

Conference on Decision and Control - 2022

Non-asymptotic Observer Design for Nonlinear Systems Based on Linearization

Kristina Korder, Matti Noack, Johann Reger

Control Engineering Group,
Department for Computer Science and Automation,
TU Ilmenau, Germany

Observers for Nonlinear Systems

06.12.2022

Motivation of particular perspective

(i)	(ii)	(iii)	(iv)	textit(v)
Finite time interval & moving horizon	Continuous-time models	Non-asymptotic/ algebraic	Signal projection	FIR implementation

Dynamic observer

$$\dot{\hat{x}} = f(\hat{x}, u) + L(t) (\hat{y} - y), \hat{x}(0) = \hat{x}_0$$

- ⊖ virtual dynamics (*digital inertia*)
- ⊕ efficient implementation
- ⊕ inherent robustness via feedback

$$[0, t], [0, \infty]$$

Algebraic observer

$$\hat{x}(t) = \langle H_1, y \rangle + \langle H_2, u \rangle$$

- ⊕ instantaneous result from alg. expr.
- ⊕ no stability issues in coupled setup
- ⊖ sensitive to model errors & numerics

$$[0, T], [t - T, t]$$

Demonstration of modulation mechanism

Operator structure:

$$\underbrace{Ly(t)} = \underbrace{f(t)}$$

Example:

$$\ddot{y} + a_1 \dot{y} + a_0 y = u(t)$$

Modulation integral: MF $\varphi : [0, T] \rightarrow \mathbb{R}$

$$\begin{aligned} \mathcal{M}[\ddot{y}] &= \langle \varphi, \ddot{y} \rangle := \int_{t-T}^t \varphi(\tau - t + T) \ddot{y}(\tau) d\tau = \varphi \dot{y} \Big|_0^T - \int_{t-T}^t \dot{\varphi}(\tau - t + T) \dot{y}(\tau) d\tau \\ &= \varphi \dot{y} \Big|_0^T - \dot{\varphi} y \Big|_0^T + \int_{t-T}^t \ddot{\varphi}(\tau - t + T) y(\tau) d\tau \end{aligned}$$

Idea: Shift of derivative

\Rightarrow **Zero Boundary Conditions:**

$$\begin{cases} \varphi(0) = \varphi(T) = 0 \\ \dot{\varphi}(0) = \dot{\varphi}(T) = 0 \end{cases} \Rightarrow \boxed{\begin{aligned} &\langle \ddot{\varphi}, y \rangle - a_1 \langle \dot{\varphi}, y \rangle \\ &+ a_0 \langle \varphi, y \rangle = \langle \varphi, u \rangle \end{aligned}}$$

Demonstration of modulation mechanism

Operator structure:

$$\underbrace{Ly(t)} = \underbrace{f(t)}$$

Example:

$$\ddot{y} + a_1 \dot{y} + a_0 y = u(t)$$

Modulation integral: MF $\varphi : [0, T] \rightarrow \mathbb{R}$

$$\begin{aligned} \mathcal{M}[\ddot{y}] = \langle \varphi, \ddot{y} \rangle &:= \int_{t-T}^t \varphi(\tau - t + T) \ddot{y}(\tau) d\tau = \varphi \dot{y} \Big|_0^T - \int_{t-T}^t \dot{\varphi}(\tau - t + T) \dot{y}(\tau) d\tau \\ &= \varphi \dot{y} \Big|_0^T - \dot{\varphi} y \Big|_0^T + \int_{t-T}^t \ddot{\varphi}(\tau - t + T) y(\tau) d\tau \end{aligned}$$

Idea: Isolate state

\Rightarrow Non-zero **BCs**:

$$\begin{cases} \varphi(0) = 0, \varphi(T) = 1 \\ \dot{\varphi}(0) = 0, \dot{\varphi}(T) = a_1 \end{cases}$$

\Rightarrow

$$\dot{y}(t) = -\underbrace{\langle L^* \varphi, y \rangle + \langle \varphi, u \rangle}_{\langle \ddot{\varphi} - a_1 \dot{\varphi} + a_0 \varphi, y \rangle}$$

Outline

- 1 Modulating Function based state estimation
- 2 Modulation of nonlinear systems by linearization
- 3 Implementation & simulation results

Agenda overview

- 1 Modulating Function based state estimation
- 2 Modulation of nonlinear systems by linearization
- 3 Implementation & simulation results

Linear differential equations

Linear output ODE:

$$\underbrace{\sum_{k=0}^n a_k(t) y^{(k)} = Ly = a^\top D y}_{a_n(t) y^{(n)} + \dots + a_1(t) \dot{y} + a_0(t) y = \xi(t)}$$

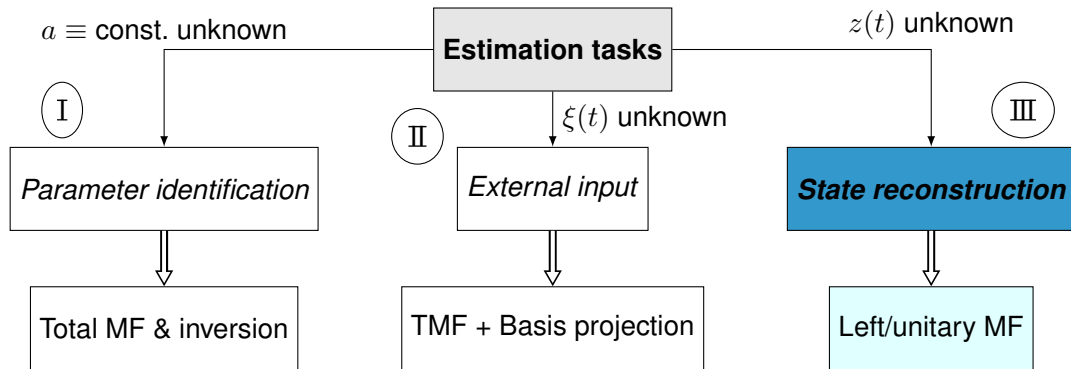
Linear differential operator L and its adjoint L^* :

$$L = \sum_{k=0}^n a_k(t) \frac{d^k}{dt^k} (\cdot) =: a(t)^\top D \quad \Rightarrow \quad L^* = \sum_{k=0}^n (-1)^k \left(a_k(t) (\cdot) \right)^{(k)}$$

Modulation w.r.t. kernel $\varphi \in \mathcal{C}^{(n-1)}([0, T], \mathbb{R}^n)$:

$$\langle \varphi, Ly \rangle = \langle L^* \varphi, y \rangle + \left[L_1^* \varphi \mid \dots \mid L_n^* \varphi \right] \overbrace{\begin{pmatrix} y \\ \vdots \\ y^{(n-1)} \end{pmatrix}}^{=z} \bigg|_0^T = \langle \varphi, \xi \rangle$$

Estimation problem formulation



Algebraic observer design

III. *State reconstruction* [JR15]: Left MF

$$\varphi^{(i)}(0) = 0, \varphi^{(i)}(T) \neq 0$$

$$\Rightarrow \underbrace{\left[L_1^* \varphi(T) \mid \cdots \mid L_n^* \varphi(T) \right]}_{=\Delta(a)} z(t) = \underbrace{\langle \varphi, \xi \rangle - \langle L^* \varphi, y \rangle}_{Q_a[y, \xi]}$$

where

$$L_k(\cdot) = \sum_{j=0}^{n-k} a_{n-j} (\cdot)^{(n-k-j)} \Rightarrow L_0 = L.$$

→ **Q:** Invertibility of $\Delta(a) \forall a$?

Choice of boundary conditions

Unitary MF (inspired by *generalized MFs* [TWLB19]): allowing $\varphi^{(i)}(T) = c_i \in \mathbb{R}$

$$\varphi_l^{(i)}(T) = \begin{cases} (-1)^{l-n} & : n - l = i \\ 0 & : \text{else} \end{cases}$$

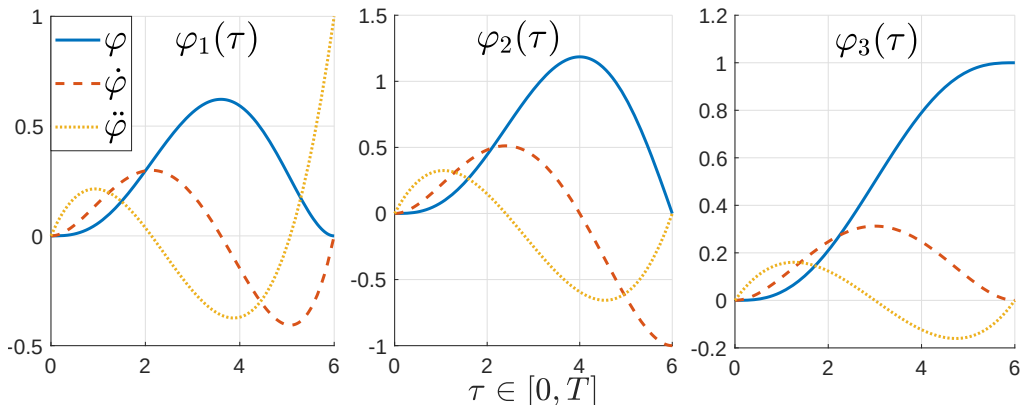
This leads to

$$\Delta(a) = \begin{pmatrix} L_1^* \varphi_1(T) & \cdots & L_n^* \varphi_1(T) \\ \vdots & \ddots & \vdots \\ L_1^* \varphi_n(T) & \cdots & L_n^* \varphi_n(T) \end{pmatrix} = \begin{pmatrix} a_n & & 0 \\ & \ddots & \\ * & & a_n \end{pmatrix} \stackrel[n=3]{a \equiv \text{const}} \begin{pmatrix} a_3 & 0 & 0 \\ a_2 & a_3 & 0 \\ a_1 & a_2 & a_3 \end{pmatrix}.$$

Usual case: $a_n \equiv 1 \Rightarrow \kappa(\Delta(a)) = 1 \forall a$ and

$$\hat{z}(t) = \Delta(a)^{-1} (\langle \varphi, \xi \rangle - \langle L^* \varphi, y \rangle).$$

Kernel construction



Connection to observability normal form

Observation canonical form (SISO LTI):

$$\underbrace{y^{(n)} + \sum_{i=0}^{n-1} a_i y^{(i)}}_{=Ly} = \underbrace{\sum_{j=0}^{n-1} b_j u^{(j)}}_{=Ru} \quad \stackrel{y=x_1}{\Rightarrow} \quad \dot{x} = \begin{pmatrix} -a_{n-1} & 1 & & \\ -a_{n-2} & 0 & \ddots & \\ \vdots & \vdots & \ddots & 1 \\ -a_0 & 0 & \cdots & 0 \end{pmatrix} x + \begin{pmatrix} b_{n-1} \\ b_{n-2} \\ \vdots \\ b_0 \end{pmatrix} u$$

Adjustment of operator form with boundaries:

$$\langle \varphi, Ly - Ru \rangle = \langle L^* \varphi, y \rangle - \langle R^* \varphi, u \rangle + \left[\varphi \mid -\dot{\varphi} \mid \cdots \mid (-1)^{n-1} \varphi^{(n-1)} \right] \overbrace{\begin{pmatrix} L_n y \\ L_{n-1} y - R_n u \\ \vdots \\ L_1 y - R_2 u \end{pmatrix}}^{=x} \bigg|_0^T$$

$$\stackrel{\text{UMF}}{\Rightarrow} \boxed{\hat{x}(t) = -\langle L^* \varphi, y \rangle + \langle R^* \varphi, u \rangle}$$

Algebraic observer discussion & overview

<p><i>Case 1 (LTI / parameters known)</i></p> $\hat{z} = \Delta(\theta)^{-1}Q(y, u)$ <p>→ offline inversion of Δ</p>	<p><i>Case 2 (LTI / parameters unknown)</i></p> $\hat{z} = \Delta(\hat{\theta})^{-1}Q(y, u)$ <p>→ guarantee full rank via UMF</p>
<p><i>Case 3 (LTV / parameters known)</i></p> $\hat{z} = \Delta(a(t))^{-1}Q(y, u)$ <p>→ TV terms as part of operator</p>	<p><i>Case 4 (LTV / parameters unknown)</i></p> $\hat{z} = \Delta(a(w(t)))^{-1}Q(y, u)$ <p>→ online update including derivatives!</p>

Other notable approaches:

- ▷ *Exact state observers* [Byr03] - input/output error sensitivity with resulting DRE
- ▷ Mazenc et. al. [MMN22] - *temporal shift* based operation (sampled data systems)
- ▷ *Deadbeat observer* [PLFP17] (F) - exceeding horizon formulation (exponential MFs)
- ▷ *Auxiliary Problem* approach with extension to *PDEs* [GNRL20]

Agenda overview

- 1 Modulating Function based state estimation
- 2 Modulation of nonlinear systems by linearization**
- 3 Implementation & simulation results

Nonlinear input-output form

State transformation (observability map) [Bes07]:

$$\mathcal{O}_k(x) = \begin{pmatrix} y \\ \dot{y} \\ \vdots \\ y^{(k)} \end{pmatrix} = \begin{pmatrix} h(x) \\ \mathcal{L}_f h(x) \\ \vdots \\ \mathcal{L}_f^k h(x) \end{pmatrix} =: z \quad \Rightarrow \quad \mathcal{O}_k(x) := \frac{\partial \mathcal{O}_k}{\partial x}(x)$$

General output **transfer behavior**:

$$\begin{aligned} y^{(n)} &= \mathcal{L}_f^n h(\mathcal{O}_k^{-1}(x)) \approx \mathcal{L}_f^n h\left(\bar{x} + \left[\frac{\partial \mathcal{O}_k}{\partial x}\right]_{\bar{x}}^{-1} (z - \underbrace{\mathcal{O}_k(\bar{x})}_{\bar{z}})\right) \\ &= F(y, \dot{y}, \ddot{y}, \dots, y^{(n-1)}, u, \dot{u}, \dots) \end{aligned}$$

Classical structuring problem

For a given function $y \in \mathcal{C}^i([0, T], \mathbb{R}^p)$ and parameter $a \in \mathbb{R}$ define:

- (i) **Linear signal:** $\xi(t) = a y^{(i)}(t)$
- (ii) **Integrable signal:** $\xi(t) = a g^{(i)}(y(t))$
- (iii) **Convolvable signal:** $\xi(t) = a g(y(t)) f^{(i)}(y(t))$
- (iv) **E-convolvable signal:** $\xi(t) = a g^{(i)}(y(t)) f^{(i)}(y(t))$

with $g, f \in \mathcal{C}^i(\mathbb{R}^p, \mathbb{R})$ arbitrary functions [CTR14].

Resulting **structuring problem** for suitable representation [Pea92]:

$$F(y, \dot{y}, \ddot{y}, \dots, y^{(n-1)}) \stackrel{?}{=} \sum_{j=0}^{n-1} a_j g_j^{(j)}(y) + \sum_{i=0}^{n-1} b_i g_i(y) f^{(i)}(y)$$

Linearization-based approach

Considered nonlin. output dyn. (ONF):

$$y^{(n)} = F(\underbrace{y, \dot{y}, \dots, y^{(n-1)}}_{=:z}, u)$$

Linearization around \bar{z} :

$$y^{(n)} = F(z, u) \approx F(\bar{z}, u) + \overbrace{\frac{\partial F}{\partial z}}_{=: \alpha(t)} \bigg|_{\bar{z}} (z - \bar{z})$$

$$\Rightarrow \underbrace{y^{(n)} - \frac{\partial F}{\partial z} \bigg|_{\bar{z}} z}_{L(a)y} = \underbrace{F(\bar{z}, u) - \frac{\partial F}{\partial z} \bigg|_{\bar{z}} \bar{z}}_{\xi(t)}$$

