

Audio Signal Processing : III. Filtering

Emmanuel Bacry

`bacry@ceremade.dauphine.fr`

`http://www.cmap.polytechnique.fr/~bacry`

III.1 Time continuous filtering

Framework :

$s(t)$ is a time continuous signal (\simeq electrical tension)

$s(t)$ is real-valued

Combination of electronic resistance and electronic capacitor leads to

$$a_N \frac{d^N v(t)}{dt^N} + \dots + a_1 \frac{dv(t)}{dt} + a_0 v(t) = b_M \frac{d^M u(t)}{dt^M} + \dots + b_1 \frac{du(t)}{dt} + b_0 u(t)$$

where

- $u(t)$ is the input voltage
- $v(t)$ is the output voltage

and the $\{a_n\}_{0 \leq n \leq N}$ and $\{b_m\}_{0 \leq m \leq M}$ are reals

III.1.a Time continuous filtering : filtering using electronic circuit

After Fourier transform

$$a_N \frac{d^N v(t)}{dt^N} + \dots + a_1 \frac{dv(t)}{dt} + a_0 v(t) = b_M \frac{d^M u(t)}{dt^M} + \dots + b_1 \frac{du(t)}{dt} + b_0 u(t)$$

gives

$$\begin{aligned} & a_N(i\omega)^N \hat{v}(\omega) + \dots + a_1(i\omega) \hat{v}(\omega) + a_0 \hat{v}(\omega) \\ &= b_M(i\omega)^M \hat{u}(\omega) + \dots + b_1(i\omega) \hat{u}(\omega) + b_0 \hat{u}(\omega) \end{aligned}$$

III.1.a Time continuous filtering : filtering using electronic circuit

And

$$\begin{aligned} & a_N(i\omega)^N \hat{v}(\omega) + \dots + a_1(i\omega) \hat{v}(\omega) + a_0 \hat{v}(\omega) \\ & = b_M(i\omega)^M \hat{u}(\omega) + \dots + b_1(i\omega) \hat{u}(\omega) + b_0 \hat{u}(\omega) \end{aligned}$$

can be rewritten

$$\hat{v}(\omega) \sum_{n=0}^N a_n (i\omega)^n = \hat{u}(\omega) \sum_{m=0}^M b_m (i\omega)^m$$

III.1.a Time continuous filtering : filtering using electronic circuit

Consequently, the operator that associates $u(t)$ (input) to $v(t)$ (output) such that

$$\hat{v}(\omega) \sum_{n=0}^N a_n(i\omega)^n = \hat{u}(\omega) \sum_{m=0}^M b_m(i\omega)^m$$

is a time-invariant linear operator (i.e., a convolution) with an impulsionnal response $h(t)$ (i.e. the filter of the convolution) whose Fourier transform is

$$\hat{h}(\omega) = \frac{\hat{v}(\omega)}{\hat{u}(\omega)} = \frac{\sum_{n=0}^N a_n(i\omega)^n}{\sum_{m=0}^M b_m(i\omega)^m}$$

III.1.a Time continuous filtering : filtering using electronic circuit

The considered electronic circuit corresponds to a filter $h(t)$ defined by

$$\hat{h}(\omega) = \frac{\sum_{m=0}^M b_m(i\omega)^m}{\sum_{n=0}^N a_n(i\omega)^n}$$

which we can rewrite

$$\hat{h}(\omega) = \frac{N(i\omega)}{D(i\omega)}$$

where N and D are two polynomials with real coefficients.

III.1.b Time continuous filtering : Causality and Stability

N and D : polynomials with real coefficients :

$$\hat{h}(\omega) = \frac{N(i\omega)}{D(i\omega)}$$

Theorem : The filter $h(t)$ is causal and stable iff

- (i) $\delta N < \delta D$
- (ii) All the solutions of $D(z) = 0$ are such that $\Re(z) < 0$

The problem : How to design an electronic circuit which corresponds to a fixed $|\hat{h}(\omega)|^2$ (we do not care about the phase) ?

III.1.c Time continuous filtering : Filter design

Rephrasing the problem : We choose a positive-valued function $H(\omega)$, and we want to find two polynomials $N(z)$ and $D(z)$ such that

- N and D have real coefficients
- The filter $\frac{N(i\omega)}{D(\omega)}$ is causal and stable, i.e.,
 - (i) $\delta N < \delta D$
 - (ii) All the solutions of $D(z) = 0$ are such that $\Re(z) < 0$
- One has

$$H(\omega) = \frac{|N(i\omega)|^2}{|D(\omega)|^2}$$

Theorem If a positive valued function $H(\omega)$ satisfies

- H is a rational fraction in $i\omega$ with real coefficients, of the form

$$H(\omega) = \frac{P(i\omega)}{Q(i\omega)}$$

with $\delta P < \delta Q$

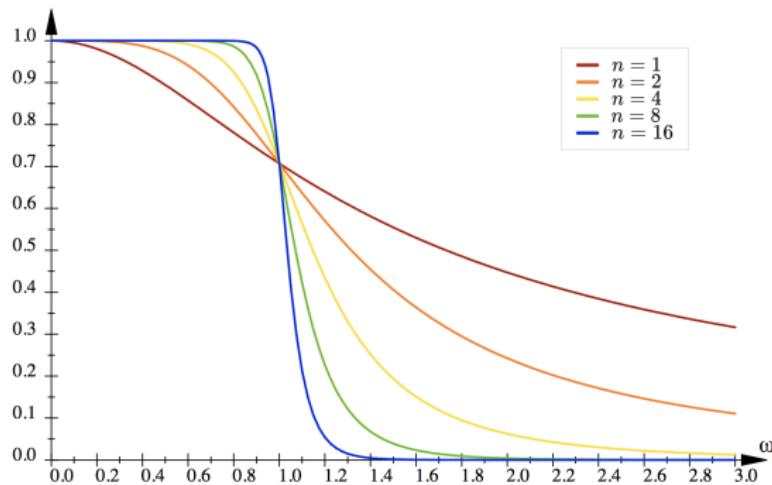
- The poles of H (i.e., the roots of $Q(z)$) are such that
 $\Re(z) \neq 0$

Then we can design an electronic circuit corresponding to a (stable and causal) filter $h(t)$ such that

$$|\hat{h}(\omega)|^2 = H(\omega)$$

Application The Butterworth low-pass filters $h_{\omega_0, n}$

$$|\hat{h}_{\omega_0, n}(\omega)|^2 = H_n(\omega) = \frac{1}{1 + (\omega/\omega_0)^{2n}}$$



What about the phase ?

- Linear phase filters
- Minimum phase filters

Framework :

- $s[n]$ is a time-discrete signal (= sampling of an analog signal)
- $s[n]$ is real-valued

Causal filtering in discrete time :

$$h * s[n] = \sum_{k \geq 0} h[k]s[n - k]$$

We want to have a finite number of operations !

⇒ we need to have $h[k]$ to be compact support

Definition : A Moving Average filtering (MA)

- $f[n]$ (resp. $g[n]$) is the input (resp. output) signal
- $g[n] = h * f[n]$

$$g[n] = \sum_{k=0}^M b_k f[n - k]$$

And in Fourier space

$$\hat{g}(e^{i\omega}) = \hat{b}(e^{i\omega})\hat{f}(e^{i\omega})$$

with

$$\hat{b}(e^{i\omega}) = \sum_{k=0}^M b_k e^{-i\omega}$$

In that case, the filter h is simply given by

$$\hat{h}(e^{i\omega}) = \hat{b}(e^{i\omega})$$

A Moving Average filtering (MA)

$$g[n] = h * f[n]$$

with

$$\hat{h}(e^{i\omega}) = \hat{b}(e^{i\omega}) = \sum_{k=0}^M b_k e^{-ki\omega}$$

This is a Finite-Impulse-Response (FIR) filter (i.e., b is compact support).

⇒ If we want to implement "sharp band filters, one need large support which will induce ... long computations.

**How could we implement a (causal)
Infinite-Impulse-Response (IIR) filter with a finite number of
operations ?**

Definition : An Auto-Regressive filtering (AR)

- $f[n]$ (resp. $g[n]$) is the input (resp. output) signal
- $g[n] = h * f[n]$

$$g[n] = f[n] - \sum_{k=1}^N a_k g[n-k], \quad \text{with } a_0 = 1$$

or equivalently

$$\sum_{k=0}^N a_k g[n-k] = f[n]$$

Then

$$\hat{h}(e^{i\omega}) = \frac{1}{\hat{a}(e^{i\omega})} = \frac{1}{\sum_{k=0}^N a_k e^{-ik\omega}}$$

Definition : An Auto-Regressive filtering (AR)

$$g[n] = h * f[n]$$

with

$$\sum_{k=0}^N a_k g[n-k] = f[n]$$

And

$$\hat{h}(e^{i\omega}) = \frac{1}{\hat{a}(e^{i\omega})} = \frac{1}{\sum_{k=0}^N a_k e^{-ik\omega}}$$

$\implies h$ is an IIR filter that can be implemented with a finite number of operations !

III.2.a Time discrete filtering : Recursive filters (ARMA)

Definition : An ARMA filter ($= \text{AR} + \text{MA}$)

$$g[n] = h * f[n]$$

with

$$\sum_{k=0}^N a_k g[n-k] = \sum_{k=0}^M b_k f[n-k] \quad \text{with } a_0 = 1$$

Thus

$$\hat{h}(e^{i\omega}) = \frac{\hat{b}(e^{i\omega})}{\hat{a}(e^{i\omega})} = \frac{\sum_{k=0}^M b_k e^{-ik\omega}}{\sum_{k=0}^N a_k e^{-ik\omega}}$$

An ARMA filter (= AR+MA)

$$\hat{h}(e^{i\omega}) = \frac{\sum_{k=0}^M b_k e^{-ik\omega}}{\sum_{k=0}^N a_k e^{-ik\omega}}$$

Thus, the Z transform is

$$\hat{h}(Z) = \frac{\sum_{k=0}^M b_k Z^{-k}}{\sum_{k=0}^N a_k Z^{-k}}$$

Let's remember that in general

$$h(Z) = \sum_n h[n] Z^{-n}$$

and the convergence domain is a ring $C = \{Z, \rho_1 < |Z| < \rho_2\}$

Thus

- **Causality**

$$\hat{h}(Z) = \sum_{n>0} h[n] Z^{-n}$$

\implies The convergence domain is of the form $C = \{\rho_1 < |Z|\}$

- **Stability**

$$\sum_n |h[n]| < +\infty$$

\implies The convergence domain is such that $1 \in C$

An ARMA filter (= AR+MA)

$$\hat{h}(Z) = \frac{\sum_{k=0}^M b_k Z^{-k}}{\sum_{k=0}^N a_k Z^{-k}} = \frac{N(Z)}{D(Z)}$$

where N and D are polynomials with real coefficients.

Thus

- **Causality** : Always ! (by definition)
- **Stability** : $1 \in C$

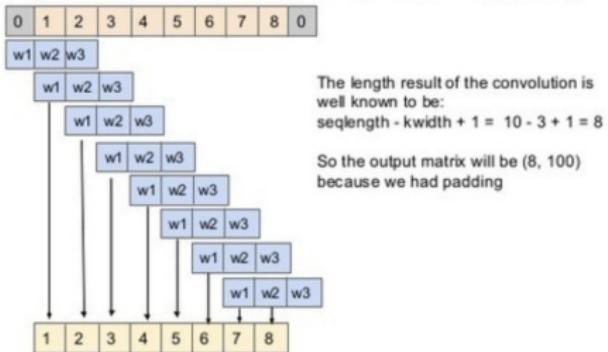
$\implies C$ is of the form $C = \{Z, |Z| > \rho\}$ with $\rho > 1$

\implies the roots of $D(Z) = 0$ verify $Z < 1$

A MA filter \simeq first layer of a 1D-CNN

1D Convolutions

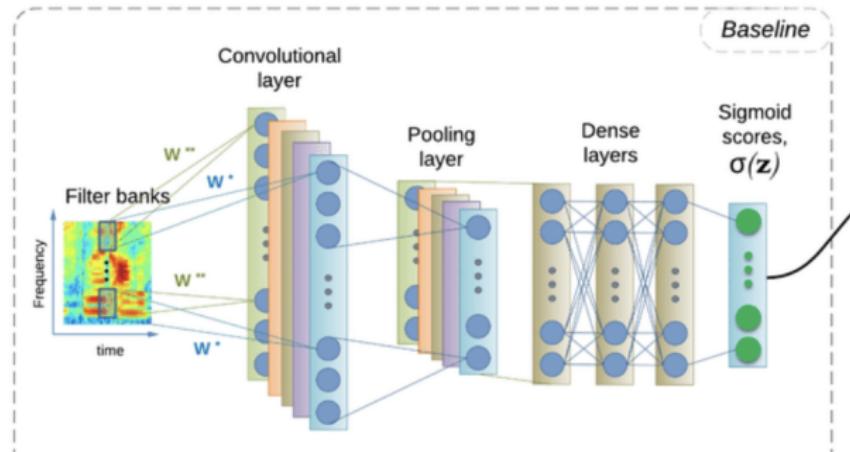
When we add zero padding, we normally do so on both sides of the sequence (as in image padding)



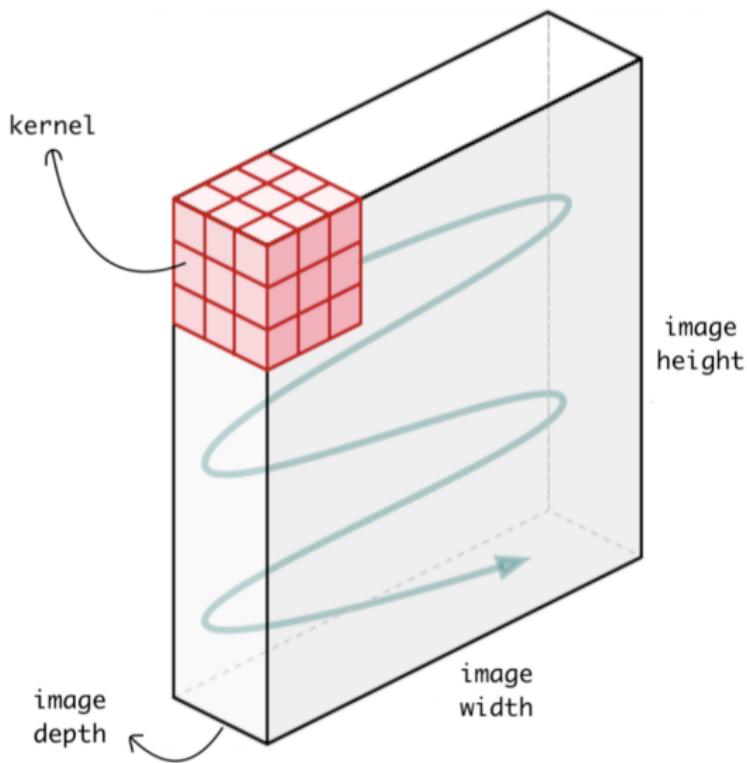
The kernel size, number of filters are hyperparameters once again.

III.2.b Time discrete filtering : MA and CNN's

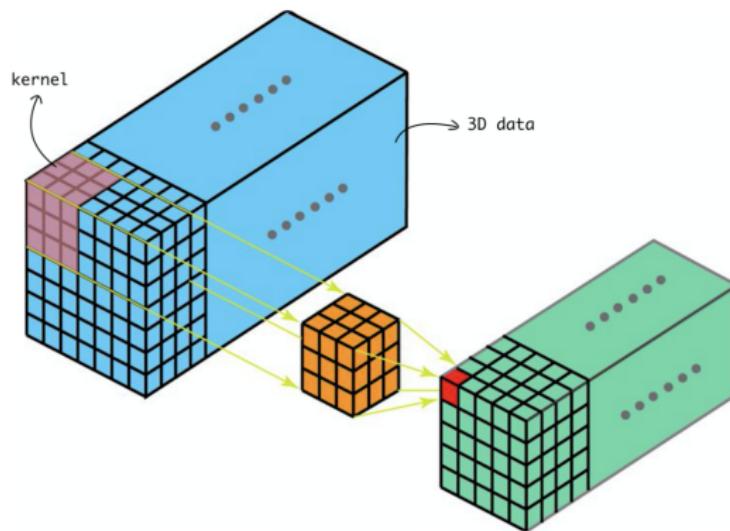
A MA filter \simeq first layer of a 1D-CNN .. In Action !



A MA filter \simeq first layer of a 2D-CNN



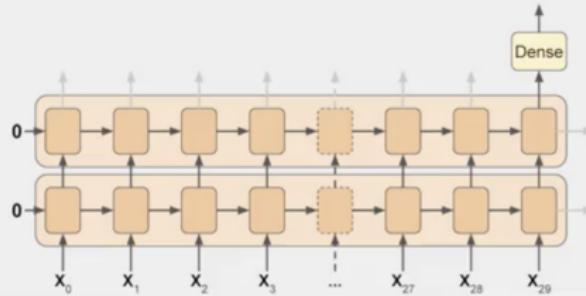
A MA filter \simeq first layer of a 3D-CNN



III.2.b Time discrete filtering : MA and CNN's

A ARMA filter \simeq first layer of a SimpleRNN

```
model = keras.models.Sequential([
    keras.layers.SimpleRNN(20, return_sequences=True,
                          input_shape=[None, 1]),
    keras.layers.SimpleRNN(20),
    keras.layers.Dense(1)
])
```



The problem : How to design a discrete time filter which corresponds to a fixed $|\hat{h}(e^{j\omega})|^2$ (we do not care about the phase) ?

Theorem If a positive valued function $H(e^{i\omega})$ satisfies

- H is a rational fraction in $e^{i\omega}$ with real coefficients, of the form

$$H(e^{i\omega}) = \frac{P(e^{i\omega})}{Q(e^{i\omega})}$$

with $\delta P < \delta Q$

- The poles of $H(Z)$ (i.e., the roots of $Q(Z)$) are such that
 $|Z| < 1$

Then we can design a discrete time ARMA filter corresponding to a (stable and causal) filter $h[n]$ such that

$$|\hat{h}(e^{i\omega})|^2 = H(e^{i\omega})$$

III.3 Time discrete filtering : Second order cell

The simplest ("interesting") ARMA filter is an AR(2) :

$$\hat{h}(Z) = \frac{b_0}{1 + a_1 Z^{-1} + a_2 Z^{-2}}$$

Thus There are two poles $\rho e^{i\omega_0}$ and $\rho e^{-i\omega_0}$



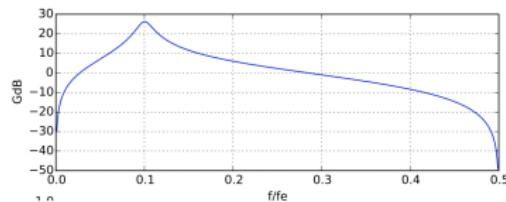
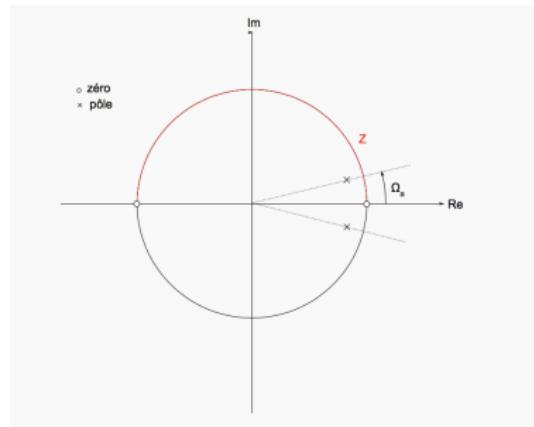
this is an IIR band-pass filter !

- ω_0 the resonance frequency
- ρ allows to tune the band-width
- b_0 is the amplitude

III.3 Time discrete filtering : Second order cell

A classical bandwidth filter AR(2) MA(2)

$$\hat{h}(Z) = \frac{(Z - 1)(Z + 1)}{1 + a_1 Z^{-1} + a_2 Z^{-2}}$$

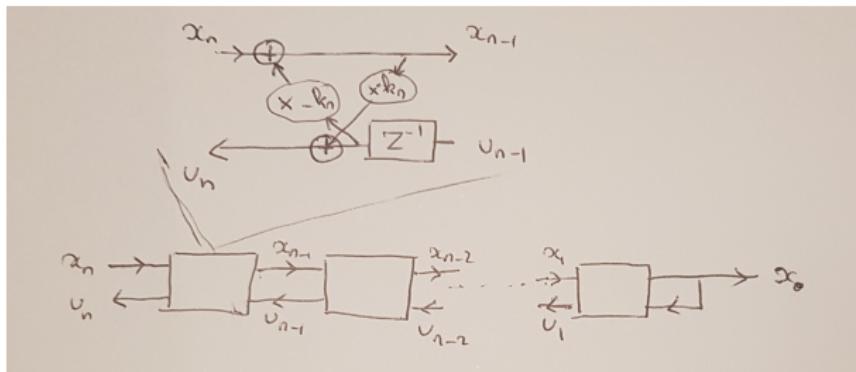


$$\hat{h}(Z) = \frac{b_0}{1 + a_1 Z^{-1} + a_2 Z^{-2}}$$

⇒ Interpolation of parameters is possible keeping stability !

Percussive sound synthesis

III.4 Time discrete filtering : An efficient implementation of second order cells



- Input : x_N
- Output : x_0

$$\begin{aligned}\hat{x}_{n-1}(Z) &= -k_n Z^{-1} \hat{u}_{n-1}(Z) + \hat{x}_n(Z) \\ \hat{u}_n(Z) &= k_n \hat{x}_{n-1}(Z) + Z^{-1} \hat{u}_{n-1}(Z)\end{aligned}$$