

Chapter 5: Fourier Spectral Analysis

• *Frequency representations, Fourier series, Fourier transforms, and key properties* •

Spatial Domain (Image)

$f(x, y)$

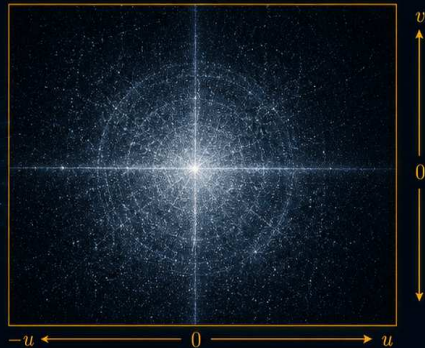


2D Fourier
Transform

$\mathcal{F}$

Frequency Domain (Magnitude Spectrum)

$|F(u, v)|$

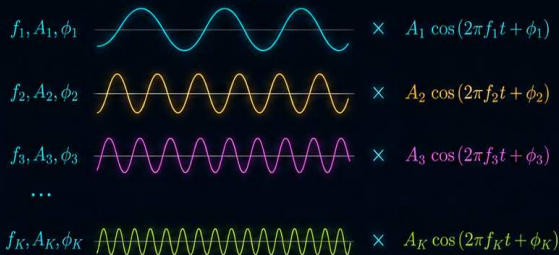


$$F(u, v) = \iint_{-\infty}^{\infty} f(x, y) e^{-j2\pi(ux + vy)} dx dy$$

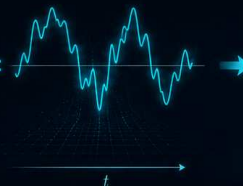
Frequency Representations

• A signal as a sum of sinusoidal components with different frequency, amplitude, and phase •

Sinusoidal Basis Components



Resulting Signal $x(t)$



Frequency-Domain Interpretation



$$x(t) = \sum_k A_k \cos(2\pi f_k t + \phi_k)$$



frequency controls oscillation rate



amplitude controls contribution strength



phase controls horizontal shift

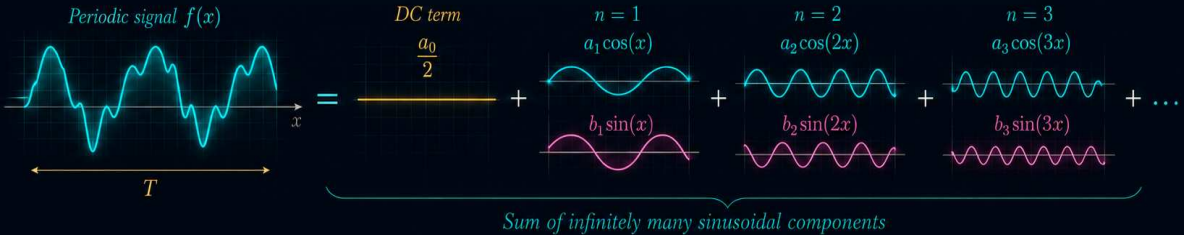


complex signals can be expressed as *weighted combinations* of *simple oscillatory components*.

Fourier Series

Any *continuous, integrable, periodic* function can be represented by an infinite series of *sines and cosines*.

$$f(x) = \frac{a_0}{2} + \sum_{n=1}^{\infty} [a_n \cos(nx) + b_n \sin(nx)]$$



Frequency
determines
wavelength.



Amplitude
determines
contribution.



Phase
can be modeled
through sine/cosine
combinations.

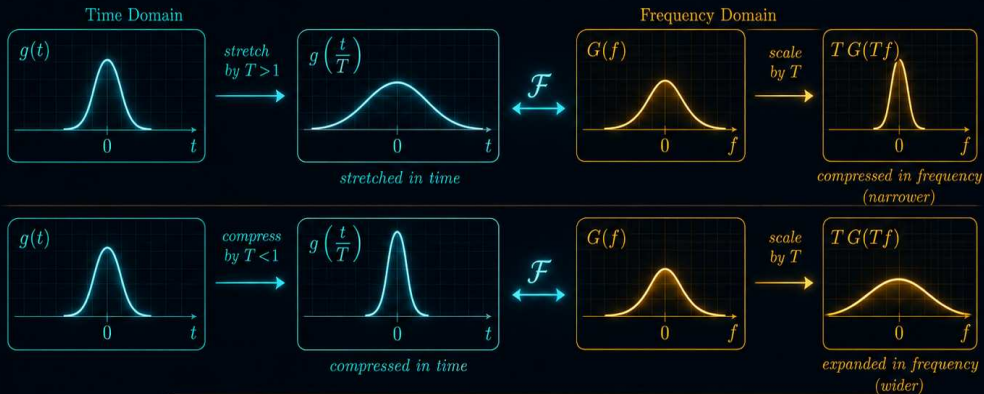


Infinite Series
more terms give a
more accurate
approximation.

Fourier Transform Properties: Scaling

Scaling in time leads to *inverse* scaling in frequency.

$$g\left(\frac{t}{T}\right) \longleftrightarrow T G(Tf)$$



- time stretching *narrows* the spectrum

- time compression *widens* the spectrum

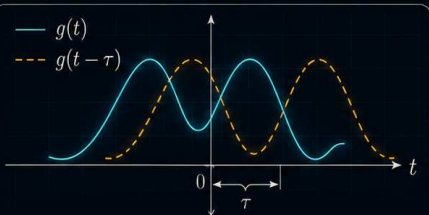
- the factor T *preserves* transform consistency

If the signal is scaled in time by T , its spectrum is scaled in frequency by $\frac{1}{T}$, and multiplied by T to *preserve* the total transform energy content.

Fourier Transform Properties: Shift

$$g(t - \tau) \longleftrightarrow G(f)e^{-j2\pi f\tau}$$

Time Domain

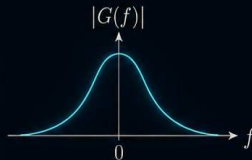


Shifting a signal to the right by τ seconds.

$\mathcal{F}$

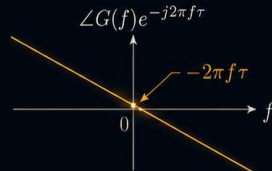
Frequency Domain

Magnitude (unchanged)



The magnitude spectrum remains the same.

Phase (linear shift)

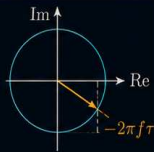


A linear phase term appears with slope $-2\pi\tau$.

A time shift introduces a
linear phase factor
in the frequency domain.

Complex exponential (unit magnitude)

$$e^{-j2\pi f\tau} = \underbrace{\cos(2\pi f\tau)}_{\text{real part}} - j \underbrace{\sin(2\pi f\tau)}_{\text{imag part}}$$



- shifting a signal in time does not change spectral magnitude
- the shift appears as a phase term in frequency
- phase encodes alignment information

Time shift in $t \longleftrightarrow$ Linear phase in f

Fourier Transform Properties: Duality

$$G(t) \longleftrightarrow g(-f)$$

• Duality swaps the roles of time and frequency. •



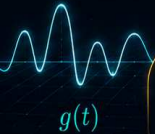
Key Takeaways

- duality swaps the roles of signal and transform
- many transform identities come in paired forms
- properties accelerate analysis and system design

Summary: Fourier Transform Properties

- (1) *Scaling* $g\left(\frac{t}{T}\right) \longleftrightarrow T G(Tf)$
- (2) *Shift* $g(t - \tau) \longleftrightarrow G(f)e^{-j2\pi f\tau}$
- (3) *Duality* $G(t) \longleftrightarrow g(-f)$

Fourier Transform Pair Properties



(a)



Scaling

$$g(t/T) \leftrightarrow TG(Tu)$$

(b)



Shift

$$g(t - T) \leftrightarrow G(u)e^{-j2\pi uT}$$

(c)



Duality

$$G(t) \leftrightarrow g(-u)$$

(d)



Linearity

$$ag(t) + bh(t) \leftrightarrow aG(u) + bH(u)$$



Fourier Transform Pair Properties

(a) → Scaling

$$g(t/T) \leftrightarrow TG(Tu)$$

(b) → Shift

$$g(t - T) \leftrightarrow G(u)e^{-j2\pi uT}$$

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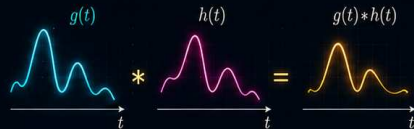
(d) → Linearity

$$ag(t) + bh(t) \leftrightarrow aG(u) + bH(u)$$

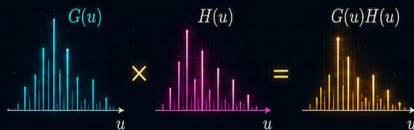
(e) → Convolution

$$g(t) * h(t) \leftrightarrow G(u)H(u)$$

Convolution in Time Domain



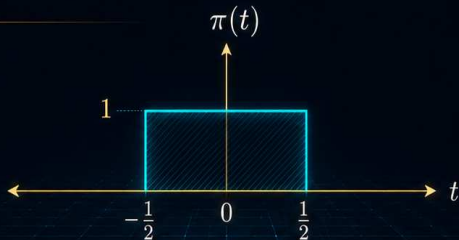
Multiplication in Frequency Domain



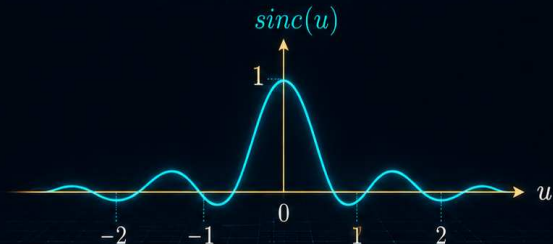
Common 1-D Transforms

Common 1-Dimensional transforms:

$$\pi(t) = \text{rect}(t) = \begin{cases} 1 & |t| < \frac{1}{2} \\ 0 & \text{else} \end{cases}$$



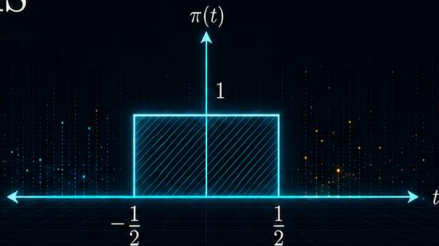
$$\text{rect}(t) \longleftrightarrow \text{sinc}(u) = \frac{\sin \pi u}{\pi u}$$



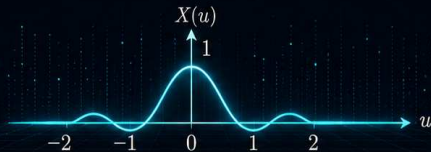
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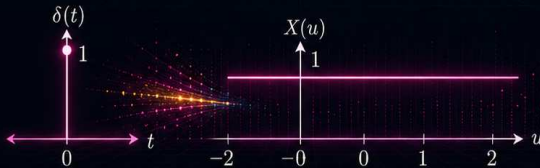
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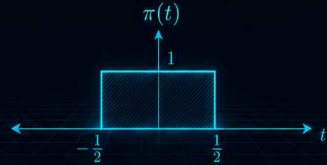
$$\delta(t) \longleftrightarrow 1$$



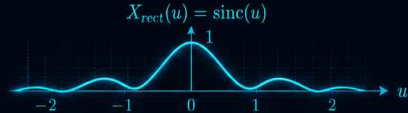
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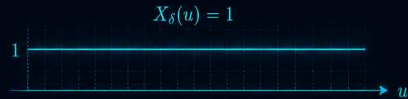
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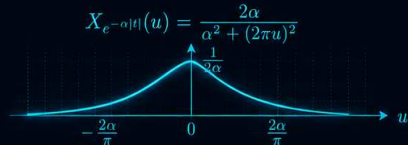
$$\text{rect}(t) \iff \text{sinc}(u) = \frac{\sin \pi u}{\pi u}$$



$$\delta(t) \iff 1$$



$$e^{-\alpha|t|}, \alpha > 0 \iff \frac{2\alpha}{\alpha^2 + (2\pi u)^2}$$



Common 1-D Transforms

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$$\pi(t) = \text{rect}(t) = \begin{cases} 1 & |t| < \frac{1}{2} \\ 0 & \text{else} \end{cases}$$

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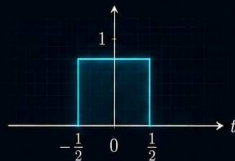
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$$\sum_{m=-\infty}^{\infty} \delta(t - mT) \quad \longleftrightarrow \quad \frac{1}{T} \sum_{m=-\infty}^{\infty} \delta\left(u - \frac{m}{T}\right)$$

Rectangular Pulse

Time Domain $\pi(t)$

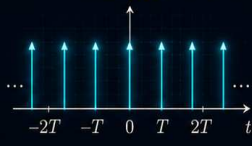


Frequency Domain $\text{sinc}(u)$

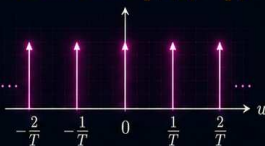


Comb Sampling

Time Domain $\sum \delta(t - mT)$



Frequency Domain $\frac{1}{T} \sum \delta\left(u - \frac{m}{T}\right)$



Common 1-D Transforms

Common 1-Dimensional transforms:

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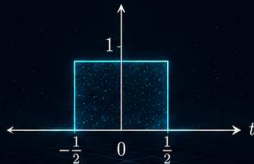
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$$\cos(2\pi u_0 t) \longleftrightarrow \frac{1}{2} [\delta(u - u_0) + \delta(u + u_0)]$$

Time Domain

$\pi(t)$



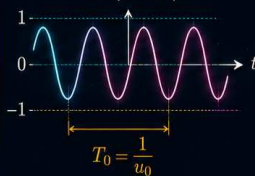
Frequency Domain

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



Time Domain

$\cos(2\pi u_0 t)$



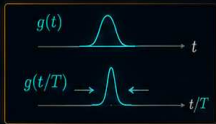
Frequency Domain

$\frac{1}{2} [\delta(u - u_0) + \delta(u + u_0)]$

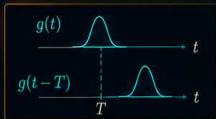


Fourier Transform Pair: Fundamental Properties

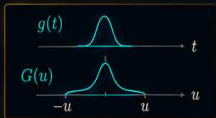
• The Fourier transform pair satisfies several useful properties: •



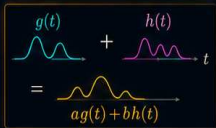
(a) Scaling: $g(t/T) \leftrightarrow TG(uT)$



(b) Shift: $g(t - T) \leftrightarrow G(u)e^{-j2\pi uT}$



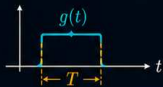
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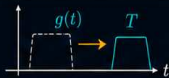
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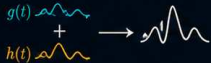
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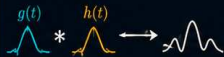
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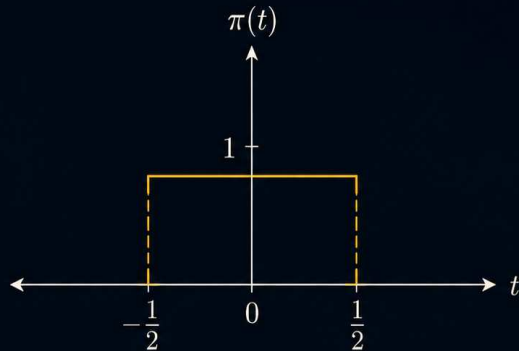
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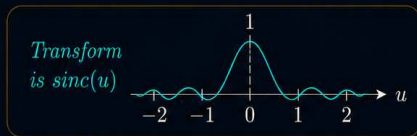
Common 1-D Transforms

- Common 1-dimensional transforms:

$$\pi(t) = \text{rect}(t) = \begin{cases} 1, & |t| < \frac{1}{2} \\ 0, & \text{else} \end{cases}$$



$$\text{rect}(t) \leftrightarrow \text{sinc}(u) = \frac{\sin(\pi u)}{\pi u}$$



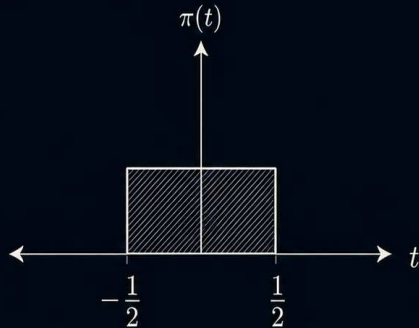
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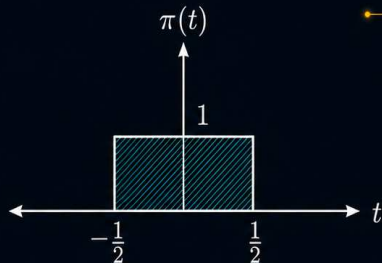
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Common 1-D Transforms

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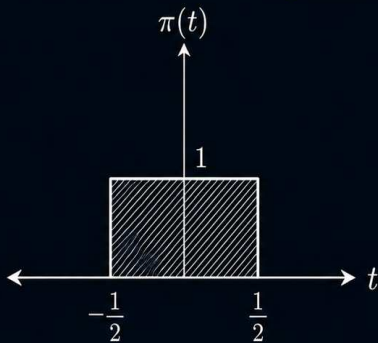
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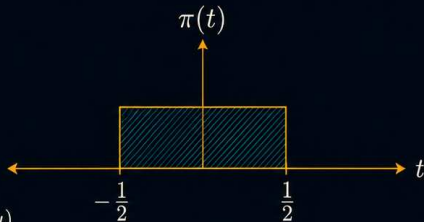
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Fourier Scaling Property

• *Compression in one domain produces expansion in the other* •

1D Scaling Theorem

If $x(t) \xrightarrow{\mathcal{F}} X(f)$, then

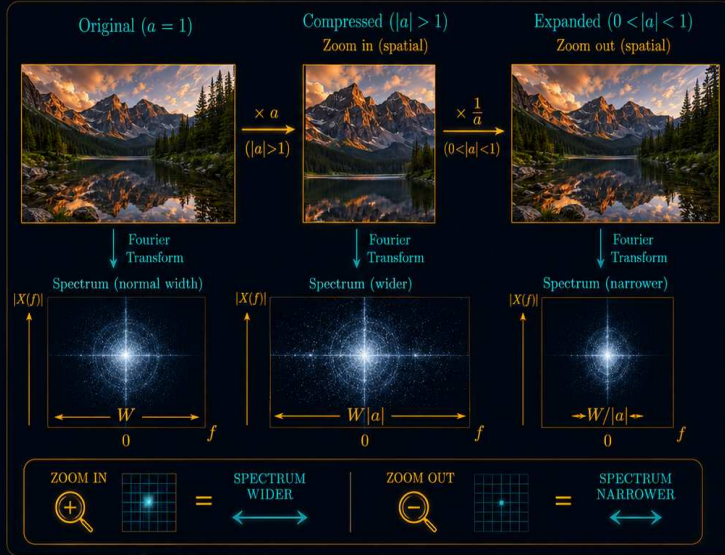
$$x(at) \xrightarrow{\mathcal{F}} \frac{1}{|a|} X\left(\frac{f}{a}\right), \quad a \neq 0.$$

2D Scaling Theorem (Image)

If $g(x, y) \xrightarrow{\mathcal{F}} G(u, v)$, then

$$g(ax, by) \xrightarrow{\mathcal{F}} \frac{1}{|ab|} G\left(\frac{u}{a}, \frac{v}{b}\right).$$

- **Spatial compression** ($|a| > 1$) *stretches the spectrum.*
- **Spatial expansion** ($0 < |a| < 1$) *compresses the spectrum.*
- The factor $1/|a|$ preserves total energy under the transform convention.



Proof of the Scaling Property

A direct change-of-variables derivation

$$\mathcal{F}\{x(at)\}(f) = \frac{1}{|a|} X\left(\frac{f}{a}\right).$$

1 $\longrightarrow \mathcal{F}\{x(at)\}(f) = \int_{-\infty}^{\infty} x(at) e^{-j2\pi ft} dt$

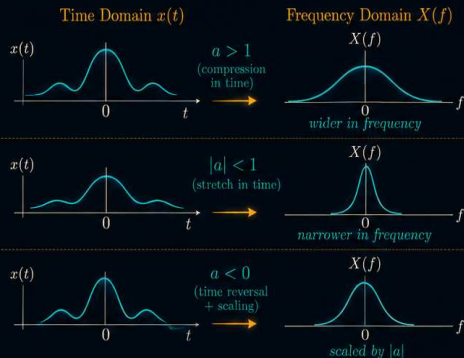
2 $\longrightarrow$ Let $u = at$, $t = \frac{u}{a}$, $dt = \frac{du}{a}$.

3 For $a > 0$: $\mathcal{F}\{x(at)\}(f) = \frac{1}{a} \int_{-\infty}^{\infty} x(u) e^{-j2\pi(f/a)u} du$

4 $\longrightarrow \mathcal{F}\{x(at)\}(f) = \frac{1}{a} X\left(\frac{f}{a}\right), \quad a > 0$

5 For $a < 0$, limits reverse, giving: $\mathcal{F}\{x(at)\}(f) = \frac{1}{|a|} X\left(\frac{f}{a}\right).$

6 $\mathcal{F}\{x(at)\}(f) = \frac{1}{|a|} X\left(\frac{f}{a}\right)$



✧ *Change of variables rescales both the frequency axis and the amplitude.*

Fourier Convolution Theorem

• *Filtering in one domain becomes multiplication in the other* •

Convolution Theorem (1D)

$$(x * h)(t) = \int_{-\infty}^{\infty} x(\tau) h(t - \tau) d\tau$$

$$\mathcal{F}\{x * h\}(f) = X(f)H(f).$$

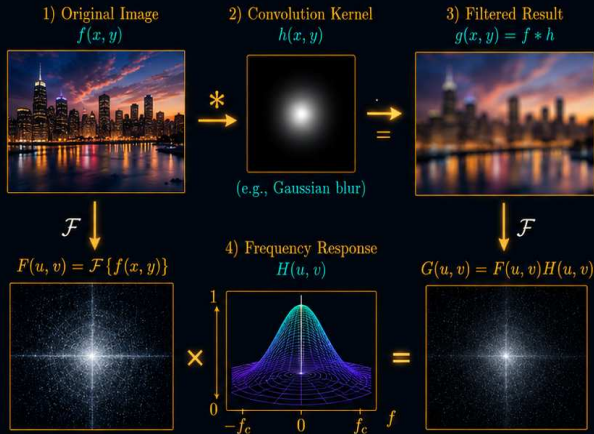
Dual (Multiplication) Property

$$\mathcal{F}\{x(t)h(t)\}(f) = X(f) * H(f).$$

• *Convolution* in time or space corresponds to *multiplication* in frequency.

• A *smoothing* kernel *attenuates* high frequencies.

• A *sharpening* or *edge* kernel *emphasizes* high frequencies.



2D Convolution Theorem

$$g(x, y) * h(x, y) \xleftrightarrow{\mathcal{F}} G(u, v)H(u, v).$$

Proof of the Convolution Theorem

Deriving multiplication in the frequency domain

Definitions:

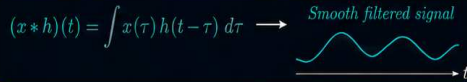
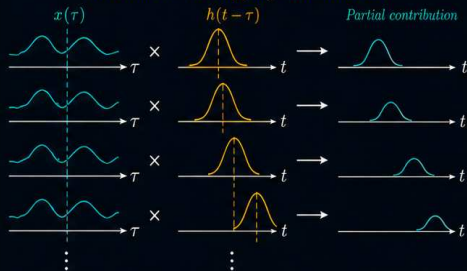
$$(x * h)(t) = \int_{-\infty}^{\infty} x(\tau) h(t - \tau) d\tau$$

$$\mathcal{F}\{x * h\}(f) = \int_{-\infty}^{\infty} (x * h)(t) e^{-j2\pi f t} dt$$

$$\begin{aligned} \textcircled{1} \quad \mathcal{F}\{x * h\}(f) &= \int_{-\infty}^{\infty} \left[\int_{-\infty}^{\infty} x(\tau) h(t - \tau) d\tau \right] e^{-j2\pi f t} dt \\ \textcircled{2} \quad &= \int_{-\infty}^{\infty} x(\tau) \left[\int_{-\infty}^{\infty} h(t - \tau) e^{-j2\pi f t} dt \right] d\tau \\ \textcircled{3} \quad \text{Let } u &= t - \tau, \quad t = u + \tau, \quad dt = du. \\ \textcircled{4} \quad &= \int_{-\infty}^{\infty} x(\tau) \left[\int_{-\infty}^{\infty} h(u) e^{-j2\pi f (u + \tau)} du \right] d\tau \\ \textcircled{5} \quad &= \int_{-\infty}^{\infty} x(\tau) e^{-j2\pi f \tau} d\tau \int_{-\infty}^{\infty} h(u) e^{-j2\pi f u} du \\ \textcircled{6} \quad &= X(f) H(f) \end{aligned}$$

$$\mathcal{F}\{x * h\}(f) = X(f)H(f)$$

Convolution: overlapping shifted kernels



★ *Note: Interchanging the order of integration is justified under standard integrability assumptions.*

Why Scaling and Convolution Matter in Imaging

From zooming to filtering

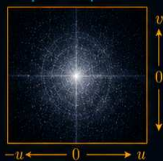
Scaling / Zooming

$$g(ax, ay) \xleftrightarrow{\mathcal{F}} \frac{1}{|a|^2} G\left(\frac{u}{a}, \frac{v}{a}\right).$$

Zoom Out ($a < 1$)



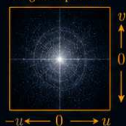
Spectrum Expanded



Original ($a = 1$)



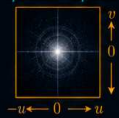
Original Spectrum



Zoom In ($a > 1$)



Spectrum Compressed



Magnification in space **compresses** the spectrum; minification **expands** it.

Filtering / Convolution

$$g(x, y) * h(x, y) \xleftrightarrow{\mathcal{F}} G(u, v)H(u, v).$$

Noisy Image $g(x, y)$



Gaussian Kernel $h(x, y)$



$$h(x, y) = \frac{1}{2\pi\sigma^2} e^{-\frac{x^2+y^2}{2\sigma^2}}$$

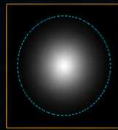
Blurred / Denoised Result



Spectrum $G(u, v)$



Low-Pass Response $H(u, v)$



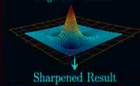
Product $G(u, v)H(u, v)$



Convolution with a kernel shapes the spectrum through **multiplication**.

Sharpening Example

High-Pass Kernel



Sharpened Result



①

Scaling explains how zoom affects frequency content.



②

Convolution explains filtering, blur, and sharpening.



③

These two properties are central to Fourier-based image analysis.

Fourier Scaling Property

• *Compression in one domain produces expansion in the other* •

1D Scaling Theorem

If $x(t) \xrightarrow{\mathcal{F}} X(f)$, then

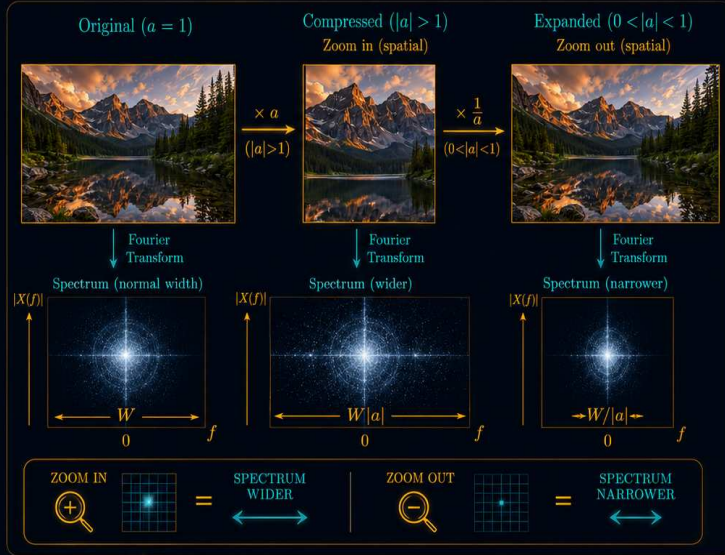
$$x(at) \xrightarrow{\mathcal{F}} \frac{1}{|a|} X\left(\frac{f}{a}\right), \quad a \neq 0.$$

2D Scaling Theorem (Image)

If $g(x, y) \xrightarrow{\mathcal{F}} G(u, v)$, then

$$g(ax, by) \xrightarrow{\mathcal{F}} \frac{1}{|ab|} G\left(\frac{u}{a}, \frac{v}{b}\right).$$

- **Spatial compression** ($|a| > 1$) *stretches the spectrum.*
- **Spatial expansion** ($0 < |a| < 1$) *compresses the spectrum.*
- The factor $1/|a|$ preserves total energy under the transform convention.



Proof of the Scaling Property

A direct change-of-variables derivation

$$\mathcal{F}\{x(at)\}(f) = \frac{1}{|a|} X\left(\frac{f}{a}\right).$$

1 $\longrightarrow \mathcal{F}\{x(at)\}(f) = \int_{-\infty}^{\infty} x(at) e^{-j2\pi ft} dt$

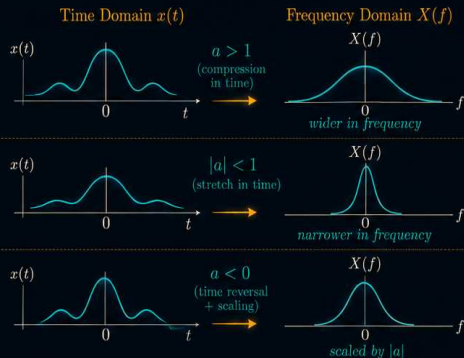
2 $\longrightarrow$ Let $u = at$, $t = \frac{u}{a}$, $dt = \frac{du}{a}$.

3 For $a > 0$: $\mathcal{F}\{x(at)\}(f) = \frac{1}{a} \int_{-\infty}^{\infty} x(u) e^{-j2\pi(f/a)u} du$

4 $\longrightarrow \mathcal{F}\{x(at)\}(f) = \frac{1}{a} X\left(\frac{f}{a}\right), \quad a > 0$

5 For $a < 0$, limits reverse, giving: $\mathcal{F}\{x(at)\}(f) = \frac{1}{|a|} X\left(\frac{f}{a}\right).$

6 $\mathcal{F}\{x(at)\}(f) = \frac{1}{|a|} X\left(\frac{f}{a}\right)$



✧ *Change of variables rescales both the frequency axis and the amplitude.*

Fourier Convolution Theorem

• *Filtering in one domain becomes multiplication in the other* •

Convolution Theorem (1D)

$$(x * h)(t) = \int_{-\infty}^{\infty} x(\tau) h(t - \tau) d\tau$$

$$\mathcal{F}\{x * h\}(f) = X(f)H(f).$$

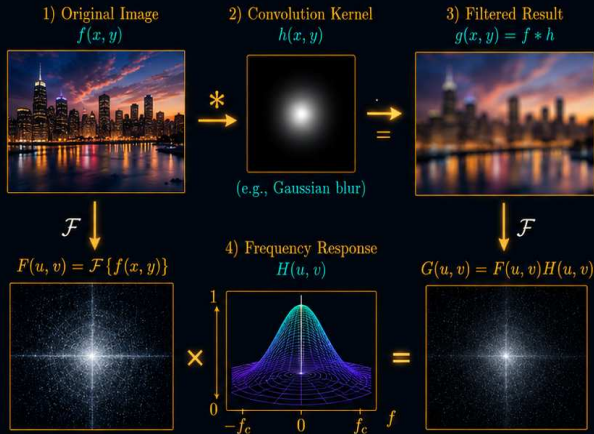
Dual (Multiplication) Property

$$\mathcal{F}\{x(t)h(t)\}(f) = X(f) * H(f).$$

• *Convolution* in time or space corresponds to *multiplication* in frequency.

• A *smoothing* kernel *attenuates* high frequencies.

• A *sharpening* or *edge* kernel *emphasizes* high frequencies.



2D Convolution Theorem

$$g(x, y) * h(x, y) \xleftrightarrow{\mathcal{F}} G(u, v)H(u, v).$$

Proof of the Convolution Theorem

Deriving multiplication in the frequency domain

Definitions:

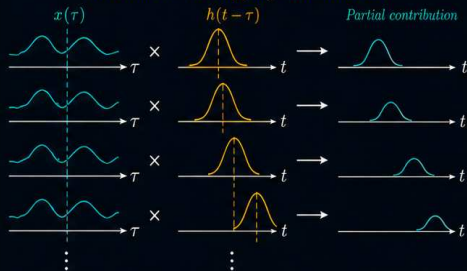
$$(x * h)(t) = \int_{-\infty}^{\infty} x(\tau) h(t - \tau) d\tau$$

$$\mathcal{F}\{x * h\}(f) = \int_{-\infty}^{\infty} (x * h)(t) e^{-j2\pi f t} dt$$

$$\begin{aligned} \textcircled{1} \quad \mathcal{F}\{x * h\}(f) &= \int_{-\infty}^{\infty} \left[\int_{-\infty}^{\infty} x(\tau) h(t - \tau) d\tau \right] e^{-j2\pi f t} dt \\ \textcircled{2} \quad &= \int_{-\infty}^{\infty} x(\tau) \left[\int_{-\infty}^{\infty} h(t - \tau) e^{-j2\pi f t} dt \right] d\tau \\ \textcircled{3} \quad \text{Let } u &= t - \tau, \quad t = u + \tau, \quad dt = du. \\ \textcircled{4} \quad &= \int_{-\infty}^{\infty} x(\tau) \left[\int_{-\infty}^{\infty} h(u) e^{-j2\pi f (u + \tau)} du \right] d\tau \\ \textcircled{5} \quad &= \int_{-\infty}^{\infty} x(\tau) e^{-j2\pi f \tau} d\tau \int_{-\infty}^{\infty} h(u) e^{-j2\pi f u} du \\ \textcircled{6} \quad &= X(f) H(f) \end{aligned}$$

$$\mathcal{F}\{x * h\}(f) = X(f)H(f)$$

Convolution: overlapping shifted kernels



$$(x * h)(t) = \int x(\tau) h(t - \tau) d\tau \rightarrow \text{Smooth filtered signal}$$

★ *Note: Interchanging the order of integration is justified under standard integrability assumptions.*

Why Scaling and Convolution Matter in Imaging

From zooming to filtering

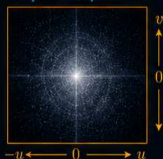
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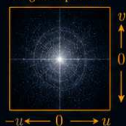
Spectrum Expanded



Original ($a = 1$)



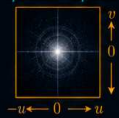
Original Spectrum



Zoom In ($a > 1$)



Spectrum Compressed



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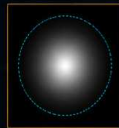
Blurred / Denoised Result



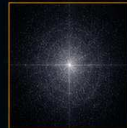
Spectrum $G(u, v)$



Low-Pass Response $H(u, v)$



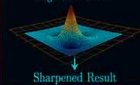
Product $G(u, v)H(u, v)$



Convolution with a kernel shapes the spectrum through **multiplication**.

Sharpening Example

High-Pass Kernel



Sharpened Result



①

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②

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These two properties are central to Fourier-based image analysis.

Example: Periodic Replication

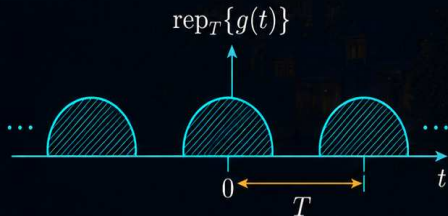
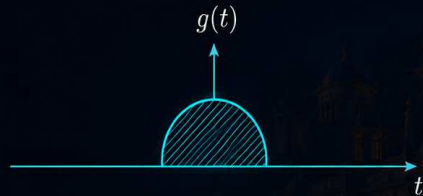
✦ We know:

$$\sum_{n=-\infty}^{\infty} \delta(t - n) \leftrightarrow \frac{1}{T} \sum_m \delta\left(u - \frac{m}{T}\right)$$

✦ Now consider:

$$\text{rep}_T\{g(t)\} = \sum_m g(t - mT)$$

$$\text{rep}_T\{g(t)\} = g(t) * \sum_m \delta(t - mT)$$



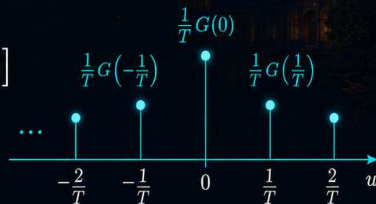
Fourier Transform of the Repeated Signal

$$F\{\text{rep}_T(g(t))\} = F\left\{g(t) * \sum_m \delta(t - mT)\right\}$$

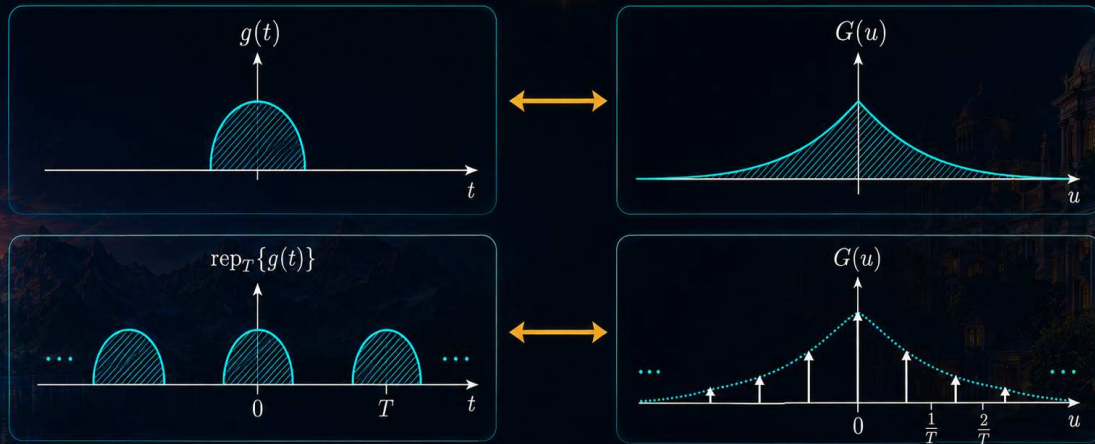
$$= G(u) \frac{1}{T} \sum_m \delta\left(u - \frac{m}{T}\right)$$

$$= \frac{1}{T} \sum_m G\left(\frac{m}{T}\right) \delta\left(u - \frac{m}{T}\right)$$

$$= \frac{1}{T} \text{comb}_{\frac{1}{T}}[G(u)]$$



Periodic Replication and Spectral Sampling

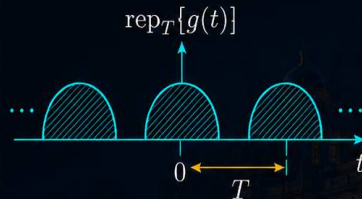


$$\mathcal{F}\{\text{rep}_T\{g(t)\}\} = \frac{1}{T} \sum_{m=-\infty}^{\infty} G\left(\frac{m}{T}\right) \delta\left(u - \frac{m}{T}\right)$$

Fourier-Series Interpretation

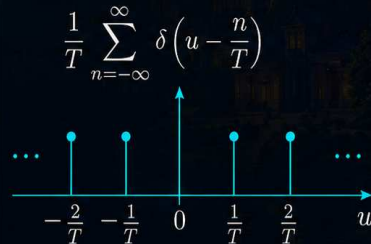
✧ Hence:

$$\text{rep}_T[g(t)] = g(t) * \frac{1}{T} \sum_n e^{j2\pi n u_0 t}$$



✧ Taking Fourier Transforms:

$$\begin{aligned} F\{\text{rep}_T[g(t)]\} &= G(u) \cdot \frac{1}{T} \sum_{n=-\infty}^{\infty} \delta\left(u - \frac{n}{T}\right) \\ &= \frac{1}{T} \sum_n G(u) \delta\left(u - \frac{n}{T}\right) \end{aligned}$$



Final Form of the Replicated-Signal Spectrum

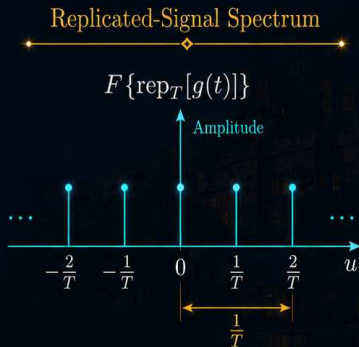
✦ Hence:

$$\text{rep}_T[g(t)] = g(t) * \frac{1}{T} \sum_n e^{j2\pi n u_0 t}$$

✦ Taking Fourier Transforms:

$$\begin{aligned} F\{\text{rep}_T[g(t)]\} &= G(u) \cdot \frac{1}{T} \sum_{n=-\infty}^{\infty} \delta\left(u - \frac{n}{T}\right) \\ &= \frac{1}{T} \sum_n G(u) \delta\left(u - \frac{n}{T}\right) \\ &= \frac{1}{T} \sum_{n=-\infty}^{\infty} G\left(\frac{n}{T}\right) \delta\left(u - \frac{n}{T}\right) \end{aligned}$$

$$= \frac{1}{T} \text{comb}_{\frac{1}{T}}[G(u)]$$



A line spectrum with spacing $\frac{1}{T}$,
with weights $\frac{1}{T}G\left(\frac{n}{T}\right)$ at $u = \frac{n}{T}$.

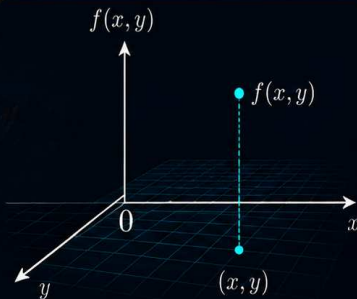
2-Dimensional Systems

In 2 dimensions, the input and output of a system are functions of **two independent variables**. In image processing, the variables are the **spatial coordinates** (x, y) and the value of the function is the **intensity** of the image at that point.

- ✧ A 2-D system is described by a function of two variables.

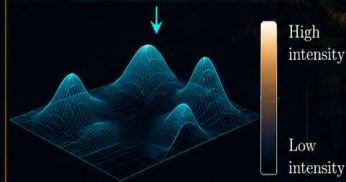
$$f : \mathbb{R}^2 \rightarrow \mathbb{R}$$

- ✧ For images, $f(x, y)$ gives the intensity (brightness) at the spatial location (x, y) .
- ✧ Here, x and y are spatial **coordinates** (horizontal and vertical positions).



The height $f(x, y)$ represents the intensity of the image at spatial location (x, y) .

Example: Image Intensity Function



- ✧ Thus, a 2-D system maps each point in the plane (x, y) to a value $f(x, y)$ — the image intensity at that point.

Impulse Response and 2-D Convolution

✧ Impulse response characterizes a linear shift-invariant 2D system ✧

$$\delta(x, y) \longrightarrow \boxed{\text{System}} \longrightarrow h(x, y)$$

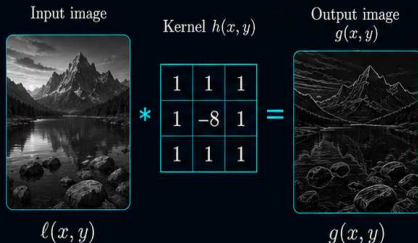
$$\ell(x, y) \longrightarrow \boxed{\text{System}} \longrightarrow g(x, y)$$

✧ Input-output relation

$$\ell(x, y) \rightarrow \boxed{\text{System}} \rightarrow g(x, y) = h(x, y) * \ell(x, y)$$

✧ 2-D convolution

$$g(x, y) = \int \int_{-\infty}^{\infty} h(x - \sigma, y - \beta) \ell(\sigma, \beta) d\sigma d\beta$$



2-D Sinusoidal Basis Functions

- ✦ Any 2-D image can be synthesized by superimposing infinitely many sinusoidal components of the form

$$\cos 2\pi(ux + vy)$$

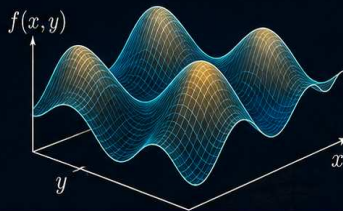
- ✦ Lines of constant amplitude (constant phase) satisfy

$$2\pi(ux + vy) = k$$

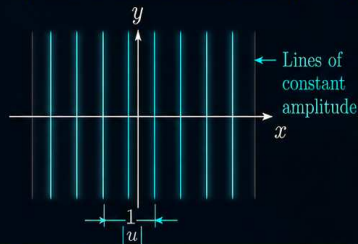
- ✦ Example

$$v = 0 \text{ (vertical frequency is zero)} \Rightarrow \cos 2\pi(ux + 0)$$

1) 2-D Sinusoidal Surface



2) Lines of Constant Amplitude ($v = 0$)



General Pattern of $\cos 2\pi(ux + vy)$

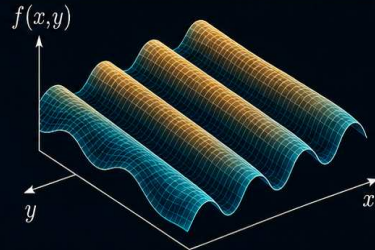
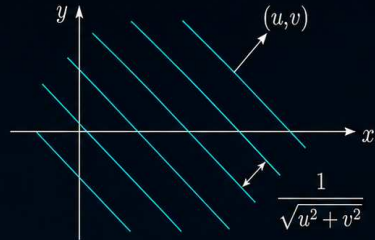
- ✧ In general, the basis function

$$\cos 2\pi(ux + vy)$$

- ✧ creates oriented stripes whose constant-phase lines satisfy

$$ux + vy = c$$

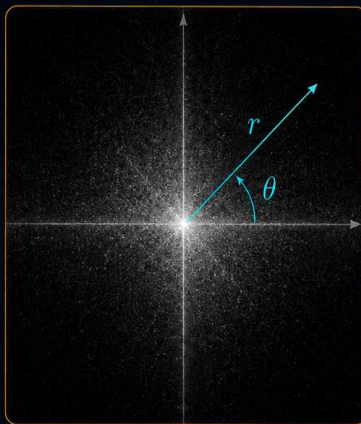
- ✧ Spacing = $\frac{1}{\sqrt{u^2 + v^2}}$



Fourier Transforms of Images



image



spectrum

✦ θ gives angle of sinusoid

✦ r gives spatial frequency

✦ **brightness** gives amplitude of sinusoid present in image

✦ complete spectrum is two images — sines and cosines

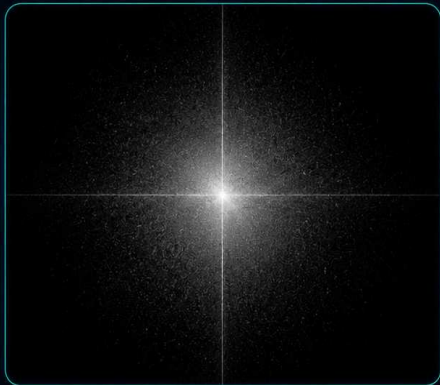
```
fourier = fftshift(fft2(image))
```

A Typical Photograph

image



spectrum



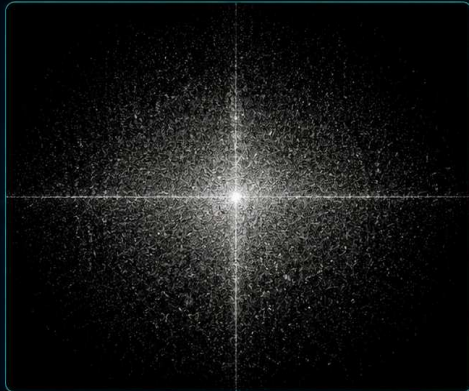
✦ Most image energy is concentrated near **low spatial frequencies** around the origin.

An Image with Higher Frequencies

image



spectrum



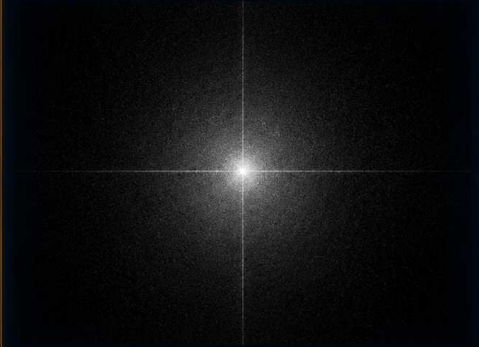
Fine detail and rapid intensity variations produce broader high-frequency content.

Blurring in the Fourier Domain

image



spectrum



Blurring suppresses high frequencies and preserves mainly low-frequency content.

Low-pass (ideal) filter

$$H(u, v) = \begin{cases} 1 & \text{if } (u, v) \text{ is inside the circle} \\ 0 & \text{otherwise} \end{cases}$$

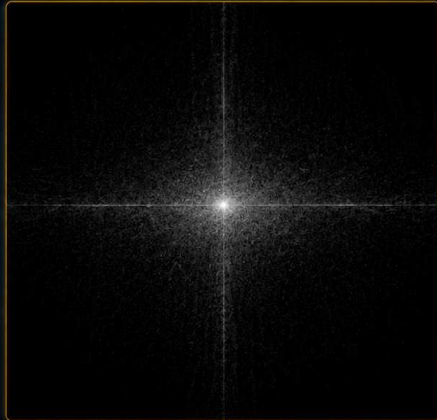
Passes low frequencies (center) and removes high frequencies (outside).

Original Flower

✧ image ✧



✧ spectrum ✧



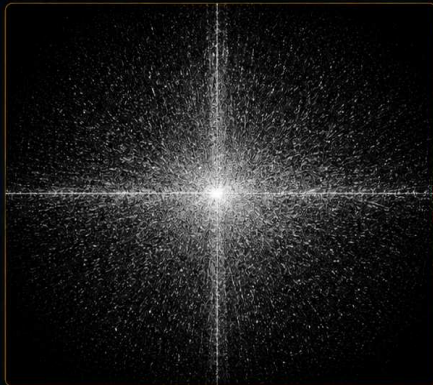
Reference image before frequency-domain filtering.

Sharpening in the Fourier Domain

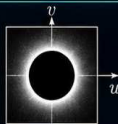
✧ image ✧



✧ spectrum ✧



Sharpening emphasizes high frequencies and enhances edges and detail.

$$H(u, v) =$$


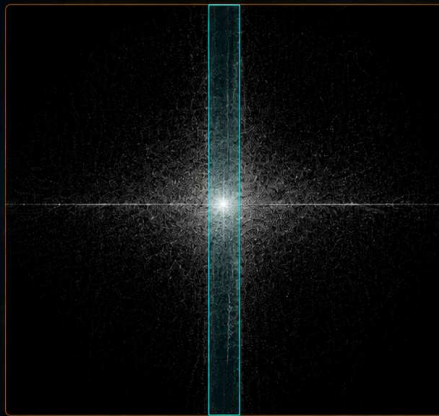
High-pass (ideal) or high-boost filter.
Passes high frequencies (outside); attenuates or boosts them.

What Does this Filtering Operation Do?

✧ image ✧



✧ spectrum ✧



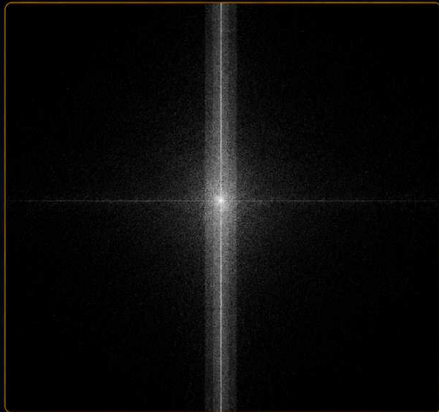
What visual effect results from retaining only a narrow vertical band of frequencies?

What Does this Filtering Operation Do?

✧ image ✧



✧ spectrum ✧



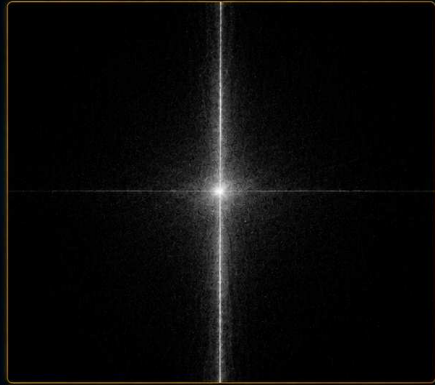
Predict the image produced by this directional spectral selection.

Blurring in x , sharpening in y

✧ image ✧



✧ spectrum ✧



argh, astigmatism!

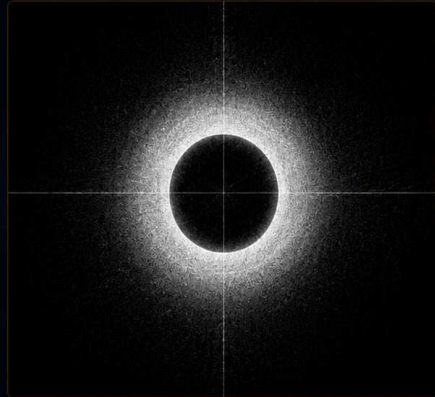
A vertical passband preserves variation in y while suppressing high frequencies in x .

Filtering – Band-pass Filter

✧ Filtered Image (Band-pass Output) ✧



✧ Frequency-Domain Band-pass Mask ✧



Band-pass filtering retains only a selected range of spatial frequencies.

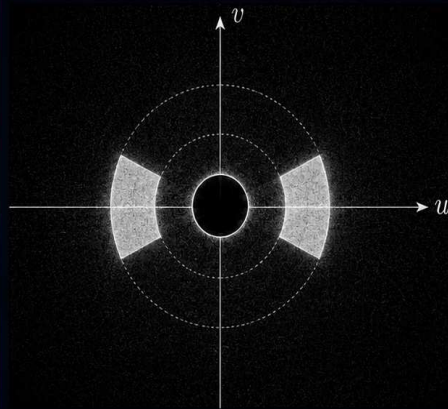
Filtering – Oriented Band-pass Filter

ELEG404/604

Spatial-domain result (vertical edges emphasized) ✦



Fourier-domain mask (oriented annular sector) ✦



- ✦ Frequencies in a narrow angular band around the horizontal u -axis (left and right annular sectors) are passed. Consequently, vertical-oriented edges and structures are retained, while horizontal details are largely suppressed.

Example: Fourier Transform of $\text{rect}[x,y]$

- ✦ Consider the separable 2-D rectangle:

$$\text{rect}[x,y] = \text{rect}(x) \text{rect}(y)$$

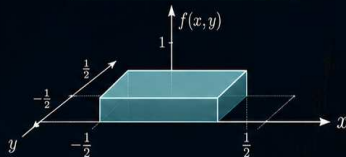
- ✦ Using separability of the Fourier transform:

$$G(u,v) = \int \text{rect}(x) e^{-j2\pi ux} dx \int \text{rect}(y) e^{-j2\pi vy} dy$$

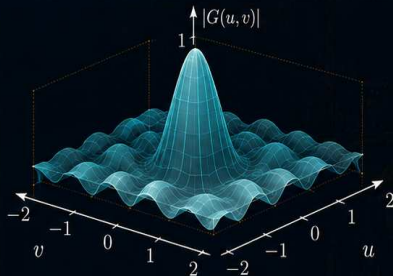
- ✦ Result:

$$G(u,v) = \text{sinc}(u) \text{sinc}(v)$$

- ✦ Spatial domain: $\text{rect}[x,y]$ ✦



- ✦ Frequency domain: $|G(u,v)| = |\text{sinc}(u) \text{sinc}(v)|$ ✦



Sampling with $\text{comb}_{XY}[g(x, y)]$

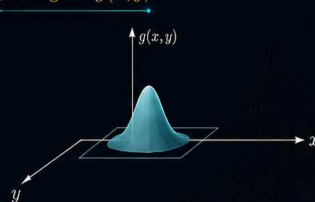
$$\begin{aligned}\diamond \text{comb}_{XY}[g(x, y)] &= \sum_m \sum_n g(mX, nY) \delta(x - mX, y - nY) \\ &= g(x, y) \sum_m \sum_n \delta(x - mX, y - nY)\end{aligned}$$

$\diamond$ Some notation:

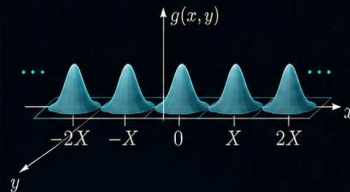
$$\diamond \text{rep}_{X, \infty}[g(x, y)] = \sum_k g(x - kX, y)$$

$$\diamond \text{rep}_{\infty, Y}[g(x, y)] = \sum_k g(x, y - kY)$$

$\diamond$ Original $g(x, y)$



$\diamond$ Replication along x (using $\text{rep}_{X, \infty}$)

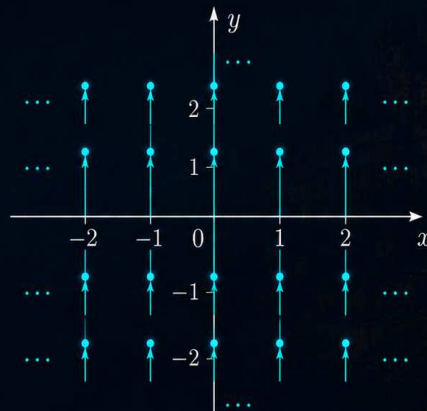


Example: Take F.T. of $comb[x, y]$

$$\begin{aligned}
 \diamond comb[x, y] &= \sum_m \sum_n \delta(x - m, y - n) \\
 &= \sum_m \sum_n \delta(x - m) \delta(y - n)
 \end{aligned}$$

◇ 2-D impulse lattice in the spatial domain.

◇ Spatial domain: $comb[x, y]$ ◇

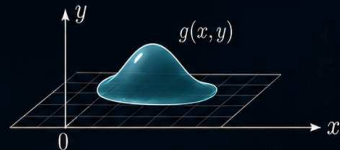


2-D Replication Operator

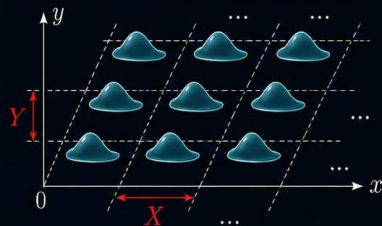
$$\text{rep}_{XY} [g(x, y)] = \sum_m \sum_n g(x - mX, y - nY)$$

- Replicates a 2-D pattern on a lattice with spacings X and Y .
- Each copy is shifted by integer multiples of X and Y .

Single 2-D function $g(x, y)$



Replicated pattern $\text{rep}_{XY} [g(x, y)]$



Common 2-Dimensional Functions

✧ 1) 2-D Rectangular Function (rect)

$$\text{rect}[x, y] = \text{rect}(x) \text{rect}(y) = f(x, y) = \begin{cases} 1, & |x|, |y| < \frac{1}{2} \\ 0, & \text{else} \end{cases}$$

✧ 2) 2-D Sinc Function (sinc)

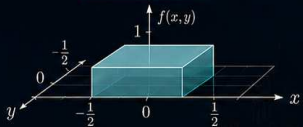
$$\text{sinc}[x, y] = \text{sinc}(x) \text{sinc}(y) = \frac{\sin \pi x}{\pi x} \frac{\sin \pi y}{\pi y}$$

✧ 3) 2-D Comb Function (comb)

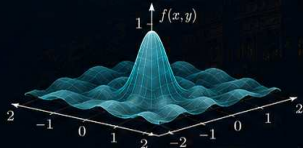
$$\text{comb}[x, y] = \sum_{m=-\infty}^{\infty} \sum_{n=-\infty}^{\infty} \delta(x - m, y - n)$$

$$\delta(x - m, y - n) = \delta(x - m) \delta(y - n)$$

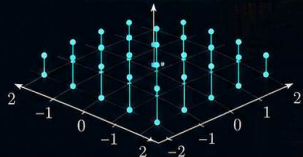
✧ rect[x, y] ✧



✧ sinc[x, y] ✧

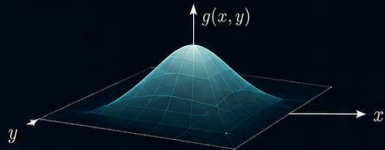


✧ comb[x, y] ✧

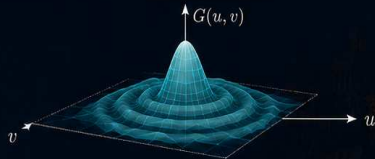


Spatial Replication and Spectral Sampling

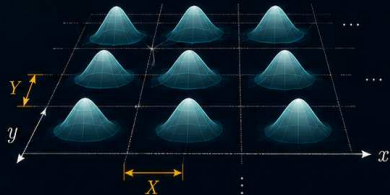
$$\star \underline{g(x, y)}$$



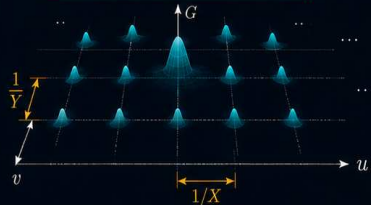
$$\star \underline{G(u, v)}$$



$$\star \underline{\text{rep}_{XY}[g(x, y)]}$$



$$\star \underline{\frac{1}{XY} \text{comb}_{\frac{1}{X}, \frac{1}{Y}}[G(u, v)]}$$



Fourier Transform of $\text{comb}[x, y]$

✦ Derivation:

$$\begin{aligned}
 \mathcal{F}\{\text{comb}[x, y]\} &= \mathcal{F}\left\{\sum_m \delta(x - m) \sum_n \delta(y - n)\right\} \\
 &= \sum_m \delta(u - m) \sum_n \delta(v - n) \\
 &= \text{comb}[u, v]
 \end{aligned}$$

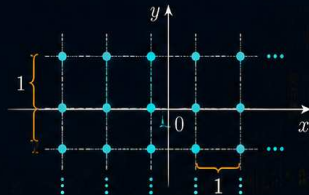
✦ Result:

$$\text{comb}[x, y] \longleftrightarrow \text{comb}[u, v]$$

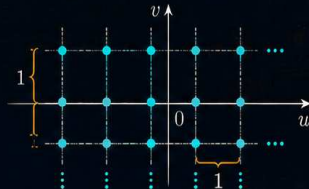
$$\text{comb}_{XY}[x, y] \longleftrightarrow \frac{1}{XY} \text{comb}_{\frac{1}{X}, \frac{1}{Y}}[u, v]$$

✦ Dual lattices ✦

Spatial domain: $\text{comb}[x, y]$



Frequency domain: $\text{comb}[u, v]$



Fourier Transform of a Replicated 2-D Function

✧ Replication in space:

$$\text{rep}_{XY}[g(x, y)] = g(x, y) * \text{comb}_{XY}[x, y]$$

✧ Taking Fourier transform:

$$\therefore \mathcal{F}\{\text{rep}\} = G(u, v) \cdot \frac{1}{XY} \sum_{m, n} \delta\left(u - \frac{m}{X}, v - \frac{n}{Y}\right)$$

✧ Using sifting property of impulse:

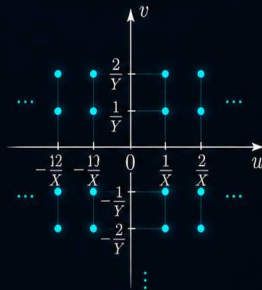
$$= \frac{1}{XY} \sum_{m, n} G\left(\frac{m}{X}, \frac{n}{Y}\right) \delta\left(u - \frac{m}{X}, v - \frac{n}{Y}\right)$$

✧ Final form:

$$= \frac{1}{XY} \text{comb}_{\frac{1}{X}, \frac{1}{Y}} [G(u, v)]$$

✧ Spectral interpretation

Spatial replication
corresponds to
spectral sampling.

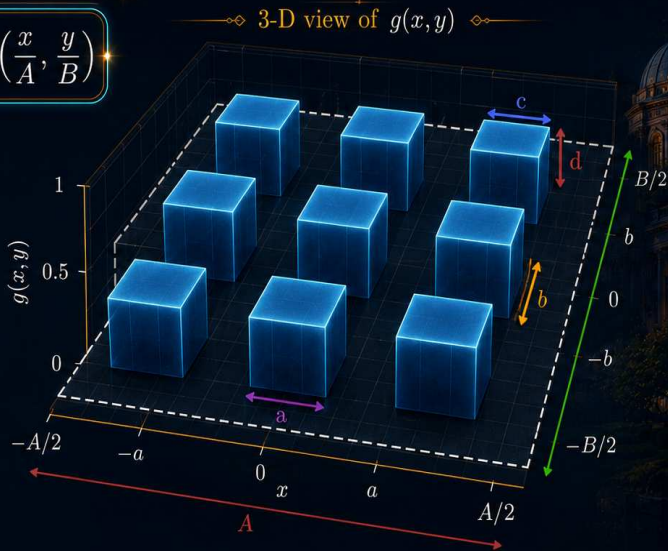
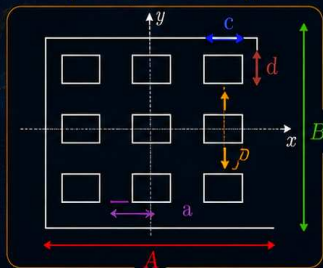


3-D Geometry of the Block Pattern

$$g(x, y) = \text{rep}_{a,b} \left[\text{rect} \left(\frac{x}{c}, \frac{y}{d} \right) \right] \text{rect} \left(\frac{x}{A}, \frac{y}{B} \right)$$

- ✦ Outer support window: $A \times B$
- ✦ Repetition periods: a along x , b along y
- ✦ Individual block size: c along x , d along y

Top view (parameter map)



3-D Spectrum of the Block Pattern

$$G(u, v) = \frac{ABcd}{ab} \sum_{m=-\infty}^{\infty} \sum_{n=-\infty}^{\infty} \text{sinc}\left(\frac{cm}{a}, \frac{dn}{b}\right) \text{sinc}\left(A\left(u - \frac{m}{a}\right), B\left(v - \frac{n}{b}\right)\right)$$

overall amplitude scale

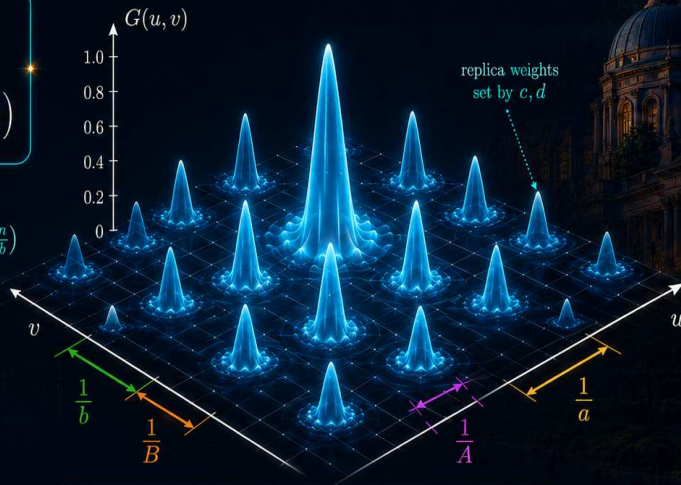
$$\frac{ABcd}{ab}$$

replica weights set by
 $\text{sinc}\left(\frac{cm}{a}, \frac{dn}{b}\right)$

2-D sinc lobe
centered at $\left(\frac{m}{a}, \frac{n}{b}\right)$

Parameter Interpretation

- Replica spacing: $\frac{1}{a}$ in u , $\frac{1}{b}$ in v
- Lobe width (main-lobe): $\sim \frac{1}{A}$ in u , $\sim \frac{1}{B}$ in v
- Replica weights: $\text{sinc}\left(\frac{cm}{a}, \frac{dn}{b}\right)$
- Overall scale factor: $\frac{ABcd}{ab}$



- Spectrum replicas are located at $(m/a, n/b)$, shaped by sinc lobes and weighted by $\text{sinc}(cm/a, dn/b)$.

Two-Dimensional Convolution Example

✦ Let $f_1(x, y)$ and $f_2(x, y)$ be as shown below, where the shaded area represents a value of 1, else 0.

✦ a. In the first case,

$$f_1(x, y) = \text{rect}\left(\frac{x}{A}, \frac{y}{A}\right)$$

$$\text{and } f_2(x, y) = \text{rect}\left(\frac{x}{B}, \frac{y}{B}\right),$$

where $A < B$.

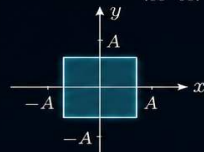
✦ b. In the second case,

$$f_1(x, y) = f_2(x, y) = \text{circ}(x, y).$$

✦ Convolve the two sets of functions and plot the results.

(a) Rectangular Functions

$$f_1(x, y) = \text{rect}\left(\frac{x}{A}, \frac{y}{A}\right)$$



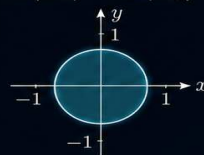
$$f_2(x, y) = \text{rect}\left(\frac{x}{B}, \frac{y}{B}\right)$$



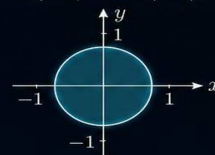
Shaded area represents a value of 1, else 0.

(b) Circular Functions

$$f_1(x, y) = \text{circ}(x, y)$$



$$f_2(x, y) = \text{circ}(x, y)$$



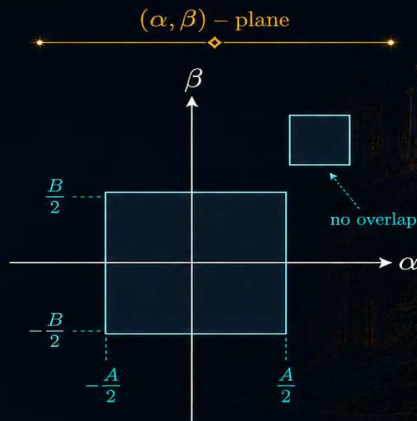
Shaded area represents a value of 1, else 0.

2-D Convolution Setup

✦ The 2 - D convolution is given by

$$g(x, y) = \int \int f_1(x - \alpha, y - \beta) f_2(\alpha, \beta) d\alpha d\beta$$

✦ for $|y|, |x| > \frac{A+B}{2}$, $g(x, y) = 0$.



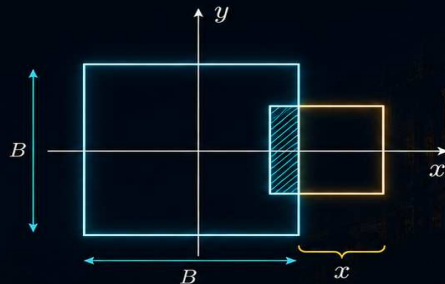
Convolution of Two Rectangles — Central and Side Regions

✦ 1. for $|y|, |x| < \frac{B-A}{2}$,

$$g(x, y) = A^2.$$

✦ 2. for $\frac{B-A}{2} < |x| < \frac{A+B}{2}$,
 $|y| < \frac{B-A}{2}$,

$$g(x, y) = A \left[\frac{B}{2} - \left(x - \frac{A}{2} \right) \right].$$



✦ **Center region** ($|x|, |y| < \frac{B-A}{2}$):
 full overlap gives constant A^2 .

✦ **Side regions** ($\frac{B-A}{2} < |x| < \frac{A+B}{2}$,
 $|y| < \frac{B-A}{2}$): overlap decreases
 linearly with $|x|$.

Convolution of Two Rectangles — Top and Corner Regions

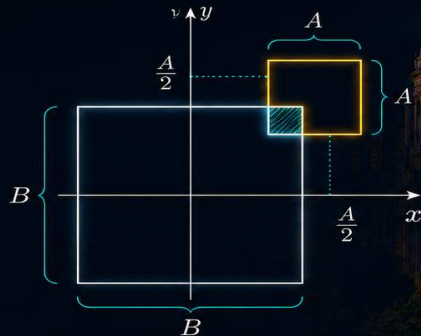
1 for $\frac{B-A}{2} < |y| < \frac{A+B}{2},$

$$|x| < \frac{B-A}{2},$$

$$g(x, y) = A \left[\frac{B}{2} - \left(y - \frac{A}{2} \right) \right].$$

2 for $\frac{B-A}{2} < |x|, |y| < \frac{A+B}{2},$

$$g(x, y) = \left[\frac{B}{2} - \left(x - \frac{A}{2} \right) \right] \left[\frac{B}{2} - \left(y - \frac{A}{2} \right) \right].$$



- ★ Top-edge case: the overlap length in y decreases linearly with y .
- ★ Corner region: overlap equals the product of two linear factors in x and y .

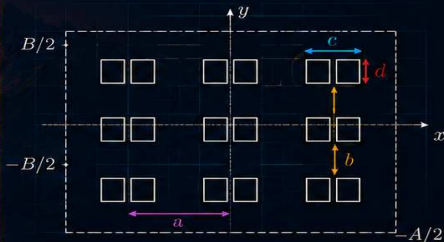
Example

Final worked example: a replicated pair of shifted rectangles convolved with a large support window.

✧ We derive $G(u, v)$ and then visualize its 3-D spectrum.

✧ 1) Spatial-domain view: $g(x, y)$ ✧

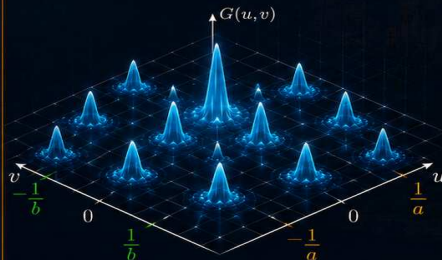
Replicated pair of shifted rectangles inside a large support window $A \times B$.



Offsets (c, d) inside each block;
replication periods (a, b) ; window $A \times B$.

✧ 2) Spectral preview: $G(u, v)$ ✧

3-D spectrum of the replicated pattern:
a lattice of weighted **sinc**-like lobes.



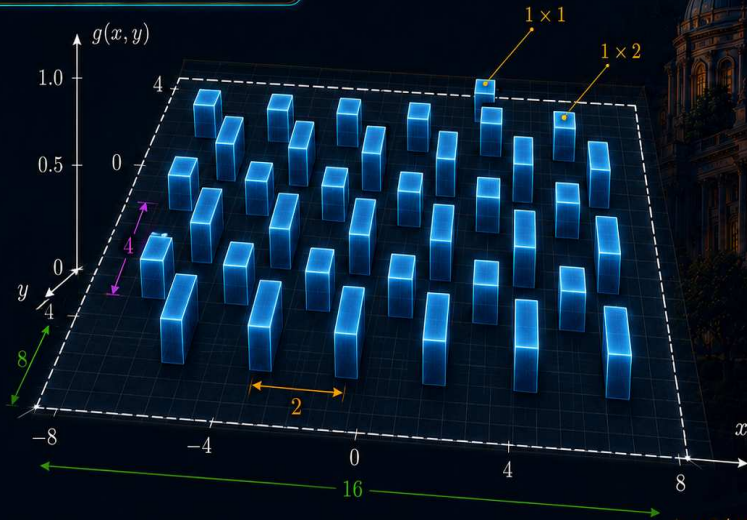
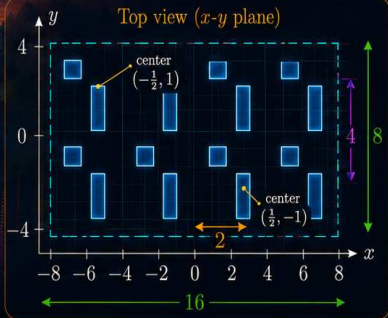
Replica spacing: $\frac{1}{a}$ in u , $\frac{1}{b}$ in v ;
shaped by sinc lobes $\text{sinc}(cm/a, dn/b)$.

3-D Spatial Plot of the Final Example

$$g(x, y) = \text{rep}_{2,4} \left[\text{rect} \left(\frac{x+1/2}{1}, \frac{y-1}{1} \right) + \text{rect} \left(\frac{x-1/2}{1}, \frac{y+1}{2} \right) \right] * \text{rect} \left(\frac{x}{16}, \frac{y}{8} \right)$$

Parameter Interpretation

- periods: 2 in x , 4 in y
- support window: 16×8
- heights: 1 on the blocks, 0 elsewhere



Final Example — Analytical Spectrum

- ✧ 1. Spatial-domain definition:

$$g(x, y) = \text{rep}_{2,4} \left[\text{rect} \left(\frac{x+1/2}{1}, \frac{y-1}{1} \right) + \text{rect} \left(\frac{x-1/2}{1}, \frac{y+1}{2} \right) \right] * \text{rect} \left(\frac{x}{16}, \frac{y}{8} \right)$$

replication lattice 1/2 by 1/4

window envelope 16 by 8

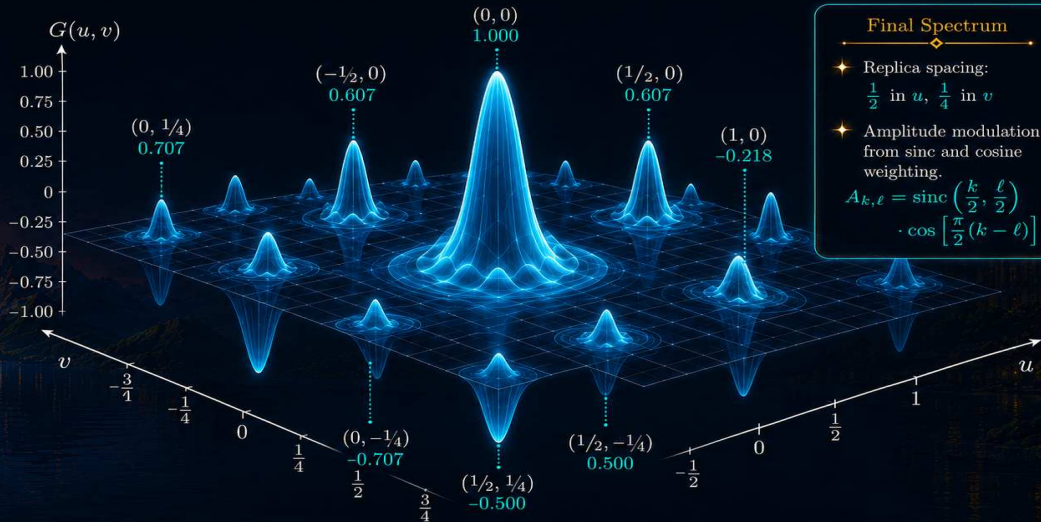
- ✧ 2. Frequency-domain expression:

$$G(u, v) = \frac{1}{8} \text{comb}_{\frac{1}{2}, \frac{1}{4}} \left[2 \text{sinc}(u, 2v) \left(e^{-j2\pi(-\frac{u}{2}+v)} + e^{j2\pi(-\frac{u}{2}+v)} \right) \right] * 2 \text{sinc}(16u, 8v)$$

- ✧ 3. Expanded form:

$$G(u, v) = 24 \sum_k \sum_\ell \text{sinc} \left(\frac{k}{2}, \frac{\ell}{2} \right) \cos \left[\pi \left(\frac{k-\ell}{2} \right) \right] \text{sinc} \left[16 \left(u - \frac{k}{2} \right), 8 \left(v - \frac{\ell}{4} \right) \right]$$

Spectrum of the Final Example



Final Spectrum

- ★ Replica spacing:
 $\frac{1}{2}$ in u , $\frac{1}{4}$ in v
- ★ Amplitude modulation from sinc and cosine weighting.

$$A_{k,\ell} = \text{sinc}\left(\frac{k}{2}, \frac{\ell}{2}\right) \cdot \cos\left[\frac{\pi}{2}(k - \ell)\right]$$

- ★ Replicas centered at $u = \frac{k}{2}$, $v = \frac{\ell}{4}$ for integers k, ℓ . ★