With $a(t) = (-F'(\bar{z}), 1)^\top = (-\alpha(t), 1)^\top$:

$$\Rightarrow \Delta((a(t)) z(t) = \mathcal{M}[\xi] - \langle L((-F'(\bar{z}), 1))^* \varphi, y \rangle$$

Final estimator form:

$$\hat{z}(t) = \Delta(a(t))^{-1} \left(\mathcal{M}[F(\bar{z}, u) - F'(\bar{z}) \bar{z}] - \langle L(a(t))^* \varphi, y \rangle \right)$$

Estimator realization

Strategy:

- last estimate $\bar{z}(t) = \hat{z}(t - T_s)$
- UMF and symbolic inversion
- FIR filter implementation

Challenges:

- ▷ inverse observability map needed
- ▷ integration over moving horizon filled with past estimates
- ▷ estimation feedback within coefficient $a(t)$ and its derivatives
- ▷ initialization and convergence behavior

Coefficient time derivatives $a^{(i)}$:

$$a^{(0)} = (-F'(\bar{z}), 1)^\top,$$

$$a^{(i)} = \frac{\partial a^{(i-1)}}{\partial z} f(\bar{z}, u) \quad \forall i \in \{1, \dots, n\}$$

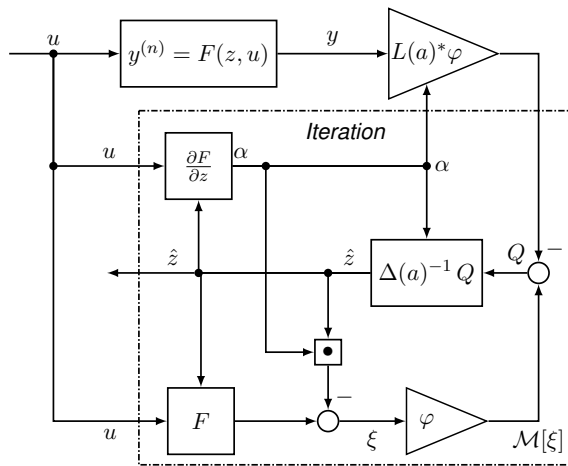
Basic ZoH assumption for *simplification*:

$$a(\tau) = \text{const.} \quad \forall \tau \in [t - T, t]$$

Agenda overview

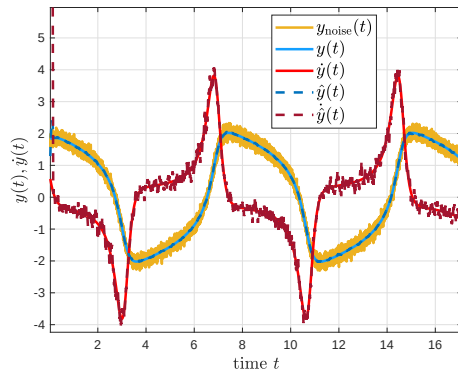
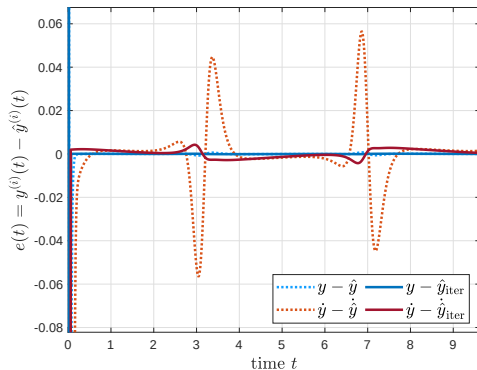
- 1 Modulating Function based state estimation
- 2 Modulation of nonlinear systems by linearization
- 3 Implementation & simulation results

Linearization-based algorithm iteration



Simulation results - Van-der-Pol oscillator

NL Output dynamics: $\ddot{y} = \mu(1 - y^2)\dot{y} - y = F(z)$



Simulation results - Two-Tank system

System dynamics:

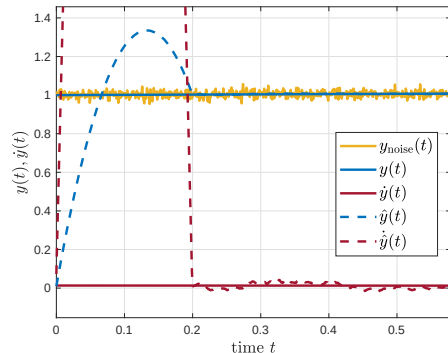
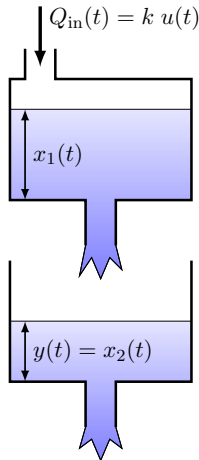
$$\dot{x}_1 = \frac{k u - a_1 \sqrt{2 g x_1}}{A_1}$$

$$\dot{x}_2 = \frac{a_1 \sqrt{2 g x_1} - a_2 \sqrt{2 g x_2}}{A_2}$$

Observability transform:

$$y^{(n)} = \mathcal{L}_f^n h(\mathcal{O}(z)^{-1})$$

$$= F(z, u)$$



Final remarks

Evaluation:

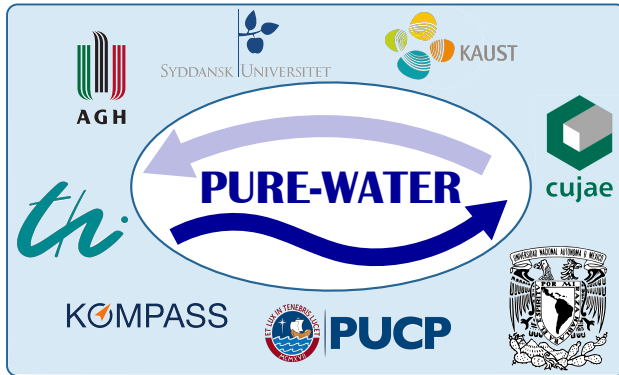
- MF operator form for LTV systems
- UMF design for guaranteeing $\Delta(a)$ inversion
- linearization of NL input-output dynamics
- efficient realization using ZoH approximation over moving horizon
- iterative processing algorithm for fixed-time estimation
- simulative demonstration of functionality and robustness

Further work:

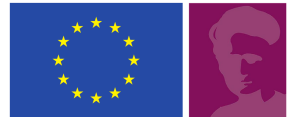
- ▶ error analysis and convergence proof
- ▶ piece-wise continuous coefficient $a(t)$ approximation instead of ZoH
- ▶ enabling larger horizon lengths T for better noise suppression
- ▶ advanced and optimal tuning options
- ▶ adaptive observation and control

Research & Innovation Staff Exchange

IMPROVED ESTIMATION ALGORITHMS FOR WATER PURIFICATION AND DESALINATION SYSTEMS



<https://zenodo.org/communities/pure-water/>



This project receives funding from the European Union's Horizon 2020 Research and Innovation Programme grant agreement No 824046.

Related Literature I



BESANÇON, Gildas:

An Overview on Observer Tools for Nonlinear Systems.

In: BESANÇON, Gildas (Hrsg.): Nonlinear observers and applications Bd. 363.
Springer, 2007, Kapitel 1, S. 1–33



BYRSKI, Witold:

The survey for the exact and optimal state observers in Hilbert spaces.

In: 2003 European Control Conference (ECC) (2003), S. 3548–3553






CIEZA, Oscar B. ; TAFUR, Julio C. ; REGER, Johann:

Frequency Domain Modulating Functions for Continuous-Time Identification of Linear and Nonlinear Systems.

