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Multichannel Identification of Room Acoustic Systems with Adaptive Filters based on Orthonormal Basis Functions

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Outline

- Adaptive Digital Filters for Room Acoustics Modeling
- Multichannel Identification Algorithm
- Simulation Results
- Conclusions

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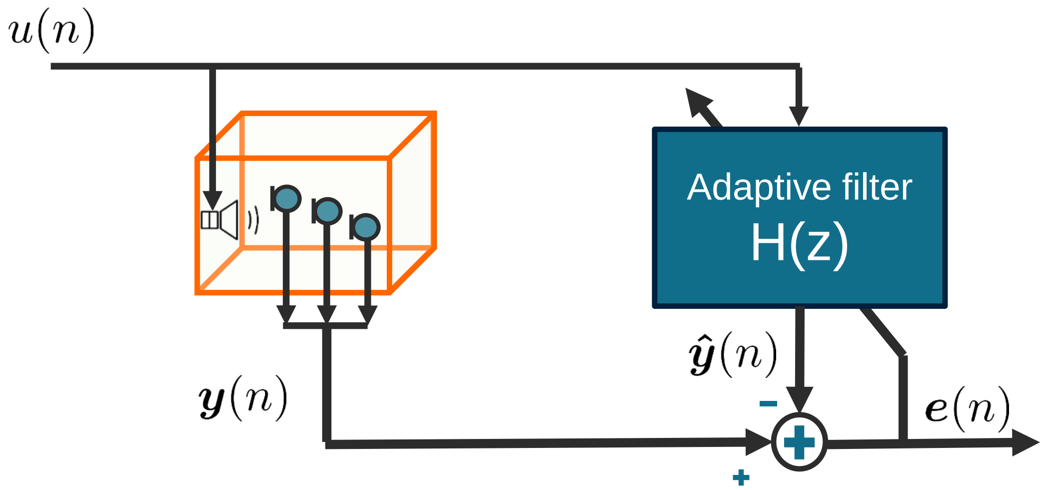
Adaptive Filters for Room Acoustics



- Modeling of RTFs
- Filter Adaptation
  - Track variations of RTFs
- SIMO system

$$\underset{\boldsymbol{a},\boldsymbol{b}}{\text{minimize}}\ \boldsymbol{e}^2(n) = [\boldsymbol{y}(n) - \hat{\boldsymbol{y}}(n)]^2$$

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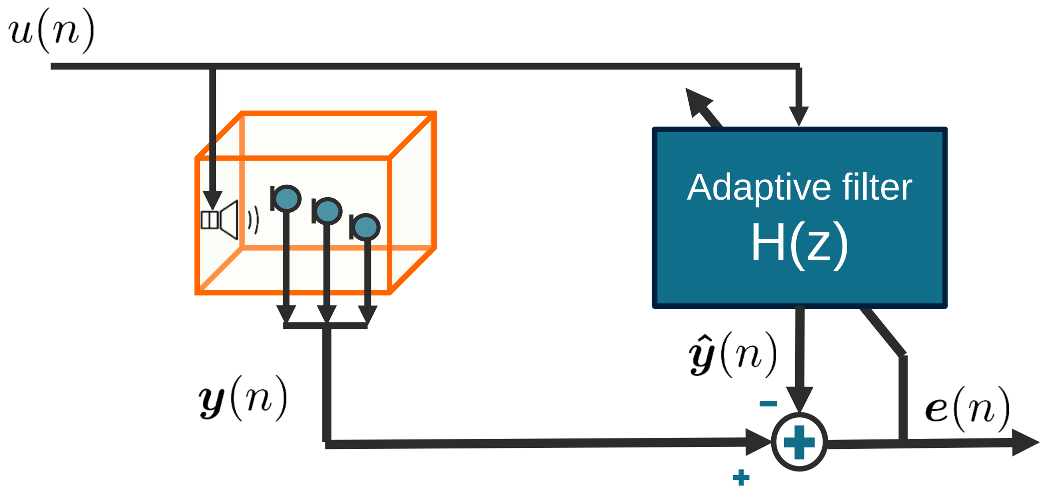

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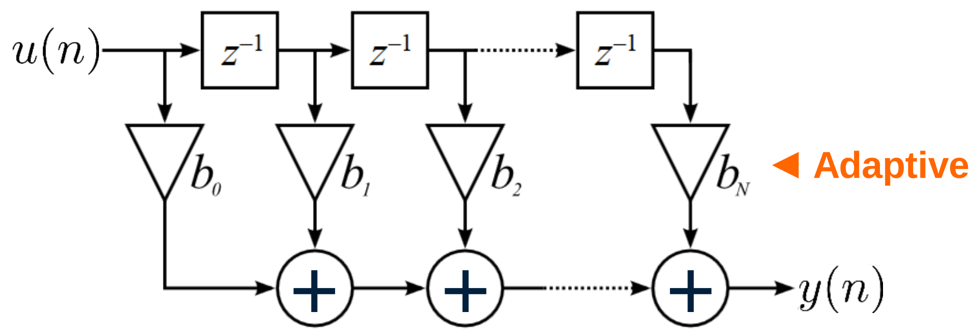
- **FIR filter (All-zero model)**
  - Simple
  - Global convergent adaptation



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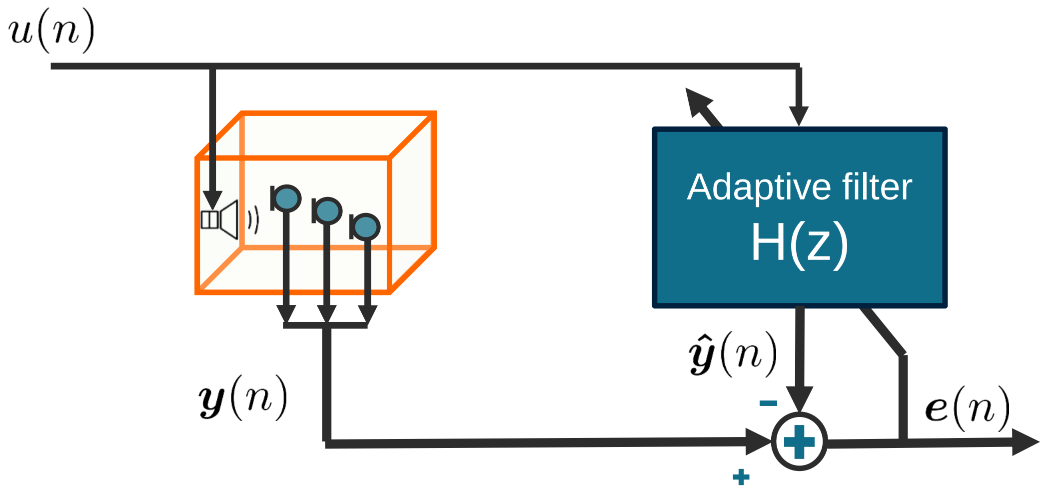

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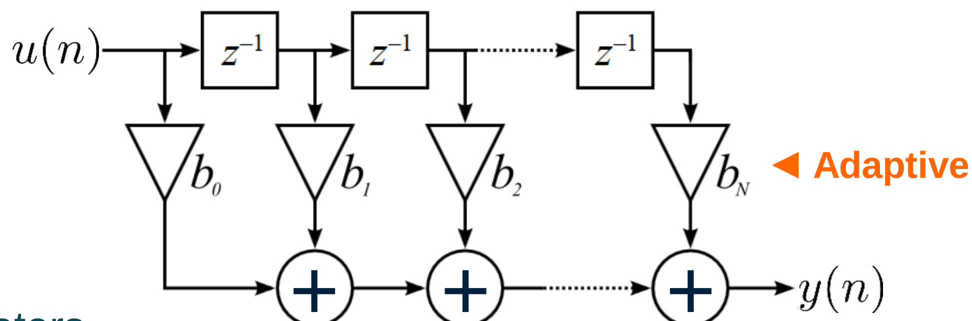
  Problems:
  - Large number of adaptive parameters
    - Excessive computational burden
    - Excess MSE (misadjustment)



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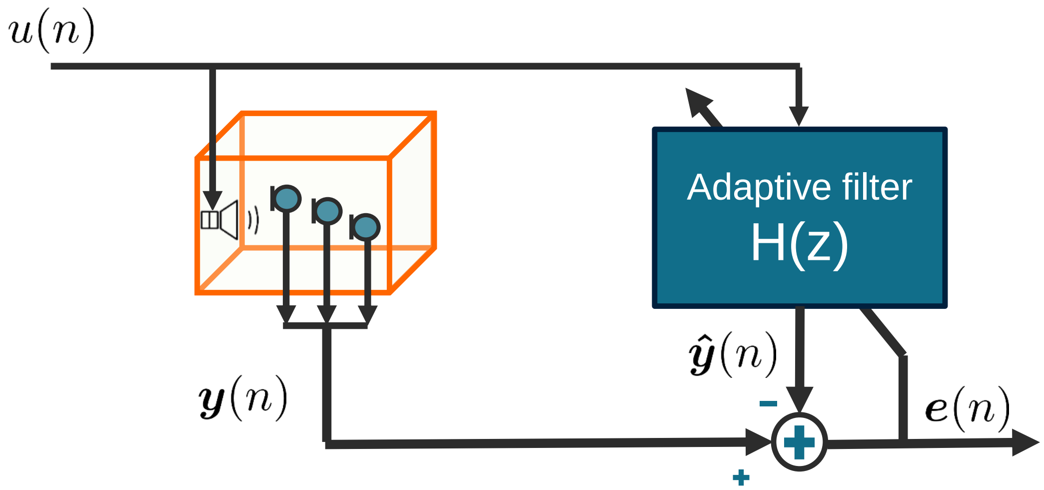

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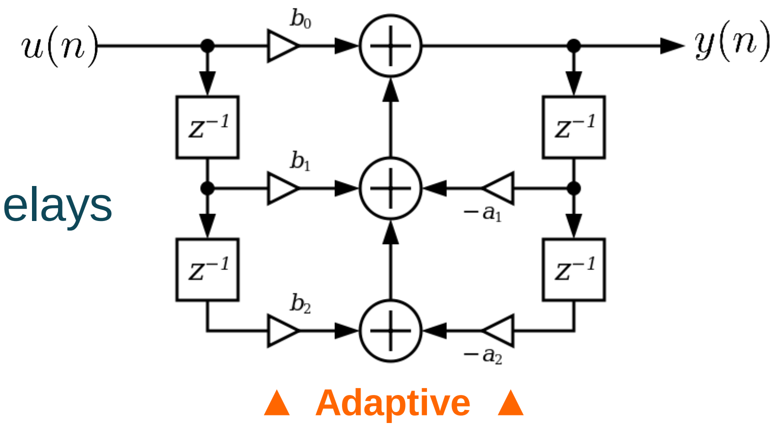
- **IIR filter (Pole-Zero model)**
  - Reduced number of parameters
  - Can describe both resonances and time-delays



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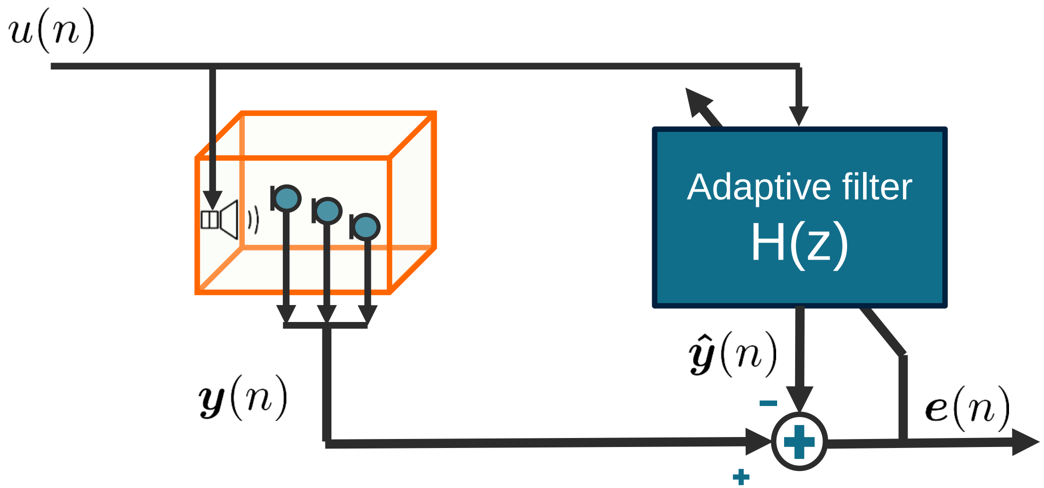
Adaptive Filters for Room Acoustics



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- **IIR filter (Pole-Zero model)**
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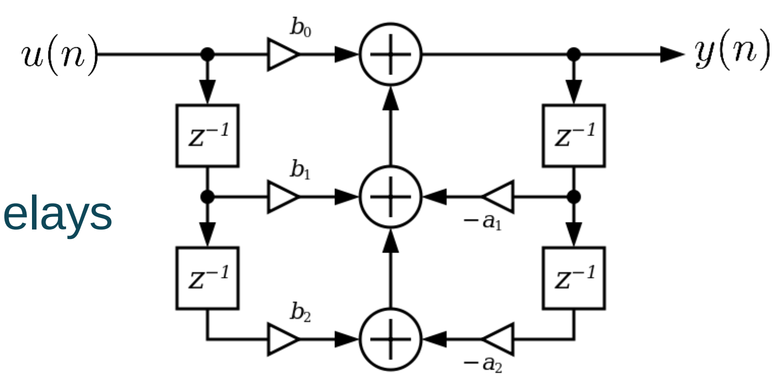
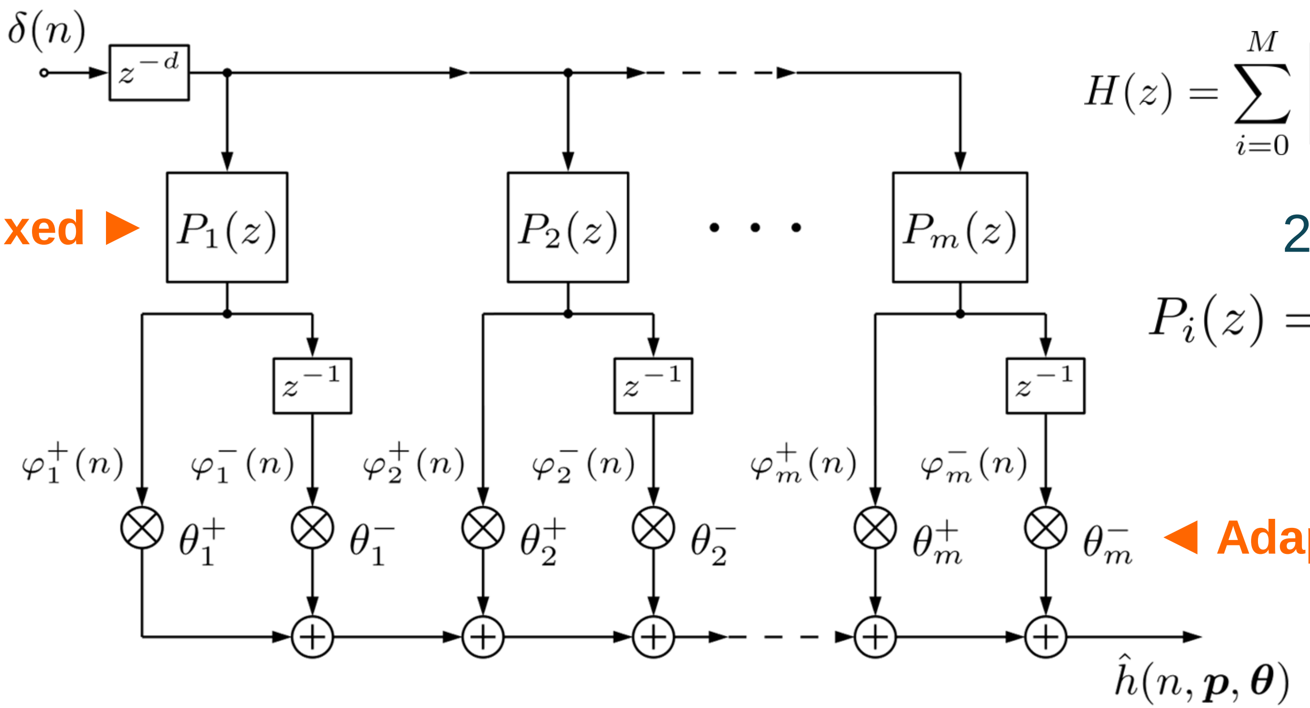
  Problems:
  - Higher complexity of the adaptive algorithm
  - Slower convergence rate of adaptation
  - Possible instability or convergence to local minima



▲ Adaptive ▲

Fixed-Pole Adaptive IIR Filters (FPAF)



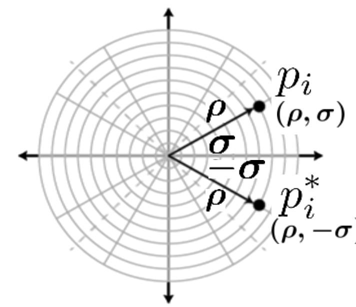
Fixed ▶

◀ Adaptive

$$H(z) = \sum_{i=0}^{M} \left[\frac{\theta_i^+(n) + \theta_i^-(n) z^{-1}}{(1 - p_i z^{-1})(1 - p_i^* z^{-1})} \right]$$

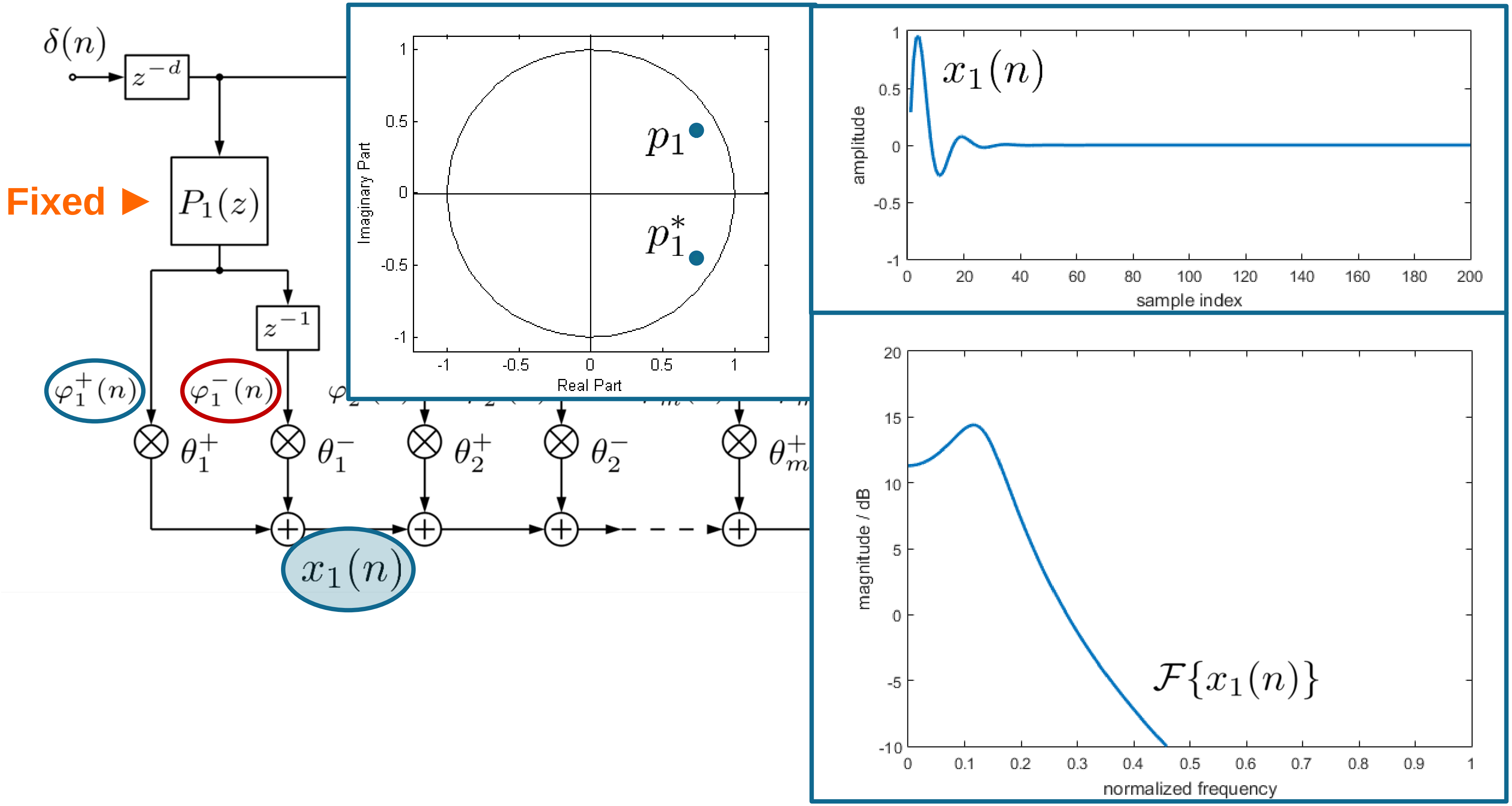
2nd-order resonator

$$P_i(z) = \frac{1}{(1-p_i z^{-1})(1-p_i^* z^{-1})}$$



$$p_i = \rho_i e^{j\sigma_i}$$

Fixed-Pole Adaptive IIR Filters (FPAF)



(All θ's equal to one and response normalized)

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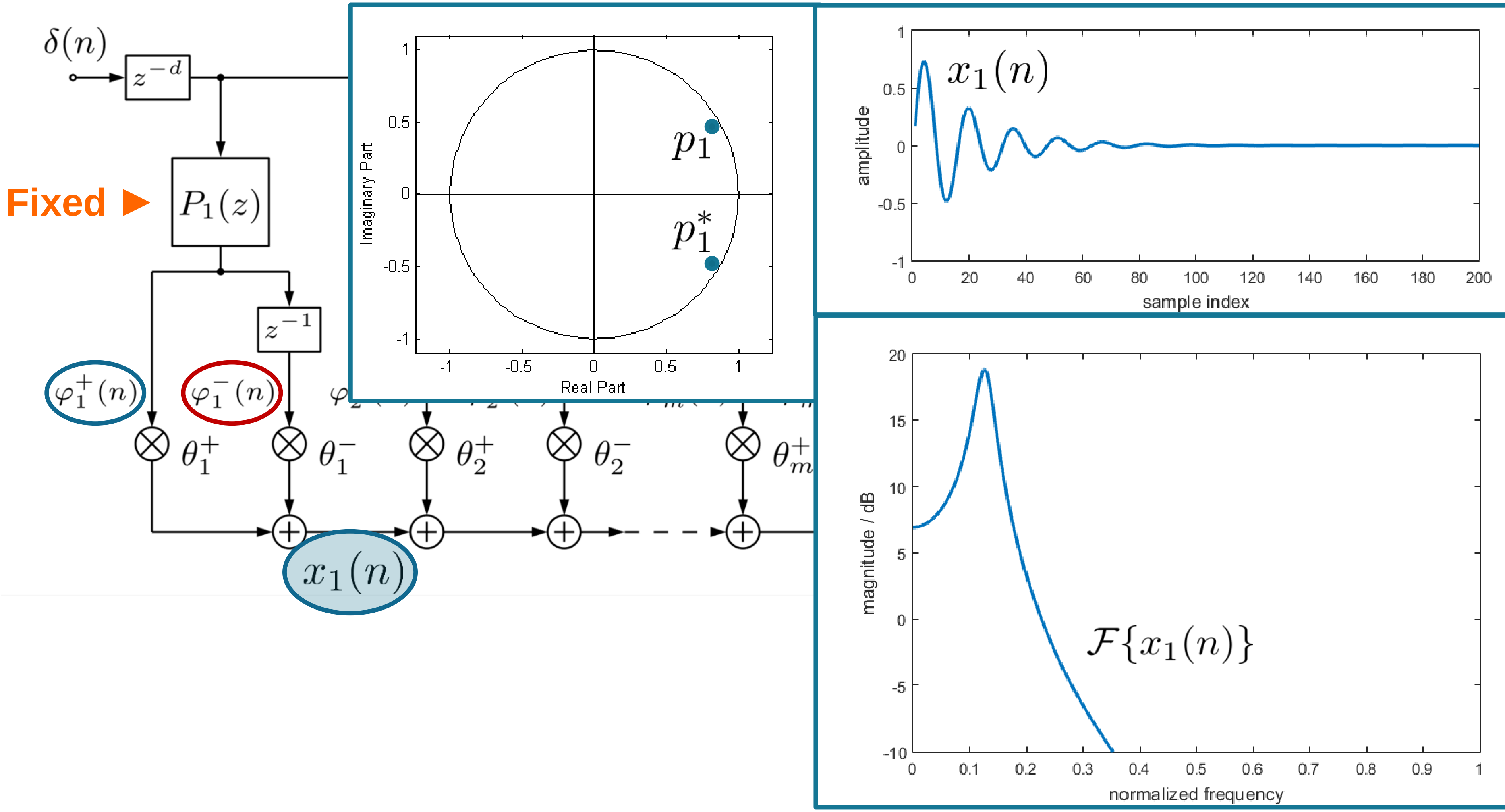

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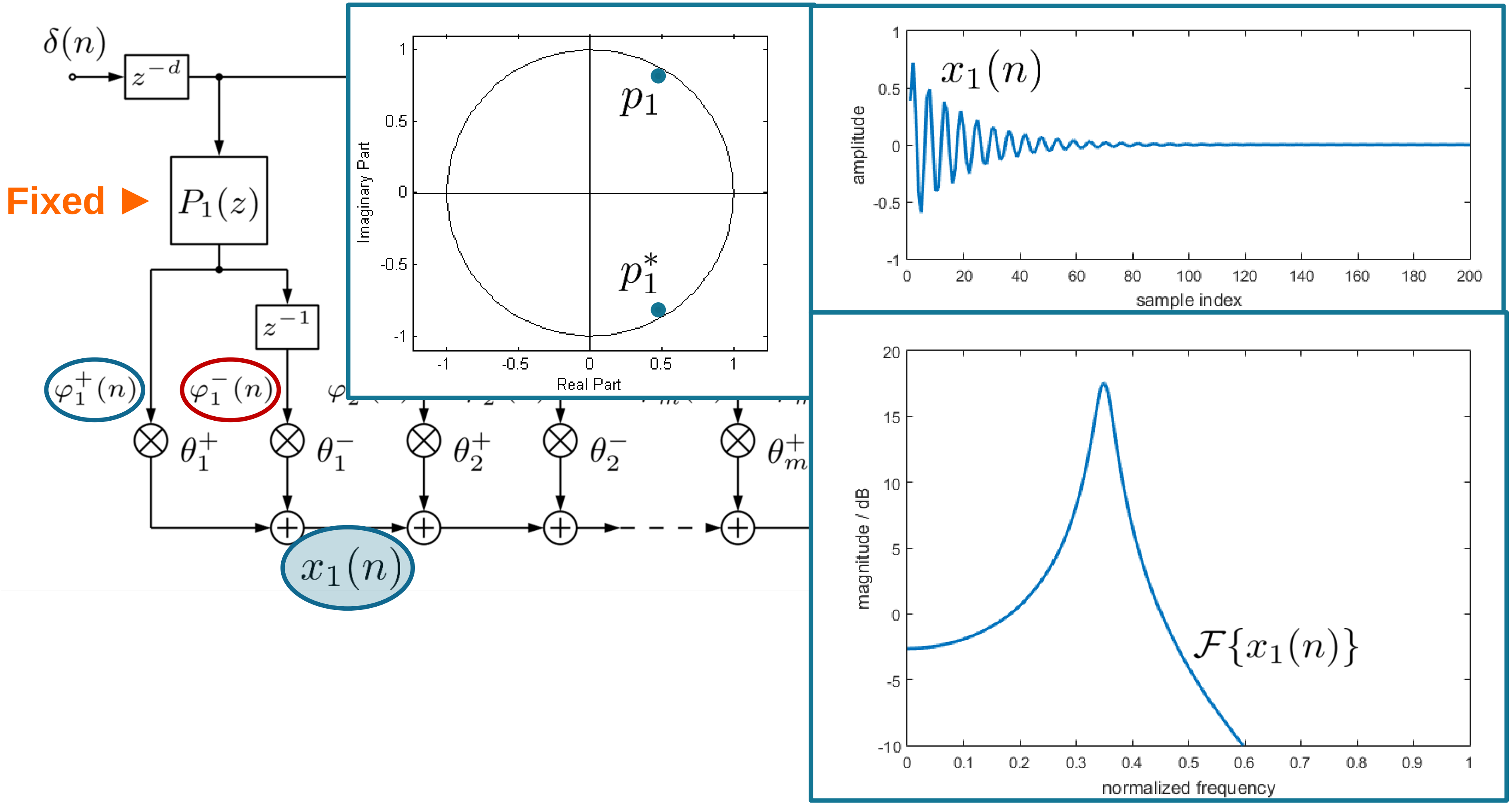


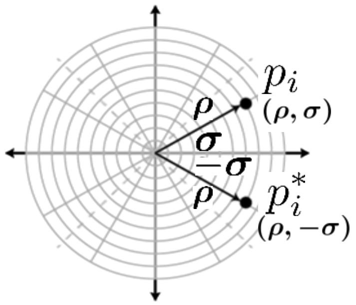
(All θ's equal to one and response normalized)

FPAFs for Room Acoustics

- FPAF Impulse Response

$$h(\boldsymbol{r}, n) = \sum_{i=0}^{M} 2|g_i(n)|\rho_i^n \cos(\sigma_i n + \angle g_i(n))$$

$$n = t/T, \quad n = 0, 1, \ldots, \quad T: \text{sampling time}$$



$$p_i = \rho_i e^{-j\sigma_i} : \text{pole}$$

$$g_i(n) = \frac{p_i \theta_i^+(n) + \theta_i^-(n)}{p_i - p_i^*}$$

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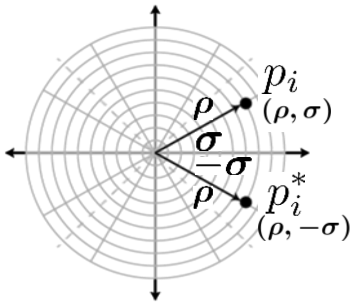

- Room Impulse Response (RIR)

$$h(\boldsymbol{r}, t) = \sum_{i=0}^{\infty} c_i(\boldsymbol{r})\, e^{-\zeta_i t} \cos(\omega_i t + \phi_i(\boldsymbol{r}))$$

$$\boldsymbol{r} = (\boldsymbol{r}_0, \boldsymbol{r}_s) : \text{ receiver-source position}$$

$$p_i = \rho_i e^{-j\sigma_i} : \text{ pole}$$

$$\rho_i = e^{-\zeta_i T} : \text{ radius}$$

$$\sigma_i = \omega_i T : \text{ angle}$$

FPAFs for Room Acoustics

- FPAF Impulse Response

$$h(\boldsymbol{r}, n) = \sum_{i=0}^{M} 2|g_i(n)|\rho_i^n \cos(\sigma_i n + \angle g_i(n))$$

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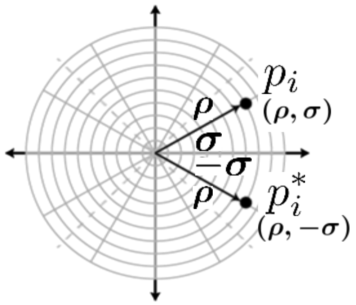

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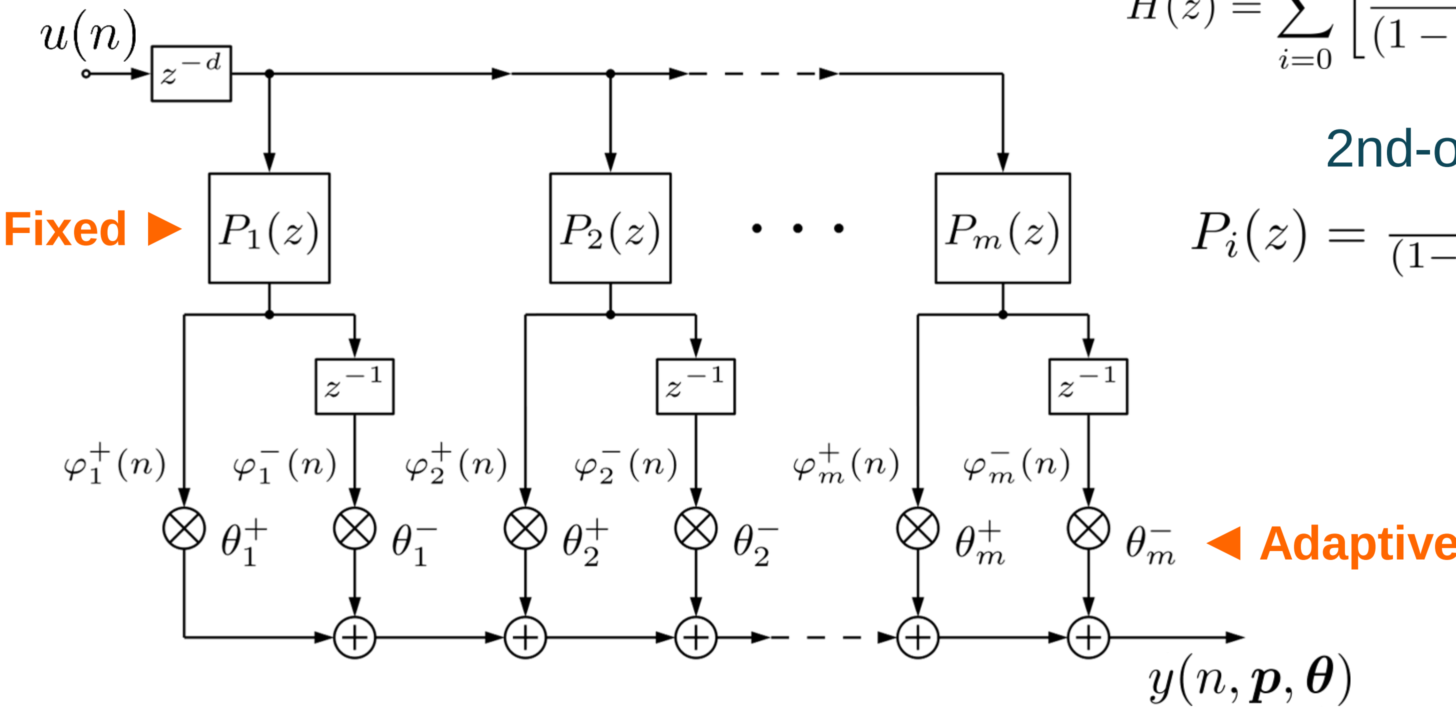
IDEA:

Use a digital filter whose impulse response is a linear combination of a finite number of exponentially decaying sinusoids (discrete in time)

- Fixed poles (common resonance frequencies and damping constants)
- Adaptive linear coefficients (variable amplitude and phase)

Fixed-Pole Adaptive IIR Filters (FPAF)

$$H(z) = \sum_{i=0}^{M} \left[\frac{\theta_i^- + \theta_i^+ z^{-1}}{(1 - p_i z^{-1})(1 - p_i^* z^{-1})} \right]$$



2nd-order resonator

$$P_i(z) = \frac{1}{(1-p_i z^{-1})(1-p_i^* z^{-1})}$$

- Filter output $\quad y(n, \boldsymbol{p}, \boldsymbol{\theta}) = \boldsymbol{\varphi}^T(n, \boldsymbol{p})\boldsymbol{\theta}(n)$

$\boldsymbol{\varphi}(n) = [\boldsymbol{\varphi}_1^{\pm}(n), \ldots, \boldsymbol{\varphi}_m^{\pm}(n)]^T$ ← Intermediate signals vector

$\boldsymbol{\theta}(n) = [\boldsymbol{\theta}_1^{\pm}(n), \ldots, \boldsymbol{\theta}_m^{\pm}(n)]^T$ ← Adaptive linear coefficients vector

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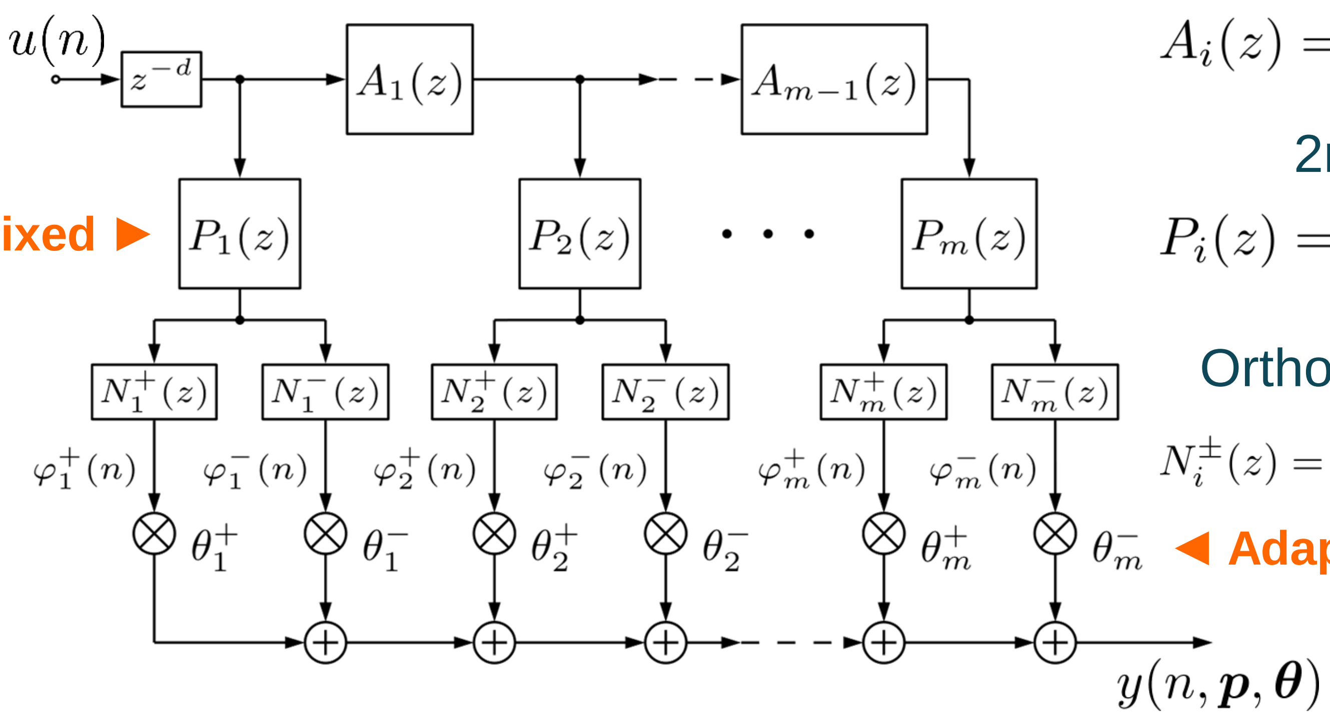
OBF filters (Kautz filters)



Fixed ▶

◀ Adaptive

All-pass filter

$$A_i(z) = \frac{(z^{-1} - p_i)(z^{-1} - p_i^*)}{(1 - p_i z^{-1})(1 - p_i^* z^{-1})}$$

2nd-order resonator

$$P_i(z) = \frac{1}{(1 - p_i z^{-1})(1 - p_i^* z^{-1})}$$

Orthonormalization filter

$$N_i^{\pm}(z) = |1 \pm p_i| \sqrt{\frac{1 - |p_i|^2}{2}} (z^{-1} \mp 1)$$

- Filter output $y(n, \boldsymbol{p}, \boldsymbol{\theta}) = \boldsymbol{\varphi}^T(n, \boldsymbol{p}) \boldsymbol{\theta}(n)$
- OBF filters and FPAFs span the same approximation space

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FPAFs and OBF filters

- Advantages:
  - Accuracy : poles are moved closer to the real poles of the system
  - Flexibility : poles can be arbitrarily fixed in the filter structure
  - Stability : poles can be fixed inside the unit circle
  - Linearity : the filter structure is linear in the tap-coefficients $\boldsymbol{\theta}$
    - Transversal filter structure $\longrightarrow$ Global convergence of adaptation
    - Same complexity of adaptation algorithm as FIR filters
  - **Orthogonality** (only OBF filters)
    - Good trade-off between accuracy and number of parameters
    - Repeated poles and pole addition/deletion
    - Numerically well-conditioning (no order restriction)
    - Faster global convergence

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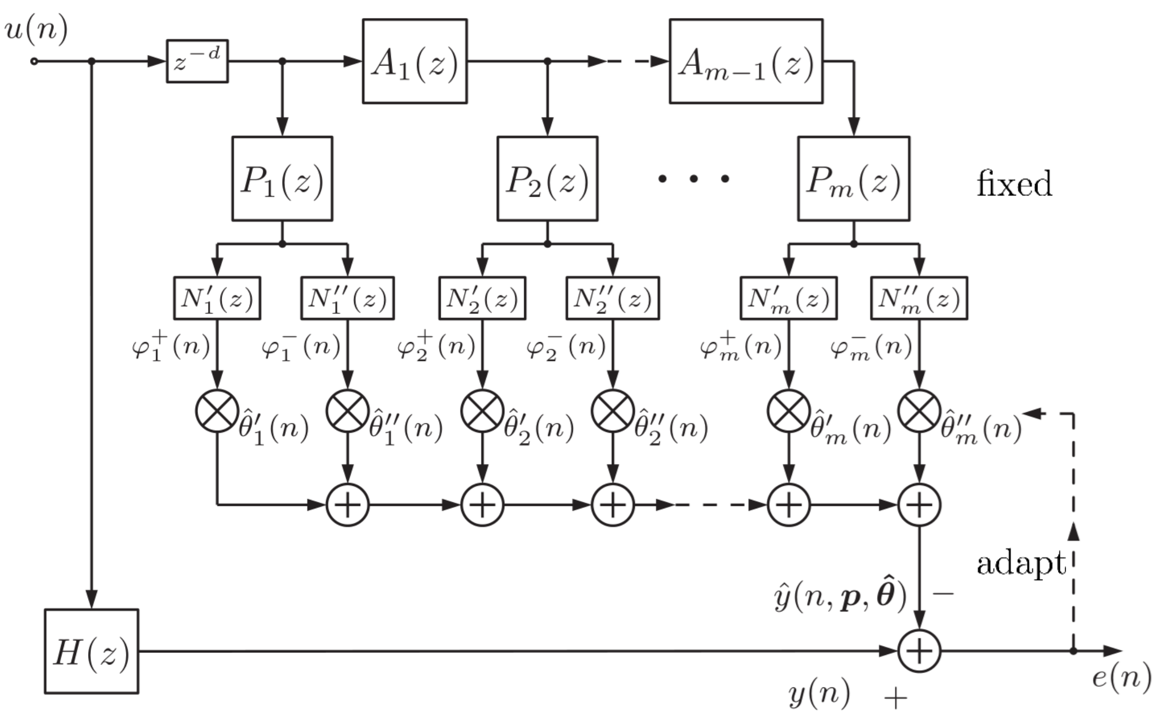
Adaptive OBF Filter



$$K_i^{\pm}(z,\boldsymbol{p}_i) = N_i^{\pm}(z)P_i(z)\prod_{j=1}^{i-1} A_j(z)$$

$$\varphi_i^{\pm}(n) = K_i^{\pm}(z,\boldsymbol{p}_i)u(n)$$

$$e(n) = y(n) - \hat{y}(n)$$

$y(n)$: output signal

$$\hat{y}(n) = \boldsymbol{\varphi}^T(n)\hat{\boldsymbol{\theta}}(n)$$

$$\boldsymbol{\varphi}(n) = [\boldsymbol{\varphi}_1^{\pm}(n), \ldots, \boldsymbol{\varphi}_m^{\pm}(n)]^T$$

$$\hat{\boldsymbol{\theta}}(n) = [\hat{\boldsymbol{\theta}}_1^{\pm}(n), \ldots, \hat{\boldsymbol{\theta}}_m^{\pm}(n)]^T$$

Adaptation Rule

$$\hat{\boldsymbol{\theta}}(n+1) = \hat{\boldsymbol{\theta}}(n) + \boldsymbol{L}(n)e(n)$$

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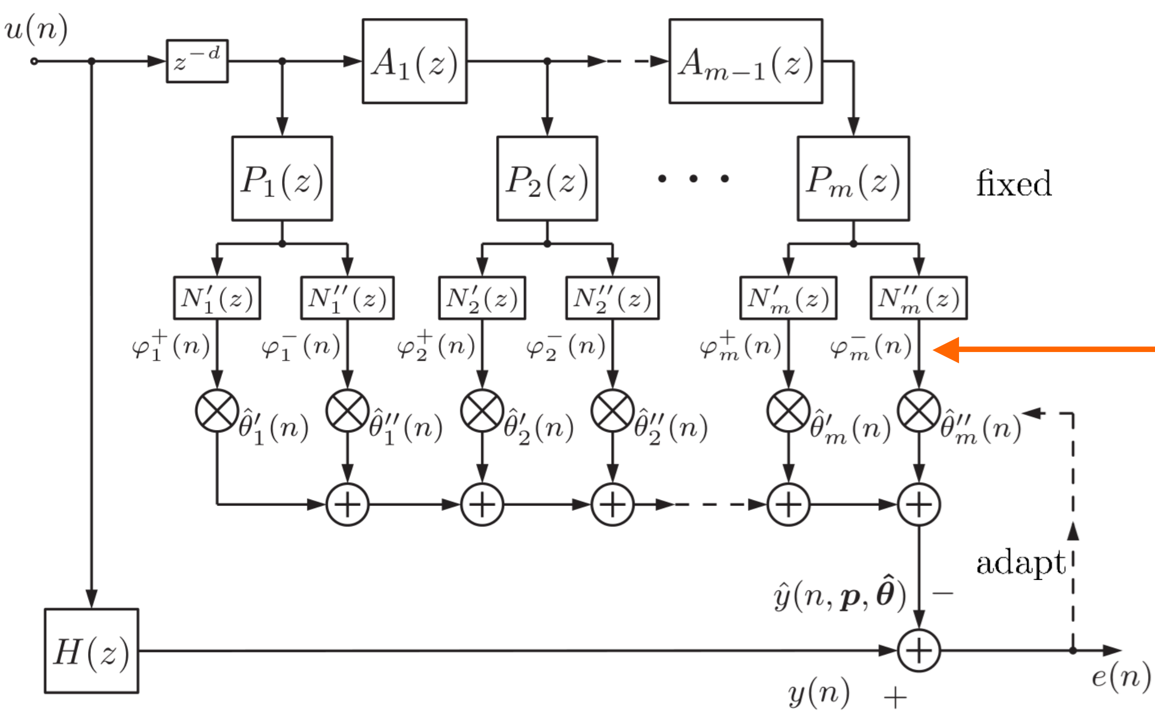
Adaptive OBF Filter - LMS



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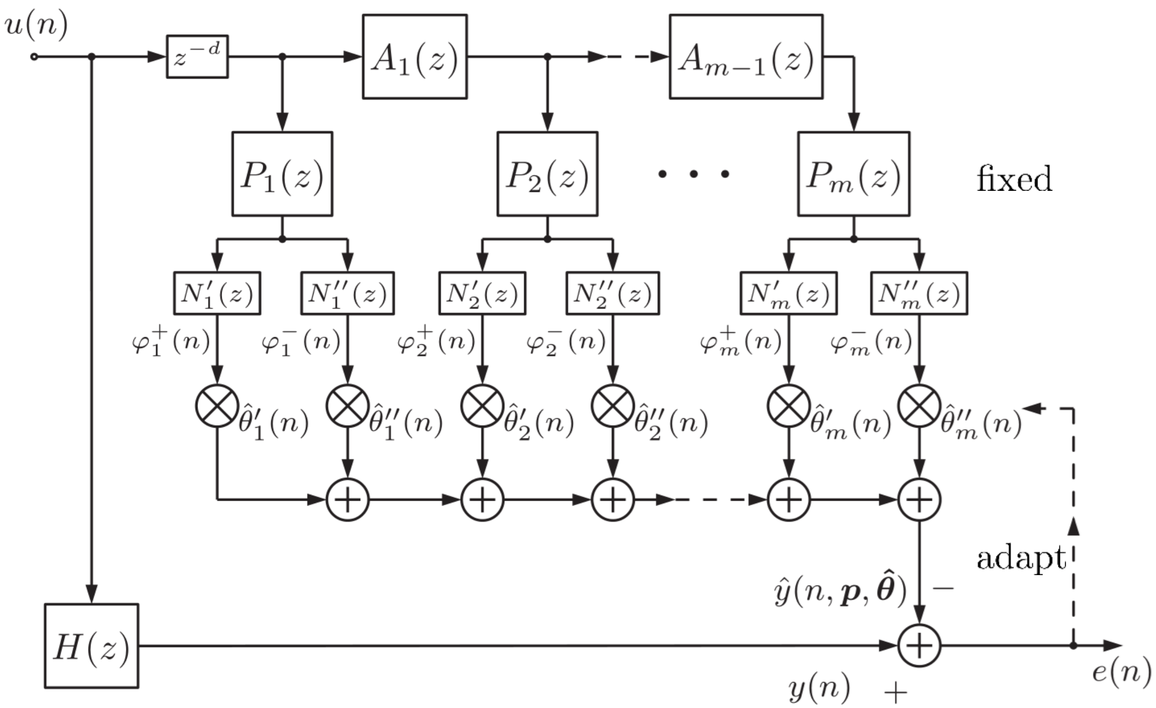
$$\boldsymbol{\varphi}(n) = [\boldsymbol{\varphi}_1^{\pm}(n), \ldots, \boldsymbol{\varphi}_m^{\pm}(n)]^T$$

Regression vector

Adaptation Rule - LMS

$$\hat{\boldsymbol{\theta}}(n+1) = \hat{\boldsymbol{\theta}}(n) + \mu\, \boldsymbol{\varphi}(n)\, e(n)$$

Adaptive OBF Filter - LMS



$$\boldsymbol{\varphi}(n) = [\boldsymbol{\varphi}_1^{\pm}(n), \ldots, \boldsymbol{\varphi}_m^{\pm}(n)]^T$$

$$\boldsymbol{R} = E\{\boldsymbol{\varphi}(n)\boldsymbol{\varphi}^T(n)\}$$

Convergence rate in the mean
no faster than

$$\left(1 - \frac{\lambda_{\min}}{\lambda_{\max}}\right)^n = \left(1 - \frac{1}{C(\boldsymbol{R})}\right)^n$$

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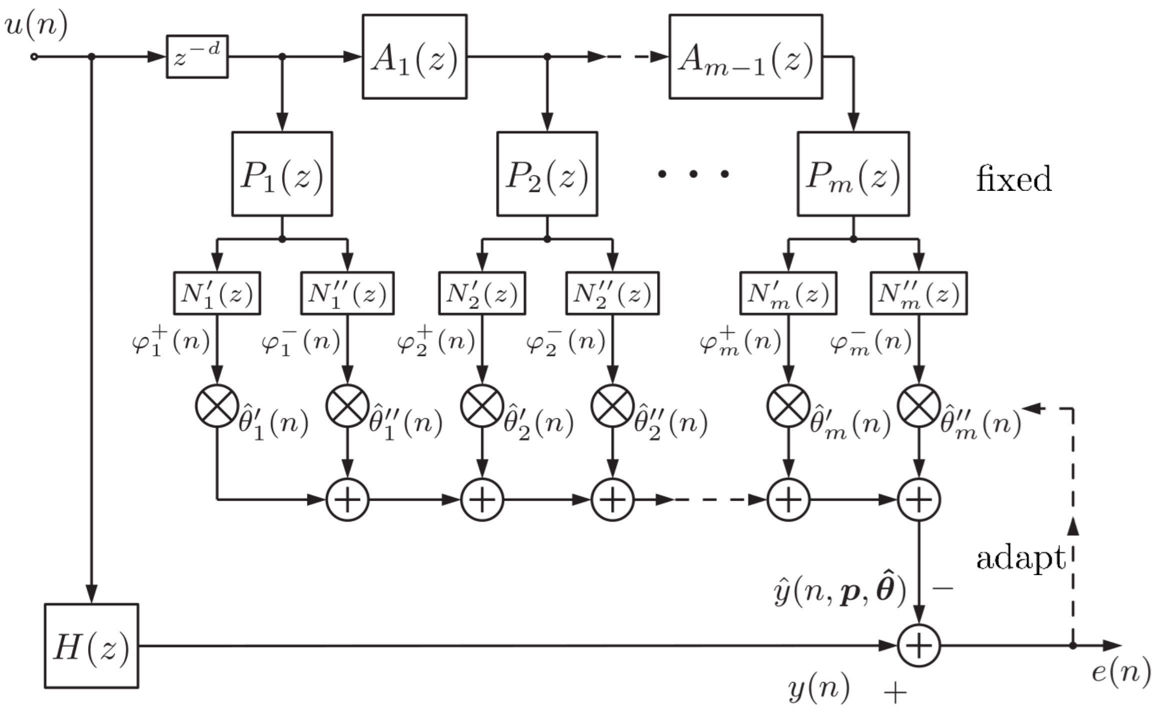

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$$\left(1 - \frac{\lambda_{\min}}{\lambda_{\max}}\right)^n = \left(1 - \frac{1}{C(\boldsymbol{R})}\right)^n$$

For white input signal $\Phi_u(\omega) = c$

$$\boldsymbol{R} = c\,\boldsymbol{I}, \;\; C(\boldsymbol{R}) = 1$$

For nonwhite input signal *

$$C(\boldsymbol{R}) \approx \frac{\max_\omega \Phi_u(\omega)}{\min_\omega \Phi_u(\omega)}$$

Adaptation Rule - LMS

$$\hat{\boldsymbol{\theta}}(n+1) = \hat{\boldsymbol{\theta}}(n) + \mu\,\boldsymbol{\varphi}(n)\,e(n)$$

B. Ninness and H. Hjalmarsson. Model structure and numerical properties of normal equations. IEEE Trans. Circuits Syst.I, Fundam. Theory Appl., 48(4):425–437, 2001.

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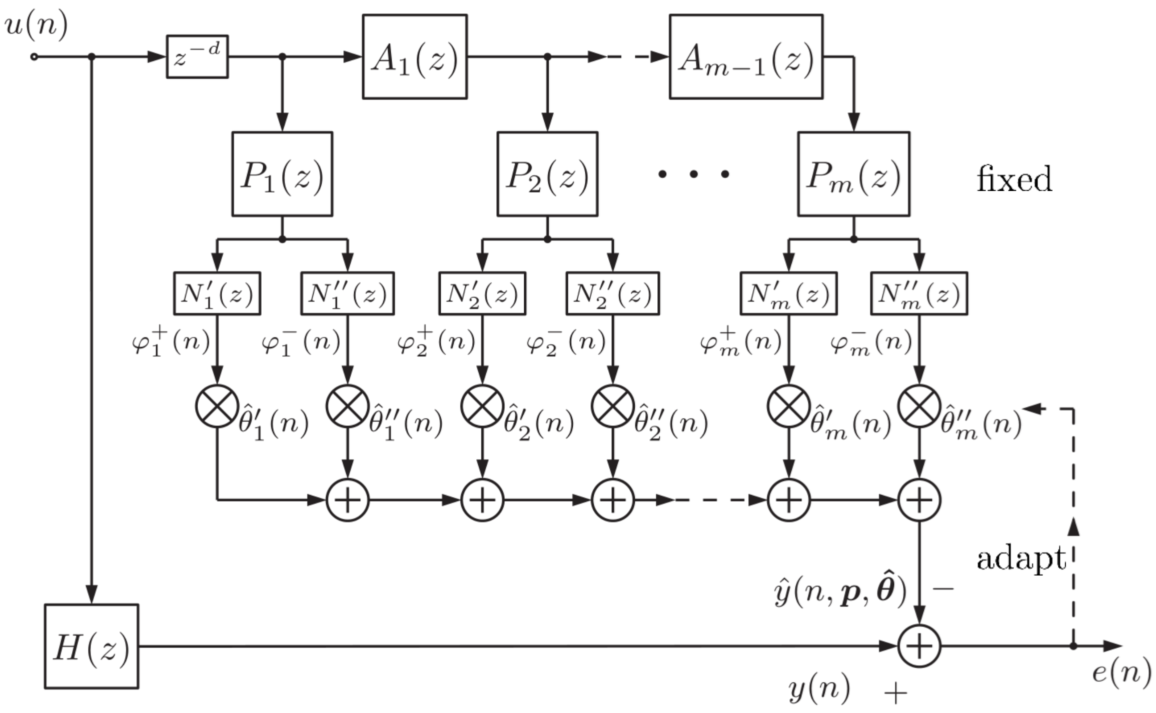
Adaptive OBF Filter - LMS



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Performance depends on the choice of the fixed pole parameters

B. Ninness and H. Hjalmarsson. *Model structure and numerical properties of normal equations*. IEEE Trans. Circuits Syst.I, Fundam. Theory Appl., 48(4):425–437, 2001.

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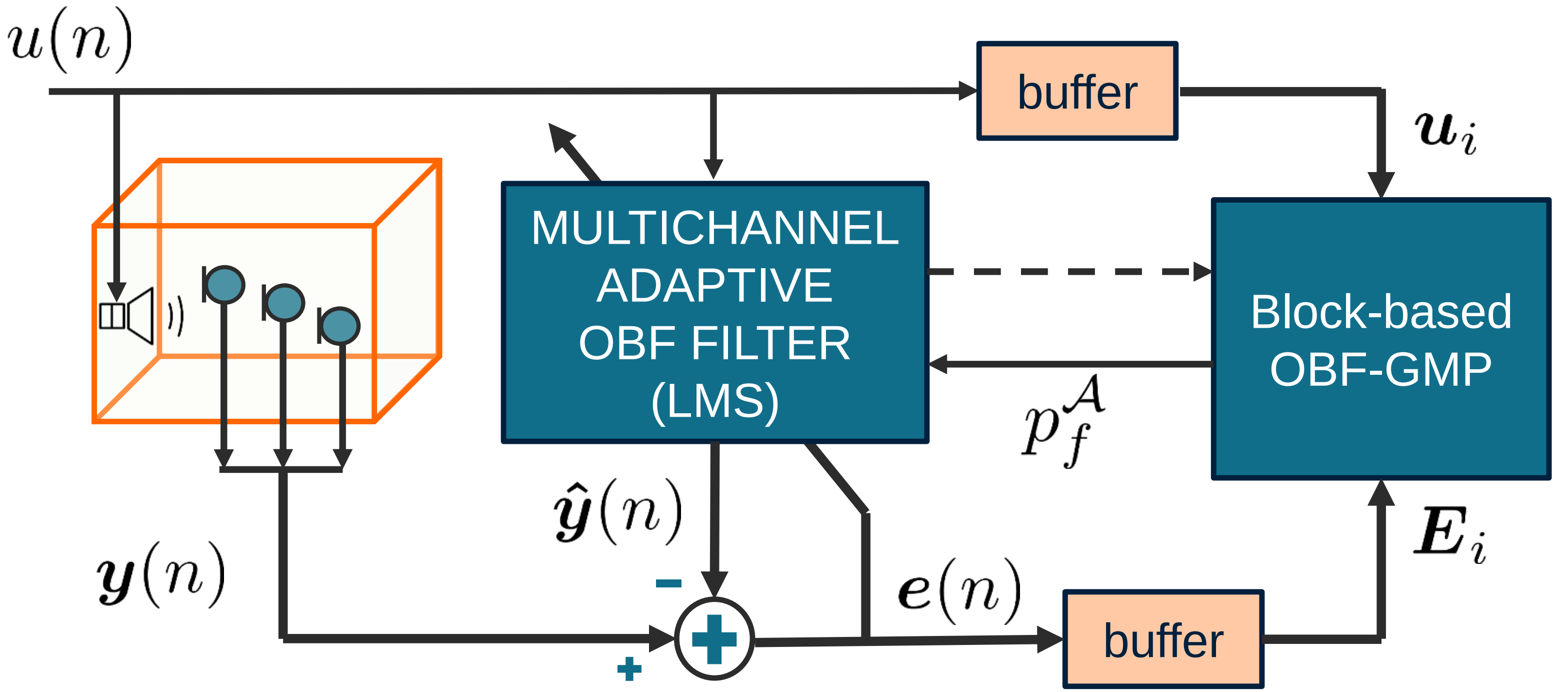
Multichannel identification algorithm

Multi-channel pole estimation (SIMO)

- Estimate the fixed poles of an **adaptive** OBF filter from **multi-channel I/O data**



Multichannel identification algorithm

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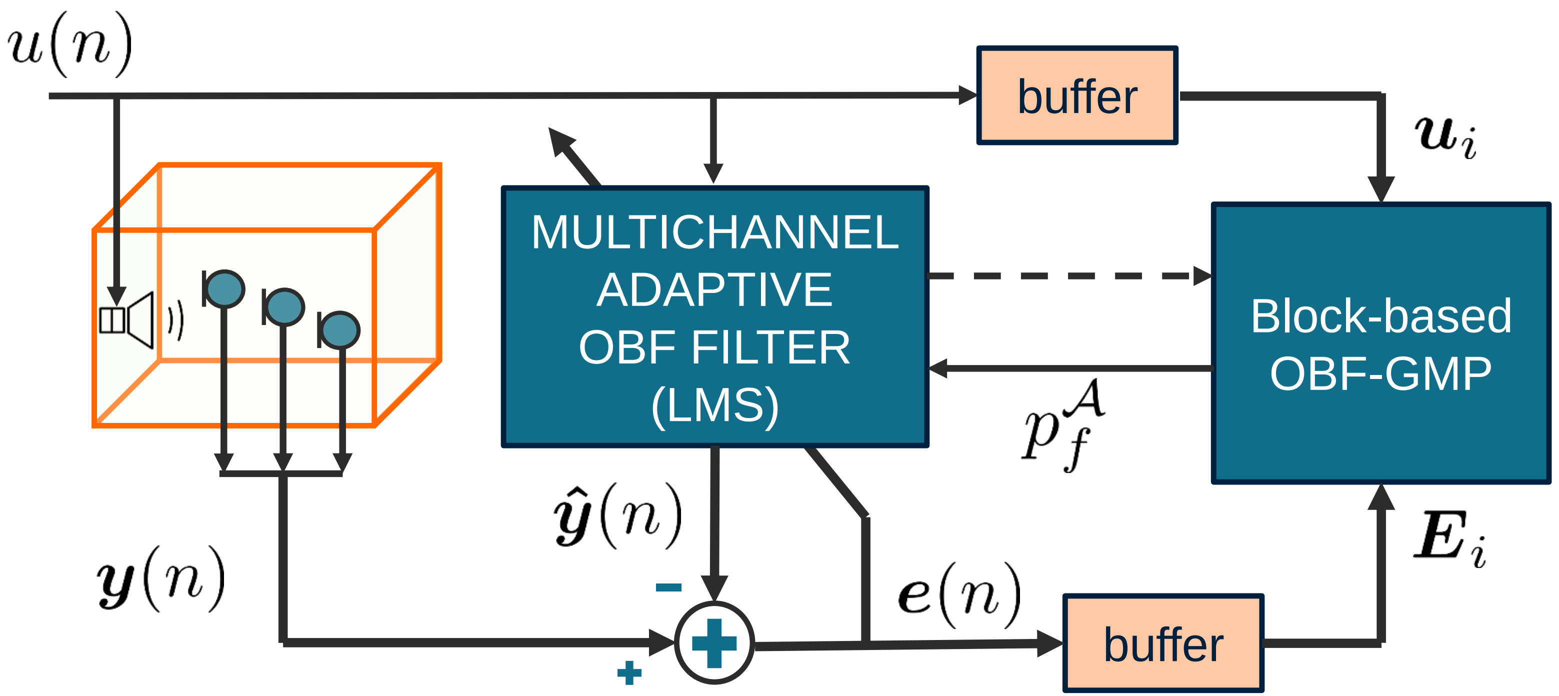
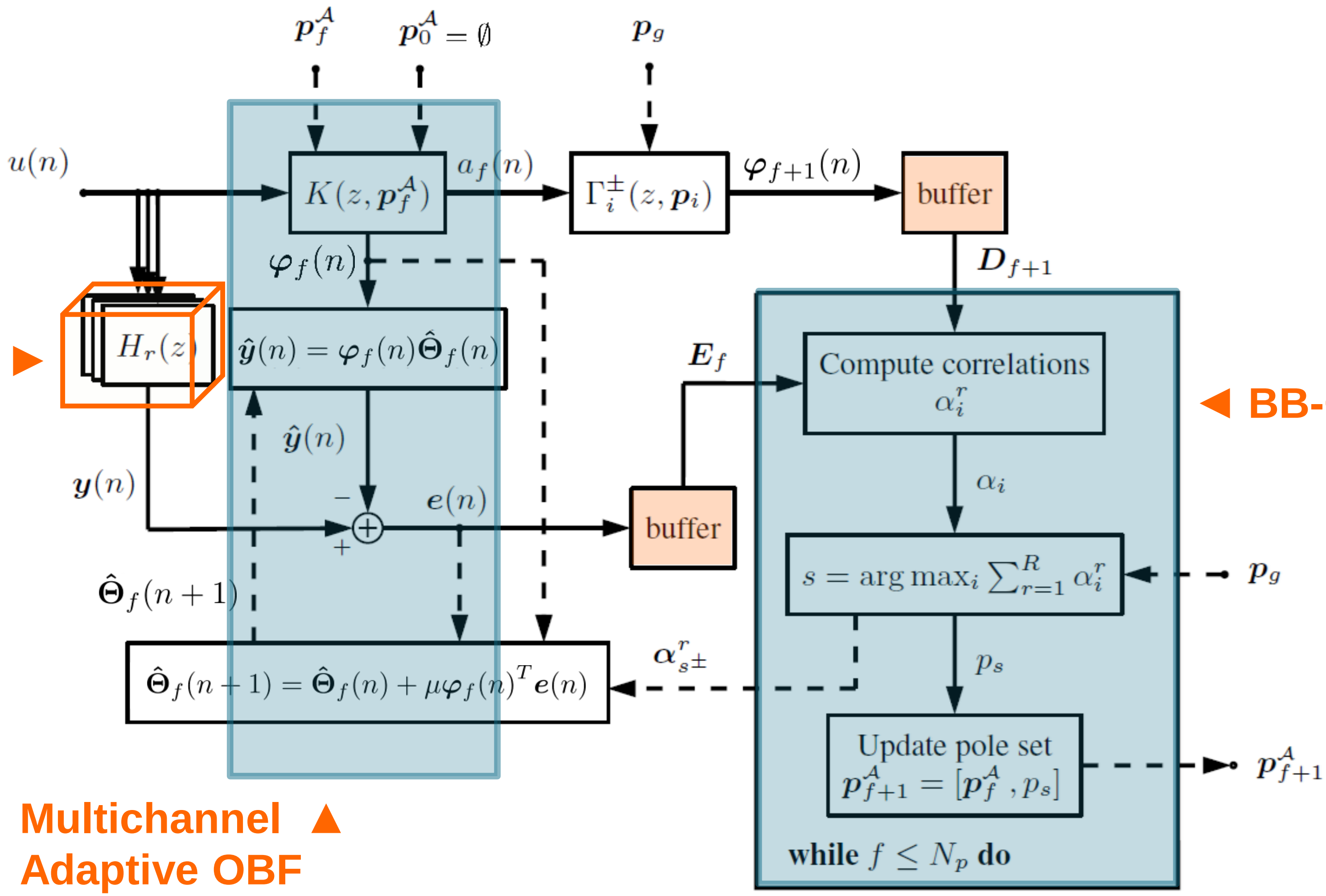


$$\underset{\boldsymbol{p}_f^{\mathcal{A}},\hat{\boldsymbol{\Theta}}(n)}{\text{minimize}}\ \boldsymbol{e}^2(n) = (\boldsymbol{y}(n) - \hat{\boldsymbol{y}}(n))^2 = \left(\boldsymbol{y}(n) - \boldsymbol{\varphi}^T(\boldsymbol{p}_f^{\mathcal{A}}, n)\hat{\boldsymbol{\Theta}}(n)\right)^2$$

Multichannel identification algorithm



RTFs ▶

◀ BB-OBF-GMP

Multichannel ▲
Adaptive OBF
Filter (LMS)

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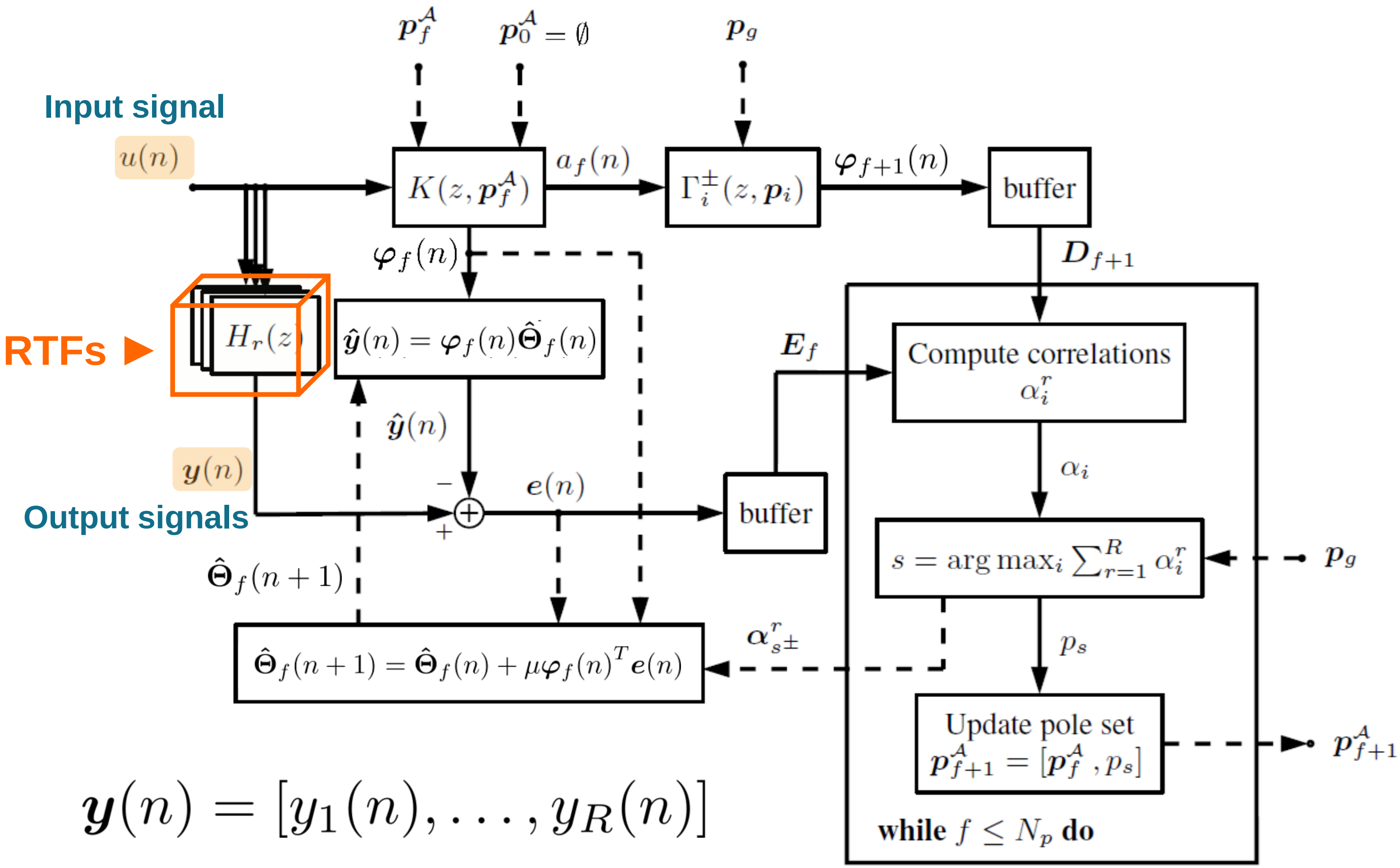
Multichannel identification algorithm



$$\boldsymbol{y}(n) = [y_1(n), \ldots, y_R(n)]$$

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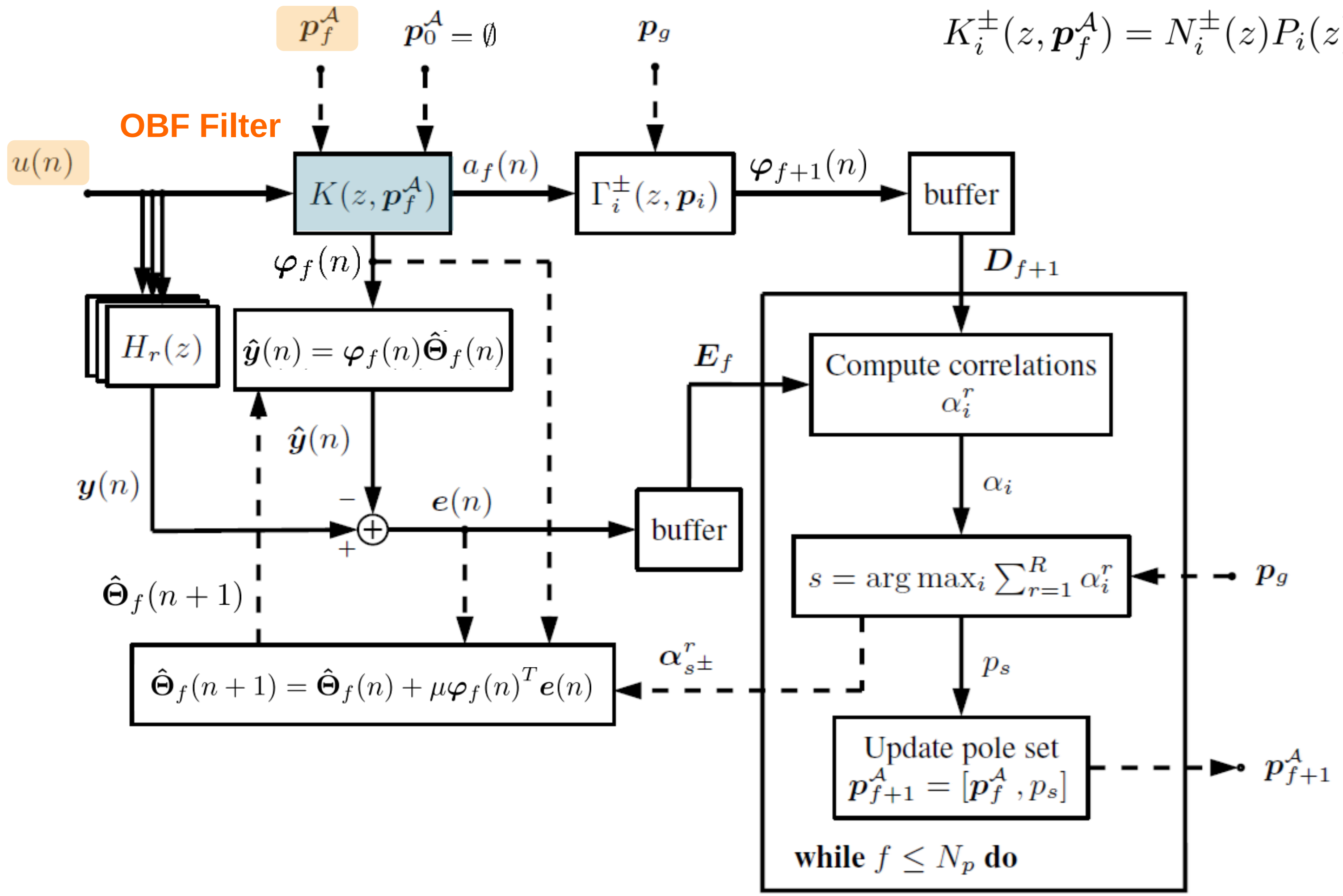
Multichannel identification algorithm

$$K_i^{\pm}(z, \boldsymbol{p}_f^{\mathcal{A}}) = N_i^{\pm}(z) P_i(z) \prod_{j=1}^{i-1} A_j(z)$$



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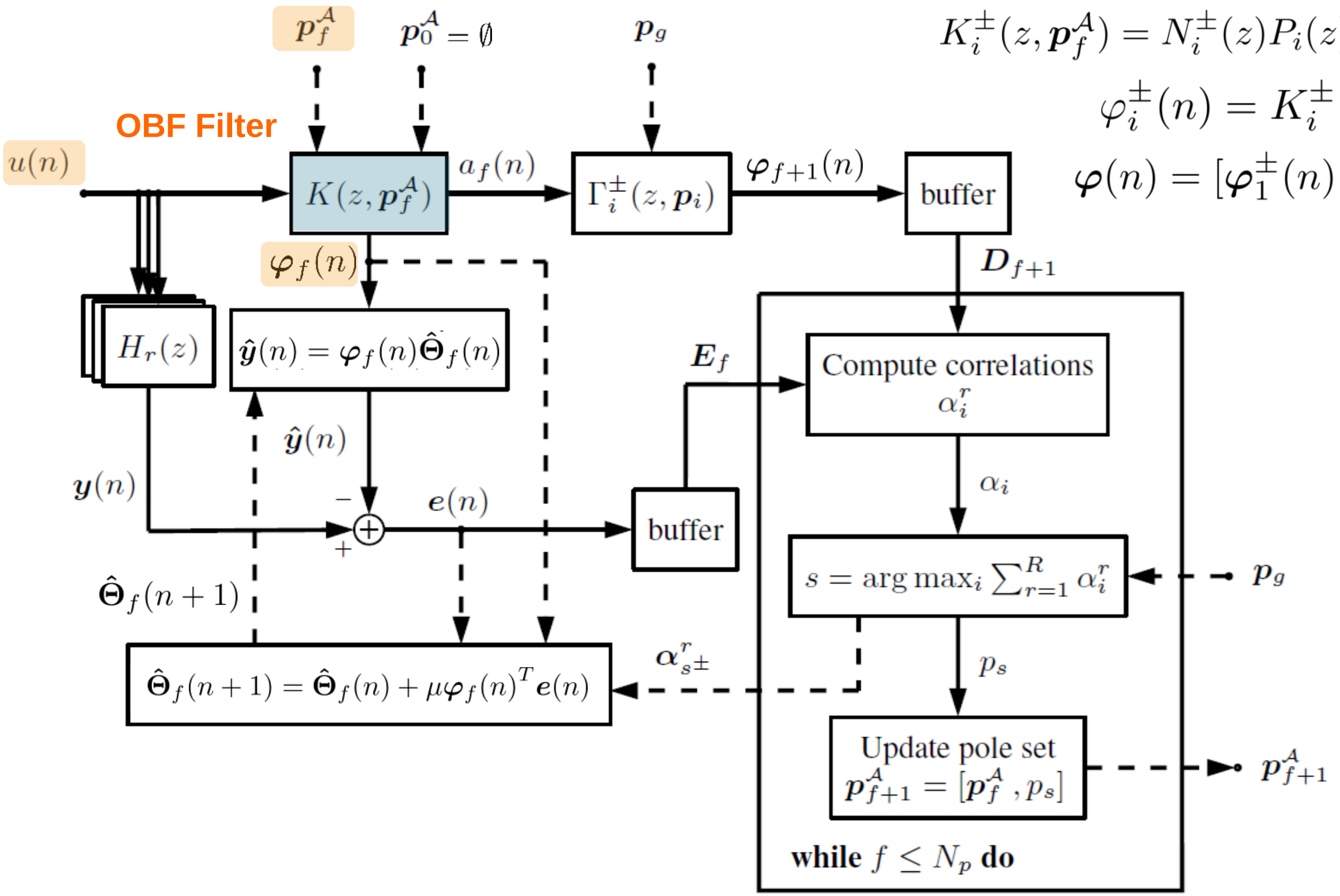

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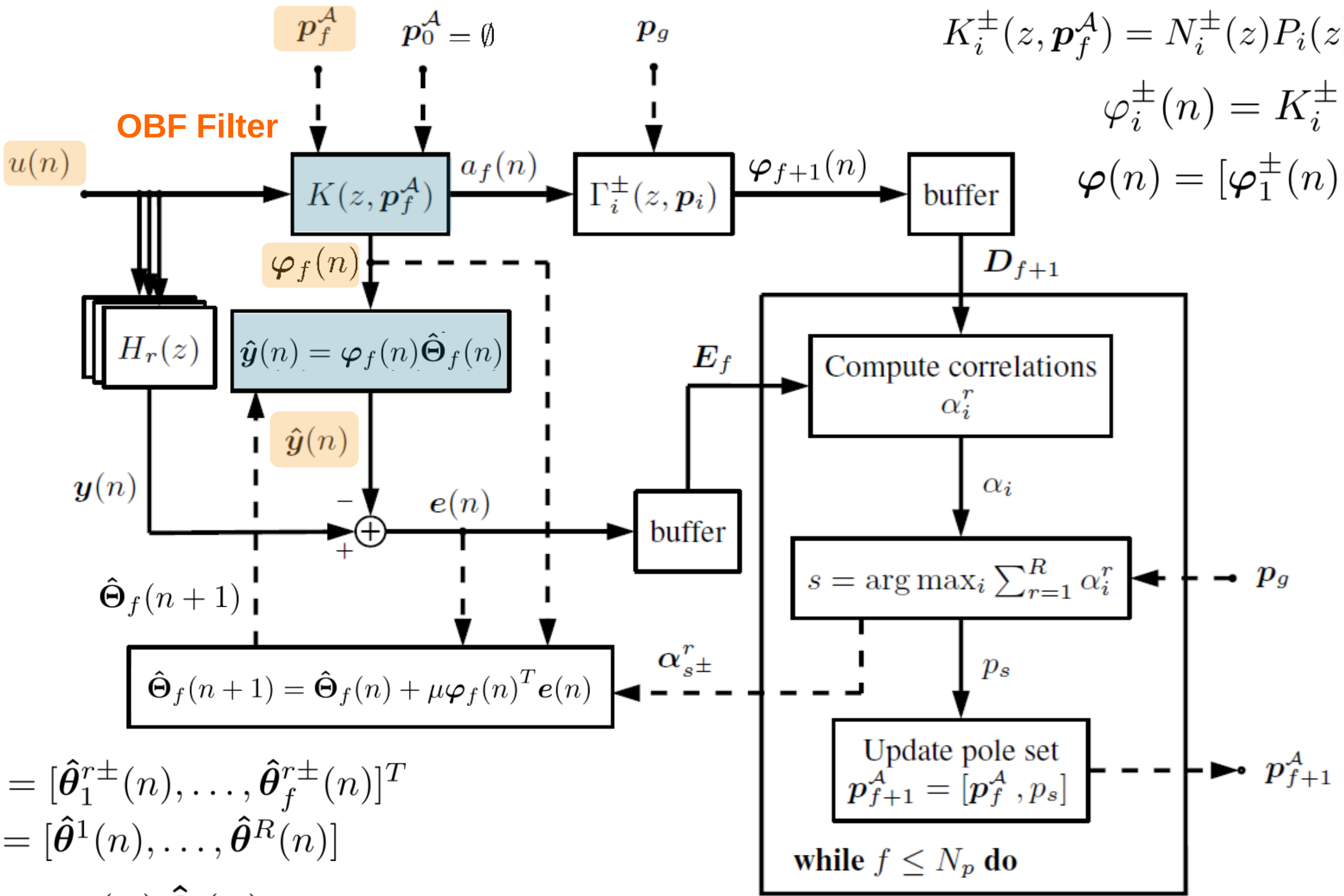

$$\hat{\boldsymbol{\theta}}^r(n) = [\hat{\boldsymbol{\theta}}_1^{r\pm}(n), \ldots, \hat{\boldsymbol{\theta}}_f^{r\pm}(n)]^T$$

$$\hat{\boldsymbol{\Theta}}(n) = [\hat{\boldsymbol{\theta}}^1(n), \ldots, \hat{\boldsymbol{\theta}}^R(n)]$$

$$\hat{\boldsymbol{y}}(n) = \boldsymbol{\varphi}(n) \hat{\boldsymbol{\Theta}}(n)$$

Filter outputs

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Multichannel identification algorithm

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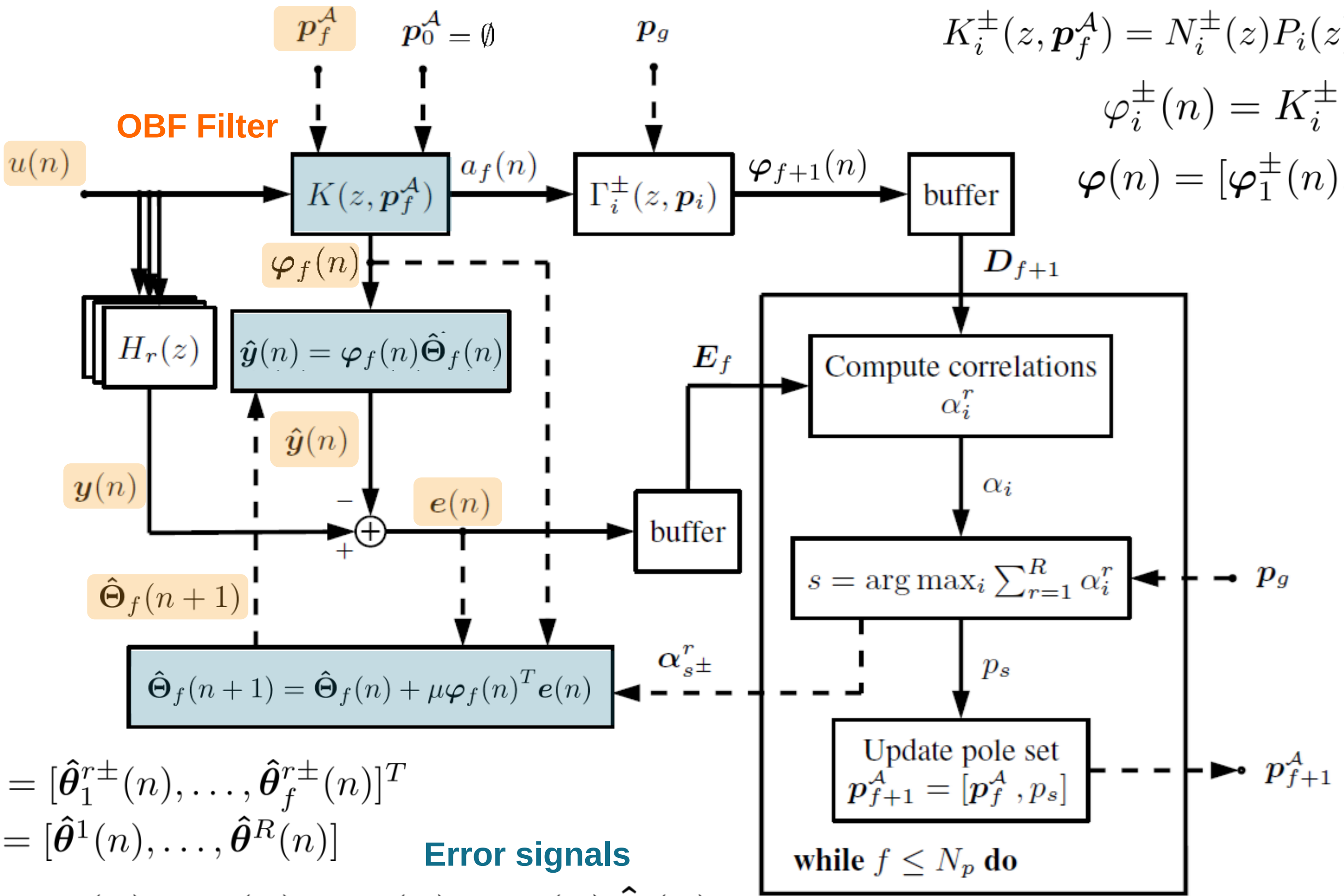

$$\hat{\boldsymbol{\theta}}^r(n) = [\hat{\boldsymbol{\theta}}_1^{r\pm}(n), \ldots, \hat{\boldsymbol{\theta}}_f^{r\pm}(n)]^T$$

$$\hat{\boldsymbol{\Theta}}(n) = [\hat{\boldsymbol{\theta}}^1(n), \ldots, \hat{\boldsymbol{\theta}}^R(n)]$$

$$\boldsymbol{e}(n) = \boldsymbol{y}(n) - \hat{\boldsymbol{y}}(n) = \boldsymbol{y}(n) - \boldsymbol{\varphi}(n)\hat{\boldsymbol{\Theta}}(n)$$

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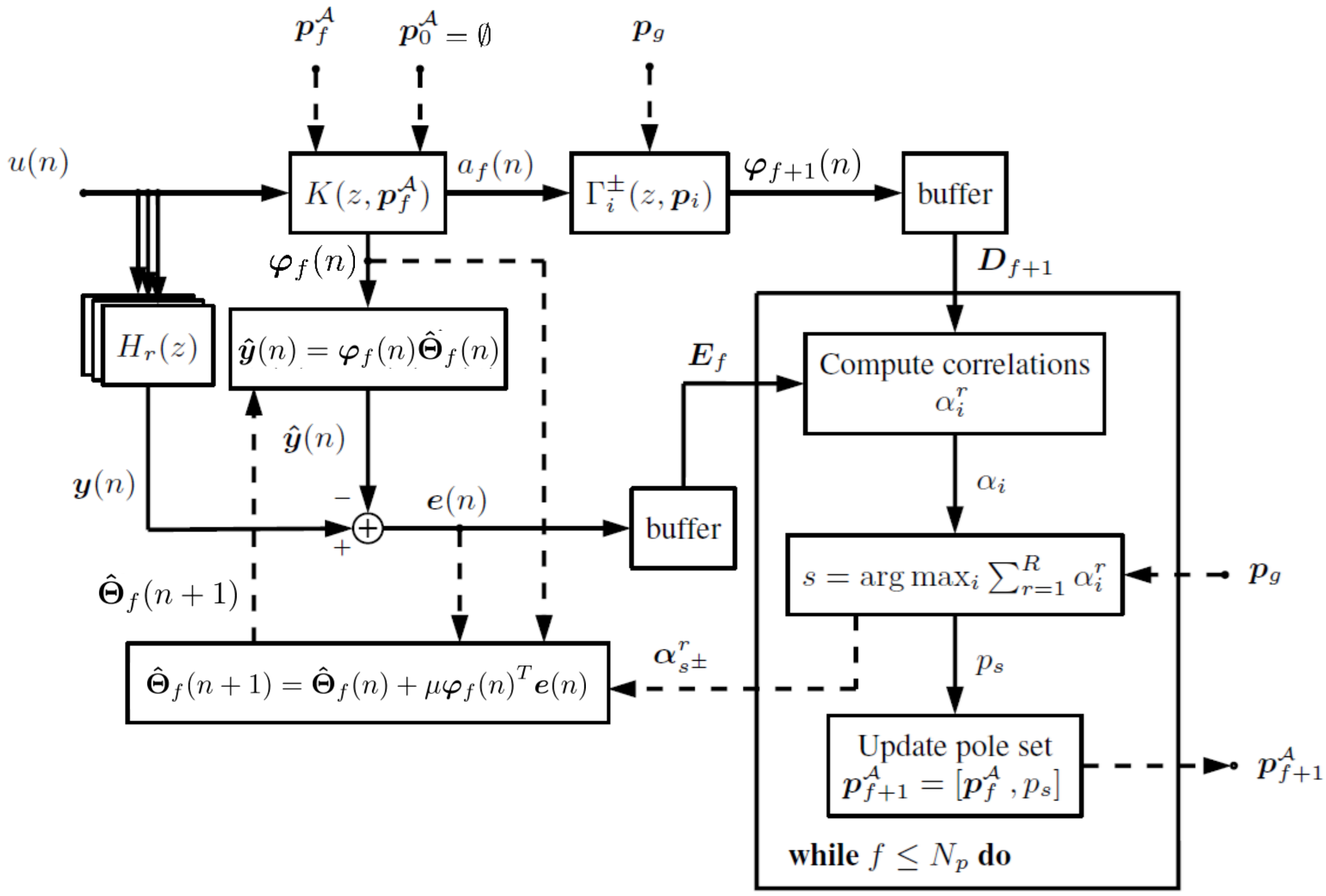
Multichannel identification algorithm



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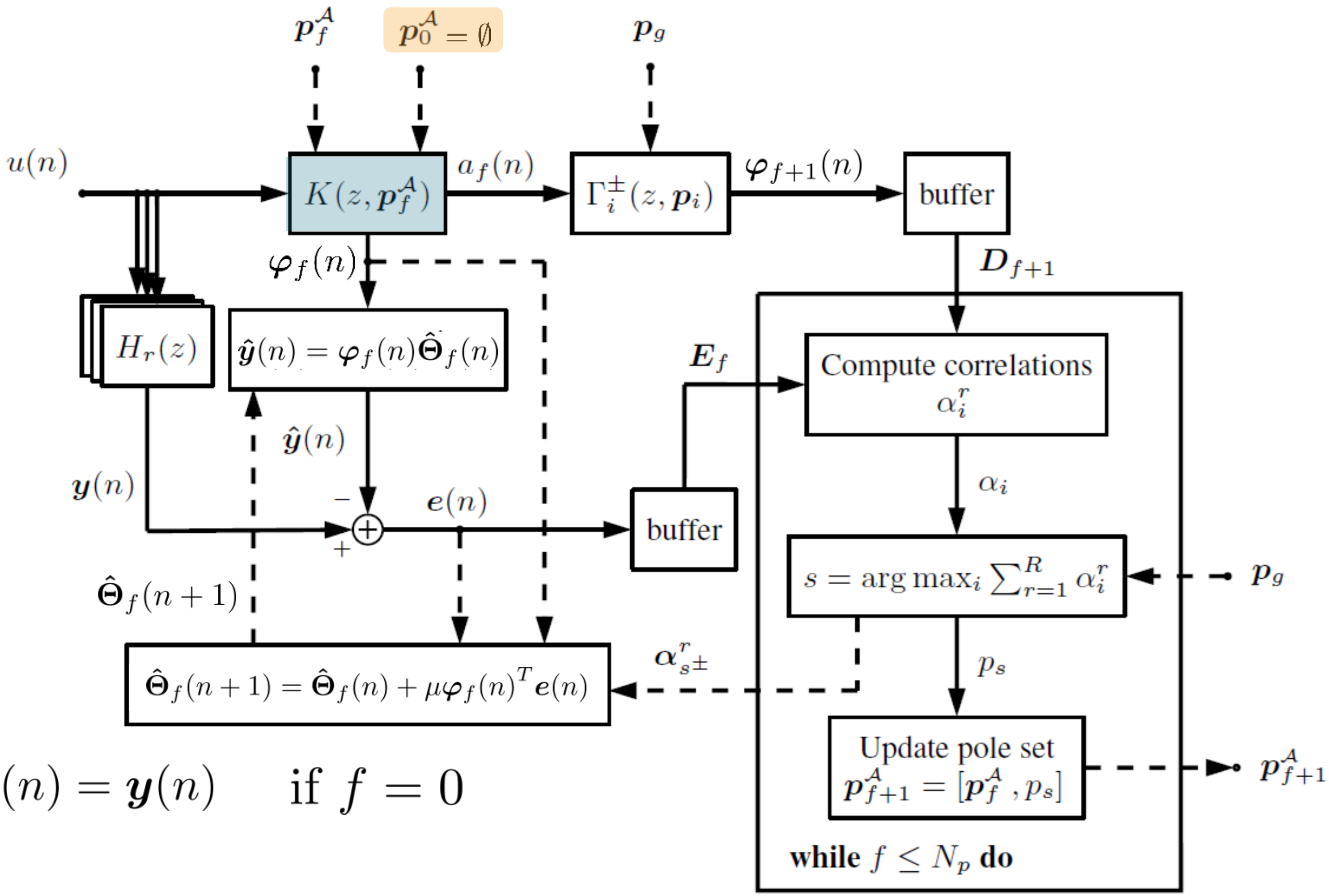
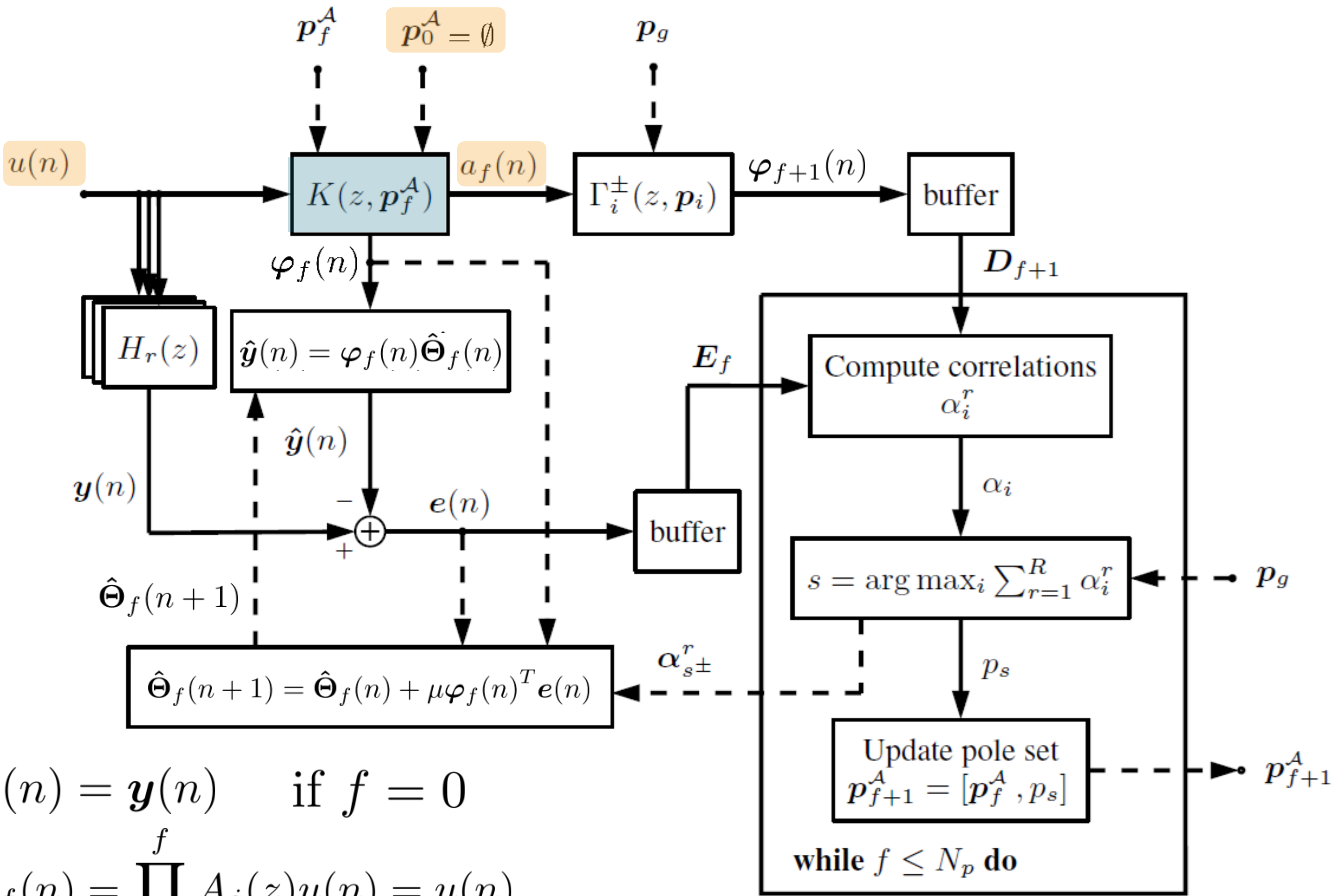
Multichannel identification algorithm



$$e(n) = y(n) \quad \text{if } f = 0$$

BB-OBF-MP

Multichannel identification algorithm



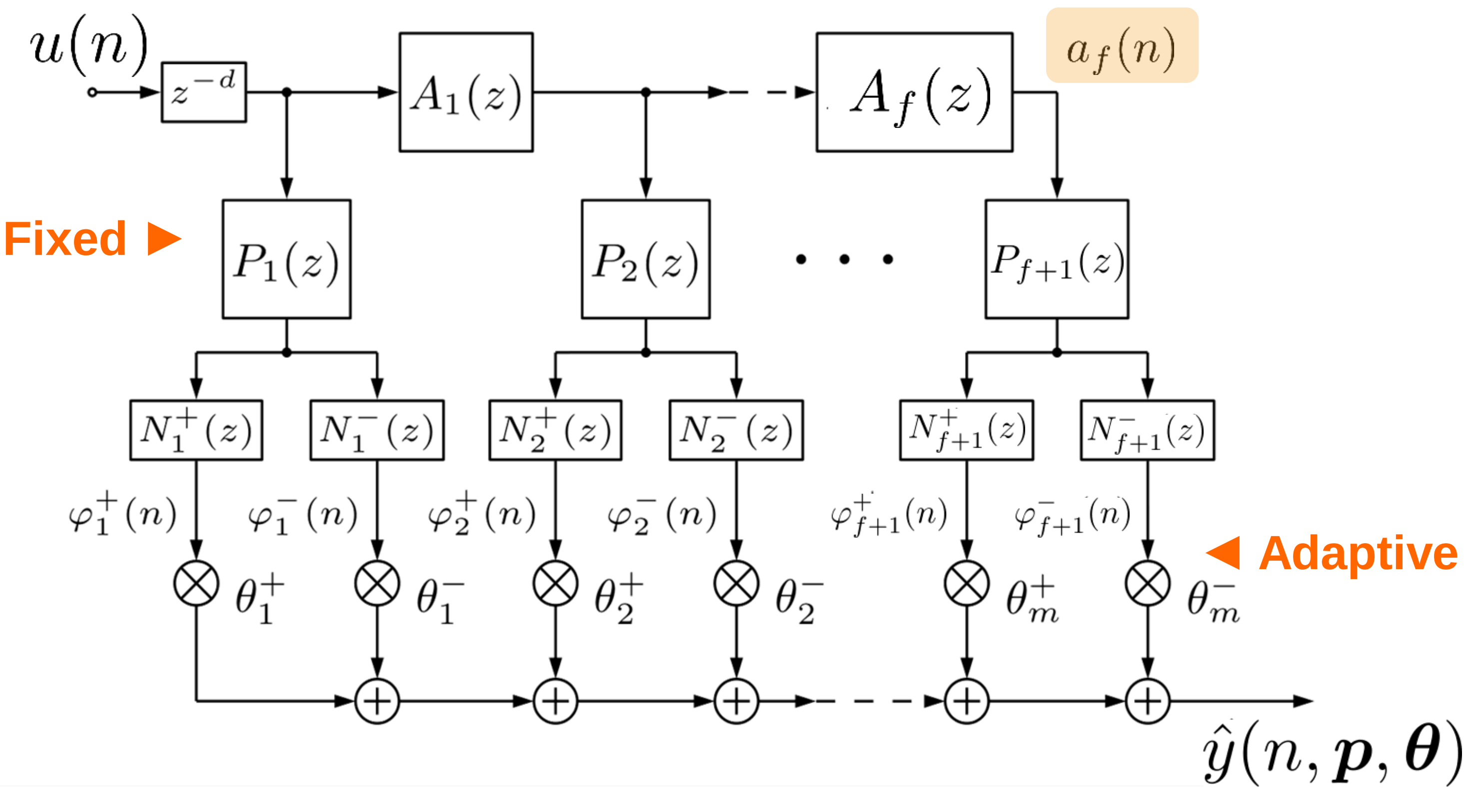
$$e(n) = y(n) \quad \text{if } f = 0$$

$$a_f(n) = \prod_{j=1}^{f} A_j(z)u(n) = u(n)$$

BB-OBF-MP

KU LEUVEN

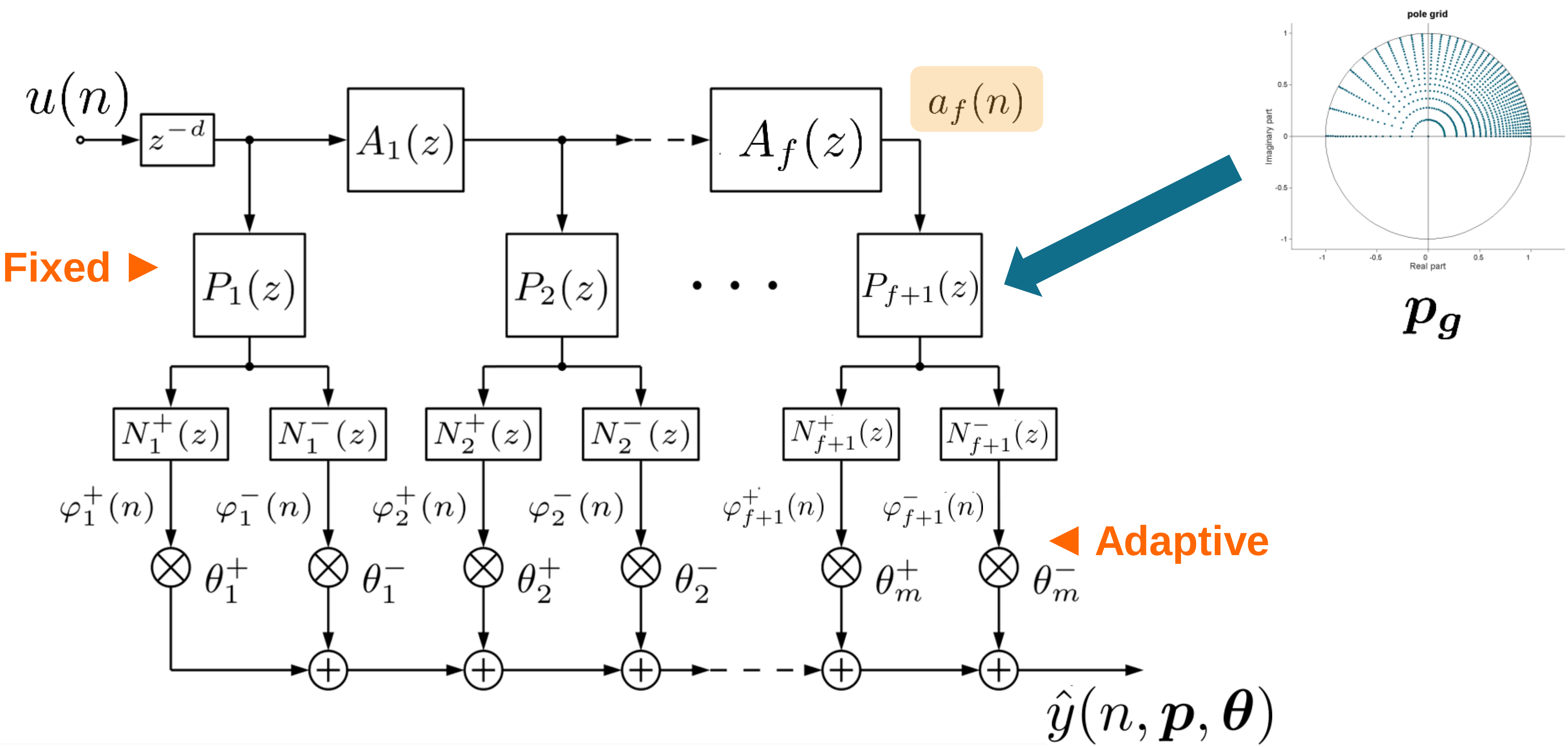
OBF filters (Kautz filters)



$$a_f(n) = \prod_{j=1}^{f} A_j(z) u(n)$$

KU LEUVEN

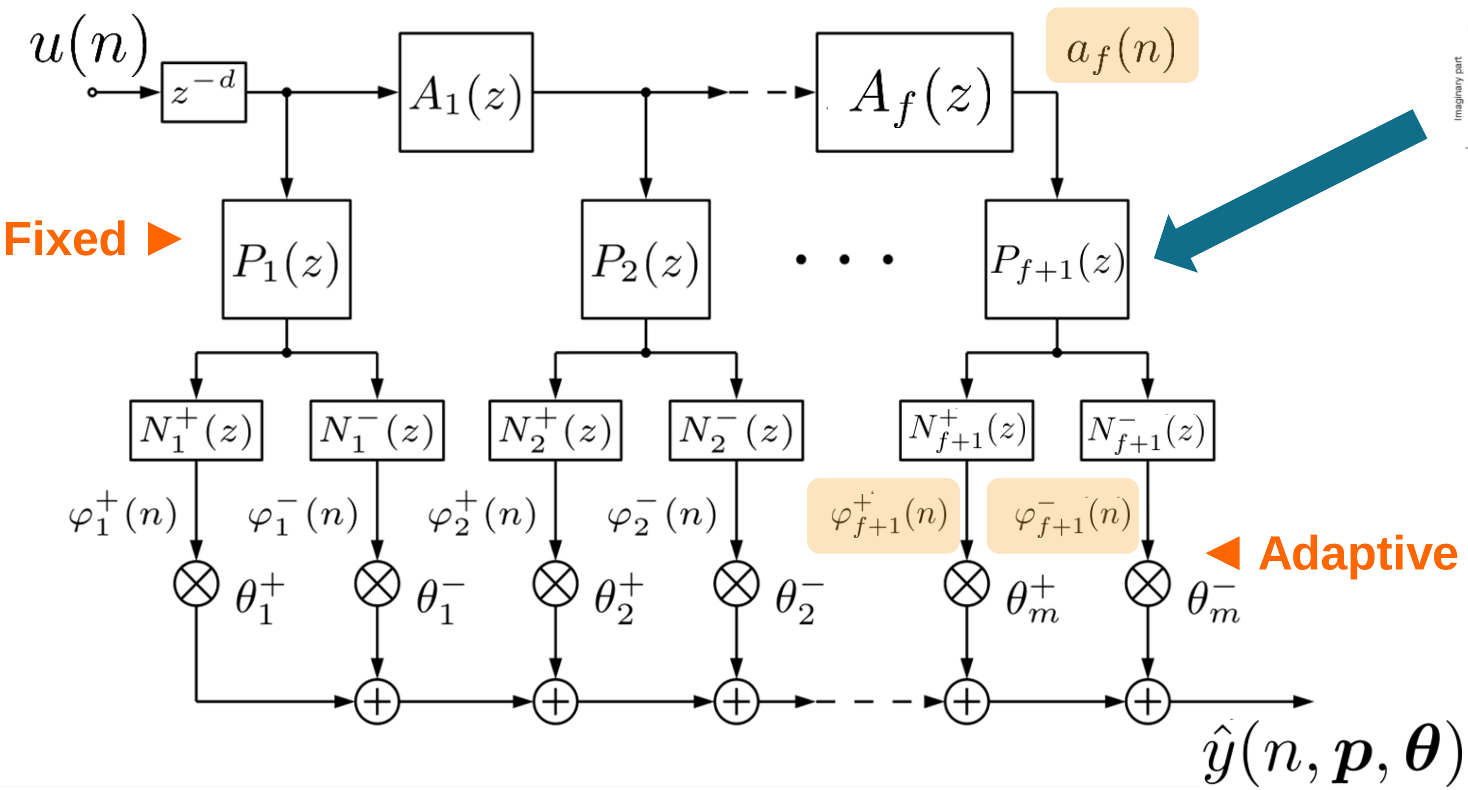
OBF filters (Kautz filters)

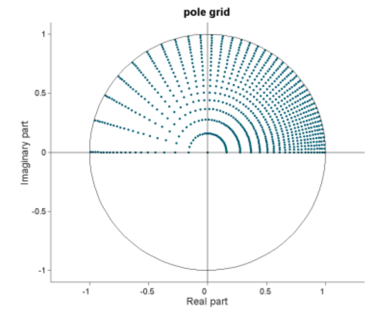


$$a_f(n) = \prod_{j=1}^{f} A_j(z)u(n)$$

KU LEUVEN

OBF filters (Kautz filters)



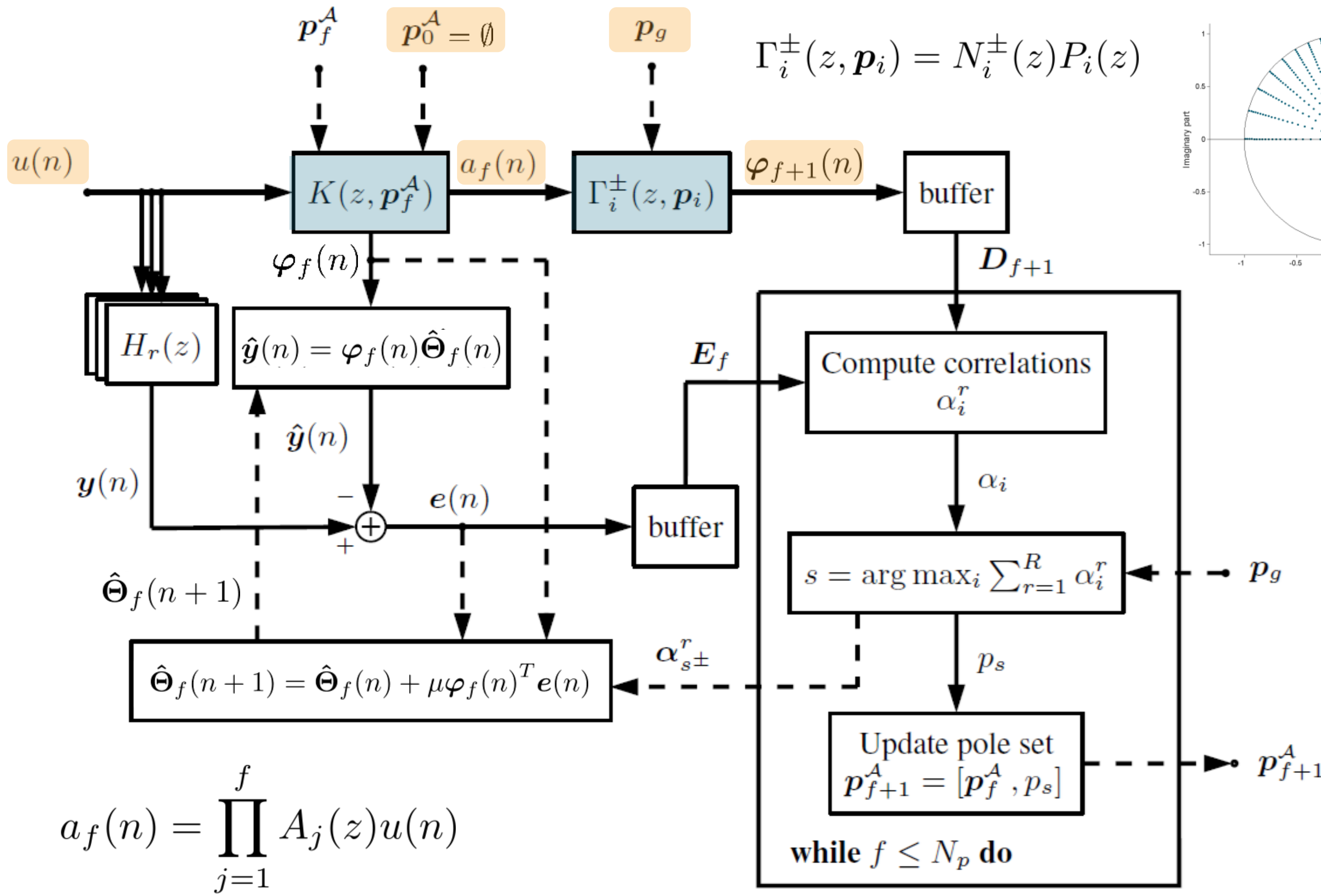


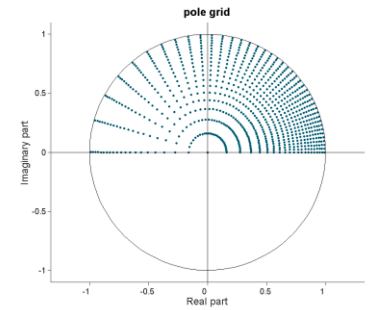
$\boldsymbol{p_g}$

$$a_f(n) = \prod_{j=1}^{f} A_j(z) u(n)$$

KU LEUVEN

Multichannel identification algorithm



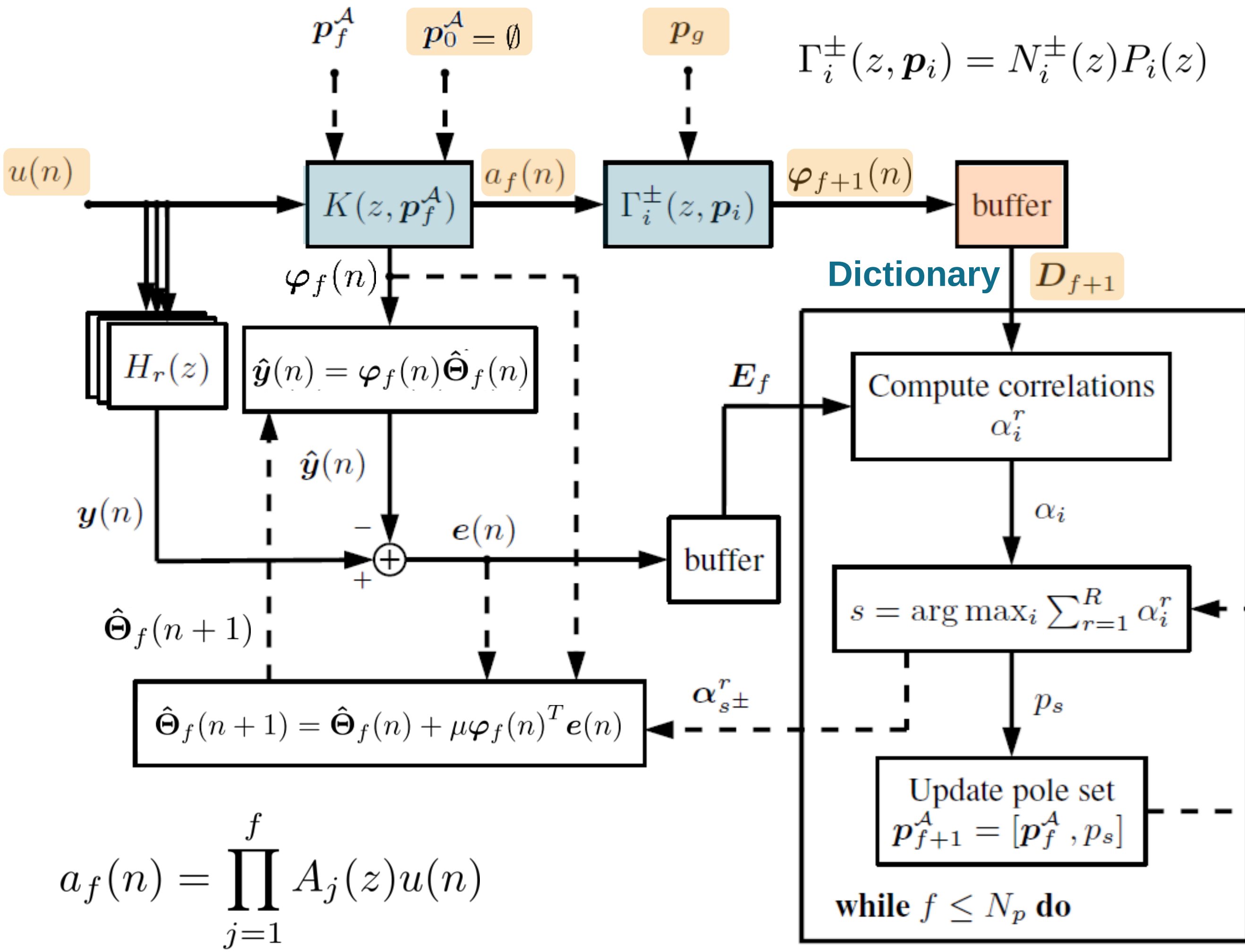


p_g

BB-OBF-MP

KU LEUVEN

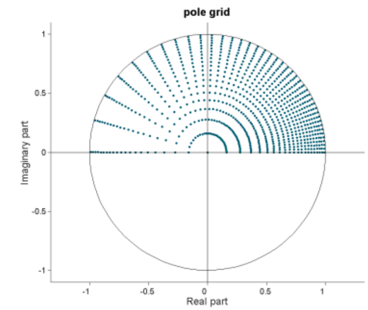
Multichannel identification algorithm



$$\Gamma_i^{\pm}(z, p_i) = N_i^{\pm}(z) P_i(z)$$

$$a_f(n) = \prod_{j=1}^{f} A_j(z) u(n)$$

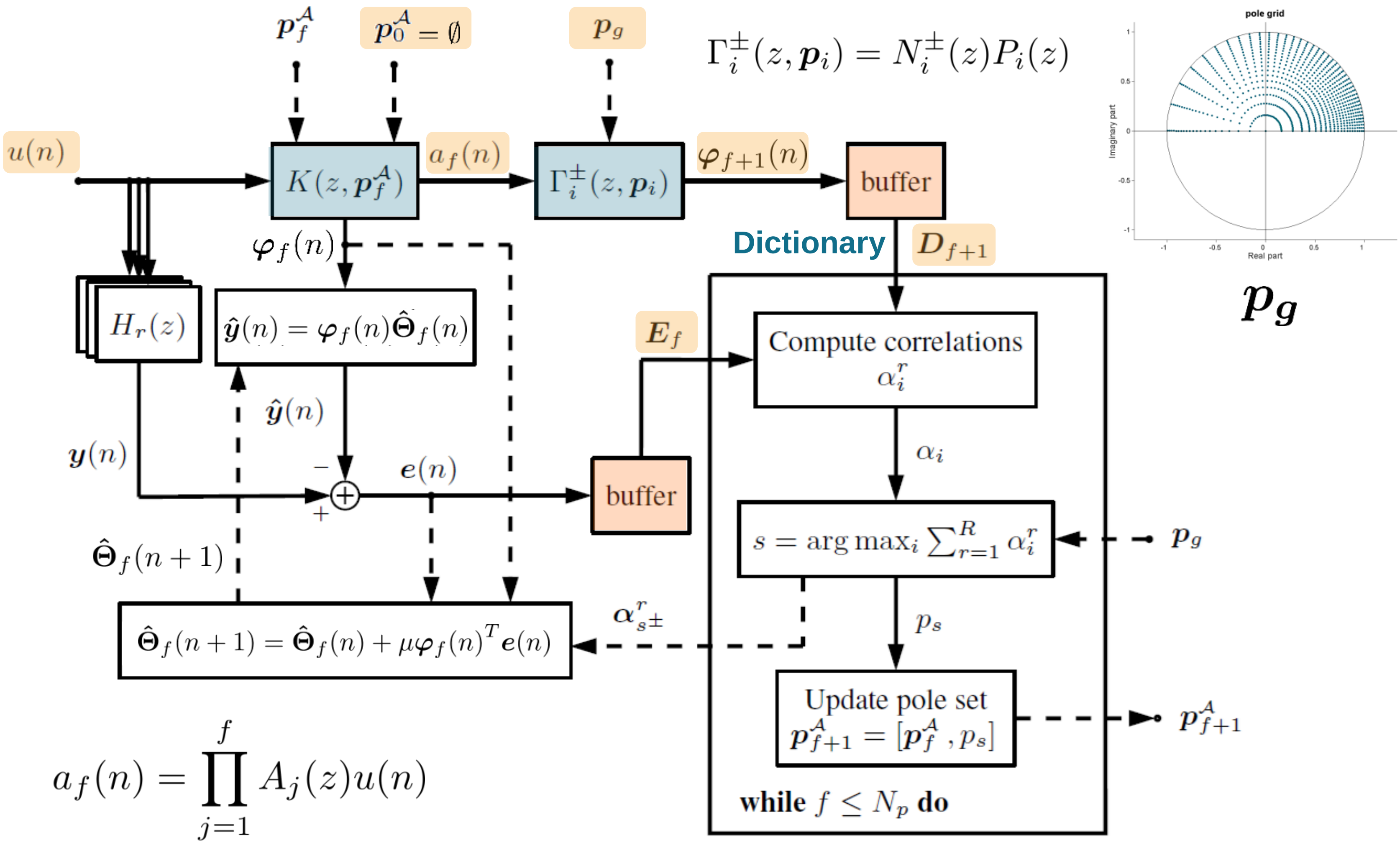
BB-OBF-MP



p_g

KU LEUVEN

Multichannel identification algorithm



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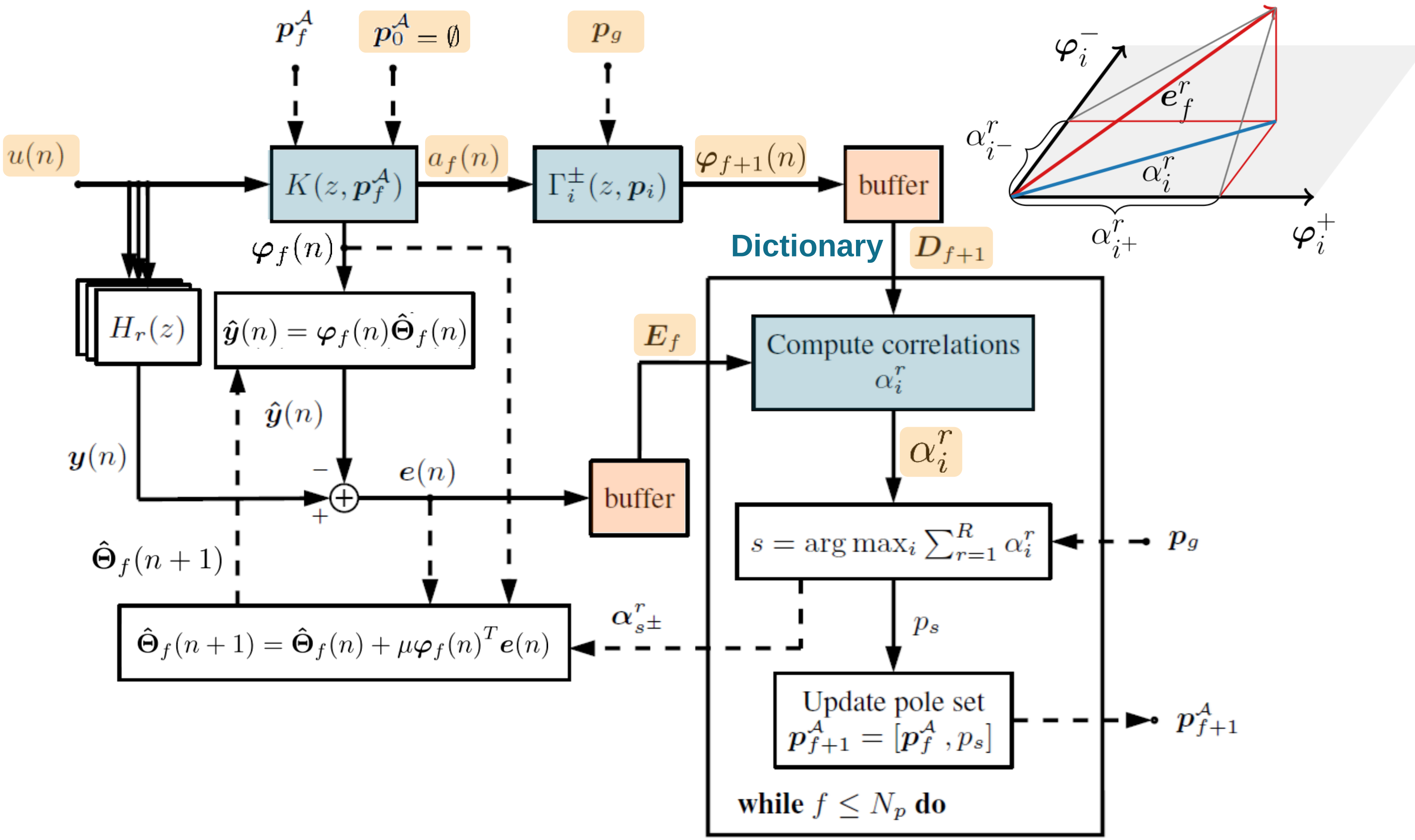
Multichannel identification algorithm



BB-OBF-MP

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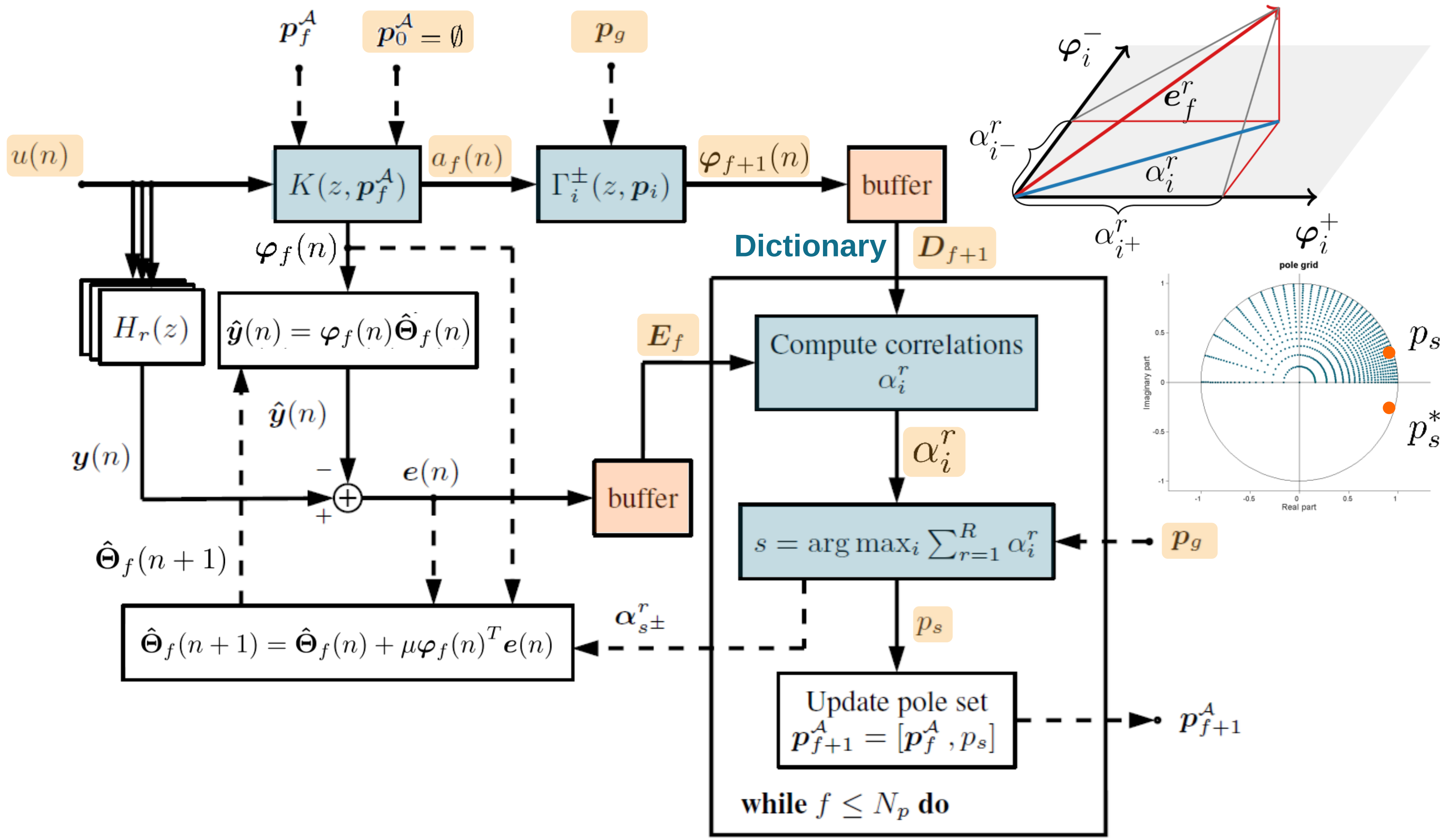
Multichannel identification algorithm



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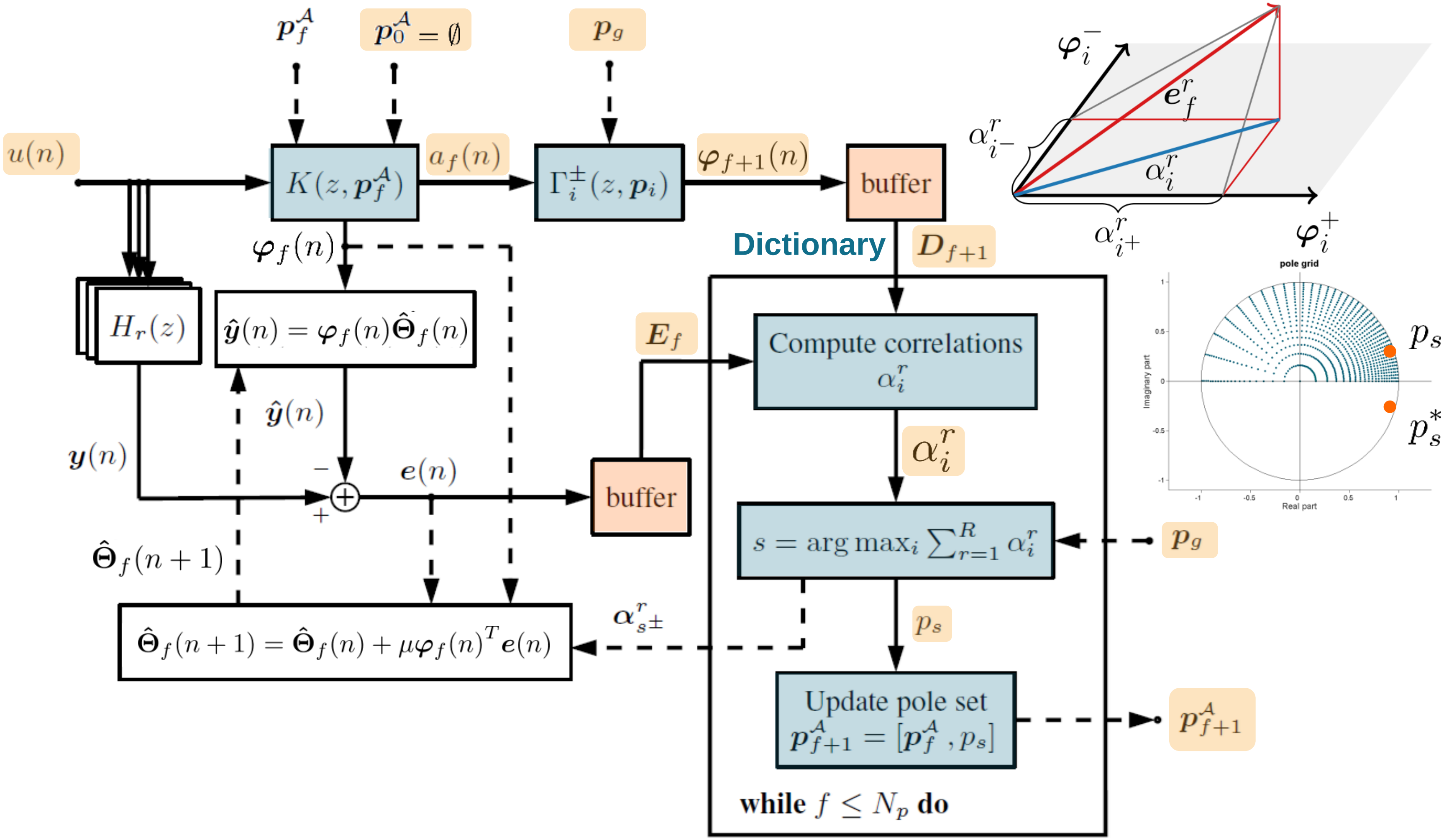
Multichannel identification algorithm



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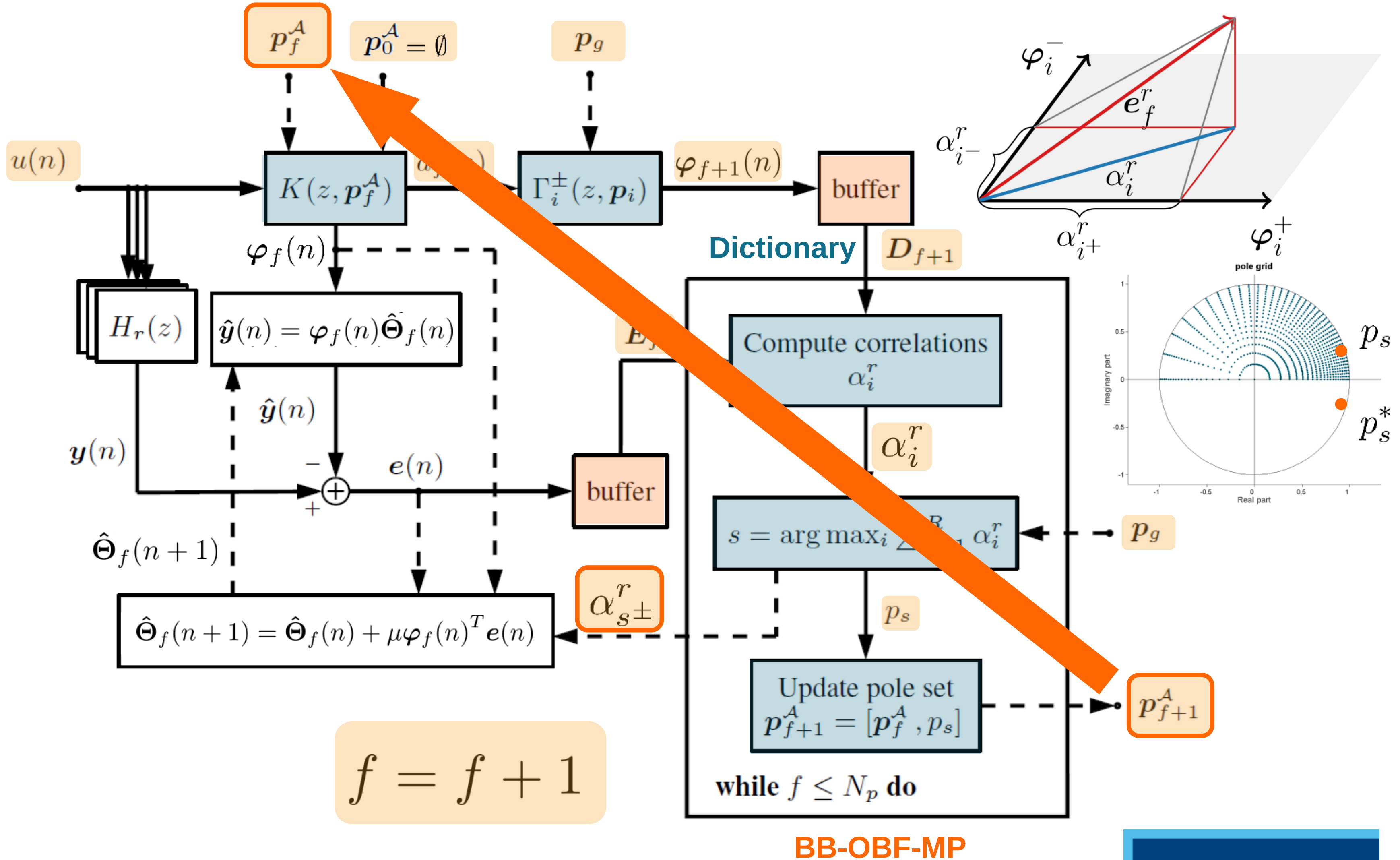
KU LEUVEN

Multichannel identification algorithm



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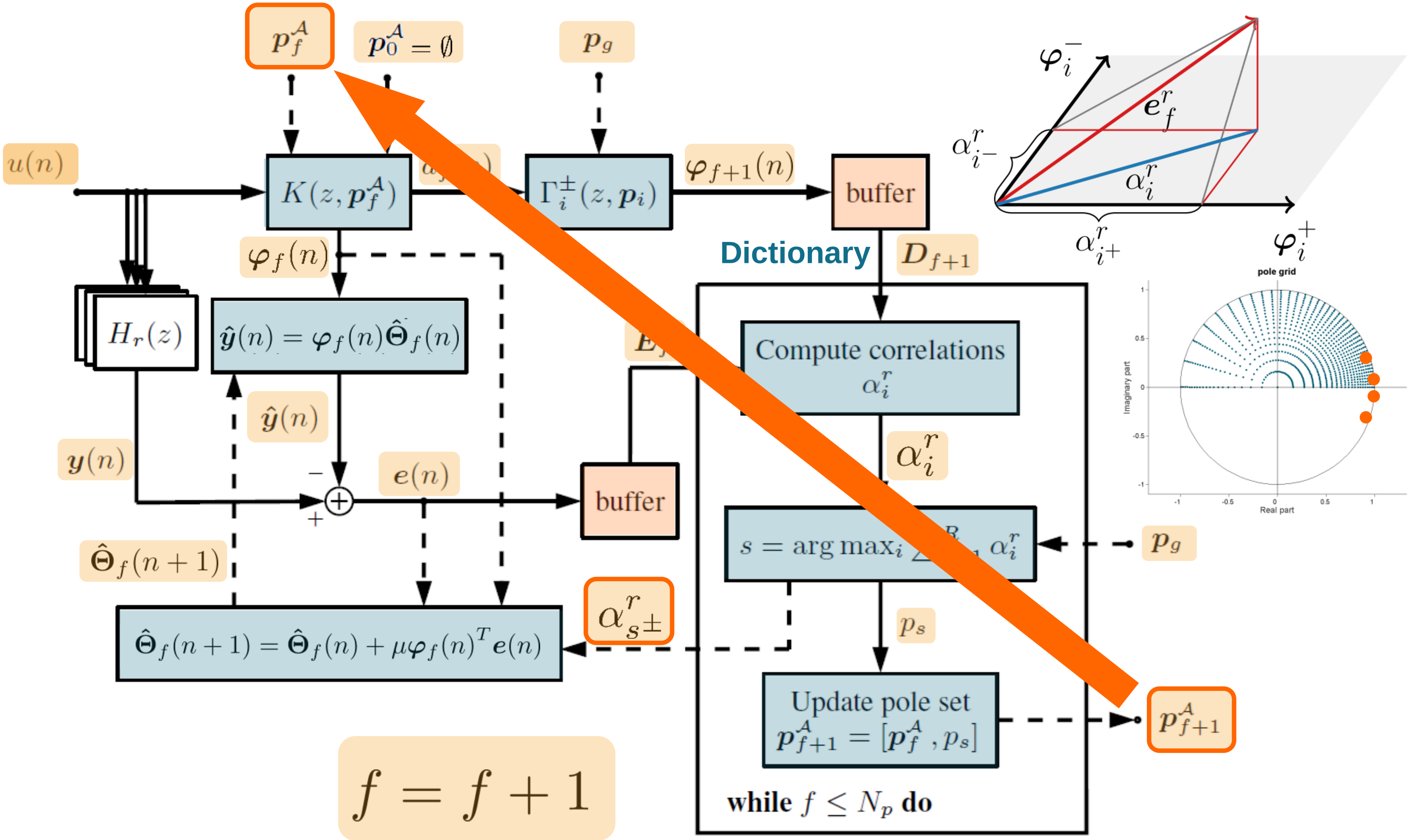
Multichannel identification algorithm



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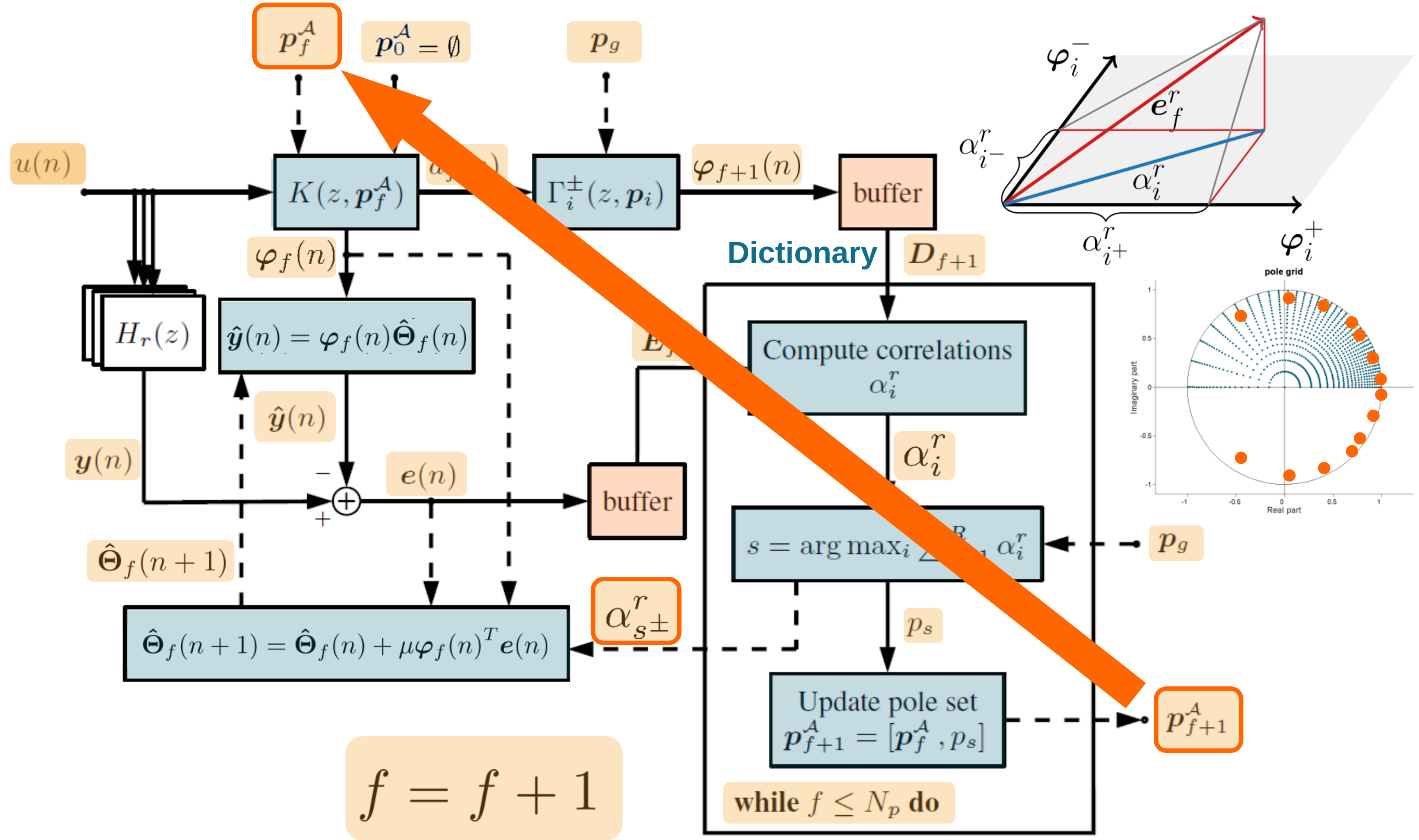
Multichannel identification algorithm



BB-OBF-MP

Outline

Adaptive Digital Filters for Room Acoustics Modeling

▶ Multichannel Identification Algorithm

Simulation Results

Conclusions

KU LEUVEN

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SUBRIR database – BANG & OLUFSEN

- unoccupied, standard domestic listening room [ISO 628-13]
- source: 2 subwoofers - Genelec 1094A (12-150 Hz) and 7050 (25-120 Hz)
- exponential sine sweep technique (3s sweeps)
- 2 mics, 2 subs, 24 s-m positions: 96 RIRs
  4 source positions, 6 microphone positions

Room Description	
Dimensions	6.35L x 4.09W x 2.40H (m)
Volume	62.3 m^3
Floor/Ceiling Materials	Wood/Wood (& Rockwool)
Reverb Time	$T_{31.5\text{Hz}} = 1.44s$ $T_{40\text{Hz}} = .69s$ $T_{50\text{Hz}} = 0.74s$
	$T_{63\text{Hz}} = 0.53s$ $T_{100\text{Hz}} = 0.47s$ $T_{125\text{Hz}} = 0.62s$

available for download (coming soon)
http://www.dreams-itn.eu/index.php/dissemination/downloads/subrir

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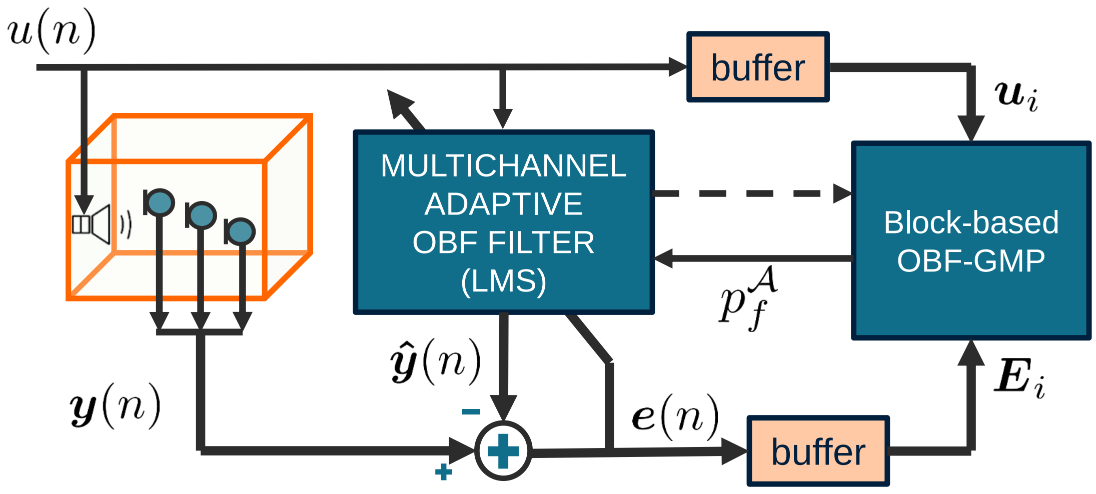
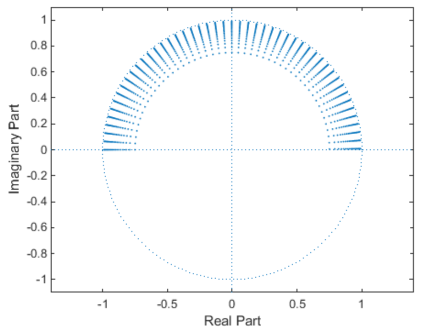
G. Vairetti et al., "A physically motivated parametric model for compact representation of room impulse responses based on orthonormal basis functions", in Proc. EURONOISE 2015.

Training – system identification





Pole grid:

3000 poles

300 angles

10 radii

Poles estimated from input-output data

Input data = white noise sequence

Output data = input data convolved with h(n)

$N_p = 20$: number of pole pairs = 40 adaptive coeffs.

$R = 6$: number of RIRs

$M = 10$: number of realizations of I/O data

$V = 120$: combinations of 2 sources - 3 microphones

$VMR = 7200$: number of estimated pole sets of 20 poles

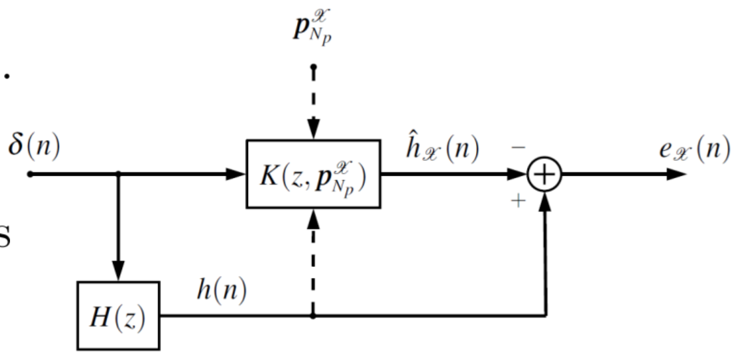
Validation setup

Compare the performances in the approximation of RIRs using an FIR filter and an adaptive OBF filter with fixed common poles

Data sets of the same size as the training set, but different combinations:

- **Set 1:** same 2 source positions, 3 different microphone positions
- **Set 2:** 2 different source positions, 3 different microphone positions

$N_p = 20$: number of pole pairs = 40 adaptive coeffs.
$R = 6$: number of RIRs
$M = 10$: number of realizations of I/O data
$V = 120$: combinations of 2 sources - 3 microphones
$VMR = 7200$: number of I/O data sequences



$$\Delta h_n = 10 \log_{10} \left[\frac{1}{VMR} \sum_{v=1}^{V} \sum_{m=1}^{M} \sum_{r=1}^{R} \frac{\| \boldsymbol{h}^r - \hat{\boldsymbol{h}}_{v,m}^{r,n} \|_2^2}{\| \boldsymbol{h}^r \|_2^2} \right]$$

Average misadjustment

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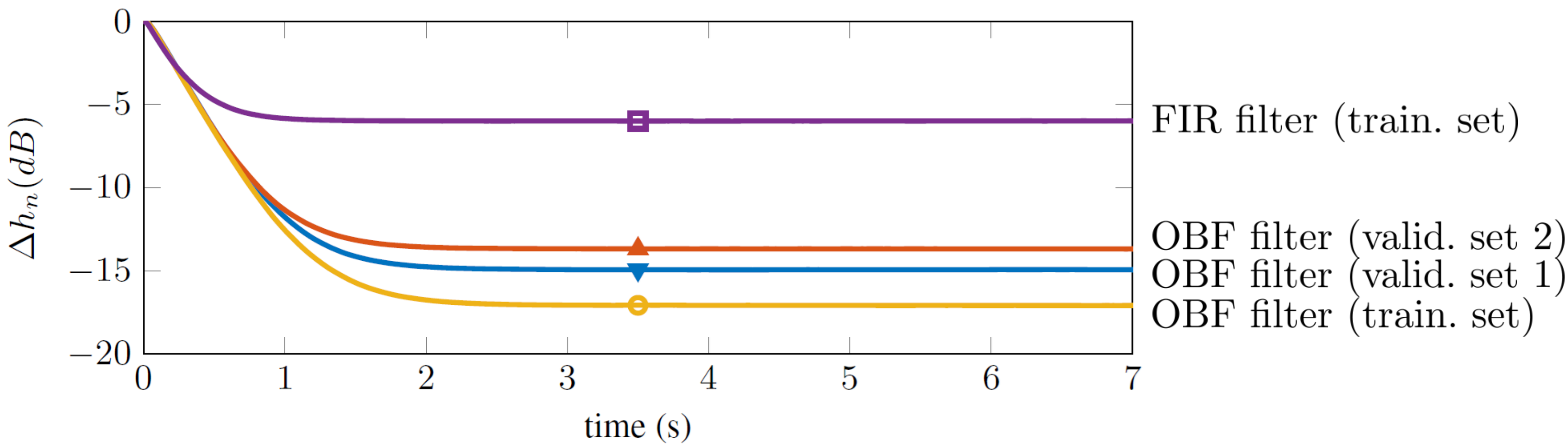
Validation results



- Orthogonality assures
  - **numerical well-conditioning**
  - **fast convergence** of the filter adaptation (same as FIR filters)
- Reduced estimation error compared to FIR filters
- Robust to variations in the RTF → poles can be fixed after estimation

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Conclusions

- Summary
  - OBF filters for modeling and identifying room acoustic systems motivated by the physical definition of the RIR and by the concept of common acoustical poles (and variable zeros)
  - Scalable, stable and well-conditioned Identification algorithm for the estimation of the poles of adaptive OBF filters from multichannel I/O data
  - Same convergence rate of adaptation as FIR filters
  - Reduced estimation error compared to FIR filters
  - Estimated common set of poles robust to variations in the RTF

http://www.dreams-itn.eu/

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