## Summary of last week's lecture

- Virtually all filtering is a local neighbourhood operation
- Convolution = linear and shift-invariant filters
- e.g. mean filter, Gaussian weighted filter
- kernel can sometimes be decomposed
- Many non-linear filters exist also
- e.g. median filter, bilateral filter
- The Fourier transform decomposes a function (image) into trigonometric basis functions (sines \& cosines).
- The Fourier transform is used to analyse frequency components of an image.


## Linear neighbourhood operation

- For each pixel, multiply the values in its neighbourhood with the corresponding weights, then sum.



## Convolution properties

- Linear:
- Scaling invariant:
$(C f) \otimes h=C(f \otimes h)$
- Distributive:
$(f+g) \otimes h=f \otimes h+g \otimes h$
- Time Invariant:
(= shift invariant)
- Commutative:
$\operatorname{shift}(f) \otimes h=\operatorname{shift}(f \otimes h)$
$f \otimes h=h \otimes f$
- Associative:
$f \otimes\left(h_{1} \otimes h_{2}\right)=\left(f \otimes h_{1}\right) \otimes h_{2}$

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## Fourier transform



$$
F\left(-\omega_{1}\right)=F^{*}\left(\omega_{1}\right)
$$

## Fourier transform pairs



|  |
| :---: |
|  |  |
|  |  |





Gaussian
 $\dagger \longrightarrow$ Gaussian


## Properties of the Fourier transform

Spatial scaling


Amplitude scaling


Addition


Translation

Convolution


$$
\mathscr{F}\{\boldsymbol{f} \otimes h\}=\mathscr{F}\{\boldsymbol{f}\} \cdot \mathscr{F}\{\boldsymbol{h}\}
$$

$$
\mathscr{F}\{\boldsymbol{f}\} \cdot \mathscr{F}\{\boldsymbol{h}\}=\mathscr{F}\{\boldsymbol{f} \otimes h\}
$$

## Today's lecture

- The Discrete Fourier transform (DFT)
- The Fourier transform in 2D
- The Fast Fourier Transform (FFT) algorithm
- Designing filters in the Fourier domain
- filtering out structured noise
- Sampling, aliasing, interpolation


## Sampling

spatial domain
continuous function

frequency domain

sampling function
sampled function


## Discrete Fourier transform

spatial domain

sampled function
continuous image
discrete image
frequency domain




$\square$


## Discrete Fourier transform

Continuous FT: $\quad F(\omega)=\int_{-\infty}^{\infty} f(x) \mathrm{e}^{-i \omega x} \mathrm{~d} x$
Discrete FT: $F[K]=\sum_{n=0}^{N-1} f[n] \mathrm{e}^{-i \frac{2 \pi}{N} k n}$
$k$ is the spatial frequency, $k \in[0, N-1]$
$\omega=2 \pi k / N$
$\omega \in[0,2 \pi[$

## Discrete Fourier transform

$$
\begin{aligned}
& F[[]]=\sum_{m=0}^{N=1} f[n] e^{-\frac{2 \pi}{0} m}
\end{aligned}
$$

Main difference with $F(\omega)$ is that $F[k]$ is defined on a limited domain ( $N$ samples), and that these samples are assumed to repeat periodically: $F[k]=F[k+N]$.

In the same way, $f[n]$ is defined by $N$ samples, which are assumed to repeat periodically: $f[n]=f[n+N]$.

## Discrete Fourier transform

- The DFT only has positive frequencies !?!?!?
- Remember: it is periodic! $F[k]=F[k+N]$
- Thus: $F[-k]=F[N-k]$



## Fourier transform in 2D, 3D, etc.

- Simplest thing there is! - the FT is separable:
- Perform transform along x-axis,
- Perform transform along y-axis of result,
- Perform transform along z-axis of result, (etc.)

$F[u, v]=\sum_{m=0}^{M-1} \sum_{n=0}^{N-1} f[n, m] \mathrm{e}^{-i 2 \pi\left(\frac{u n}{N}+\frac{v m}{M}\right)}=\sum_{m=0}^{M-1}\left(\sum_{n=0}^{N-1} f[n, m] \mathrm{e}^{-i \frac{2 \pi}{N} u n}\right) \mathrm{e}^{-i \frac{2 \pi}{M} v m}$

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## 2D Fourier transform pairs


box


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## 2D Fourier transform pairs

pillbox


Gauss

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## 2D transform example 1



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## 2D transform example 1



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## 2D transform example 2



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## 2D transform example 2



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## 2D transform example 3



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## 2D transform example 4



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## 2D transform example 5



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## What is more important?



magnitude

phase

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## What is more important?





## The Fast Fourier Transform (FFT)

- Clever algorithm to compute the DFT.
- Runs in $\mathrm{O}(N \log N)$ time, rather than $\mathrm{O}\left(N^{2}\right)$ time.
- Because of symmetry of the forward and inverse Fourier transforms, FFT can also compute the IDFT.

$$
\begin{gathered}
F[k]=F_{\text {even }}[k]+F_{\text {odd }}[k] \mathrm{e}^{-i \frac{2 \pi}{N} k} \quad N=2 M \\
F[k+M]=F_{\text {even }}[k]-F_{\text {odd }}[k] \mathrm{e}^{-i \frac{2 \pi}{N} k} \\
N=2^{n}
\end{gathered}
$$

## Convolution in the Fourier domain

- The Convolution property of the Fourier transform:

$$
\mathscr{F}\{f \otimes h\}=\mathscr{F}\{f\} \cdot \mathscr{F}\{h\}
$$

- Thus we can calculate the convolution through:
- $F=$ FFT( $f$ )
- $H=\operatorname{FFT}(h)$
- $G=F \cdot H$
- $g=\operatorname{IFFT}(G)$
- Convolution is an operation of $\mathrm{O}(N M)$
- $N$ image pixels, $M$ kernel pixels
- Through the FFT it is an operation of $\mathrm{O}(N \log N)$
- Efficient if $M$ is large!


## Low-pass filtering

- Linear smoothing filters are all low-pass filters.
- Mean filter (uniform weights)
- Gauss filter (Gaussian weights)
- Low-pass means low frequencies are not altered, high frequencies are attenuated



## High-pass filtering

- The opposite of low-pass filtering: low frequencies are attenuated, high frequencies are not altered
- The "unsharp mask" filter is a high-pass filter
- The Laplace filter is a high-pass filter



## Band-pass filtering

- You can choose any part of the frequency axis to preserve (band-pass filter).
- Or you can attenuate a specific set of frequencies (band-stop filter).


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## Example: low-pass filtering


input image $f$


Fourier transform $F$

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## Example: frequency domain filtering



Fourier filter $H$

$G=F H$

filtered image $g$

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## Why the ringing?



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## What is the solution?



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## Example: frequency domain filtering



Fourier filter $H$

$G=F H$

filtered image $g$

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## Structured noise



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## Structured noise



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## Filtering structured noise



Notch filter


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## Filtering structured noise



Notch filter, Gaussian


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## Fourier analysis of sampling

$$
F(\omega)=\int_{-\infty}^{\infty} f(x) \mathrm{e}^{-i \omega x} \mathrm{~d} x
$$



band limit
(cutoff frequency)
$F(\omega)=0, \omega>\omega_{c}$

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## Fourier analysis of sampling

spatial domain
frequency domain

sampling function

sampled function


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## Fourier analysis of interpolation

spatial domain
sampled function


## Aliasing

## spatial domain

continuous function

frequency domain

sampling function

sampled function


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## Aliasing




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Aliasing


## Avoid aliasing

## frequency domain



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## Example: aliasing



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## Example: aliasing



## Example: aliasing



When we downsample, we only keep this part!

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## Example: aliasing



The spectrum is replicated, higher frequencies being duplicated as lower frequencies.

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## Example: Moire



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## Example: Moire



## Summary of today's lecture

- The Fourier transform
- decomposes a function (image) into trigonometric basis functions (sines \& cosines)
- is used to analyse frequency components
- is computed independently for each dimension
- The DFT can be computed efficiently through the FFT algorithm
- Convolution can be studied through the FT
- and filters can be designed in the Fourier domain
- $\mathscr{F}\{f \otimes h\}=\mathscr{F}\{f\} \cdot \mathscr{F}\{h\}$
- Aliasing can be understood through the FT


## Reading assignment

- The Fourier transform and the DFT
- Sections 4.2, 4.4, 4.5, 4.6, 4.11.1
- Filtering in the Fourier domain
- Sections 4.7, 4.8, 4.9, 4.10, 5.4
- Sampling and aliasing
- Sections 4.3, 4.5.4
- The FFT
- Section 4.11.3
- Exercises:
- 4.14, 4.21, 4.22, 4.42, 4.43
- 4.27, 4.29
(feel free to solve these in MATLAB)