In: Latinamerican Control Conference, 2014, S. 690–695

Related Literature II

-  **GHAFFOUR, Lilia ; NOACK, Matti ; REGER, Johann ; LALEG-KIRATI, Taous-Meriem:**
Non-asymptotic State Estimation of Linear Reaction Diffusion Equation using
Modulating Functions.
In: [IFAC-PapersOnLine](#) 53 (2020), S. 4196–4201
-  **JOUFFROY, Jerome ; REGER, Johann:**
Finite-time simultaneous parameter and state estimation using modulating functions.
In: [IEEE Conference on Control Applications](#), 2015, S. 394–399
-  **MAZENC, Frédéric ; MALISOFF, Michael ; NICULESCU, Silviu-Iulian:**
Sampled-data estimator for nonlinear systems with uncertainties and arbitrarily fast rate
of convergence.
In: [Automatica](#) 142 (2022), S. 110361

Related Literature III



PEARSON, A.E.:

Explicit parameter identification for a class of nonlinear input/output differential operator models.

In: [\[1992\] Proceedings of the 31st IEEE Conference on Decision and Control](#), 1992, S. 3656–3660 vol.4



PIN, Gilberto ; LI, Peng ; FEDELE, Giuseppe ; PARISINI, Thomas:

A Deadbeat Observer for Two and Three-dimensional LTI Systems by a Time/Output-Dependent State Mapping.

In: [IFAC-PapersOnLine](#) 50 (2017), Nr. 1, S. 6452–6457. –
20th IFAC World Congress

Related Literature IV



PREISIG, HA ; RIPPIN, DWT:

Theory and application of the modulating function method - I. Review and theory of the method and theory of the spline-type modulating functions.

In: [Computers & chemical engineering](#) 17 (1993), Nr. 1, S. 1–16



TIAN, Yang ; WEI, Yan-Qiao ; LIU, Da-Yan ; BOUTAT, Driss:

Fast and robust estimation for positions and velocities from noisy accelerations using generalized modulating functions method.

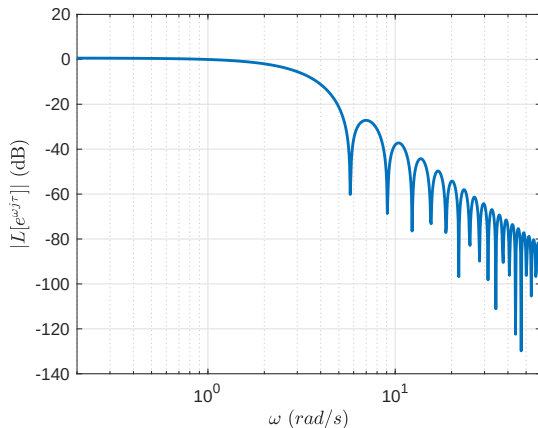
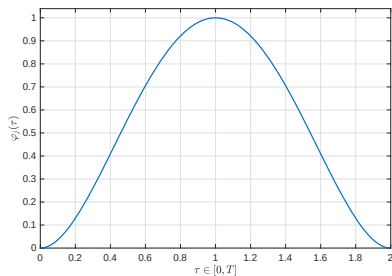
In: [Mechanical Systems and Signal Processing](#) 133 (2019), S. 106270

Filtering characteristics

Frequency sweep: $\omega \in \Omega$ (compare to [PR93])

$$\langle \varphi, e^{j\omega \cdot} \rangle = \int_0^T \varphi(\tau) e^{j\omega \tau} d\tau$$

Bode plot: ideal case

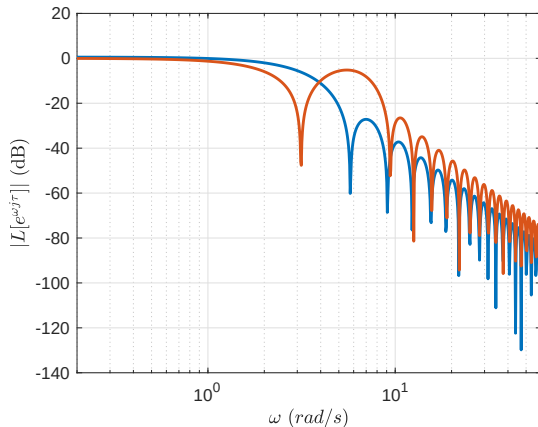
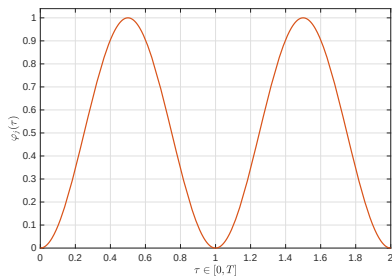


Filtering characteristics

Frequency sweep: $\omega \in \Omega$ (compare to [PR93])

$$\langle \varphi, e^{j\omega \cdot} \rangle = \int_0^T \varphi(\tau) e^{j\omega \tau} d\tau$$

Bode plot: *ideal case*

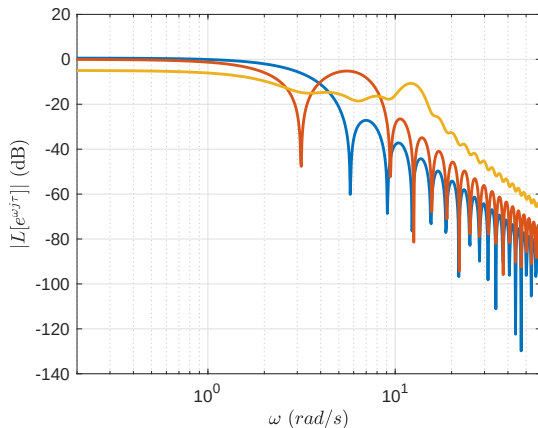
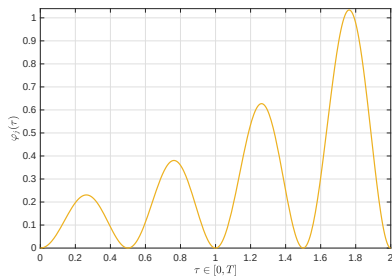


Filtering characteristics

Frequency sweep: $\omega \in \Omega$ (compare to [PR93])

$$\langle \varphi, e^{j\omega \cdot} \rangle = \int_0^T \varphi(\tau) e^{j\omega \tau} d\tau$$

Bode plot: *ideal case*

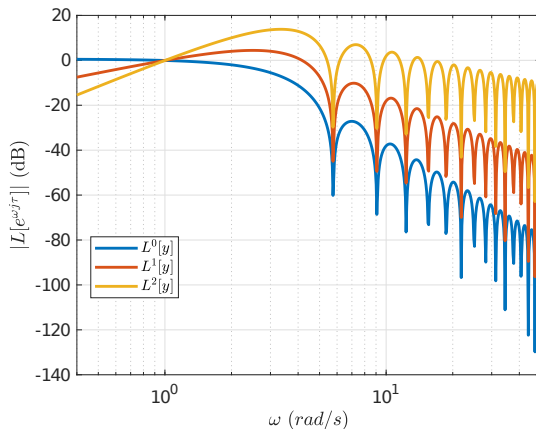
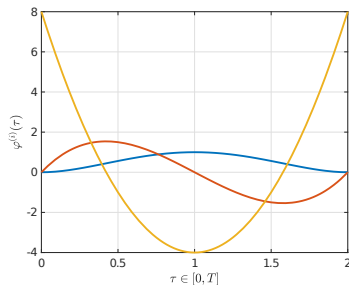


Filtering characteristics

Frequency sweep: $\omega \in \Omega$ (compare to [PR93])

$$\langle \varphi, e^{j\omega \cdot} \rangle = \int_0^T \varphi(\tau) e^{j\omega \tau} d\tau$$

Bode plot: ideal case



Note: Numerical realization

Receding horizon MF operator realization as an **FIR filter** gain:

$$\begin{aligned}\mathcal{M}^i[y] &= (-1)^i \int_{t-T}^t \varphi^{(i)}(\tau - t + T) y(\tau) d\tau \approx (-1)^i \sum_{k=0}^N W_k \varphi^{(i)}(k) y(l - N + k) \\ &= \begin{pmatrix} K_\varphi^0 & \cdots & K_\varphi^N \end{pmatrix} \begin{pmatrix} y(l - N) \\ \vdots \\ y(l) \end{pmatrix} =: K_\varphi Y\end{aligned}$$

RT implementation of moving horizon projection gain in Simulink:

