Contrast and Color

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Some Examples

Some Examples

Some Examples

Outline

Outline

Color: Description

Definition of color

Color is:

a. an attribute of things that results from the light they reflect, transmit, or emit in so far as this light causes a visual sensation that depends on its wavelength,

b. the aspect of visual perception by which an observer recognizes this attribute,

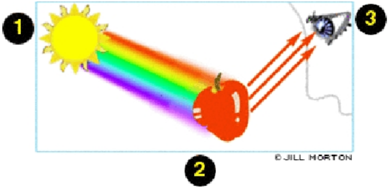
c. the quality of the light producing this aspect of visual perception."

Color: Description

Color description

Three elements are necessary for the existence of color:

- A light source, to light the scene.
- The objects, which reflect, spread, absorb or diffract the light.
- A receptor, which captures the spectrum reflected by the object.



Human vision

Two levels

In the human vision system, the information related with color perception is encoded at two fundamental levels.

The first level occurs in the receptors which are located on the retina. It is a level related with the existence of three types of receptors called cones.

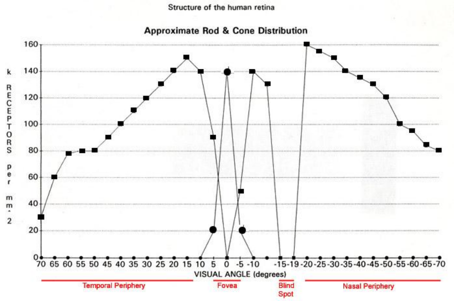
Their responses are the starting point for the second level, which is based on the activity of three opponent mechanisms.

First level of human vision

Rods and cones

In human vision, cones and rods in the eyes are the receptors of information from the external world.

- Rods are responsible for our ability to see in dim light
- Cones are the color receptors.

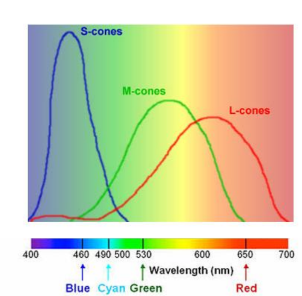


First level of human vision

L, M and S cones

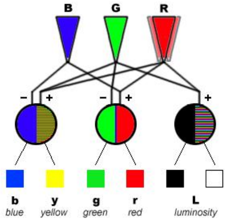
Each rod or cone contains a pigment that absorbs some wavelengths better than others. Three different types of cones:

- L, for the long wavelengths;
- M, for the medium wavelengths;
- S, for the short ones.



Second level of human vision

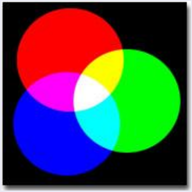
Opponent process theory proposes that trichromatic signals from the cones feed into a subsequent neural stage and exhibit three major classes of information processing in the superior cells of the retina.
The first mechanism is red-green; the second one is yellow-blue; and, the third one is white-black.
Positive response means a biochemical process in the receptors that produces a chemical substance; whereas, negative response means the breakdown of this chemical molecule.

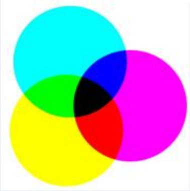


Creating colors

Additive and substractive mixture

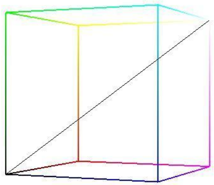
- Additive mixture, addition of different wavelengths. It is produced by light mixture. Red, green and blue are used as additive primary colors.
- Subtractive mixture, subtraction or cancelation of bands of wavelengths by the combination of light absorbing materials. It is produced by mixing paints. Yellow, cyan and magenta are used as subtractive primary colors.





RGB Color space

- The RGB model is the most natural space and the most commonly used.
- This model is based on the cartesian coordinate system.
- Pure red, green and blue are situated in three vertices of the cube, while the other three vertices correspond to pure yellow, cyan and magenta.
- Black has coordinates $(0,0,0)$ and, at the opposite vertex, stands the white color.
- We call the line that joins the black vertex to the white vertex the *grey axis*, in which the three coordinate values are equal.



RGB Color space

Disadvantges

- Perceptual non-uniformity
- Psychological non-uniformity
- A powerful correlation between the different coordinates

HSI Color space

Definition

- **Intensity or lightness** is the visual sensation through which a surface that is illuminated by a given luminous source seems to project more or less light. It corresponds to light, dark or faint terms.
- **Hue** is the visual sensation that corresponds to the color purity. The hue is defined by the dominant wavelength in the spectral distribution.
- **Saturation** measures the proportion on which the pure color is diluted with white light. It corresponds to pale, faded or brilliant terms.

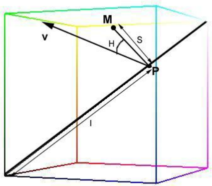
HSI Color space

Advantatges:

- Intensity component is decoupled from the chrominance information represented as hue and saturation.
- Hue is invariant with respect to shadows and reflections.

Disadvantages:

- Hue has a nonremovable singularity on the grey axis. This singularity occurs whenever $R = G = B$.



Outline

Definition.

Histogram definition

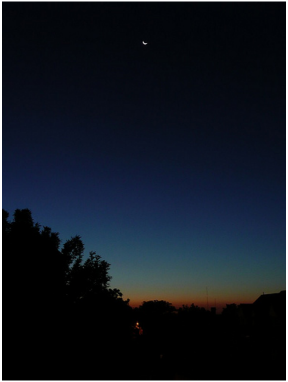
The histogram of a digital image of dimensions $n_x \times n_y$, with L total possible levels in the range $[min, max]$ is defined as the discrete function

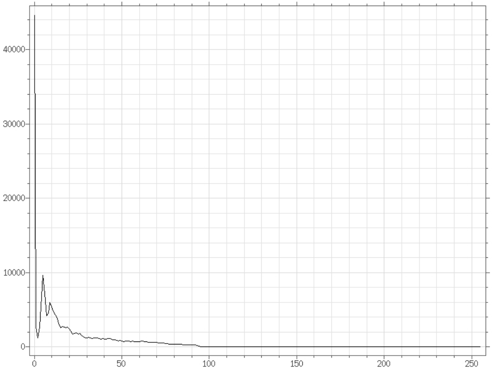
$$h(l_k) = n_k,$$

where l_k is the kth intensity level in the interval $[min, max]$ and n_k is the number of pixels in the image whose intensity level is l_k.

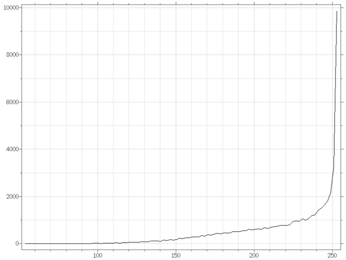
The histogram provides a global description of the appearance of an image.

Examples. Dark image

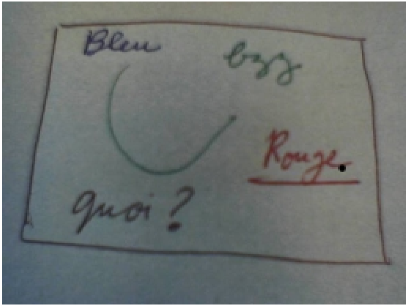


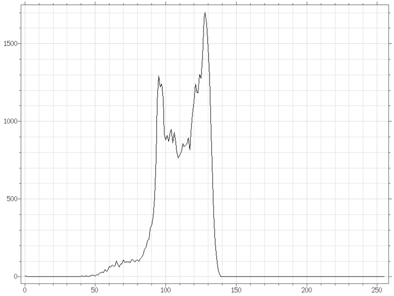


Examples. Bright image

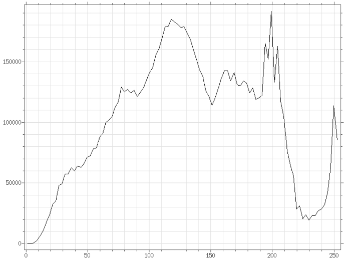


Examples. Low contrast image





Examples. Well contrasted image



Linear transformation of the intensity

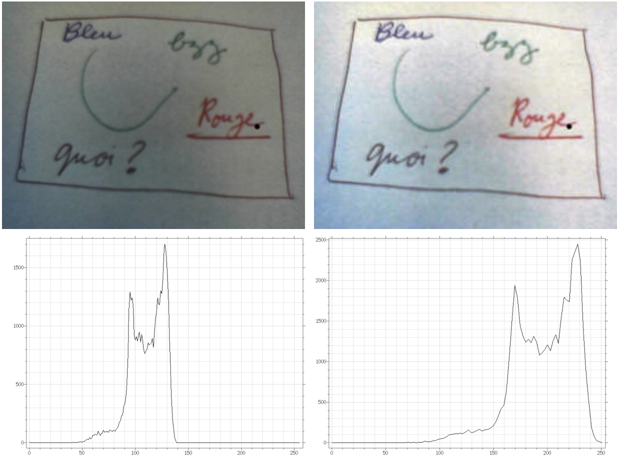
Linear transformation of the intensity

$$T(l) = \frac{s_{max} - s_{min}}{l_{max} - l_{min}}(l - l_{min}) + s_{min}$$

where l_{max} and l_{min} are the maximum and minimum values of the intensity levels in the image, s_{max} and s_{min} are the desired maximum and minimum values in the histogram.

If the ratio $\frac{s_{max}-s_{min}}{l_{max}-l_{min}}$ is smaller than 1 this transformation contract the histogram, if the ratio is larger than 1 the transformation stretch the histogram and if $s_{max} = 255$ and $s_{min} = 0$ the transformation stretches, as much as it can, the histogram.

Examples of linear transformation. Good Results



Examples of linear transformation. Insufficient Result

The histogram of the image occupies all the range $[0, 255]$ due to the little light.

Examples of linear transformations. Insufficient Result

Little improvement in back-lighting images

Simplest Color Balance Algorithm

When the dynamic range of the image occupies $[0, 255]$ due to a few aberrants pixels, thus, spectacular image color improvement is obtained by saturating a small percentage of the pixels with the highest values to 255 and a small percentage of the pixels with the lowest values to 0, before applying the affine transform

$$T(l) = \frac{s_{max} - s_{min}}{l_{max} - l_{min}}(l - l_{min}) + s_{min}$$

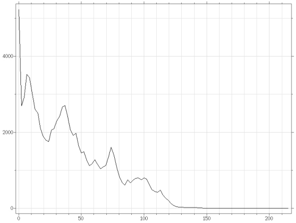
The minimum l_{min} and the maximum l_{max} are such that the number of pixels out of the range $[l_{min}, l_{max}]$ are some percentage of the total number of pixels. Choose $s_{min} = 0$ and $s_{max} = 255$.

Algorithm. Simplest color balance

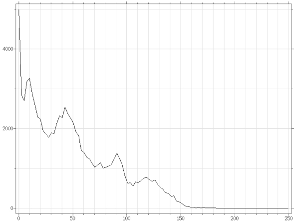
Given an image of dimensions $N = n_x \times n_y$ and given the saturation level $s \in [0, 1)$, the steps of the algorithm are:

1. Cumulative histogram $H(l_k) = \sum_{j=0}^{k} h(l_j)$.
2. $l_{min} = arg\min\{l : \; H(l) \geq N \times s/2\}$
   $l_{max} = arg\max\{l : \; H(l) \leq N \times (1 - s/2)\}$
3. Saturate the pixels.
4. Affine transform with $s_{min} = 0$ and $s_{max} = 255$.

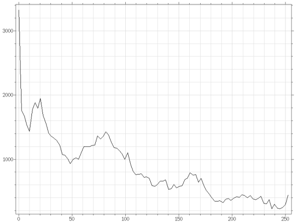
Examples. Simplest Color Balance



Original Image

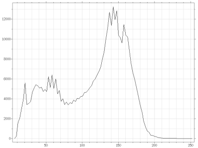


Result with $s = 0$



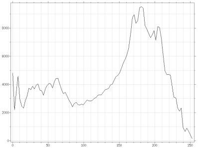
Result with $s = 3\%$

Examples. Simplest color balance



Original image

Examples. Simplest color balance



Saturation of 3%

Bad Results

Result with a saturation of 3%. Unnatural colors.

Outline

Modifications in the gradient domain

The goal is to modify the image, modifying its gradient. Given a **guidance vector field** $\mathbf{V}$. The problem is to find the image whose gradient field is the closest, in L_2-norm, to the prescribed “guidance vector field”. This problem writes

$$\min_u \int_R |\nabla u - \mathbf{V}|^2$$

The minimizer is uniquely determined by the Euler-Lagrange equation

$$\Delta u = \operatorname{div} \mathbf{V}, \quad \text{over } R, \quad \frac{\partial u}{\partial \mathbf{n}} = 0 \quad \text{over } \partial R,$$

with homogeneous Neumann boundary conditions, where $\mathbf{n}$ is the direction orthogonal to the boundary.

Local contrast adjustment

Idea

Amplify the image gradient in the dark regions of the image. Then recover the image using the Poisson equation

To select the dark regions on the image we have used a threshold T. If Ω denote the dark region , then

$$\Omega = \{x \in R : \ f(x) \leq T\}$$

$T = 50$ seems to be correct.


Local contrast adjustment. Algorithm

Given an image f and with the values for T and α the proposed algorithm is fully automatic:

- Select the dark region Ω by the threshold T.
- Define the guidance vector field by

$$\mathbf{V} = \begin{cases} \nabla f & in\ R \setminus \Omega \\ \alpha \nabla f & in\ \Omega \end{cases}$$

  where $\alpha \in [2, 3]$ and in the experiment we have took $\alpha = 2.5$.
- Solve the Poisson equation with Neumann boundary conditions using the Fourier transform as explained in a posterior section.

$$\Delta u = \text{div}\ \mathbf{V}, \quad \text{over}\ R, \quad \frac{\partial u}{\partial \mathbf{n}} = 0 \quad \text{over}\ \partial R,$$

Local contrast adjustment. Examples

Local contrast adjustment. Examples

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Local contrast adjustment. Examples

Copy-Paste

Idea

The idea is to make a copy-paste of a part of an image into another from the gradients and then solve the Poisson equation.

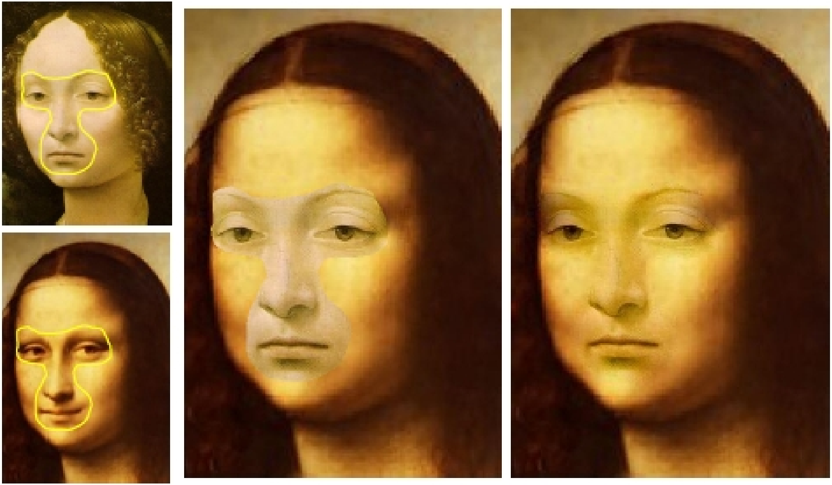
The algorithm is :

- Select $\Omega \subset R$ the region from the image source g we want to paste on the image f.
- Define the guidance vector field as

$$\mathbf{V} = \begin{cases} \nabla f & in\ R \setminus \Omega \\ \nabla g & in\ \Omega \end{cases}$$

- Solve the Poisson equation with Neumann boundary conditions using Fourier method.

Copy-Paste. Examples



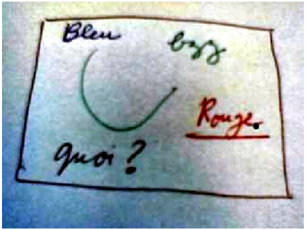
source/destination | cloning | seamless cloning

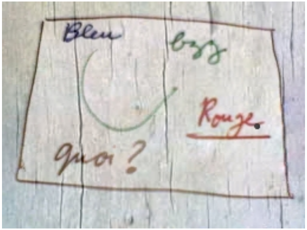
Copy-Paste. Examples

Source image Destination image

Copy-Paste result

Another example. Image Fusion





Retinex

In 1964 Edwin H. Land formulated the Retinex theory, the first attempt to simulate and explain how the human visual system perceives color. His theory and an extension, the "reset Retinex" were further formalized by Land and McCann in 1971. This algorithm modify the RGB values at each pixel to give an estimate of the physical color independent of the shading.

The basic Retinex model is based on the assumption that the HVS operates with three retinal-cortical systems, each one processing independently the low, middle and high frequencies of the visible electromagnetic spectrum. Each system produces one lightness value which determines, by superposition, the perception of color in the HVS.

Original Retinex

The image data $I(x)$ is the intensity value for each chromatic channel at x. Land and McCann consider a collection of N paths $\gamma_1, \ldots, \gamma_k, \ldots, \gamma_N$ starting at x and ending at an arbitrary image pixel y_k. Let n_k be the number of pixels of the path γ_k, and denote by $x_{t_k} = \gamma_k(t_k)$ for $t_k = 1, \ldots, n_k$ and by $x_{t_k+1} = \gamma_k(t_k + 1)$ the subsequent pixel of the path so that $\gamma_k(1) = x$ and $\gamma_k(n_k) = y_k$.

Retinex definition

The **lightness** $L(x)$ of a pixel x in a given chromatic channel is the average of the relative lightness at x over all paths, that is

$$L(x) = \frac{\sum_{k=1}^{N} L(x; y_k)}{N} ,$$

where $L(x; y_k)$ denotes the **relative lightness** of a pixel x with respect to y_k on the path γ_k defined by

$$L(x; y_k) = \sum_{t_k=1}^{n_k} \delta \left[\log \frac{I(x_{t_k})}{I(x_{t_k+1})} \right] ,$$

and, for a fixed contrast threshold t,

$$\delta(s) = \begin{cases} s & \text{if } |s| \geq t \\ 0 & \text{if } |s| < t \end{cases} .$$

Original Reset Retinex

The reset mechanism proposes an adaptation of the above definition to ensure that all paths start from regions where the maximal luminance value is attained.

Extrema Retinex

The **lightness** $L(x)$ of a pixel x in a given chromatic channel is the average of the relative lightness at x over all paths linking x to an arbitrary image extremum y_k, the path meeting no other extremum before reaching y_k. We therefore have

$$L(x) = \frac{\sum_{k=1}^{N} L(x; y_k)}{N}$$

where $L(x; y_k)$ is given by previous definition.

A PDE Formalization of Retinex Theory

Theorem

The lightness value in a chromatic channel L is the unique solution of the discrete Poisson equation

$$\begin{cases} -\Delta_d L(x) = F(x) & x \in R \\ \frac{\partial L}{\partial n} = 0 & x \in \partial R \end{cases}$$

where $\Delta_d L$ denotes the discrete Laplace operator and

$$F(x) = f\left(\frac{I(x)}{I(x_{-0})}\right) + f\left(\frac{I(x)}{I(x_{+0})}\right) + +f\left(\frac{I(x)}{I(x_{0-})}\right) + f\left(\frac{I(x)}{I(x_{0+})}\right),$$

where $f(x) = \delta(\log(x))$, $x_{-0} = (i-1, j)$, $x_{0-} = (i, j-1)$, $x_{+0} = (i+1, j)$, and $x_{0+} = (i, j+1)$.

A PDE Formalization of Retinex Theory

Corollary

Let $\mathbf{Y}$ be the set of image maxima. The Extrema Retinex lightness value in a chromatic channel L is the unique (M, N) symmetric and periodic solution of the discrete Poisson equation

$$\begin{cases} -\Delta_d L(x) = F(x) & x \notin \mathbf{Y} \\ L(x) = 0 & x \in \mathbf{Y} \end{cases}.$$

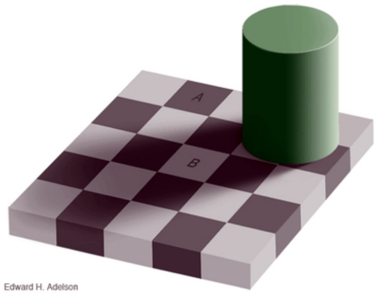
Retinex and Poisson image editing

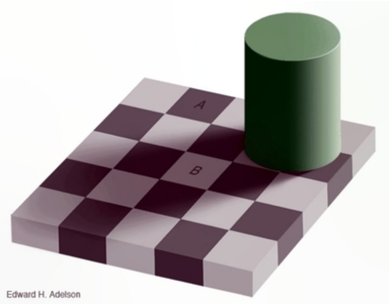
The equation obtained in this theorem is very similar, to the Poisson editing equation proposed in Perez et al.
These authors propose a texture flattening application, whose goal it is to wash out the texture and keep only the edges.
Using the same notation as in the previous section they consider a guidance vector field

$$\mathbf{v} = \begin{cases} \nabla I & \text{if there is an edge} \\ 0 & \text{in other case} \end{cases},$$

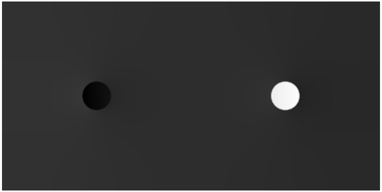
but they do not specify which kind of edge detector they use.
Using as edge detector a threshold functions of the gradient applied to the gradient, then the texture flattening of Perez et al. is equal to the Retinex equation.

Examples

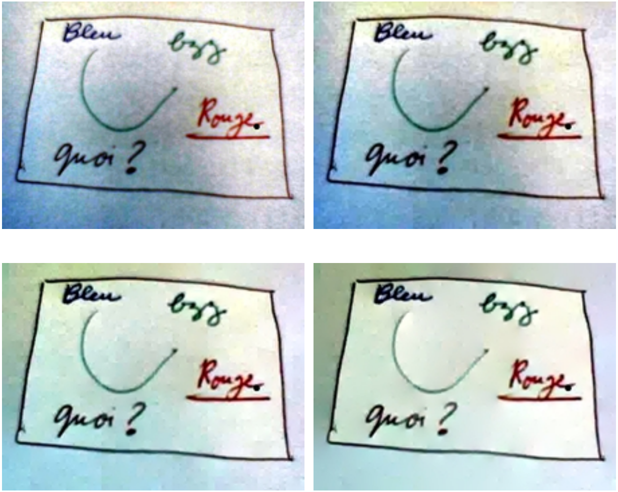




Examples



Examples



Some Examples

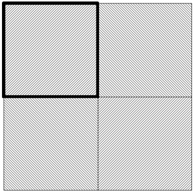
Outline

Implementation by Fourier method

The Fourier method applies directly to solve the Poisson equation with Neumann conditions

$$\Delta u = \text{div}\ \mathbf{V}, \quad \text{over } R, \quad \frac{\partial u}{\partial \mathbf{n}} = 0 \quad \text{over } \partial R$$

The Neumann boundary condition is implicitly imposed by extending the original image symmetrically across its sides, so that the extended image, which is four times bigger, becomes symmetric and periodic.



Fourier Implementation

Discrete Fourier Transform

$$\widehat{u}_{mn} = \sum_{j=0}^{J-1} \sum_{l=0}^{L-1} u_{jl} e^{-i\frac{2\pi mj}{J}} e^{-i\frac{2\pi nl}{L}}$$

with $m = 0, 1, \ldots, J-1$ i $n = 0, 1, \ldots, L-1$.

Inverse Discrete Fourier Transform

$$u_{jl} = \frac{1}{JL} \sum_{m=0}^{J-1} \sum_{n=0}^{L-1} \widehat{u}_{mn} e^{i\frac{2\pi jm}{J}} e^{i\frac{2\pi ln}{L}}$$

with $j = 0, 1, \ldots, J-1$ i $j = 0, 1, \ldots, L-1$.

Fourier Implementation

The equation

$$\Delta u = \mathrm{div}\mathbf{V}$$

becomes by Fourier method

$$\left(\left(\frac{2\pi m}{J}\right)^2 + \left(\frac{2\pi n}{L}\right)^2\right)\widehat{u}_{mn} = \frac{2\pi i m}{J}\widehat{V_1}_{mn} + \frac{2\pi i n}{L}\widehat{V_2}_{mn},$$

where $\mathbf{V} = (V_1, V_2)$.

Fourier Implementation

- Quadruplicate by symmetry the discrete domain and $\mathbf{V}$.

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- Compute the discrete Fourier transforms of V_1 and V_2.

Fourier Implementation

- Quadruplicate by symmetry the discrete domain and $\mathbf{V}$.
- Compute the discrete Fourier transforms of V_1 and V_2.
- Compute the discrete Fourier transform of the solution $\widehat{u}_{mn}$ as

$$\widehat{u}_{mn} = \frac{\frac{2\pi i m}{J}\widehat{V_1}_{mn} + \frac{2\pi i n}{L}\widehat{V_2}_{mn}}{\left(\frac{2\pi m}{J}\right)^2 + \left(\frac{2\pi n}{L}\right)^2}.$$

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- Obtain the samples u_{jl} of the solution by the inverse discrete Fourier transform.

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- Obtain the samples u_{jl} of the solution by the inverse discrete Fourier transform.
- Restrict them to the initial domain.

Outline

Local contrast enhancement by “center-surround” filters

The aim of this project is to stretch locally the histogram from three measures, the mid point of the local dynamic range, the mean intensity value or the median intensity value.
Given an image I defined on a rectangle R, for each point $x \in R$, consider a x-neighborhood of radius r, $B_r(x)$. The algorithm consists on:

- Compute $m(x) = \min_{B_r(x)} I(y)$ and $M(x) = \max_{B_r(x)} I(y)$.
- Compute the values:

$$mp(x) = \frac{m(x) + M(x)}{2} \quad mean(x) = (I * \chi_{B_r(x)})\frac{1}{\pi r^2}$$

$$med(x) = median_{B_r(x)} I(y)$$

Local contrast enhancement by “center-surround” filters

- Stretch the local histogram as

$$I'(x) = I(x) + k(I(x) - V(x))$$

where k is some constant corresponding to the factor range of stretching, and $V(x)$ is one of the three values $mp(x)$, $mean(x)$ or $med(x)$.

Local histogram equalization preserving the level sets

Lecture and compression of the work of Vicent Caselles, Jose Luis Lisani, Jean-Michel Morel and Guillermo Sapiro, **Shape Preserving Local Histogram Modification** to design an optimal strategy to implement the model . This work consists on a local histogram equalization algorithm preserving the level sets of the image.