

Fourier Expansion of Hammerstein Models for Nonlinear Acoustic System Identification

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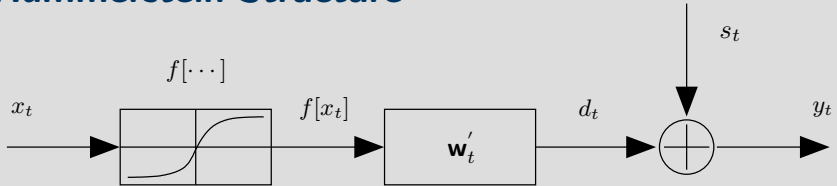
Outline

- 1 Motivation**
- 2 Basis Functions for Nonlinear Expansion**
- 3 Basis-Generic Signal Model in DFT-Domain**
- 4 Equivalent Multichannel Representation**
- 5 Results**
- 6 Conclusions**

Identification of Nonlinear Acoustic Systems

- ▶ **A Hammerstein structure enables the inclusion of:**
 - ▶ Memoryless nonlinearity
 - ▶ Linear FIR system
- ▶ **Possibilities of modeling the nonlinearity in the system via, e.g.,:**
 - ▶ Power series, i.e., polynomial expansion basis (*traditional*)
 - ▶ Odd Fourier series, i.e., an orthogonal expansion basis (*proposed*)
- ▶ **Effects on ensuing equivalent multichannel system identification:**
 - ▶ Quality and rate of convergence
 - ▶ Learning of the underlying system nonlinearity

Hammerstein Structure



- ▶ x_t : Input signal
- ▶ $f[\dots]$: Memoryless nonlinearity
- ▶ $f[x_t]$: Nonlinearly mapped input signal
- ▶ \mathbf{w}'_t : Linear FIR system
- ▶ s_t : Observation noise
- ▶ y_t : Observation

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Resolution of Nonlinearity in Hammerstein Model

- Expansion model $f[x_t]$ of the input signal x_t :

$$f[x_t] = \sum_{i=1}^p a_i \phi_i(x_t)$$

where $\phi_i(x_t)$ and p denotes the basis function and the order of expansion, respectively

- Types of basis functions:

- Polynomial basis (*traditional*), i.e., $f[x_t] = \sum_{i=1}^p a_i x_t^i$

where a_i is the i -th polynomial coefficient

- Fourier basis, i.e., $f[x_t] = \sum_{i=1}^p a_i \cdot \sin(\pi \cdot i \cdot \frac{x_t}{L})$

where a_i is the i -th Fourier coefficient and $2L$ is the fundamental period

Computation of Nonlinear Expansion Coefficients

► For a given function $f[x_t]$ in the data range, $x_t \in [-1, 1]$:

► Computation of Power series coefficients in the least squares sense via

$$a_i = \arg \min_{\tilde{a}_i} \int_{-1}^{+1} \left[f[x_t] - \sum_{i=1}^p \tilde{a}_i x_t^i \right]^2 dx_t, \forall i$$

► Closed-form computation of odd Fourier series coefficients via

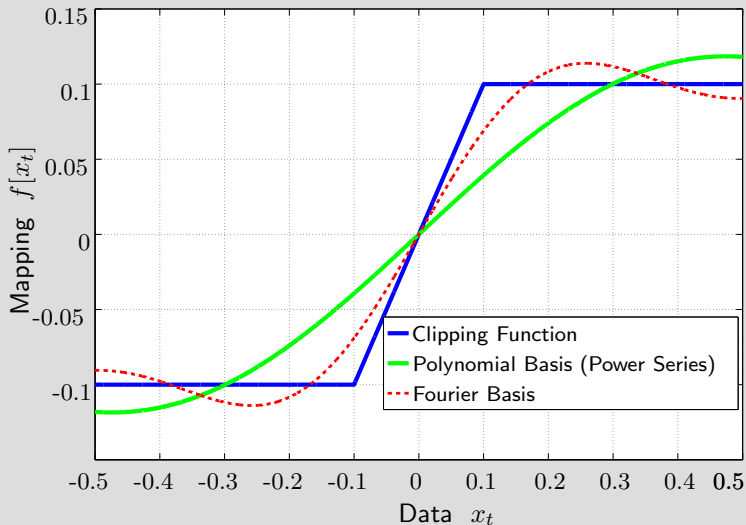
$$a_i = \frac{1}{L} \cdot \int_{-L}^{+L} f[x_t] \cdot \sin(\pi \cdot i \cdot \frac{x_t}{L}) dx_t, \forall i$$

► Example of the nonlinearity as a clipping function:

$$f[x_t] = \begin{cases} x_t & \text{if } |x_t| \leq x_{max} \\ x_{max} & \text{if } x_t > x_{max} \\ -x_{max} & \text{if } x_t < -x_{max} \end{cases}$$

where x_{max} is the clipping threshold

Fitting Ability: $x_{max} = 0.1, p = 5, L = 1.5$



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Block-Based Nonlinearly Mapped Input Signal

► Block-based input and nonlinearly mapped signal:

$$\mathbf{x}_\tau = [x_{\tau R-M+1}, x_{\tau R-M+2}, \dots, x_{\tau R}]^H$$

$$\mathbf{f}_\tau = \{ f[x_{\tau R-M+1}], f[x_{\tau R-M+2}], \dots, f[x_{\tau R}] \}^H$$

with R is the block-shift and M the block-size, with τ as the block-index

► Compact notation for the linear combination:

$$\begin{aligned} \mathbf{f}_\tau &= \left\{ \sum_{i=1}^p a_i \phi_i(x_{\tau R-M+1}), \dots, \sum_{i=1}^p a_i \phi_i(x_{\tau R}) \right\}^H \\ &= \sum_{i=1}^p a_i \{ \phi_i(x_{\tau R-M+1}), \phi_i(x_{\tau R-M+2}), \dots, \phi_i(x_{\tau R}) \}^H \\ &= \sum_{i=1}^p a_i \mathbf{x}_{\tau,i} \end{aligned}$$

where $\mathbf{x}_{\tau,i} = \{ \phi_i(x_{\tau R-M+1}), \phi_i(x_{\tau R-M+2}), \dots, \phi_i(x_{\tau R}) \}^H$

DFT-Domain Single Channel Signal Model

- Applying diagonalization and DFT-Matrix \mathbf{F}_M to \mathbf{f}_τ :

$$\tilde{\mathbf{X}}_\tau = \text{diag} \{ \mathbf{F}_M \mathbf{f}_\tau \} = \sum_{i=1}^p a_i \text{diag} \{ \mathbf{F}_M \mathbf{x}_{\tau,i} \} = \sum_{i=1}^p a_i \mathbf{X}_{\tau,i}$$

where $\mathbf{X}_{\tau,i} = \text{diag} \{ \mathbf{F}_M \mathbf{x}_{\tau,i} \}$

- Modeling $M - R$ non-zero coefficients of the echo path $\mathbf{w}_\tau = \mathbf{w}'_{t=\tau R}$:

$$\mathbf{W}_\tau = \mathbf{F}_M \begin{bmatrix} \mathbf{w}_\tau^H & \mathbf{0}_R \end{bmatrix}^H$$

- Overlap-save convolution model of the observation $\mathbf{Y}_\tau = \mathbf{F}_M \mathbf{Q} \mathbf{y}_\tau$:

$$\begin{aligned} \mathbf{Y}_\tau &= \mathbf{F}_M \mathbf{Q} \mathbf{Q}^H \mathbf{F}_M^{-1} \tilde{\mathbf{X}}_\tau \mathbf{W}_\tau + \mathbf{S}_\tau \\ &= \mathbf{G} \tilde{\mathbf{X}}_\tau \mathbf{W}_\tau + \mathbf{S}_\tau = \tilde{\mathbf{C}}_\tau \mathbf{W}_\tau + \mathbf{S}_\tau \end{aligned}$$

where $\tilde{\mathbf{C}}_\tau = \mathbf{G} \tilde{\mathbf{X}}_\tau$ and $\mathbf{G} = \mathbf{F}_M \mathbf{Q} \mathbf{Q}^H \mathbf{F}_M^{-1}$. Symbol $\mathbf{Q}^H = (\mathbf{0} \ \mathbf{I}_R)^H$ is an $R \times M$ projection matrix and $\mathbf{y}_\tau = \{y_{\tau R-R+1}, y_{\tau R-R+2}, \dots, y_{\tau R}\}^H$

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Equivalent Multichannel Structure

- Substituting $\tilde{\mathbf{X}}_\tau = \sum_{i=1}^p a_i \mathbf{X}_{\tau,i}$ for making the coefficients visible:

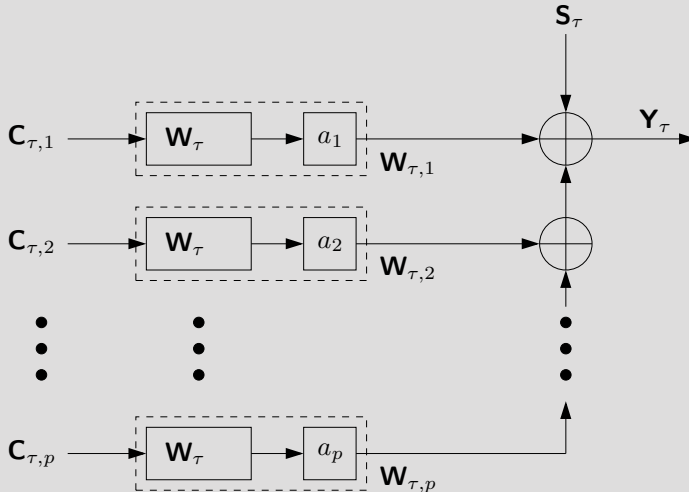
$$\mathbf{Y}_\tau = \mathbf{G} \tilde{\mathbf{X}}_\tau \mathbf{W}_\tau + \mathbf{S}_\tau = \mathbf{G} \sum_{i=1}^p a_i \mathbf{X}_{\tau,i} \mathbf{W}_\tau + \mathbf{S}_\tau$$

- Expressing using matrix-vector formulation and absorbing nonlinear coefficients into the echo path:

$$\begin{aligned} \mathbf{Y}_\tau &= \mathbf{G} [\mathbf{X}_{\tau,1} \ \mathbf{X}_{\tau,2} \ \cdots \ \mathbf{X}_{\tau,p}] \begin{bmatrix} a_1 \mathbf{I}_M \\ a_2 \mathbf{I}_M \\ \vdots \\ a_p \mathbf{I}_M \end{bmatrix} \mathbf{W}_\tau + \mathbf{S}_\tau = \mathbf{G} \underline{\mathbf{X}}_\tau \begin{bmatrix} a_1 \mathbf{W}_\tau \\ a_2 \mathbf{W}_\tau \\ \vdots \\ a_p \mathbf{W}_\tau \end{bmatrix} + \mathbf{S}_\tau \\ &= \underline{\mathbf{C}}_\tau \underline{\mathbf{W}}_\tau + \mathbf{S}_\tau . \end{aligned}$$

where $\underline{\mathbf{C}}_\tau = [\mathbf{C}_{\tau,1} \ \mathbf{C}_{\tau,2} \ \cdots \ \mathbf{C}_{\tau,p}]$, while $\mathbf{C}_{\tau,i} = \mathbf{G} \mathbf{X}_{\tau,i}$.

Equivalent Multichannel Signal Model



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Multichannel Adaptive Algorithm

► Multichannel frequency-domain adaptive filter (MCFDAF):

- Error and update equations of MCFDAF

$$\begin{aligned}\mathbf{E}_\tau &= \mathbf{Y}_\tau - \underline{\mathbf{C}}_\tau \widehat{\underline{\mathbf{W}}}_{\tau-1} \\ \widehat{\underline{\mathbf{W}}}_\tau &= \widehat{\underline{\mathbf{W}}}_{\tau-1} + \underline{\boldsymbol{\mu}}_\tau^H \mathbf{E}_\tau\end{aligned}$$

where stepsize for i -th channel $\mu_{\tau,i}$ is given as a function of the power spectral density $\Psi_{\underline{\mathbf{x}}_\tau \underline{\mathbf{x}}_\tau}$ and the individual adaptation constant in the range $0 < \alpha_i < 1$, i.e.,

$$\mu_{\tau,i} = \alpha_i \Psi_{\underline{\mathbf{x}}_\tau \underline{\mathbf{x}}_\tau}^{-1}$$

- Computation of diagonal $M \times M$ matrix $\Psi_{\underline{\mathbf{x}}_\tau \underline{\mathbf{x}}_\tau}$ by recursive averaging, i.e.,

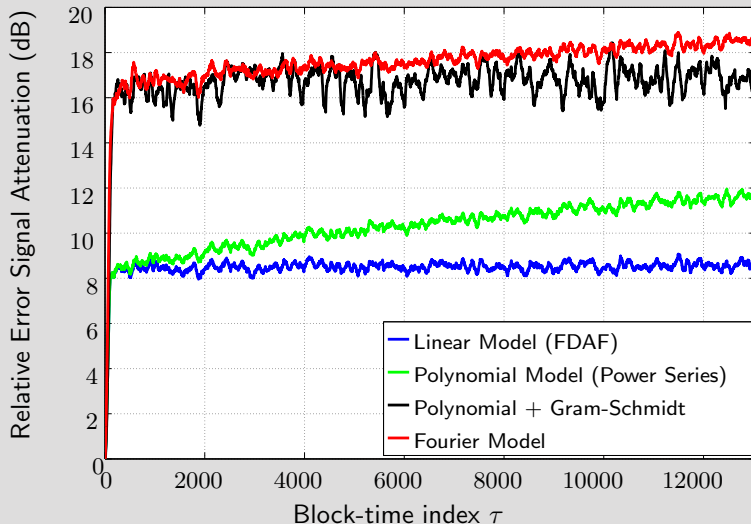
$$\Psi_{\underline{\mathbf{x}}_\tau \underline{\mathbf{x}}_\tau} = \gamma \Psi_{\underline{\mathbf{x}}_{\tau-1} \underline{\mathbf{x}}_{\tau-1}} + (1 - \gamma) \underline{\mathbf{x}}_\tau \underline{\mathbf{x}}_\tau^H$$

with γ as a forgetting factor in the range $0 < \gamma < 1$

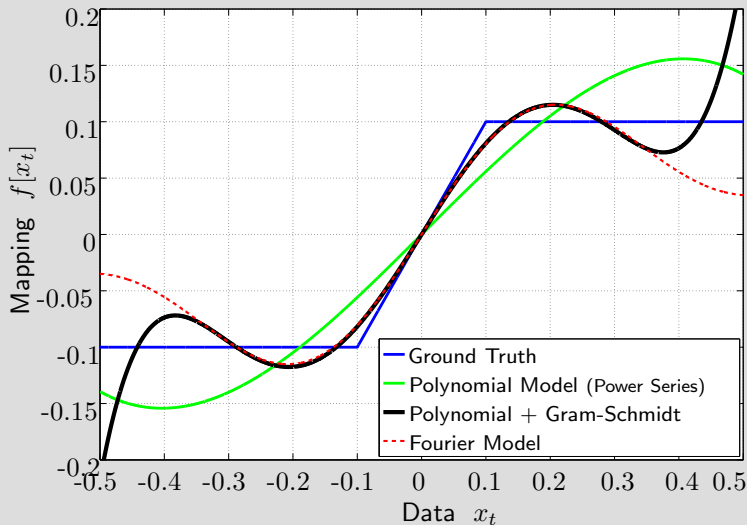
Analysis Configurations

- ▶ MCFDAF was configured to $M = 256$ and $R = 64$, respectively
- ▶ Linear-to-nonlinear power ratio SNR_{NL} of $\sigma_{x_t}^2 / \sigma_{x_t - f[x_t]}^2 = 5$ and 20 dB
- ▶ Signal-to-observation noise power ratio set to $\text{SNR} = 60$ dB
- ▶ Two types of basis expansions:
 - ▶ Power series
 - ▶ Odd Fourier series
- ▶ Performance measured with respect to:
 - ▶ Relative error signal attenuation $\text{ESA} = \sigma_{\mathbf{Y}_\tau}^2 / \sigma_{\mathbf{E}_\tau}^2$
 - ▶ Inspection of the estimated nonlinear mapping $\hat{f}[\cdot \dots]$
- ▶ Nonlinear coefficients extracted in least-squares sense:
 - ▶ $a_i = (\mathbf{W}_\tau^H \widehat{\mathbf{W}}_{\tau,i}) / (\mathbf{W}_\tau^H \mathbf{W}_\tau)$
 where $\widehat{\mathbf{W}}_{\tau,i}$ is the estimate of the i -th channel

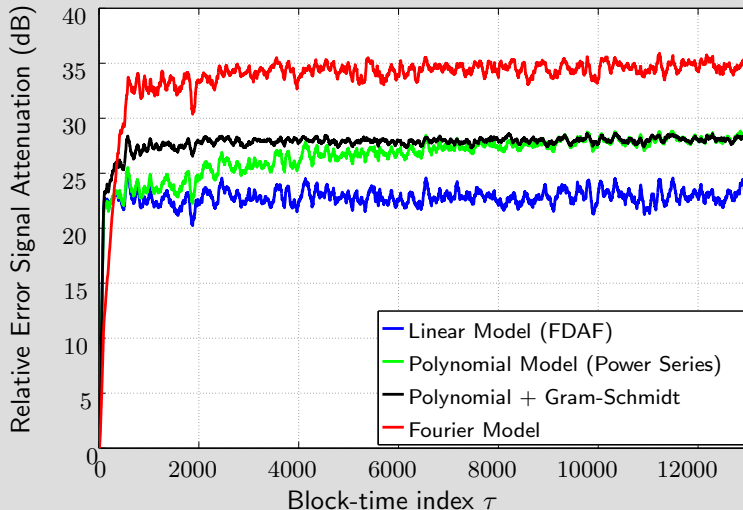
Performance Comparison: $\text{SNR}_{NL} = 5 \text{ dB}$



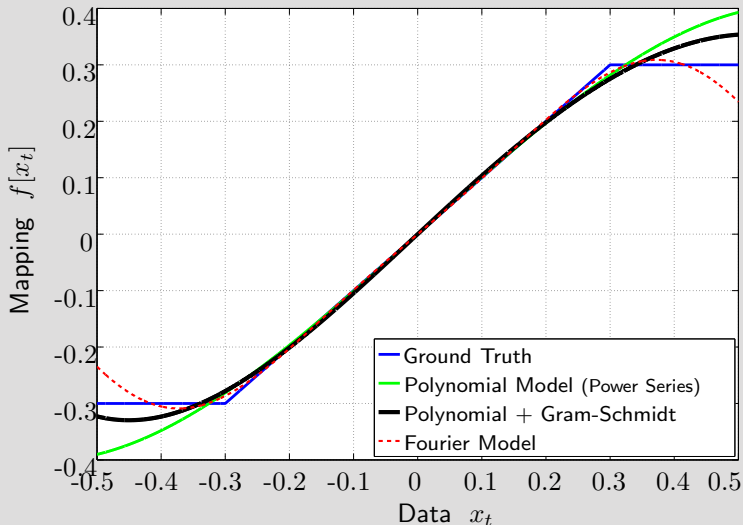
Extracted Nonlinear Mapping: $x_{max} = 0.1$



Performance Comparison: $\text{SNR}_{NL} = 20 \text{ dB}$



Extracted Nonlinear Mapping: $x_{max} = 0.3$



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Conclusions

► Quasi-linear expansion of nonlinear Hammerstein models:

- Traditional Power series
- Odd orthogonal Fourier series

► Signal model in block frequency-domain:

- Contained basis-generic derivation
- Efficient multichannel representation based on FFT

► Results of multichannel adaptive identification:

- Orthogonal Fourier series lines up with polynomial modeling with Gramm-Schmidt orthogonalization
- High error signal attenuation and effective imitation of the nonlinear response