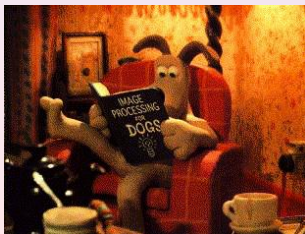


Introduction to Image Processing #5/7

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2006

Outline

- 1 Introduction
- 2 Distributions
 - About the Dirac Delta Function
 - Some Useful Functions and Distributions
- 3 Fourier and Convolution
- 4 Sampling
- 5 Convolution and Linear Filtering
- 6 Some 2D Linear Filters
 - Gradients
 - Laplacian

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Filtering

Filtering images

- is a low-level process
- can be linear or not (!)
- is often useful
 - either to get “better” data
e.g., with enhanced contrast, less noise, etc.
 - or to transform data to make it suitable for further processing

New Approach

An image is a function.

We have

- **sampling:** image values are only known at given points I_p with $p = (r, c) \in \mathbb{N}^2$
- **quantization:** image values belong to a restricted set for instance $[0, 255]$ for a gray-level with 8 bit encoding

An image is a *digital* signal
(contrary: *analog*).

Background

This lecture background is
digital signal processing.

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- 2 Distributions**
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Dirac Delta Function (1/2)

The Dirac delta function, denoted by \uparrow , is defined by:

$$\int_{-\infty}^{\infty} s(t) \uparrow(t) dt = s(0)$$

where s is a test function.

Dirac Delta Function (2/2)

Please note that:

- \uparrow is *not* a function,
- it is a *distribution* (or generalized function).

We have:

$$\int_{-\infty}^{\infty} \uparrow(t) dt = 1.$$

Weird Definition (1/2)

Just *think* of \uparrow being something like:

$$\uparrow(t) = \begin{cases} 1 \times \infty & \text{if } t = 0 \\ 0 & \text{if } t \neq 0. \end{cases}$$

but it cannot be a proper definition!

Weird Definition (2/2)

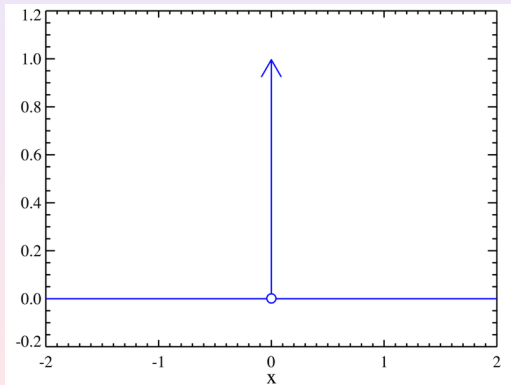
Here α is a constant in \mathbb{R} or \mathbb{C} .

We do *not* have $\alpha\uparrow = \uparrow$, but:

$$\uparrow(t) = \begin{cases} \alpha \times \infty & \text{if } t = 0 \\ 0 & \text{if } t \neq 0. \end{cases}$$

Indeed we should have $\int_{-\infty}^{\infty} \alpha\uparrow(t)dt$ being equal to α .

Dirac Representation



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Foreword

Understand that the Dirac delta function is the *most* important distribution we can think of.

Sinc (1/2)

The (unnormalized, historical, mathematical) sinc function is:

$$\text{sinc}(t) = \frac{\sin(t)}{t}.$$

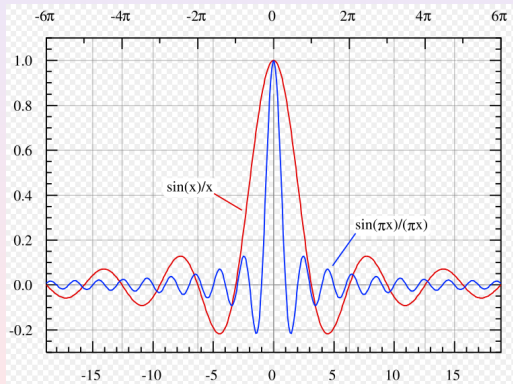
The normalized sinc function is:

$$\text{sinc}(t) = \frac{\sin(\pi t)}{\pi t}.$$

so that:

$$\int_{-\infty}^{\infty} \text{sinc}(t) dt = 1.$$

Sinc (2/2)

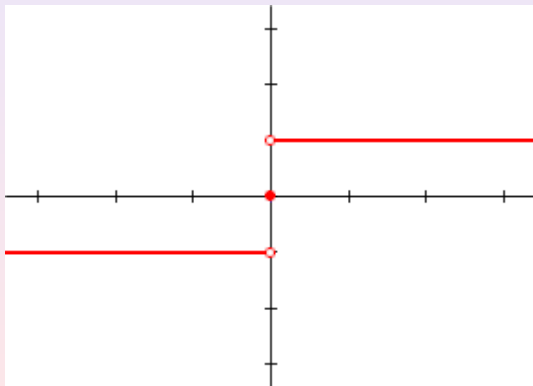


Sign Function (1/2)

The sign function is:

$$\text{sgm}(t) = \begin{cases} -1 & \text{if } t < 0 \\ 0 & \text{if } t = 0 \\ 1 & \text{if } t > 0. \end{cases}$$

Sign Function (2/2)



Heaviside Step Function (1/2)

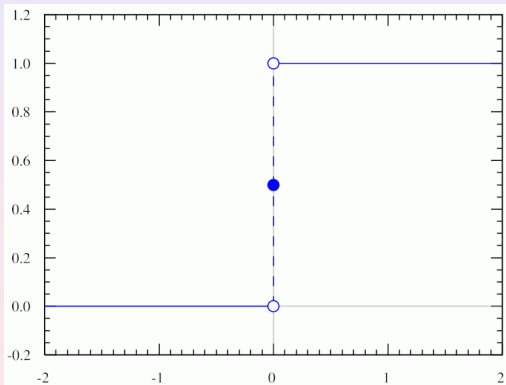
$$u(t) = \frac{1}{2}(1 + \operatorname{sgn}(t)) = \begin{cases} 0 & \text{if } t < 0 \\ 1/2 & \text{if } t = 0 \\ 1 & \text{if } t > 0. \end{cases}$$

We have:

$$u(t) = \int_{-\infty}^t \uparrow(\tau) d\tau.$$

Put differently $\dot{u} = \uparrow$.

Heaviside Step Function (2/2)



Rect (1/2)

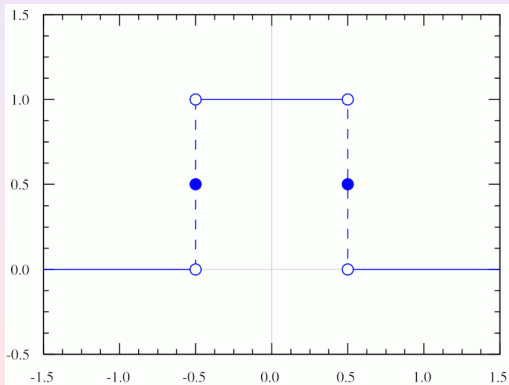
The rectangular function is:

$$\text{rect}(t) = \begin{cases} 1 & \text{if } |t| < 1/2 \\ 1/2 & \text{if } |t| = 1/2 \\ 0 & \text{if } |t| > 1/2. \end{cases}$$

We have:

$$\text{rect}(t) = u(t + 1/2) u(1/2 - t).$$

Rect (2/2)

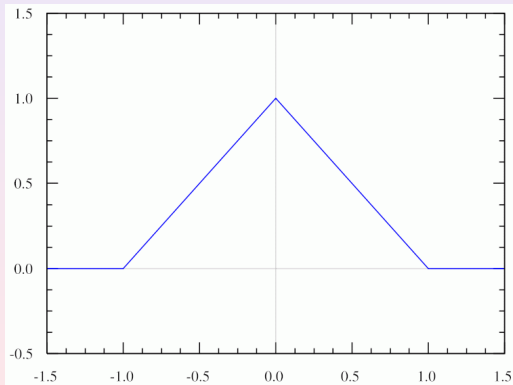


Tri (1/2)

The triangular function is:

$$tri(t) = \begin{cases} 1 - |t| & \text{if } |t| < 1 \\ 0 & \text{if } |t| \geq 1. \end{cases}$$

Tri (2/2)



Dirac Delta Function as a Limit

We can define \uparrow as a limit of functions d_α in the sense that:

$$\lim_{\alpha \rightarrow 0} \int_{-\infty}^{\infty} s(t) d_\alpha(t) dt = s(0).$$

We can choose d_α in:

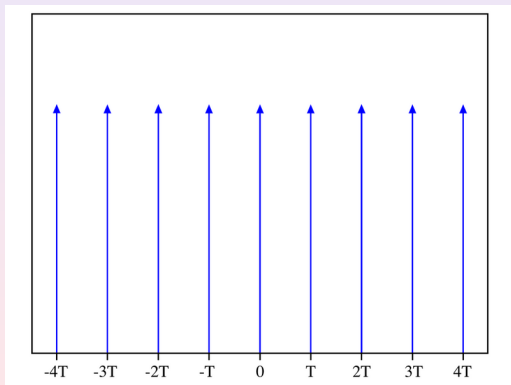
- $t \rightarrow \mathcal{N}(0; \alpha)(t)$ normal distribution
- $t \rightarrow \text{rect}(t/\alpha)/\alpha$ rectangular function
- $t \rightarrow \text{tri}(t/\alpha)/\alpha$ triangular function
- ...

Dirac Comb (1/2)

The Dirac comb is:

$$\mathbb{H}_T(t) = \sum_{k=-\infty}^{\infty} \uparrow(t - kT).$$

Dirac Comb (2/2)



URLs (1/2)



- **Distribution**

`http://en.wikipedia.org/wiki/Distribution_\(mathematics\)`

- **Dirac delta**

`http://en.wikipedia.org/wiki/Dirac_delta_function`

- **Dirac comb**

`http://en.wikipedia.org/wiki/Dirac_comb`

URLs (2/2)



- **Sign**

`http://en.wikipedia.org/wiki/Sign_function`

- **Sinc**

`http://en.wikipedia.org/wiki/Sinc_function`

- **Tri**

`http://en.wikipedia.org/wiki/Triangularfunction`

- **Rect**

`http://en.wikipedia.org/wiki/Rectangular_function`

- **Heaviside step**

`http://en.wikipedia.org/wiki/Heaviside_step_function`

Fourier Series

You know that:

$$\begin{aligned} s(x) &= \frac{1}{2}a_0 + \sum_{n=1}^{\infty} (a_n \cos(nx) + b_n \sin(nx)) \\ &= \sum_{n=-\infty}^{\infty} S_n e^{inx}. \end{aligned}$$

its generalization is...

Discrete Fourier Transform

...the discrete Fourier transform of a discrete function s :

$$s_k = \sum_{n=0}^{N-1} a_n e^{-i2\pi nk/N}$$

$$\text{where } a_n = \frac{1}{N} \sum_{k=0}^{N-1} f_k e^{i2\pi nk/N}$$

Fourier Transform

In the continuous case, S is the Fourier transform of s :

$$S(f) = \int_{-\infty}^{\infty} s(t) e^{-i2\pi ft} dt$$

$$s(t) = \int_{-\infty}^{\infty} S(f) e^{i2\pi ft} df.$$

where f is a frequency.

Notations

We will denote with capital letters the Fourier transforms.

Considering that \mathcal{F} is the Fourier operator on the set of complex-valued functions:

$$S = \mathcal{F}(s).$$

Some Nice Properties

Parseval's theorem:

$$\int_{-\infty}^{\infty} |s(t)|^2 dt = \int_{-\infty}^{\infty} |S(f)|^2 df.$$

$$\begin{aligned}\mathcal{F}^2(s)(t) &= s(-t) \\ \mathcal{F}^* &= \mathcal{F}^{-1}\end{aligned}$$

Amazing:

$$g(t) = \alpha e^{-(t-\beta)^2/2}$$

is an eigenvalue of \mathcal{F} .

Convolution (1/2)

The convolution of two functions h and s is the function:

$$s'(t) = h(t) * s(t) = \int_{-\infty}^{\infty} h(\tau) s(t - \tau) d\tau.$$

The convolution operator is denoted by “*”.

Convolution (2/2)

FIXME: figure.

Exercise

Show that:

$$\text{rect} * \text{rect} = \text{tri}.$$

Convolution Properties

We have:

commutativity

$$a * b = b * a$$

associativity

$$a * (b * c) = (a * b) * c$$

distributivity

$$a * (b + c) = (a * b) + (a * c)$$

associativity with scalar

$$\alpha(b * c) = (\alpha b) * c = b * (\alpha c)$$

Differentiation rule:

$$D(a * b) = D(a) * b = a * D(b).$$

Dirac and Convolution (1/2)

We have:

$$(\uparrow * s)(t) = \int_{-\infty}^{\infty} \uparrow(\tau) s(t - \tau) d\tau = s(t) \quad \forall t.$$

So $\uparrow * s = s$:

\uparrow is the neutral element for the $*$ operator.

Dirac and Convolution (2/2)

Let us note by:

$$\uparrow_{t'}(t) = \uparrow(t - t')$$

the translation to t' of the Dirac delta function
put differently it is a Dirac impulse centered at t'

We have:

$$\begin{aligned} (\uparrow_{t'} * s)(t) &= \int_{-\infty}^{\infty} \uparrow(\tau - t') s(t - \tau) d\tau \\ &= s(t - t'). \end{aligned}$$

Convolving a function with a Dirac delta function centered at t'
means *shifting* this function at the value $t = t'$.

Convolution and Fourier = a Theorem

The convolution theorem is:

$$\mathcal{F}(a * b) = \mathcal{F}(a) \mathcal{F}(b)$$

We also have:

$$\mathcal{F}(a b) = \mathcal{F}(a) * \mathcal{F}(b)$$

Dirac and Fourier

$$\int_{-\infty}^{\infty} 1(t) e^{-i2\pi ft} dt = \uparrow(f).$$

Some Fourier Transforms (1/2)

	\mathcal{F}
$rect(\alpha t)$	$\frac{1}{ \alpha } sinc(\frac{f}{\alpha})$
$sinc(\alpha t)$	$\frac{1}{ \alpha } rect(\frac{f}{\alpha})$
$sinc^2(\alpha t)$	$\frac{1}{ \alpha } tri(\frac{f}{\alpha})$
$tri(\alpha t)$	$\frac{1}{ \alpha } sinc^2(\frac{f}{\alpha})$
$1(t)$	$\uparrow(f)$
$\uparrow(t)$	$1(f)$
$\cos(\alpha t)$	$1/2(\uparrow(f - \frac{\alpha}{2\pi}) + \uparrow(f + \frac{\alpha}{2\pi}))$

Some Fourier Transforms (2/2)

A remarkable Fourier transform:

$$\mathcal{F}(\mathbb{1}_T)(t) = \frac{1}{T} \sum_{k=-\infty}^{\infty} \delta(f - k/T) = \frac{1}{T} \mathbb{1}_{1/T}(f).$$

URLs



- **Fourier series**

`http://en.wikipedia.org/wiki/Fourier_series`

- **Discrete Fourier transform**

`http://en.wikipedia.org/wiki/Discrete_fourier_transform`

- **Fourier transform**

`http://en.wikipedia.org/wiki/Fourier_transform`

- **Parseval's theorem**

`http://en.wikipedia.org/wiki/Parseval's_theorem`

- **Convolution**

`http://en.wikipedia.org/wiki/Convolution`

- **Convolution theorem**

`http://en.wikipedia.org/wiki/Convolution_theorem`

Analog Function

Consider an analog function:

$$s : \begin{cases} \mathbb{R} & \rightarrow \mathbb{R} \\ t & \mapsto s(t) \end{cases}$$

FIXME: figure.

From Analog to Digital (1/2)

A discrete function s_d is sampled from s with the sampling frequency $f_d = 1/T$:

$$\begin{aligned} s_d(t) &= \sum_{k=-\infty}^{\infty} s(kT) \uparrow(t - kT) \\ &= s(t) \times \uparrow_T(t). \end{aligned}$$

So:

$$\begin{aligned} S_d(f) &\propto S(f) * \uparrow_{f_d}(f) \\ &\propto S(f) * \sum_{k=-\infty}^{\infty} \uparrow(f - kf_d) \\ &\propto \sum_{k=-\infty}^{\infty} S(f) * \uparrow(f - kf_d) \\ &\propto \sum_{k=-\infty}^{\infty} S(f - kf_d) \end{aligned}$$

From Analog to Digital (2/2)

FIXME: figure.

From Digital to Analog (1/2)

An analog function s_a is reconstructed from the digital one s_d :

$$S_a(f) = S_d(f) \times \text{rect}\left(\frac{f}{2f_d}\right).$$

So:

$$\begin{aligned} s_a(t) &\propto s_d(t) * \text{sinc}(t/T) \\ &\propto \left(\sum_{k=-\infty}^{\infty} s(kT) \uparrow(t - kT) \right) * \text{sinc}(t/T) \\ &\propto \sum_{k=-\infty}^{\infty} \left(s(kT) \uparrow(t - kT) * \text{sinc}(t/T) \right) \\ &\propto \sum_{k=-\infty}^{\infty} \left(s(kT) \text{sinc}\left(\frac{t-kT}{T}\right) \right) \end{aligned}$$

From Digital to Analog (2/2)

FIXME: figure.

Shanon Sampling Theorem (1/2)

The minimum sampling frequency to be able to perfectly reconstruct an analog signal is twice the maximum signal frequency.

So we should have:

$$f_d > 2 f_{\max}.$$

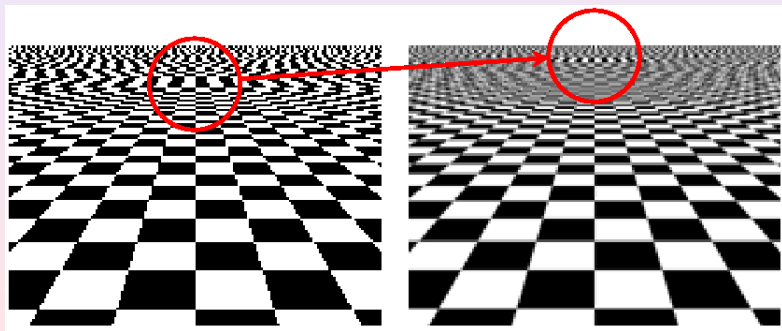
Practically this condition is (usually) never satisfied.

Shanon Sampling Theorem (2/2)

FIXME: figure.

Aliasing

The right image is anti-aliased:



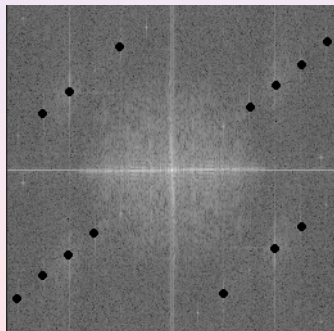
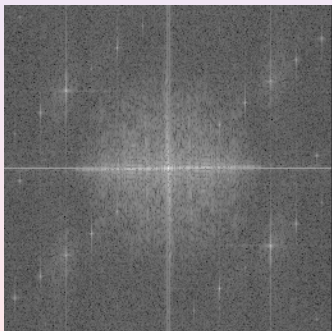
Removing the Moire Effect (1/3)

An image with aliasing presence (left) and a detail (right):



Removing the Moire Effect (2/3)

The original Fourier spectrum (left) and after removing folded peaks (right):



Removing the Moire Effect (3/3)

The result (right) compared to the original (left):



URLs



- **Signal processing**

`http://en.wikipedia.org/wiki/Signal_processing`

- **Sampling**

`http://en.wikipedia.org/wiki/Sampling_\(signal_processing\)`

- **Shannon's sampling theorem**

`http:`

`//en.wikipedia.org/wiki/Nyquist-Shannon_sampling_theorem`

- **Aliasing**

`http://en.wikipedia.org/wiki/Aliasing`

- **Anti-aliasing**

`http://en.wikipedia.org/wiki/Anti-aliasing_filter`

Discrete Convolution

The convolution between a and b :

$$s'(t) = h(t) * s(t) = \int_{-\infty}^{\infty} h(\tau) s(t - \tau) d\tau.$$

can be turned into a discrete convolution:

$$s'[t] = (h * s)[t] = \sum_{\tau=-\infty}^{\infty} h[\tau] s[t - \tau] = \sum_{\tau=-\infty}^{\infty} h[t - \tau] s[\tau]$$

where t and τ are now $\in \mathbb{Z}$.

Discrete Convolution in 2D (1/2)

$$\begin{aligned} s'[r][c] &= (h * s)[r][c] \\ &= \sum_{r'=-\infty}^{\infty} \sum_{c'=-\infty}^{\infty} h[r-r'][c-c'] s[r'][c'] \\ &= \sum_{r'=-\infty}^{\infty} \sum_{c'=-\infty}^{\infty} h[r-r'][c-c'] s[r'][c'] \end{aligned}$$

Discrete Convolution in 2D (2/2)

FIXME: figure.

Linear Filters (1/2)

A filter ϕ is linear if

$$\phi(\alpha \mathbf{s}_1 + \beta \mathbf{s}_2) = \alpha \phi(\mathbf{s}_1) + \beta \phi(\mathbf{s}_2)$$

for all α and β scalars, and \mathbf{s}_1 and \mathbf{s}_2 functions.

ϕ is a linear filter $\Leftrightarrow h_\phi$ exists such as $\phi = h_\phi *$

Put differently:

- we can write $\phi(\mathbf{s}) = h_\phi * \mathbf{s}$
- convolutions are the only linear filters.

Linear Filters (2/2)

Consider that a filter ϕ is a black box.

If this filter is linear, we want to know h_ϕ .

When you input the Dirac delta function (an impulse) into the black box, the resulting function (signal) is:

$$h_\phi * \uparrow = h_\phi.$$

h_ϕ is the impulse response of ϕ .

Dirac Delta Function

Before all:

$$\uparrow[r][c] = \begin{cases} 1 & \text{if } r = 0 \text{ and } c = 0 \\ 0 & \text{otherwise.} \end{cases}$$

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Gradients as Linear Filters (1/3)

Consider the gradient of a 2D function s :

$$\nabla s = \begin{pmatrix} \frac{\delta s}{\delta x} \\ \frac{\delta s}{\delta y} \end{pmatrix}$$

The gradient is linear; with $\phi_{\nabla}(s) = \nabla s$, we have:

$$\phi_{\nabla}(\alpha s_1 + \beta s_2) = \alpha \phi_{\nabla}(s_1) + \beta \phi_{\nabla}(s_2)$$

...so it can be expressed with convolutions!

Gradients as Linear Filters (2/3)

Assuming that sampling is isotropic ($T_x = T_y = 1$), some discrete approximations of the gradient are:

$$\nabla s[r][c] \approx \nabla^{ante} s[r][c] = \begin{pmatrix} s[r][c] - s[r][c-1] \\ s[r][c] - s[r-1][c] \end{pmatrix}$$

or:

$$\nabla s[r][c] \approx \nabla^{post} s[r][c] = \begin{pmatrix} s[r][c+1] - s[r][c] \\ s[r+1][c] - s[r][c] \end{pmatrix}$$

and even:

$$\nabla s[r][c] \approx \frac{\nabla^{ante} s[r][c] + \nabla^{post} s[r][c]}{2} = \begin{pmatrix} \frac{s[r][c+1] - s[r][c-1]}{2} \\ \frac{s[r+1][c] - s[r-1][c]}{2} \end{pmatrix}$$

Gradients as Linear Filters (3/3)

With:

$$\nabla s = \left(h_{\nabla}^x * s h_{\nabla}^y * s \right)$$

and considering the “*post*” version:

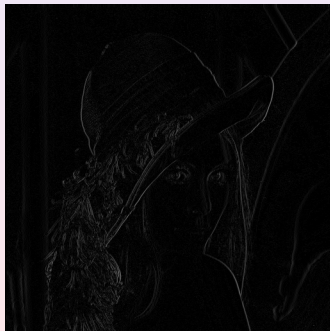
$$\begin{aligned} \nabla^x s[r][c] &\approx s[r][c+1] - s[r][c] \\ &\approx h^x[0][-1] s[r-0][c-(-1)] \\ &\quad + h^x[0][0] s[r-0][c-0] \end{aligned}$$

we have:

$$h^x[r][c] = \begin{cases} 1 & \text{if } r = 0 & \text{and } c = -1 \\ -1 & \text{if } r = 0 & \text{and } c = 0 \\ 0 & \text{otherwise} \end{cases}$$

Gradients Illustrated (1/2)

LENA (left) and the x gradient (right):



Gradients Illustrated (1/2)

crops of resp. the x gradient (left) and the y gradient (right):



Please note that, to better view images, contrast is enhanced and values are inverted (the lowest values are now the brightest).

Graphical Representation

To depict functions we use a graphical representation:

$$h^x = \begin{array}{|c|c|c|} \hline 0 & 0 & 0 \\ \hline 1 & -1 & 0 \\ \hline 0 & 0 & 0 \\ \hline \end{array}$$

In such representations, the origin is always centered and we do not represent null values that lay outside the window.

Gradient Magnitude (1/2)

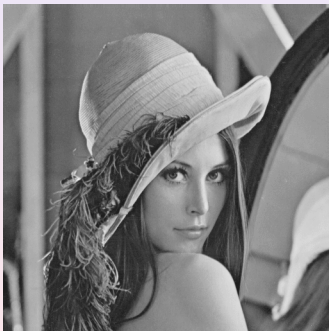
The magnitude is often approximated with a L_1 norm, so:

$$|\nabla s| = \left| \frac{\delta s}{\delta x} \right| + \left| \frac{\delta s}{\delta y} \right|.$$

For instance with the “*post*” version:

$$|\nabla^{post} s|[r][c] = |s[r+1][c] - s[r][c]| + |s[r][c+1] - s[r][c]|$$

Gradient Magnitude (2/2)



Warning: magnitude is also video inverted here.

Other Versions of Gradient Magnitude (1/3)

Many versions of the gradient magnitude exist... for instance this one (the Roberts filter):

$$|\nabla^{\text{roberts}} s|[r][c] = |s[r+1][c+1] - s[r][c]| + |s[r][c+1] - s[r+1][c]|$$

Other Versions of Gradient Magnitude (2/3)

A noise-“insensitive” version of the gradient magnitude is the Sobel filter:

$$h_{Sobel}^x = \frac{1}{4} \begin{array}{|c|c|c|} \hline -1 & 0 & 1 \\ \hline -2 & 0 & 2 \\ \hline -1 & 0 & 1 \\ \hline \end{array}$$

Exercise: explain why it is less sensitive to noise.

Other Versions of Gradient Magnitude (3/3)

Result of the Sobel filter:

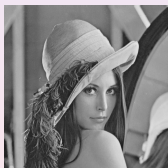


Warning: magnitude is also video inverted here.

Exercise: explain why contours/edges look thicker here than in

Extracting Object Contours (1/2)

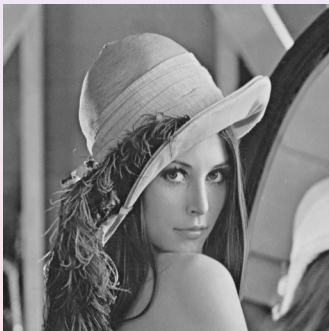
Extracting contours/edges can be performed thru thresholding the gradient magnitude:



Exercise: is it great?

Extracting Object Contours (2/2)

Full size:



Exercise: is it great?

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Definition

The Laplacian of s is:

$$\Delta s = \frac{\delta^2 s}{\delta x^2} + \frac{\delta^2 s}{\delta y^2}$$

Exercise: express h_{Δ} .

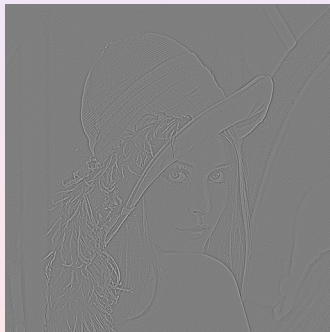
Solution

You should end up with:

$$h_{\Delta} = \begin{array}{|c|c|c|} \hline 0 & -1 & 0 \\ \hline -1 & 4 & -1 \\ \hline 0 & -1 & 0 \\ \hline \end{array}$$

Filtering (1/2)

Result:



Filtering (2/2)

Crop:

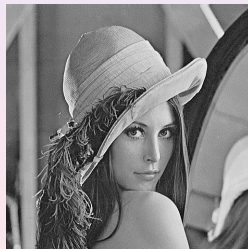
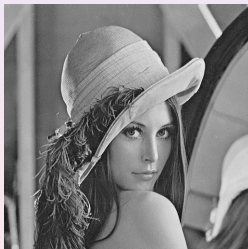
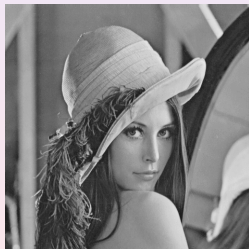


Exercise:

- find how to sharpen image contours/edges,
- express h_{sharpen} in function of a strength parameter.

Edge Sharpening (1/2)

Contour/edge sharpening results:



Edge Sharpening (2/2)

Contour/edge sharpening results:

