Fourier transform, key concepts for image analysis

- 1. Convolution
- 2. Aliasing

Fourier Transform (FT)

$$F(k) = \int_{-\infty}^{\infty} f(x)e^{-2i\pi kx}dx$$

Discrete Fourier Transform (DFT)

$$F[k] = \sum_{n=0}^{N-1} f[n]e^{-2i\pi \frac{kn}{N}}$$
Periodic
$$F[k] = F[k+m*N]$$

Discrete Time Fourier Transform

$$(ext{DTFT})$$
 ∞ $F[k] = \sum_{n=-\infty}^{\infty} f[n]e^{-2i\pi kn}$ or $\sum_{n=-\infty}^{\text{Periodic}} f[k] = \sum_{n=-\infty}^{\text{Periodic}} f[k] = \sum_{n=-\infty}^{\text{Periodic}} f[k] = \sum_{n=-\infty}^{\text{Periodic}} f[n]e^{-2i\pi kn}$ or $\sum_{n=-\infty}^{\text{Periodic}} f[n]e^{-2i\pi kn}$ $\sum_{n=-\infty}^{\text{Periodic}} f[n]e^{-2i\pi kn}$

$$F[\mu] = \sum_{-\infty}^{\infty} f[n]e^{-i2\pi\mu n\Delta T}$$

$$\mu = \frac{k}{\Delta T}$$

Definition up to a normalization term!

The convolution theorem

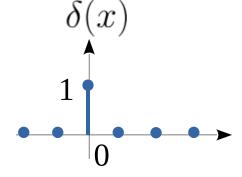
Convolution

Reminder

$$(f*w)(x) = \sum_{k \in \mathbb{Z}} f(k)w(x-k) = \sum_{s \in \mathbb{Z}} f(x-s)w(s)$$

Neutral element: Kronecker delta

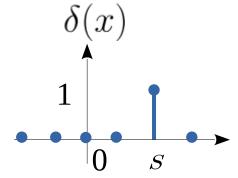
$$(f * \delta)(x) = f(x)$$



Shifted delta:

$$\delta_s(x) = \delta(x - s)$$

$$(f * \delta_s)(x) = f(x - s)$$



A convolution with a shifted delta shifts the function

Illustrating the convolution theorem with a first example: translation in space

- Discrete Time Fourier Transform $F(k) = \sum_{n} f(n)e^{-2i\pi nk}$
- Discrete Time Fourier Transform of the shifted kronecker delta $-2i\pi nk$

$$\sum_{n} \delta_s(n) e^{-2i\pi nk} = e^{-2i\pi sk}$$

$$\sum_{k=-\infty}^{\infty} F(k) e^{-j2\pi ks} e^{j2\pi kn} = \sum_{k=-\infty}^{\infty} F(k) e^{j2\pi k(n-s)} = f(n-s) = f * \delta_s(n)$$
FT of f FT of δ Convolution

Multiplication of 2 FTs

• Shift in time (or space) is a multiplication by a phase factor in Fourier

$$f * \delta_s \Leftrightarrow F(k)e^{-j2\pi ks}$$
Convolution Multiplication

- Vice versa: Fourier transform of $f(n)e^{j2\pi sn}$
- A shift in Frequency:

$$\sum_{n=-\infty}^{\infty} f(n)e^{j2\pi ks}e^{-j2\pi kn} = \sum_{n=-\infty}^{\infty} f(t)e^{-j2\pi(k-s)t} = F(k-s)$$
Multiplication

Convolution with δ
In the Fourier space!

Convolution Theorem

• General property, for any function f and g

It works for continuous FT and DTFT and DFT (with a slight adjustement)!

Important concept! Remember spatial filtering: filter using convolution We can now filter using a simple multiplication!

PROOF

We will do that in the exercise session. (hint: you need to make a change of variables)

But you can see a proof of the convolution theorem for example here:

https://tinyurl.com/4kuzuwe9

Discrete Fourier Transform and Convolution

Convolution theorem holds with a cyclic convolution for the DFT

$$DFT(f^*w)[k] = F[k]W[k] \qquad \qquad DFT(fw) = (F * W)[k]$$

with the cyclic convolution: N-1

$$(f * w)[n] = \sum_{m=0}^{\infty} f[m]w[(n-m)_N]$$

 $(n-m)_N$ is (n-m) modulo N (stays in the range [0,N])

DFT periodizes the function/filter, «live on a circle»

Discrete Fourier Transform and periodicity

DFT periodizes the function/filter, «live on a circle»

DFT and inverse DFT:

$$F[k] = \sum_{n=0}^{N-1} f[n]e^{-2i\pi\frac{kn}{N}} \qquad f[n] = \frac{1}{N} \sum_{k=0}^{N-1} F[k]e^{i2\pi k\frac{n}{N}}$$

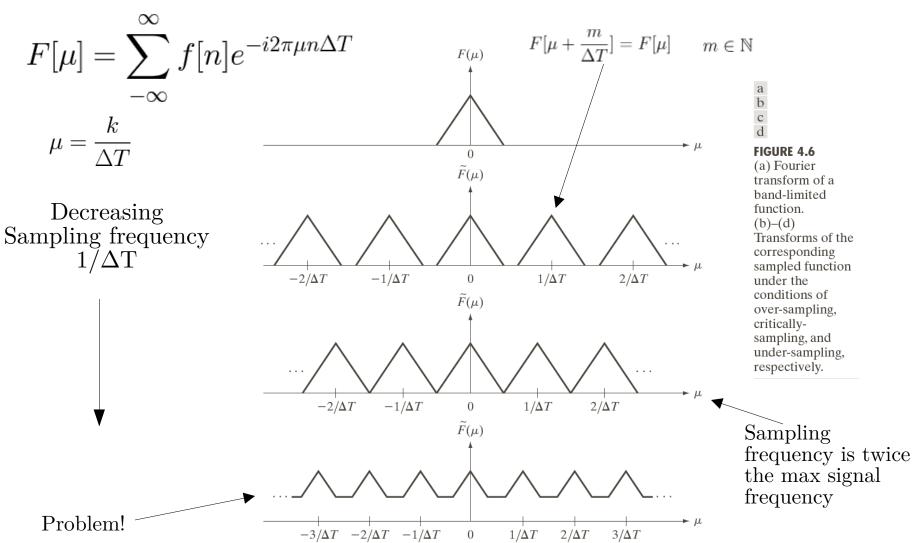
The complex exponential periodize the function The variable n can have values > N

• Remark: Zero-padding reduces the effect of periodization

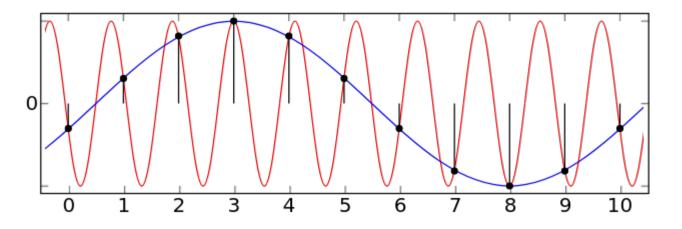
We will see now the link between discrete FTs and periodization and its consequences

Aliasing

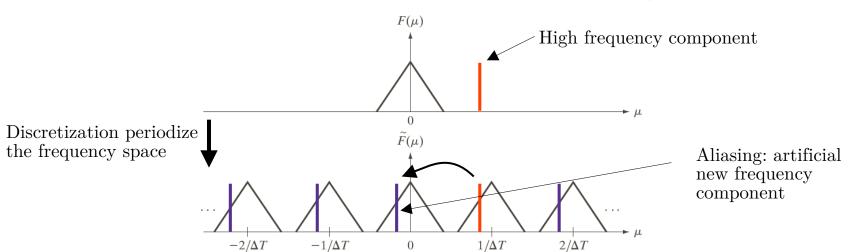
Discretization -> frequency periodization



Aliasing phenomenon

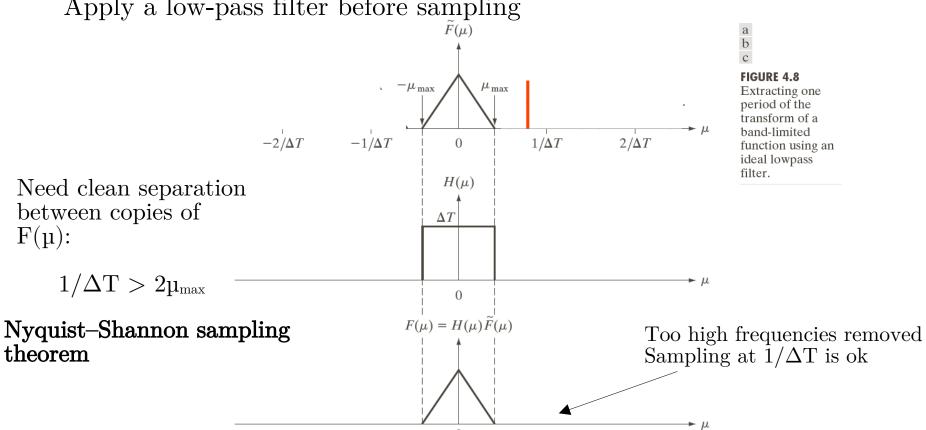


Variations of the function are faster than the sampling



Solution, anti-aliasing:

Apply a low-pass filter before sampling



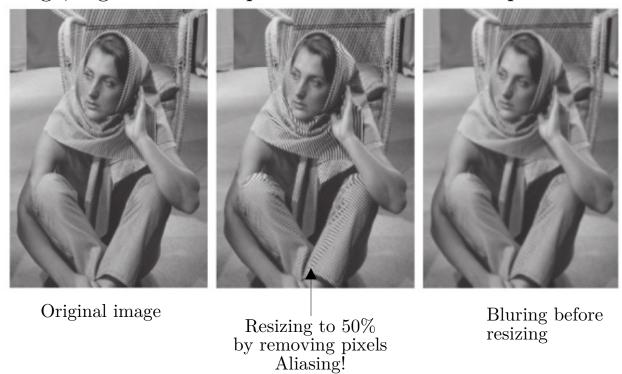
 $-\mu_{\text{max}}$ 0

 $\mu_{\rm max}$

Aliasing on images

Sampling:

- natural (continuous) image -> pixels
- resizing image, high number of pixels -> low number of pixels



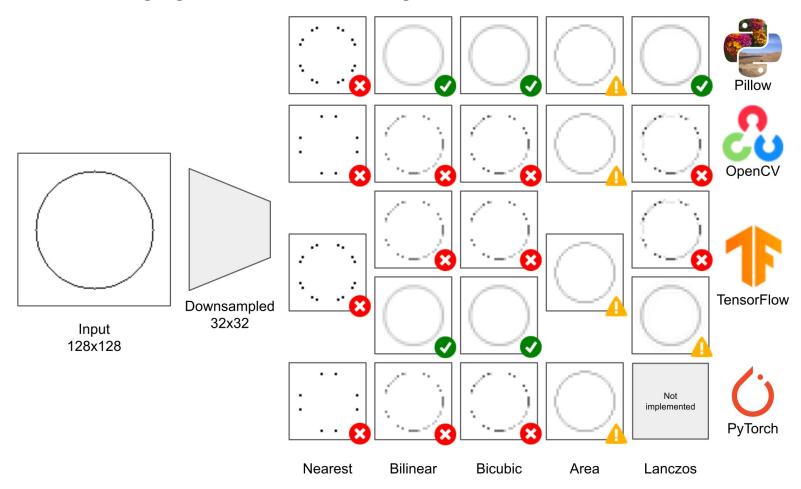
Other example:

https://www.adobe.com/creativecloud/photography/discover/anti-aliasing.html Visual example (aliasing in time):

https://www.youtube.com/watch?v=yr3ngmRuGUc

Aliasing on images

• Not so long ago in machine learning...



From blog post:

https://blog.zuru.tech/machine-learning/2021/08/09/the-dangers-behind-image-resizing

Aliasing on images

- Solution:
- 1) low-pass filter -> blur the image, the thin line becomes much thicker
- 2) downsample the blurry image



Deep learning and aliasing on images

• See also: https://richzhang.github.io/antialiased-cnns/ (Results from 2019)