

Frequency Approach in IP processing

- 2D DFT
- FT of basic images
- FFT
- Frequency domain filtering.

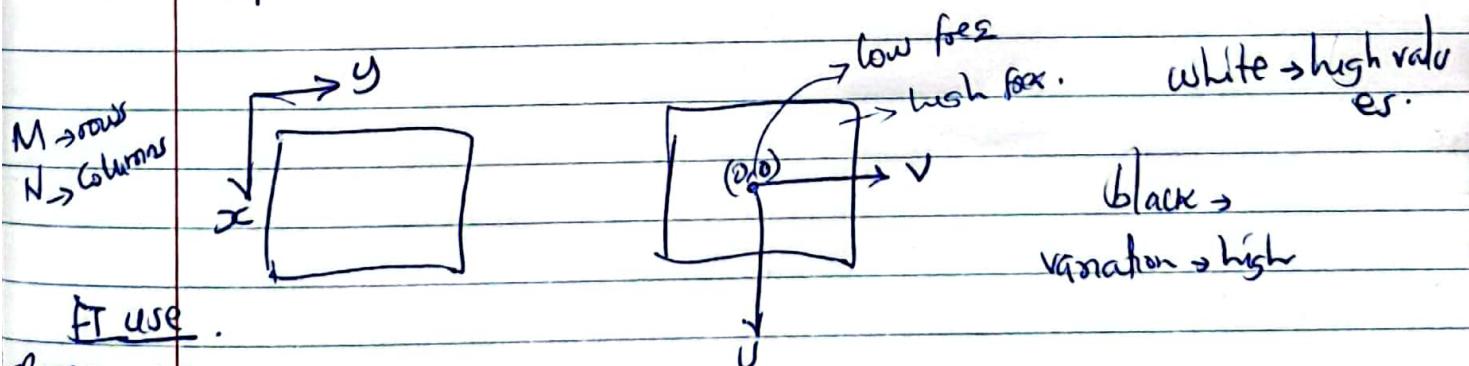
Recall:

- Variation in space (x) not t (spatial domain).
- $\mathcal{U} \rightarrow$ frequency domain

$$\int_{-\infty}^{\infty} f(x) \delta(x - x_0) dx = f(x_0) \rightarrow \text{dirac shifted by } x_0$$

FT of Rectangular pulse.

$\Gamma \rightarrow$ spread (width).



FT use.

Remove noise

Review pages

$a f(x, y) \rightarrow$ brightness

$f(a_0x, b_0y) \rightarrow$ zoom

TD1§2: Fourier Transform of 2D

Ex 1: Properties of FT

1. Linearity of FT

$$\text{FT} \{ f(x) \} = F(u) = \int f(x) \exp(-2\pi j ux) dx.$$

$$F \{ a f(x) + b g(x) \} = a F \{ f(x) \} + b F \{ g(x) \}.$$

$$\int (a f(x) + b g(x)) e^{-2\pi j ux} dx$$

$$= \int a f(x) e^{-2\pi j ux} dx + \int b g(x) e^{-2\pi j ux} dx$$

$$= a F(u) + b G(u) \rightarrow \text{Superposition}$$

→ 2. FT of the transposed function $f(-x)$. $dy = -dx$

→ 3. Scaling. FT of $f(ax)$.

$$F \{ f(ax) \} = \int f(ax) e^{-2\pi j ux} dx$$

$$y = ax \Rightarrow dy = a dx$$

$$\begin{cases} f(x) \rightarrow F(u) \\ f(ax) \rightarrow \frac{1}{a} F\left(\frac{u}{a}\right) \end{cases}$$

Case $a > 0 = x \rightarrow -\infty \Rightarrow y \rightarrow -\infty$

F $x \rightarrow +\infty \Rightarrow y \rightarrow +\infty$

$$F = \int_{-\infty}^{+\infty} f(y) e^{-2\pi j \frac{u}{a} y} \frac{dy}{a}$$

$$= \frac{1}{a} \cdot \int_{-\infty}^{+\infty} f(y) e^{-2\pi j \frac{u}{a} y} dy = \frac{1}{a} F\left(\frac{u}{a}\right)$$

Case $a < 0$

$$x \rightarrow -\infty \Rightarrow y \rightarrow +\infty$$

$$x \rightarrow +\infty \Rightarrow y \rightarrow -\infty$$

$$F = \int_{+\infty}^{-\infty} f(y) e^{-2\pi j \frac{u}{a} y} \frac{dy}{a}$$

$$F = -\frac{1}{a} F\left(\frac{u}{a}\right) \Rightarrow \frac{1}{|a|} F\left(\frac{u}{a}\right)$$

4. FT of translated function

$$= \int f(x-a) e^{-2\pi j u x} dx$$

$$y = x-a$$

$$dx = dy$$

$$\int f(y) e^{-2\pi j u (y+a)} = \int f(y) e^{-2\pi j u y} e^{-2\pi j u a} dy$$

$$= F(y) e^{-2\pi j u a}$$

$$= f(x-a) e^{-2\pi j u a}$$

$$\text{hence } F\{f(x-a)\} \rightarrow F(u) e^{-2\pi j u a}$$

$$\text{if } F\{f(x)\} = F(u)$$

5. FT of modulated function $f(x) \exp(2\pi j u_0 x)$

$$\text{FT}\{f(x) e^{2\pi j u_0 x}\} = \int f(y) e^{2\pi j u_0 x} e^{-2\pi j u_0 y} dy$$

$$uv - \int v du$$

$$= \int_{-\infty}^{\infty} f(\omega) e^{-2\pi j \omega (u - u_0)} du = F(u - u_0)$$

6. FT of the derivative function $f'(x)$

$$\int_{-\infty}^{\infty} \frac{df(x)}{du} e^{-2\pi j \omega u} du = \left[f(u) \cdot e^{-2\pi j \omega u} \right]_{-\infty}^{\infty} + 2\pi j \omega \int_{-\infty}^{\infty} f(u) \cdot e^{-2\pi j \omega u} du$$

$$\int u dv = uv - \int v du$$

$$= f(-\infty) \cdot e^0 + 2\pi j \omega F(\omega) \\ = 2\pi j \omega F(\omega)$$

another way

$$\begin{aligned} F'(u) &= \frac{d}{dt} \left(\frac{1}{2\pi} \int_{-\infty}^{\infty} f(\omega) e^{i\omega t} d\omega \right) \\ &= \frac{1}{2\pi} \int_{-\infty}^{\infty} i\omega f(\omega) e^{i\omega t} d\omega \\ &\boxed{\text{FT of } F'(u)} \\ &= i\omega F(\omega) \end{aligned}$$

7. $\frac{\delta F(u)}{\delta u} = \int_{-\infty}^{\infty} g(x) \cdot e^{-2\pi j \omega x} dx \Rightarrow u \text{ and } x \text{ are independent.}$

$$F(u) = \int_{-\infty}^{\infty} g(x) \left(\int_{-\infty}^{\infty} e^{-2\pi j \omega u} du \right) dx = \int_{-\infty}^{\infty} \frac{g(x)}{-2\pi j \omega} e^{-2\pi j \omega x} dx$$

$$\Rightarrow g(x) = -2\pi j \omega f(x).$$

↓

$$\text{FT } \{g(x)\} G(\omega) = 2\pi j \omega F(\omega)$$

T T

Ex 2: Fourier T & Conv.

1. Show $\mathcal{F}\{f * g\} = \mathcal{F}\{f\} \mathcal{G}\{g\}$

Conv. property $\int_{-\infty}^{\infty} f(\tau) g(t-\tau) d\tau \leftrightarrow \mathcal{F}\{f\} \mathcal{G}\{g\}$

$$\text{let } Y(t) = \int_{-\infty}^{\infty} f(\tau) g(t-\tau) d\tau = f(t) * g(t)$$

FT of $y(t)$ and plug conv. integral.

$$Y(w) = \int_{-\infty}^{\infty} y(t) e^{-jwt} dt = \int_{-\infty}^{\infty} \int_{-\infty}^{\infty} f(\tau) g(t-\tau) d\tau e^{-jwt} dt$$

We can switch the order of two integrals and let $v = t - \tau$

$$Y(w) = \int_{-\infty}^{\infty} f(\tau) \int_{-\infty}^{\infty} g(t-\tau) dt d\tau$$

$$= \int_{-\infty}^{\infty} f(\tau) \int_{-\infty}^{\infty} g(v) e^{-jw(v+\tau)} dv d\tau$$

$$= \underbrace{\int_{-\infty}^{\infty} f(\tau) e^{-jw\tau} d\tau}_{F(w)} \cdot \underbrace{\int_{-\infty}^{\infty} g(v) e^{-jwv} dv}_{G(w)}$$

$$Y(w) = F(w) \cdot G(w)$$

$$Y(w) = \mathcal{F}\{f\} \cdot \mathcal{G}\{g\}$$

Ex2:

$$F(u) = F\{f(x)\} = \int f(x) \exp(-2\pi j u x) dx.$$

$$F\{f * g\} = \iint f(t) g(x-t) dt \cdot e^{-2\pi j u t} dy$$

$$= \int f(t) \int g(x-t) e^{-2\pi j u x} dx dt \quad \text{let } u = x-t \\ du = dx$$

$$= \int f(t) \int g(u) e^{-2\pi j u (u+t)} du dt.$$

$$= \int f(t) e^{-2\pi j u t} dt \int g(u) e^{-2\pi j u u} du = F(u) \cdot G(u)$$

$$F\{f * g(u)\} = F\{\int f(t) g(x-t) dt\},$$

Ex3: FT $F(u)$ of $f(x) = \exp(-\pi x^2)$ - use property 6 & 7

Method 1.

$$F'(u) = - \dots$$

use property 6 & 7

$$F\{f(u)\} = 2\pi j u F(u)$$

$$F\{-2\pi j x f(u)\} = \frac{dF}{du}$$

Method 2.

$$F(u) = \int \exp(-\pi x^2) \exp(-2\pi j u x) dx \xrightarrow{\text{exp}(-\pi u^2)}.$$

Suppose we multiply by $\exp(-\pi u^2) \exp(\pi u^2)$.

Or

$$f(x) = \exp(-\pi x^2) F \{ f(x) \} = F(u) = \exp(-\pi u^2).$$

Using method 1.

$$f(x) = e^{-\pi x^2} \Rightarrow f'(x) = -2\pi x e^{-\pi x^2} = -2\pi x F(u)$$

$$F \{ f'(x) \} = F \{ -2\pi x f(x) \}$$

$$2\pi i u \cdot F(u) = \frac{1}{j} \frac{d F(u)}{du} \Rightarrow \frac{d F(u)}{du} = -2\pi u \cdot du.$$

$$\ln(F(u)) = -\pi u^2 + C \Rightarrow F(u) = e^{-\pi u^2}$$

2. Using change of variable -

FT. of = use

$$f(x) = \frac{1}{\sigma \sqrt{2\pi}} \exp\left(-\frac{x^2}{2\sigma^2}\right)$$

$$F \left\{ \frac{1}{\sigma \sqrt{2\pi}} \exp\left(-\frac{x^2}{2\sigma^2}\right) \right\}$$

$$\left[\begin{array}{l} F \{ a f(x) \} = a F(u) \\ F \{ f(ax) \} = \frac{1}{|a|} F\left(\frac{u}{a}\right) \end{array} \right]$$

$$-\pi a^2 u^2 = -\frac{u^2}{2\sigma^2} \Rightarrow a = \sqrt{\frac{1}{2\pi\sigma^2}}$$

$$F \left\{ \frac{1}{\sigma \sqrt{2\pi}} \cdot f(x) \right\} = \frac{1}{\sigma \sqrt{2\pi}} \cdot \frac{1}{|a|} e^{-\pi \left(\frac{u}{a}\right)^2}$$

$$= \frac{1}{2\pi\sigma^2} e^{-2\pi^2\sigma^2 u^2}$$

→ Comment: It is inverse of each other → due to it.

① Gaussian
② Laplacian } important

Ex 4. 2D FT

$$F(u, v) = \iint_{x, y} f(x, y) \exp[-2\pi i(ux + vy)] dx dy.$$

→ We can reduce this expression to a composition of two monodimensional transformations.

$$\begin{aligned} F(u, v) &= \iint_{x, y} f(x, y) \underbrace{\exp(-2\pi j ux)}_{= \int_x f(x, y) \exp(-2\pi j vx) dy} \underbrace{\exp(-2\pi j vy)}_{= \int_y F(x, y) \exp(-2\pi j ux) dx} dx dy \\ &= \int_x \underbrace{\int_y f(x, y) \exp(-2\pi j vx) dy}_{= F(x, v)} \exp(-2\pi j ux) dx = f(u) \end{aligned}$$

Ex 5. FT of a Laplacian.

$$\nabla^2 = \frac{\delta^2 f}{\delta x^2} + \frac{\delta^2 f}{\delta y^2}$$

$$f(x, y) \rightarrow F(u, v)$$

$$F \left\{ \frac{\delta^2 f}{\delta x^2} + \frac{\delta^2 f}{\delta y^2} \right\}$$

$$F(\nabla^2) = F\left(\frac{\delta^2 f}{\delta x^2}\right) + F\left(\frac{\delta^2 f}{\delta y^2}\right)$$

$$\text{let } \frac{df}{dx} = g(x) \text{ and } \frac{df}{dy} = h(y)$$

$$F\{g(x)\} = 2\pi j u F(u, v)$$

hence

$$F(\nabla^2) = F\{g(x)\} + F\{h(y)\}$$

$$= 2\pi j u$$

$$F\{g(x)\} = 2\pi j u F(u, v)$$

$$\text{hence } F(\nabla^2) = F\{g'(x)\} + F\{h'(y)\}$$

$$= 2\pi j u F\{y(x)\} + 2\pi j v F\{h(y)\}$$

$$= (2\pi j u)^2 F(u, v) + (2\pi j v)^2 F(u, v)$$

$$= -4\pi^2 (u^2 + v^2) F(u, v)$$

Ex 6. DFT

$$F_{k0} = \sum_0^3 f(a) e^{-2\pi j K \frac{a}{4}}$$

$$= 2 \cdot e^{-2\pi j K \frac{0}{4}} + 3 e^{-2\pi j K \frac{1}{4}} + 4 e^{-2\pi j K \frac{2}{4}} + 4 e^{-2\pi j K \frac{3}{4}}$$

$$= 2 + 3e^{-\frac{\pi j K}{2}} + 4e^{-\frac{\pi j K}{4}} + 4e^{-\frac{3\pi j K}{2}}$$

$$F_0 = 2 + 3 + 4 + 4 = 13$$

$$F(1) = 2 + 3e^{-\frac{\pi j}{2}} + 4e^{-\frac{\pi j}{4}} + 4e^{-\frac{3\pi j}{2}} = -2 + j$$

$$F(2) = 2 + 3e^{-\pi j} + 4e^{-2\pi j} + 4e^{-3\pi j} = -1$$

$$F(3) = 2 + 3e^{-\frac{3\pi j}{2}} + 4e^{-3\pi j} + 4e^{-\frac{8\pi j}{2}} = -2 - j$$

Q.

$f(-1, -1)$	$f(-1, 0)$	$f(-1, 1)$
$f(0, -1)$	$f(0, 0)$	$f(0, 1)$
$f(1, -1)$	$f(1, 0)$	$f(1, 1)$



$F(0, 0)$		

0	-1	0
-1	4	-1
0	-1	0

Replacing filters with high pass filters \rightarrow use fft2

$$f(x,y) * h(x,y) = F(u,v) * H(u,v)$$

↓ filters.

$$F(u,v) = \sum_x \sum_y f(x,y) \exp \left[-2\pi j \left(\frac{ux}{N} + \frac{vy}{N} \right) \right], N=3$$

$$= \sum_{x=1}^1 \sum_{y=-1}^1 f(x,y) \exp \left[-\frac{2\pi j}{3} (ux + vy) \right]$$

$$F(0,0) = f(0,0) \exp \left[-\frac{2\pi j}{3} (0u+0v) \right] +$$

$$f(0,1) \exp \left[-\frac{2\pi j}{3} (0u+v) \right] +$$

$$f(1,0) \exp \left[-\frac{2\pi j}{3} (u+0v) \right] +$$

$$f(1,1) \exp \left[-\frac{2\pi j}{3} (u+v) \right] +$$

$$f(-1,0) \exp \left[-\frac{2\pi j}{3} (-u+0v) \right] +$$

$$f(-1,1) \exp \left[-\frac{2\pi j}{3} (-u+v) \right] + f(-1,-1) \exp \left[-\frac{2\pi j}{3} (-u-v) \right]$$

$$+ f(0,-1) \exp \left[-\frac{2\pi j}{3} (0u-v) \right] + f(1,-1) \exp \left[-\frac{2\pi j}{3} (u-v) \right].$$

$$F(0,0) = 4 - 1 \exp \left[\frac{2\pi j v}{3} \right] - 1 \exp \left[\frac{-2\pi j u}{3} \right] - 1 \exp \left[\frac{2\pi j u}{3} \right]$$

$$- 1 \exp \left[\frac{-2\pi j v}{3} \right].$$

$$F(0,0) = 4 - 1 - 1 - 1 - 1 = 0$$

$$F(0,1) = 4 - 1 \exp \left[\frac{2\pi j}{3} \right] - 1 - 1 - 1 \exp \left[\frac{2\pi j}{3} \right] \dots \text{etc.}$$

$$F(1,0) =$$

Matlab:

$$L = \begin{bmatrix} 0 & -1 & 0 \\ -1 & 4 & -1 \\ 0 & -1 & 0 \end{bmatrix}$$

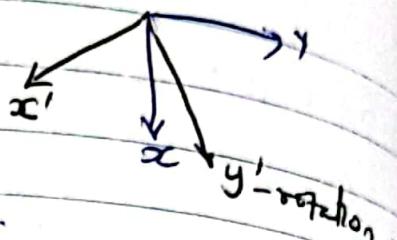
`fftshift(fft2(L))`

$$\begin{bmatrix} x' \\ y' \end{bmatrix} = \begin{bmatrix} \cos \theta & -\sin \theta \\ \sin \theta & \cos \theta \end{bmatrix} \begin{bmatrix} x \\ y \end{bmatrix}$$

Ex 8: Isotropy.

$$\text{Suppose } x' = x \cos \theta - y \sin \theta$$

$$y' = x \sin \theta + y \cos \theta$$



$f \rightarrow \text{image}$

$$\frac{\delta^2 f}{\delta x^2} + \frac{\delta^2 f}{\delta y^2} = \frac{\delta^2 f}{\delta x'^2} + \frac{\delta^2 f}{\delta y'^2}$$

$f \neq L$

$f' \rightarrow \text{new image}$

Show that ∇^2 is an isotropic operator. (Inv.)

$$g = \frac{\delta f}{\delta x'} = \frac{\delta f}{\delta x} \frac{\delta x}{\delta x'} + \frac{\delta f}{\delta y} \frac{\delta y}{\delta x'}$$



$$\frac{\delta f}{\delta y'} = \frac{\delta f}{\delta x} \frac{\delta x}{\delta y'} + \frac{\delta f}{\delta y} \frac{\delta y}{\delta y'}$$

Method 1

$$\text{let } \cos \theta = c$$

$$\sin \theta = s$$

first der.

$$\frac{\delta f}{\delta x'} = \frac{\delta f}{\delta x} c + \frac{\delta f}{\delta y} s$$

$$\frac{\delta f}{\delta y'} = -\frac{\delta f}{\delta x} s + \frac{\delta f}{\delta y} c$$

Second der.

$$\frac{\delta^2 f}{\delta x'^2} = \frac{\delta}{\delta x} \left(\frac{\delta f}{\delta x} \right) c + \frac{\delta}{\delta x} \left(\frac{\delta f}{\delta y} \right) s$$

①

$$\frac{\delta^2 f}{\delta y'^2} = \frac{\delta}{\delta y} \left(\frac{\delta f}{\delta x} \right) s + \frac{\delta}{\delta y} \left(\frac{\delta f}{\delta y} \right) c$$

②

~~①~~
$$\frac{\delta \left(\frac{\delta f}{\delta x} \right)}{\delta x'} =$$

Method 2:
first
der

$$\frac{\delta f}{\delta x'} = \frac{\delta f}{\delta x} \frac{\delta x}{\delta x'} + \frac{\delta f}{\delta y} \frac{\delta y}{\delta x'} = \frac{\delta f}{\delta x} \cos \theta + \frac{\delta f}{\delta y} \sin \theta \approx g$$

$$\frac{\delta f}{\delta y'} = \frac{\delta f}{\delta x} \frac{\delta x}{\delta y'} + \frac{\delta f}{\delta y} \frac{\delta y}{\delta y'} = \frac{\delta f}{\delta x} (-\sin \theta) + \frac{\delta f}{\delta y} \cos \theta \approx h$$

Second
der

$$\frac{\delta g}{\delta x'} = \frac{\delta g}{\delta x} \frac{\delta x}{\delta x'} + \frac{\delta g}{\delta y} \frac{\delta y}{\delta x'} = \frac{\delta f^2}{\delta x^2} \cos \theta \cos \theta + \frac{\delta f^2}{\delta y^2} \sin \theta \sin \theta$$

$$\frac{\delta h}{\delta x'} = \frac{\delta h}{\delta x} \frac{\delta x}{\delta y'} + \frac{\delta h}{\delta y} \frac{\delta y}{\delta y'} = \frac{\delta f^2}{\delta x^2} (-\sin \theta) (-\sin \theta) + \frac{\delta f^2}{\delta y^2} \cos \theta \cos \theta$$

$$\Rightarrow \frac{\delta^2 f}{\delta x^2} \cos^2 \theta + \frac{\delta^2 f}{\delta y^2} \sin^2 \theta + \frac{\delta^2 f}{\delta x^2} \sin^2 \theta + \frac{\delta^2 f}{\delta y^2} \cos^2 \theta$$

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

Ex 9. Average filter $\rightarrow 8$ pixels (excluding middle (all are 0))

1. Av. filter: $h = \frac{1}{8} \begin{bmatrix} 1 & 1 & 1 \\ 1 & 0 & 1 \\ 1 & 1 & 1 \end{bmatrix}$

with

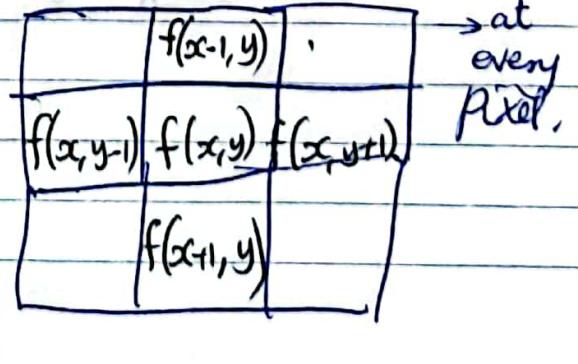
to
normalize

$$\cdot H(u, v) = \frac{1}{8} \begin{bmatrix} 1 & 1 & 1 \\ 1 & 0 & 1 \\ 1 & 1 & 1 \end{bmatrix}$$

2. use $\begin{bmatrix} 0 & 1 & 0 \\ 1 & 0 & 1 \\ 0 & 1 & 0 \end{bmatrix}$

2. if $h = \begin{bmatrix} 0 & 1 & 0 \\ 1 & 0 & 1 \\ 0 & 1 & 0 \end{bmatrix}$

filter \downarrow
3x3 hence
N=3
4-connectivity.



low pass \rightarrow high value in origin $e^{-2\pi j u}$

high pass \rightarrow low value in middle $e^{-2\pi j v}$

$\int f(t) h(x-t) dt$ filter that we are moving with time t.

$$F\{f * h\} = F\{f(x-1, y) + f(x, y-1) + f(x, y+1) + f(x+1, y)\}$$

$$F\{f(x, y)\} = F(u, v) \rightarrow \text{use translation property (shifting convolution)}$$

max in middle

$$\rightarrow F\{f(x, y)\} \text{ Recall } F\{f(x+a)\} = e^{-2\pi j au} F(u)$$

$$F(u, v) = e^{2\pi j \frac{u}{3}} F(u, v) + e^{2\pi j \frac{v}{3}} F(u, v) + e^{-2\pi j \frac{u+v}{3}} F(u, v)$$

$$+ e^{-2\pi j \frac{u+v}{3}} F(u, v)$$

$$= 2F(u, v) \left[e^{2\pi j \frac{u}{3}} + e^{-2\pi j \frac{u}{3}} + e^{2\pi j \frac{v}{3}} + e^{-2\pi j \frac{v}{3}} \right]$$

$$= 2F(u, v) \left[\cos\left(2\pi \frac{u}{3}\right) + \cos\left(2\pi \frac{v}{3}\right) \right] \text{ max } = (0, 0) \text{ at } (u, v) \text{ hence it is a LPF}$$

Here $H(u, v)$ has a maximum at $(u=0, v=0)$

h is a low pass filter.

Ex 10. $\rightarrow 0$ in the middle

\rightarrow High pass filter

$$L = \begin{bmatrix} 0 & -1 & 0 \\ -1 & 4 & -1 \\ 0 & -1 & 0 \end{bmatrix}$$

Ex 11. $\bar{f} = f * h = f(x-1, y) + f(x, y-1) + f(x, y+1) + f(x+1, y) + f(x, y)$

$$\nabla^2 = f * L = -f(x, y)$$

$$Ex 11: \nabla^2 \simeq f - \bar{f}$$

$$\bar{f} = f * h = \frac{1}{5} \{ f(x-1, y) + f(x, y-1) + f(x, y+1) + f(x+1, y) \\ + f(x, y) \}$$

$$\nabla^2 = f * L = -f(x-1, y) - f(x, y-1) + 4f(x, y) - f(x, y+1) \\ - f(x+1, y)$$

$$f - \bar{f} = \frac{1}{5} f(x, y) - \frac{1}{5} \{ f(x-1, y) + f(x, y-1) + f(x, y+1) + \\ + f(x+1, y) \}$$

$$\nabla^2 = \frac{f - \bar{f}}{5} \Rightarrow \nabla^2 \simeq \frac{f - \bar{f}}{5}$$

Filtering in Spatial Domain

- ✓ Linear filters - convolution.
- ✓ Non-linear filters

Properties of filters

- Symmetry: Center

- Separability

- Cascading

LFF

rectangular.

④ Average filtering → reduces noise

$$\frac{1}{9} \begin{bmatrix} 1 & 1 & 1 \\ 1 & 1 & 1 \\ 1 & 1 & 1 \end{bmatrix}$$

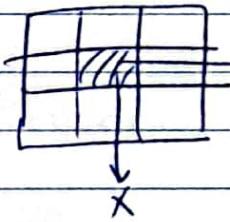
Normalized.

→ Not good like Gaussian.

→ Cannot remove high frequencies
Cos or Sinc

More size of Av. filter → more blur

④ Gaussian filter



y - replace (x,y) in G

- choose the right value of σ

- Big value of σ & filter has to be big also
& vice versa (pg 12)

- Normalize - divide by minimum value to have integral values in the filter

④ Binomial filters - Approximation of Gaussian - Preserve edges
→ Ω is integral (Normalized).

1D B.F. → Convolve several times same filter.

2D B.F. → use separability property of filters. Average.

$$\begin{matrix} & & 1 \\ 1 & 2 & 1 & 2 \\ & & 1 \end{matrix}$$

Since

④ Nagao Filter

- Where the average value doesn't make sense like if the variance is big. Choose possibility of low variance i.e. average with low variance.

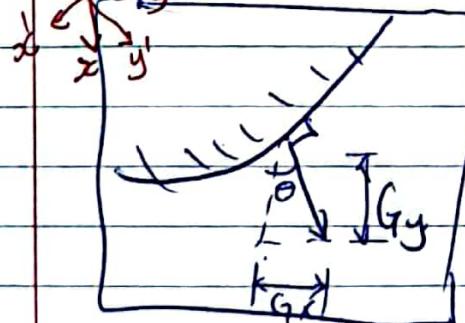
HPF.

* 1D

\rightarrow Max \downarrow deri \rightarrow point of transition.

(crosses zero at second derivative.)

- * 2D (Gradient) \rightarrow first derivative
- \rightarrow Compute Vector at each pixel \rightarrow orientation \rightarrow as by.



$$G(x, y) = \begin{pmatrix} G_x = \frac{\delta f}{\delta x} = f * \begin{bmatrix} 1 \\ 1 \end{bmatrix} \\ G_y = \frac{\delta f}{\delta y} = f * \begin{bmatrix} -1 \\ 1 \end{bmatrix} \end{pmatrix}$$

Norm $|G| = \sqrt{G_x^2 + G_y^2} > \text{threshold}$ - high variation

$$\frac{\delta f}{\delta y} = (f(x, y+1) - f(x, y)) = f * \begin{bmatrix} 1 \\ -1 \end{bmatrix} \rightarrow \text{symmetry on conv}$$

$$\frac{\delta f}{\delta x} = f * \begin{bmatrix} 1 \\ -1 \end{bmatrix}$$

- min 0 max
0 128 255
black grey white

- ⑤ Robert Kernels - variant of Gradients
- We have less noise.

- ⑥ Prewitt Kernels \rightarrow Average filter + first derivative.
- Smoothing + derivative

⑦ (Gabor)

Hirsch Kernels

- choose the filter that gives us maximum value of convolution. ∇ is considered as norm or gradient. and I will know the orientation in the filter $\frac{\partial}{\partial}$

1st order

$$\textcircled{1} \quad G_x = f * \begin{bmatrix} -1 \\ 1 \end{bmatrix} \quad \left. \begin{array}{l} \\ \end{array} \right\} \cdot \vec{G} = \sqrt{G_x^2 + G_y^2} \rightarrow \text{threshold (high value)} \\ G_y = f * \begin{bmatrix} -1 & 1 \end{bmatrix} \quad \left. \begin{array}{l} \\ \end{array} \right\} \quad \theta = \arctg \frac{G_y}{G_x}$$

$$\textcircled{2} \quad f * K_i = G_i \rightarrow \text{image} \quad \vec{K}_1, \vec{K}_2, \dots$$

edge = Norm $\vec{G} = \max \{ G_i \} \rightarrow \text{threshold.} \rightarrow \text{highest max value.}$

zero crossing orientation $\theta = i \max$.

Laplacian
Second derivative.

PG 32

1st image \rightarrow B/w positive & -ve value \rightarrow zero crossings (white marks)

2nd image \rightarrow Combine with smoothing filter (LPF - Gaussian or average)

$\text{LOG} \rightarrow$ 2nd der. of Gaussian.

$\text{LOG}(x, y)$ sum of second derivatives \rightarrow mexican hat.

DOG \rightarrow Subtracting two Gaussians we get LOG

2nd order

→ $f * L \rightarrow$ Zero crossings (but noisy).

$$f * G_0 * L \rightarrow \text{Zero Crossings}$$

LOG

$\Rightarrow f * G_{\sigma_1} - f * G_{\sigma_2} = f * (G_{\sigma_1} - G_{\sigma_2}) \rightarrow \text{Zero Crossings}$

shape
same; at end
N same
DOG
earlier

Non-linear Filter

→ Non-linear fnctn of the neighbour

- neighbour value.
- Size.

④ Median Filter (m.F)

- median value of neighbourhood.
- remove impulse noise.
- We can't change relevant value of image unlike in average filter.

→ Increase size of (m.F.) → less noise.

TD2: Filtering in Spatial Domain.

Ex 1: Calculate & name the foll. filters

$$f \quad g$$

$$\underbrace{[1 \ 1]}_{f} * \underbrace{[1 \ 1]}_{g} \quad f * g = \sum_t f(t) g(x-t)$$

Average 1×2 .

$$f \quad [1 \ 1] \quad \xrightarrow{\text{sum}} \quad [1 \ 2 \ 1] \quad \text{binomial } 1 \times 3$$

$$g \quad [1 \ 0] \quad \xrightarrow{1} \quad [1 \ 0] \quad \xrightarrow{2} \quad [1 \ 0] \quad \xrightarrow{1}$$

Low pass

Sum diff than 0 = low pass
Otherwise HPF.

② $\underbrace{[1 \ 1]}_{\text{Av.}} * \underbrace{[-1 \ 1]}_{\delta F}$

$$\underbrace{[1 \ 1]}_{\delta F} = [-1 \ 0 \ 1] \quad \text{Differential } 1 \times 3.$$

$$[1 \ -1] \xrightarrow{-1}$$

$$[1 \ -1] \xrightarrow{0}$$

$$[1 \ -1] \xrightarrow{1}$$

High pass

③ $\underbrace{[1 \ \frac{\delta F}{\delta y}]}_{\delta F} * \underbrace{[1 \ -1]}_{\frac{\delta F}{\delta y}}$

$$\begin{bmatrix} 0 & -1 \\ -1 & 0 \end{bmatrix} = \begin{bmatrix} 1 & -2 & 1 \end{bmatrix}$$

$$\begin{bmatrix} 0 & -1 \\ -1 & 0 \end{bmatrix} \xrightarrow{1}$$

$$\begin{bmatrix} 1 & -1 \\ -1 & 1 \end{bmatrix} \xrightarrow{-2}$$

$$\begin{bmatrix} -1 & 1 \end{bmatrix} \xrightarrow{1}$$

2nd derivative $\left(\frac{\delta^2 F}{\delta y^2}\right)$

High pass.

$$4. \begin{matrix} f \\ \begin{bmatrix} 0 & x & x & x \\ -1 & 1 & 1 & 1 \\ x & x & x & x \end{bmatrix} \end{matrix} \xrightarrow{g.} \begin{bmatrix} 0 & x & x & x \\ -1 & 1 & 1 & 1 \\ x & x & x & x \end{bmatrix} \begin{bmatrix} 1 & 0 \\ 0 & -1 \end{bmatrix}$$

$$\begin{bmatrix} -1 & -1 & -1 \\ 0 & 0 & 0 \\ 1 & 1 & 1 \end{bmatrix} + \begin{bmatrix} 0 & 0 & 0 \\ 1 & -2 & 1 \\ 0 & 0 & 0 \end{bmatrix} = \begin{bmatrix} -1 & -1 & -1 \\ 1 & -2 & 1 \\ 1 & 1 & 1 \end{bmatrix}$$

Av 1x3

$$\begin{bmatrix} * \text{ average } 2 \times 1 \\ * \frac{\delta f}{\delta x} 2 \times 1 \end{bmatrix}$$

$$\frac{\delta^2 f}{\delta y^2}$$

$$\text{Av } 1 \times 3 \times \text{Av } 2 \times 1 \times \frac{\delta f}{\delta x} + \frac{\delta^2 f}{\delta y^2} \approx \frac{\delta f}{\delta x} + \frac{\delta^2 f}{\delta y^2} \rightarrow \text{detect direction in both directions (x, y).}$$

$$\begin{bmatrix} -1 & 0 & 1 \end{bmatrix} \rightarrow \begin{bmatrix} -1 \\ 0 \\ 1 \end{bmatrix} \begin{bmatrix} 1 \\ -1 \\ 1 \end{bmatrix} * \begin{bmatrix} 1 \\ -1 \\ 1 \end{bmatrix}$$

$$5. \begin{bmatrix} 0 & 0 & 1 & 0 & 0 \\ 0 & 1 & 0 & 0 & 0 \\ 1 & 0 & 1 & 0 & 0 \\ 0 & 1 & 1 & 0 & 0 \end{bmatrix} * \begin{bmatrix} 0 & 1 & 0 \\ 1 & 0 & 1 \\ 0 & 1 & 0 \end{bmatrix} = \begin{bmatrix} 0 & 2 & 2 & 2 & 0 \\ 1 & 2 & 5 & 2 & 1 \\ 0 & 2 & 2 & 2 & 0 \\ 0 & 0 & 1 & 0 & 0 \end{bmatrix}$$

① (vector)
⑤ (vector)
put (into 2 everywhere)
Avg Avg = Binomial (low pass)

$$6. \begin{bmatrix} 1 & 0 \\ 0 & -1 \end{bmatrix} \otimes \begin{bmatrix} 0 & 1 \\ 1 & 0 \end{bmatrix} = \begin{bmatrix} 0 & 1 & 0 \\ 1 & 0 & -1 \\ 0 & -1 & 0 \end{bmatrix}$$

Derivative Average Derivative (high pass)

$$7. \begin{bmatrix} -1 & 0 & 1 \end{bmatrix} * \begin{bmatrix} 1 & 1 & 1 \end{bmatrix} = \begin{bmatrix} -1 & -1 & 0 & 1 & 1 \end{bmatrix}$$

Av 1x2 $\otimes \frac{df}{dy}$ Av 1x3 high pass

$$\begin{bmatrix} 1 & 1 & 1 & 1 \end{bmatrix} * \begin{bmatrix} -1 & 0 & 1 \end{bmatrix}$$