Image Transforms

4.1 INTRODUCTION

Definition: Image transform = operation to change the default representation space of a digital image (spatial domain -> another domain) so that:

- (1) all the information present in the image is preserved in the transformed domain, but represented differently;
- (2) the transform is reversible, i.e., we can revert to the spatial domain

Generally: in the transformed domain -> image information is represented in a more compact form => main goal of the transforms: **image compression**.

Other usage: image analysis - a new type of representation of different types of information present in the image.

Note: Most image transforms = "generalizations" of frequency transforms => the representation of the image by a DC component and several AC components.

Definition: "original representation space" of the image $\mathbf{U}[M \times N] = a MN-dimensional space:$

- each coordinate of the space = a spatial location (m,n) in the digital image;
- the value of the coordinate of ${\bf U}$ on an axis = the grey level in ${\bf U}$ in this spatial location (m,n).

 $x_1 = (0,0); x_2 = (0,1); x_3 = (0,2); \dots x_{MN} = (M-1,N-1).$

=> A unitary transform of the image U = a rotation of the MN-dimensional space, defined by a rotation matrix A in MN-dimensions.

$$\{u(n), 0 \le n \le N-1\}$$
; **A** - unitary matrix, $\mathbf{A}^{-1} = \mathbf{A}^{*T}$

$$\mathbf{v} = \mathbf{A}\mathbf{u}, \quad or \quad v(k) = \sum_{n=0}^{N-1} a(k,n)u(n), \quad 0 \le k \le N-1 \quad (4.1)$$

$$\mathbf{u} = \mathbf{A}^{*T} \mathbf{v} \qquad or \quad u(n) = \sum_{k=0}^{N-1} a^{*}(k, n) v(k), \quad 0 \le n \le N-1$$

$$a_{k}^{*} = \{a^{*}(k, n), \quad 0 \le n \le N-1\},$$

4.2 UNITARY ORTHOGONAL TWO-DIMENSIONAL TRANSFORMS

$$v(k,l) = \sum_{m=0}^{N-1} \sum_{n=0}^{N-1} a_{k,l}(m,n) \cdot u(m,n), \quad 0 \le k,l \le N-1$$
 (4.3)

$$u(m,n) = \sum_{k=0}^{N-1} \sum_{l=0}^{N-1} a_{k,l}^*(m,n) \cdot v(k,l), \quad 0 \le k,l \le N-1$$
(4.4)

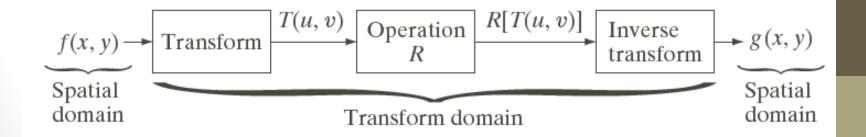
Mathematical Background: Complex Numbers (cont'd)

• Euler's formula

$$e^{\pm j\theta} = cos(\theta) \pm jsin(\theta)$$

Image Transforms

- Many times, image processing tasks are best performed in a domain other than the spatial domain.
- Key steps:
 - (1) Transform the image
 - (2) Carry the task(s) in the transformed domain.
 - (3) Apply inverse transform to return to the spatial domain.



Notation

- Continuous Fourier Transform (FT)
- Discrete Fourier Transform (DFT)
- Discrete Cosine Transform (DCT)

Fourier Series Theorem

 Any periodic function f(t) can be expressed as a weighted sum (infinite) of sine and cosine functions of varying frequency:

$$f(t) = a_0 + \sum_{n=1}^{\infty} a_n \cos(nf_0 t) + \sum_{n=1}^{\infty} b_n \sin(nf_0 t)$$

 f_0 is called the "fundamental frequency"

Continuous Fourier Transform (FT)

• Transforms a signal (i.e., function) from the **spatial** (x) domain to the **frequency** (u) domain.

Forward FT:
$$F(f(x)) = F(u) = \int_{-\infty}^{\infty} f(x)e^{-j2\pi ux} dx$$

$$\underbrace{\text{Inverse FT:}}_{\text{(IFT)}} F^{-1}(F(u)) = f(x) = \int_{-\infty}^{\infty} F(u)e^{j2\pi ux} du$$

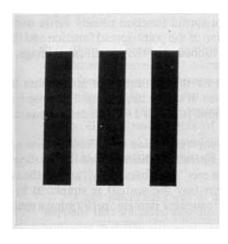
where
$$e^{\pm j\theta} = \cos(\theta) \pm j\sin(\theta)$$

Why is FT Useful?

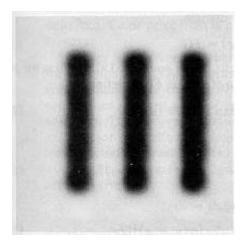
- Easier to remove undesirable frequencies.
- Faster perform certain operations in the **frequency** domain than in the **spatial** domain.

How do frequencies show up in an image?

- Low frequencies correspond to slowly varying information (e.g., continuous surface).
- High frequencies correspond to quickly varying information (e.g., edges)

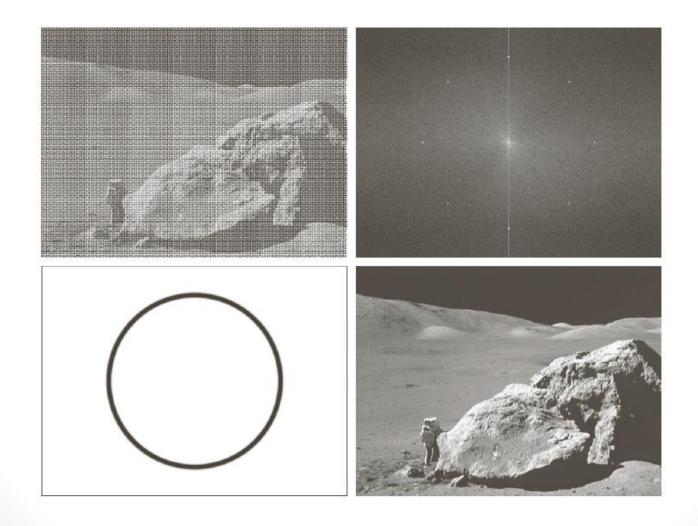


Original Image



Low-passed

Example of noise reduction using FT



Extending FT in 2D

Forward FT

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

$$F^{-1}(F(u,v)) = f(x,y) = \int_{-\infty}^{\infty} \int_{-\infty}^{\infty} F(u,v)e^{j2\pi(ux+uy)}dudv$$

Discrete Fourier Transform (DFT) (cont'd)

Forward DFT

$$F(u) = \frac{1}{N} \sum_{x=0}^{N-1} f(x) e^{\frac{-j2\pi ux}{N}}, u = 0, 1, \dots, N-1$$

Inverse DFT

$$f(x) = \sum_{u=0}^{N-1} F(u)e^{\frac{j2\pi ux}{N}}, x = 0, 1, \dots, N-1$$

Extending DFT to 2D

- Assume that f(x,y) is M x N.
- Forward DFT

$$F(u, v) = \frac{1}{MN} \sum_{x=0}^{M-1} \sum_{y=0}^{N-1} f(x, y) e^{-j2\pi(\frac{ux}{M} + \frac{vy}{N})}$$

$$(u = 0, 1, ..., M - 1, v = 0, 1, ..., N - 1)$$

Inverse DFT:

$$f(x,y) = \sum_{u=0}^{M-1} \sum_{v=0}^{N-1} F(u,v) e^{j2\pi (\frac{ux}{M} + \frac{vy}{N})}$$

$$(x = 0, 1, ..., M-1, y = 0, 1, ..., N-1)$$

Extending DFT to 2D (cont'd)

Special case: f(x,y) is N x N.

Forward DFT

$$F(u,v) = \frac{1}{N} \sum_{x=0}^{N-1} \sum_{y=0}^{N-1} f(x,y) e^{-j2\pi(\frac{ux+vy}{N})},$$

$$u,v = 0,1,2,...,N-1$$

Inverse DFT

$$f(x,y) = \frac{1}{N} \sum_{u=0}^{N-1} \sum_{v=0}^{N-1} F(u,v) e^{j2\pi (\frac{ux+vy}{N})},$$

$$x,y = 0,1,2,...,N-1$$

Visualizing DFT

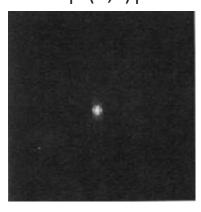
- Typically, we visualize |F(u,v)|
- The dynamic range of |F(u,v)| is typically very large
- Apply streching:

$$D(u, v) = c \log(1 + |F(u, v)|)^{t}$$

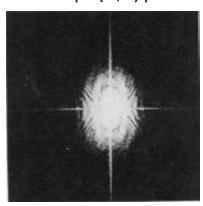
$$|F(u,v)| \qquad |D(u,v)|$$



original image



before stretching



after stretching

2-D DCT using a 1-D DCT Pair

• 1-D DCT:

$$X(k) = \sqrt{\frac{2}{N}}C(k)\sum_{i=0}^{N-1} x(i)\cos[\frac{(2i+1)k\pi}{2N}]$$

• 1-D IDCT:

$$x(i) = \sqrt{\frac{2}{N}} \sum_{k=0}^{N-1} C(k) X(k) \cos\left[\frac{(2i+1)k\pi}{2N}\right]$$

$$k = 0, 1, 2, ..., N-1.$$

and $i = 0, 1, 2, ..., N-1.$

$$C(k) = \begin{cases} \frac{1}{\sqrt{2}} & \text{for } k = 0\\ 1 & \text{otherwise.} \end{cases}$$

Implementation of the DCT

- DCT-based codecs use a two-dimensional version of the transform.
- The 2-D DCT and its inverse (IDCT) of an N x N block are shown below:

$$F(u,v) = \frac{2}{N}C(u)C(v)\sum_{y=0}^{N-1}\sum_{x=0}^{N-1}f(x,y)\cos\left[\frac{(2x+1)u\pi}{2N}\right]\cos\left[\frac{(2y+1)v\pi}{2N}\right]$$

$$f(x,y) = \frac{2}{N} \sum_{v=0}^{N-1} \sum_{u=0}^{N-1} C(u)C(v)F(u,v) \cos\left[\frac{(2x+1)u\pi}{2N}\right] \cos\left[\frac{(2y+1)v\pi}{2N}\right]$$

$$C(k) = \begin{cases} \frac{1}{\sqrt{2}} & \text{for } k = 0\\ 1 & \text{otherwise.} \end{cases}$$

Note: The DCT is similar to the DFT since it decomposes a signal into a series of harmonic cosine functions.

