sigma(Y)} \tag{22}$$

Object recognition experiments

- Image database under one illuminant
  - Each image represents an object
  - The choice reference dataset had little effect on the indexing results
  - We try to match the query to the database images with color histogram
  - If the closest database histogram to the query is the correct answer

– **Table 1.** Indexing performance of Lee and Berwick dataset (rank are % of the dataset)

Methods	Average percentile	Rank 1	Rank 2	Rank > 2	Worst rank
Nothing	69.84	33.33	33.33	33.33	8 out of 8
Grey-world	98.41	88.89	11.11	0	2 out of 8
Non-iterative	100	100	0	0	1 out of 8
Comprehensive	100	100	0	0	1 out of 8
Log gamma	100	100	0	0	1 out of 8

– **Table 2.** Indexing performance of Swain's dataset (rank are % of the dataset)

Methods	Average percentile	Rank 1	Rank 2	Rank > 2	Worst rank
Nothing	98.54	93.33	3.33	3.33	9 out of 66
Grey-world	98.77	83.33	13.33	3.34	21 out of 66
Non-iterative	99.59	83.33	13.33	3.34	5 out of 66
Comprehensive	98.46	86.67	3.33	10	9 out of 66
Log gamma	98.05	56.67	26.67	16.66	17 out of 66

– **Table 3.** Indexing performance of Simon Fraser dataset (rank are % of the dataset)

Methods	Average percentile	Rank 1	Rank 2	Rank > 2	Worst rank
Nothing	73.08	30.77	15.38	53.85	13 out of 13
Grey-world	98.08	84.62	11.54	3.84	4 out of 13
Non-iterative	98.40	84.62	11.54	3.84	2 out of 13
Comprehensive	98.08	84.62	11.54	3.84	4 out of 13
Log gamma	97.76	84.62	7.69	7.69	4 out of 13

– **Table 4.** Indexing performance of composite dataset (rank are % of the dataset)

Methods	Average percentile	Rank 1	Rank 2	Rank > 2	Worst rank
Nothing	93.92	58.46	6.15	35.38	65 out of 87
Grey-world	92.11	56.92	9.23	33.85	72 out of 87
Non-iterative	99.71	95.38	1.15	3.47	4 out of 87
Comprehensive	99.71	92.31	2.3	5.39	3 out of 87
Log gamma	98.60	84.62	4.62	10.76	19 out of 87

– **Table 5.** Indexing performance of Large Simon Fraser dataset (rank are % of the dataset)

Methods	Average percentile	Rank 1	Rank 2	Rank > 2	Worst rank
Nothing	73.50	28	12	60	20 out of 20
Grey-world	94.21	72.50	10.5	17	20 out of 20
Non-iterative	99.13	91.00	3.5	5.5	5 out of 20
Comprehensive	98.84	91.00	3.5	5.5	16 out of 20
Log gamma	97.61	84.50	6	9.5	10 out of 20

– Performance of each of the three normalization methods

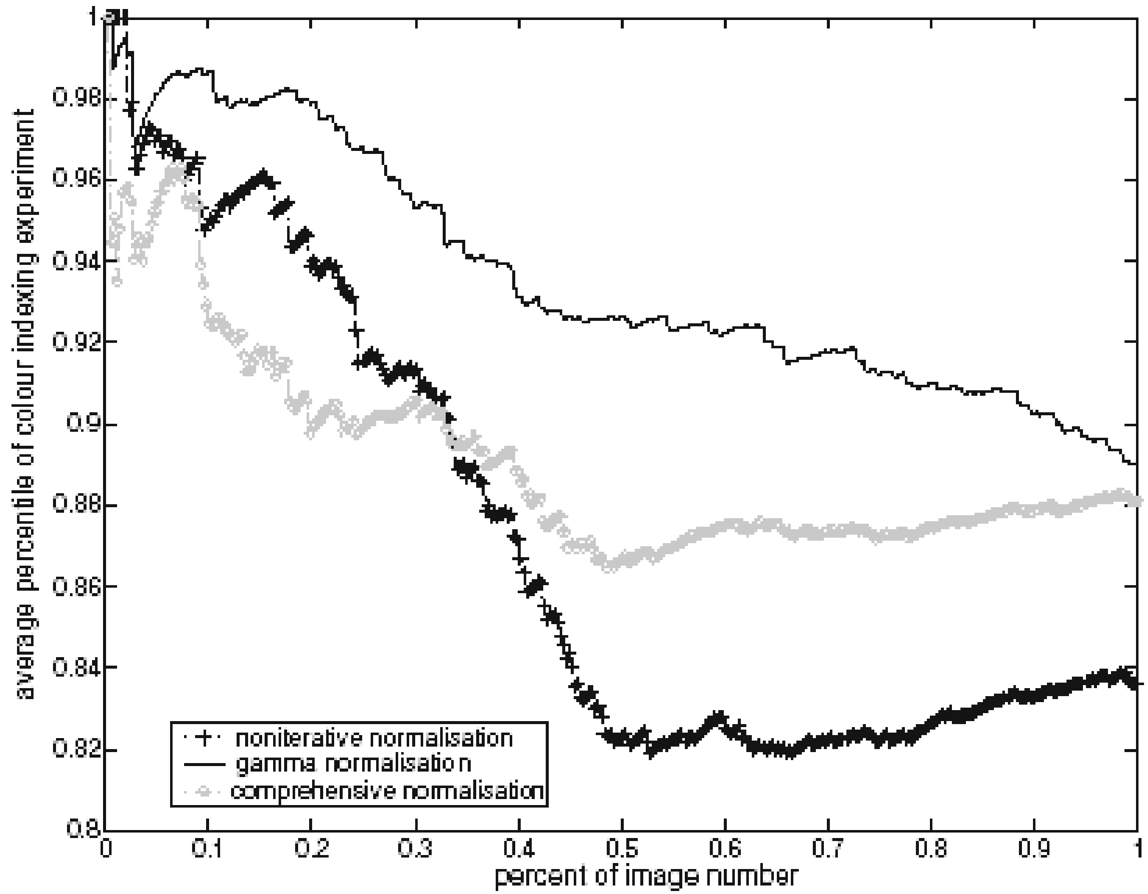

Fig. 3. This figure shows performance of log gamma, non-iterative and comprehensive normalization on the design dataset. The x-axis corresponds to the proportion of query images for which average mach percentile (y-axis) is investigated. The query set is sorted according to how well the images conform to a diagonal-gamma model.

Discussion

- Non-iterative comprehensive normalization
  - Removing image dependence on lighting geometry and illumination at the same time
- Gamma normalization
  - Extending the first to additionally cancel the effect of power functions which are typically applied to captured images
  - Obtaining with non-linearity

→ **Being valid in most practical situations**