

Clock synchronization over networks using sawtooth models

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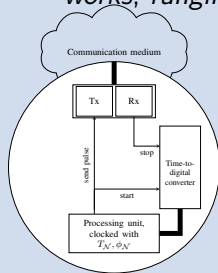
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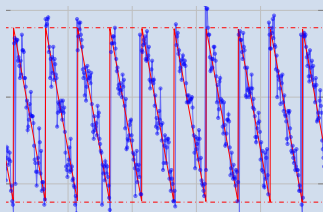
https://github.com/poldap/clock_sync_and_range

Clock synchronization

*identifiability, estimation theory,
sawtooth signals, wireless net-
works, ranging, synchronization*



→ : Internal signaling
Tx : Transmitter
Rx : Receiver



$$Y[n] = \alpha + W[n] + \psi \bmod_1(\beta n + \gamma + V[n])$$

- Introduction to the sawtooth model
- Cramér-Rao Lower Bounds
- Estimation
- Results

Authors and funding



J. Jaldén



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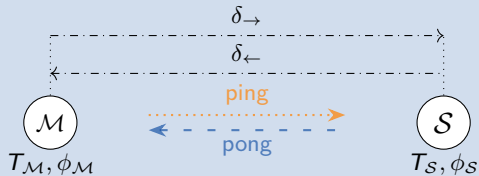


P. Händel

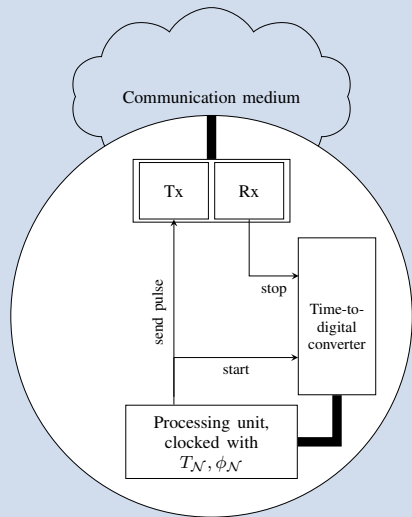
SRA ICT TNG: PITA

T. Oechtering, A. Proutiere, J. Jaldén

Introduction to the sawtooth model - RTT for ranging (I)



Initially proposed in (De Angelis, Dwivedi, Händel, 2013).



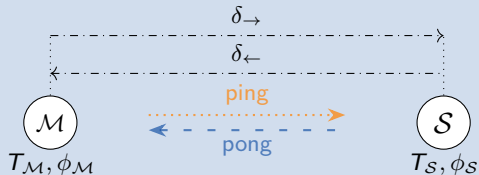
→ : Internal signaling

— : Data bus

Tx : Transmitter

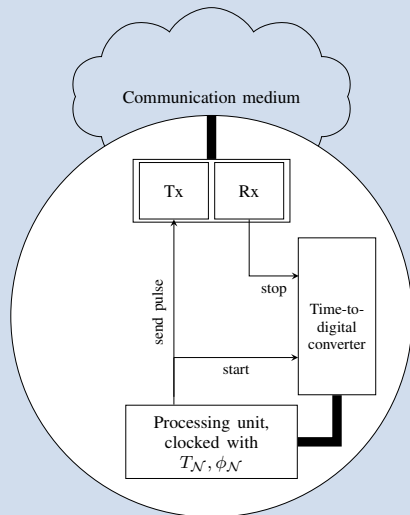
Rx : Receiver

Introduction to the sawtooth model - RTT for ranging (I)



Initially proposed in (De Angelis, Dwivedi, Händel, 2013).

- Low communication overhead



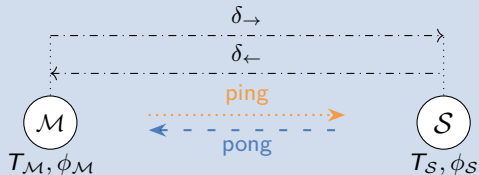
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■ : Data bus

Tx : Transmitter

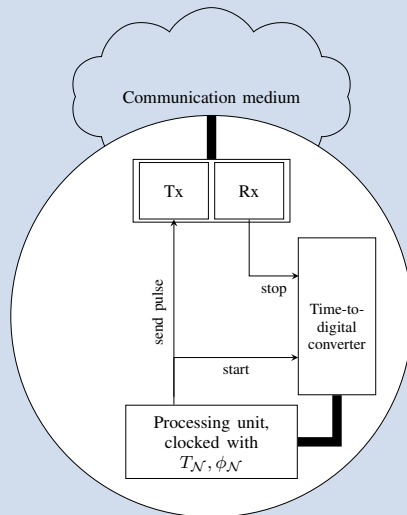
Rx : Receiver

Introduction to the sawtooth model - RTT for ranging (I)



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- ▶ Low communication overhead
- ▶ Low power consumption



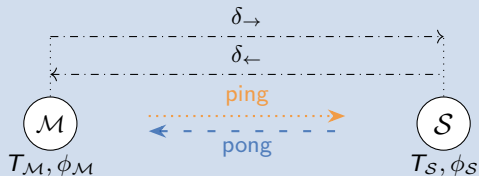
→ : Internal signaling

— : Data bus

Tx : Transmitter

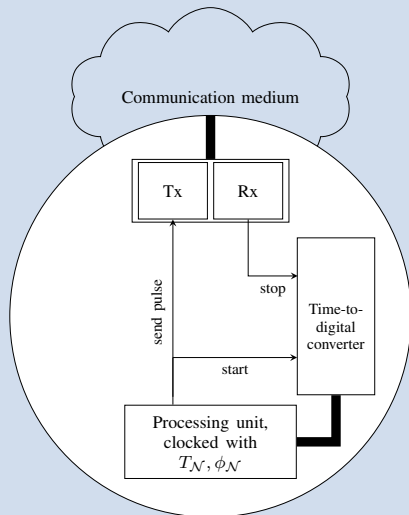
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Introduction to the sawtooth model - RTT for ranging (I)



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- ▶ Low communication overhead
- ▶ Low power consumption
- ▶ High measurement accuracy



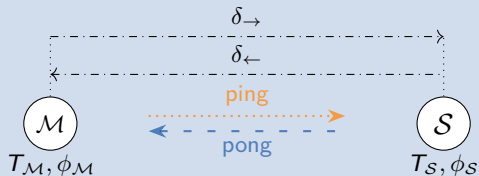
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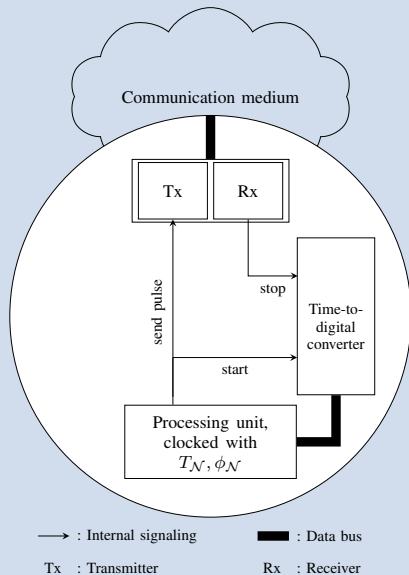
Rx : Receiver

Introduction to the sawtooth model - RTT for ranging (I)

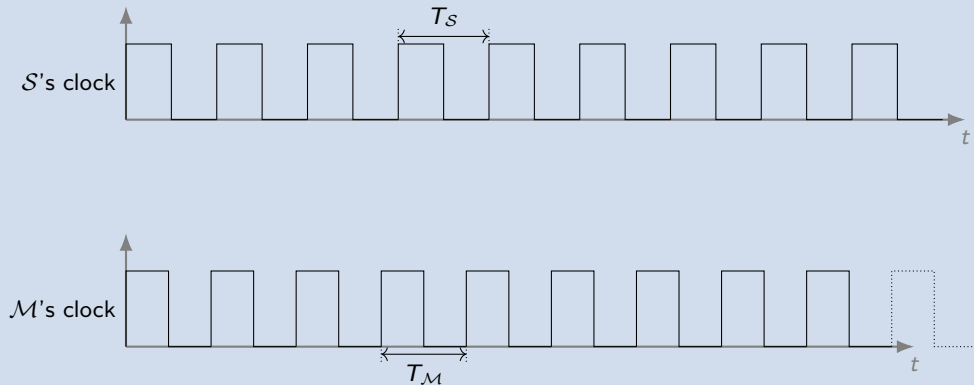


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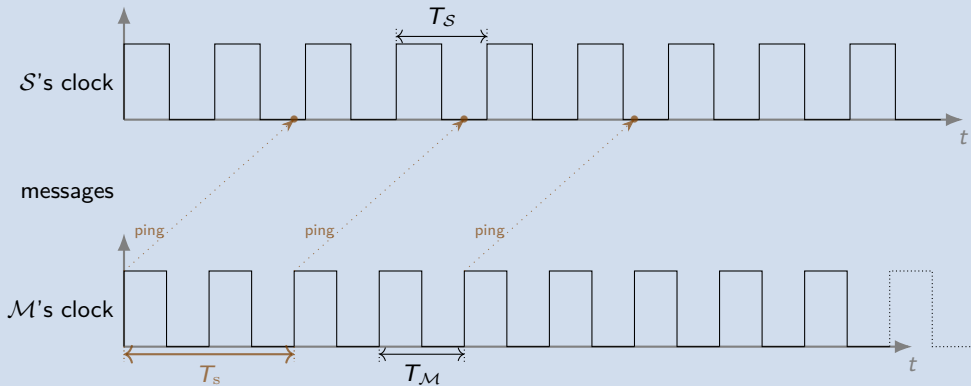
- ▶ Low communication overhead
- ▶ Low power consumption
- ▶ High measurement accuracy
- ▶ Nodes can measure their own clock period



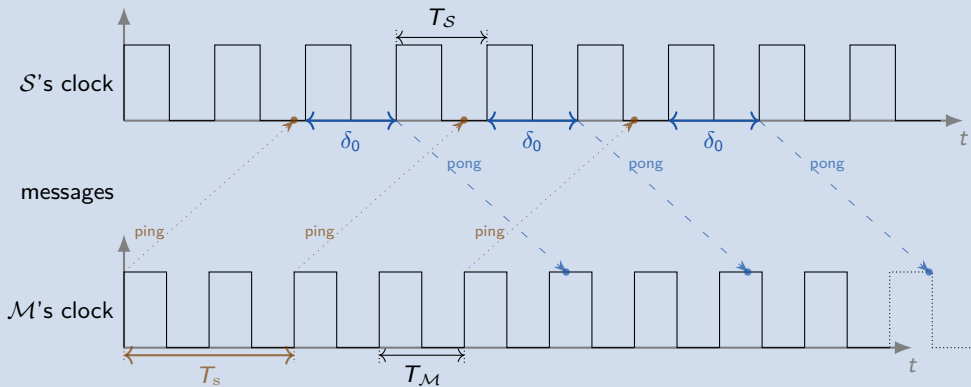
Introduction to the sawtooth model - RTT for ranging (II)



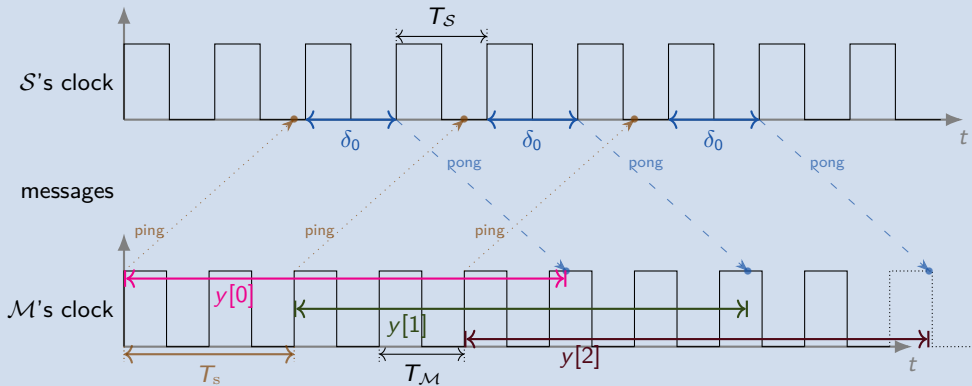
Introduction to the sawtooth model - RTT for ranging (II)



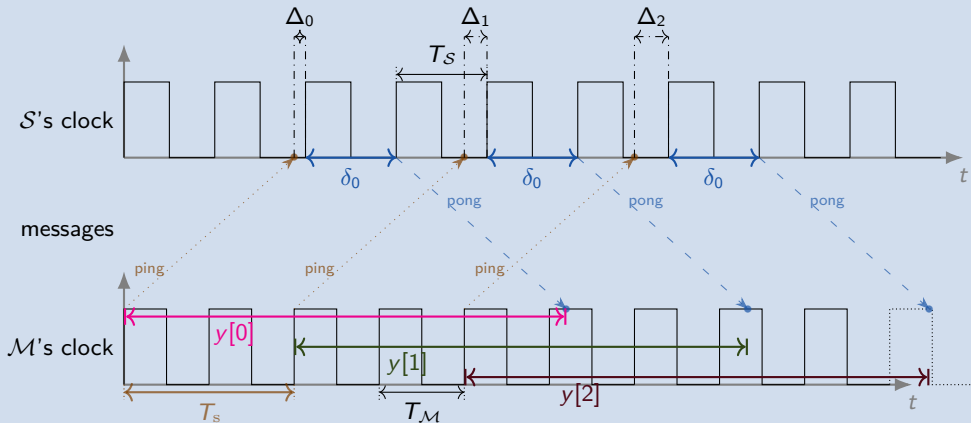
Introduction to the sawtooth model - RTT for ranging (II)



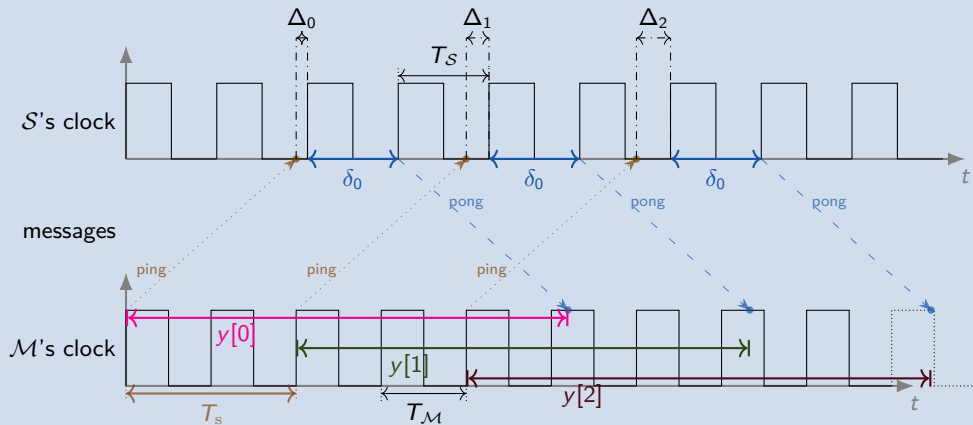
Introduction to the sawtooth model - RTT for ranging (II)



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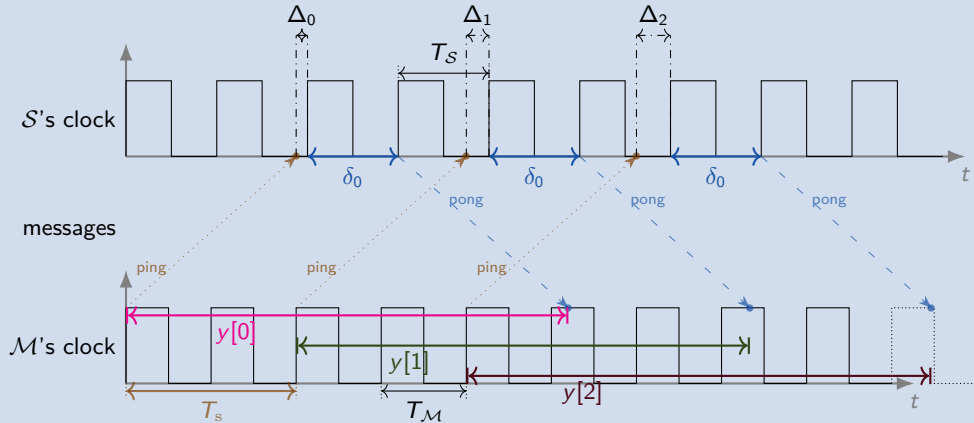


Introduction to the sawtooth model - RTT for ranging (II)



$$y_{\text{det}}[n] = \delta_0 + \delta_{\leftrightarrow} + \Delta_n, \text{ with } \delta_{\leftrightarrow} = \delta_{\rightarrow} + \delta_{\leftarrow} \approx 2\delta_{\rightarrow}$$

Introduction to the sawtooth model - RTT for ranging (II)

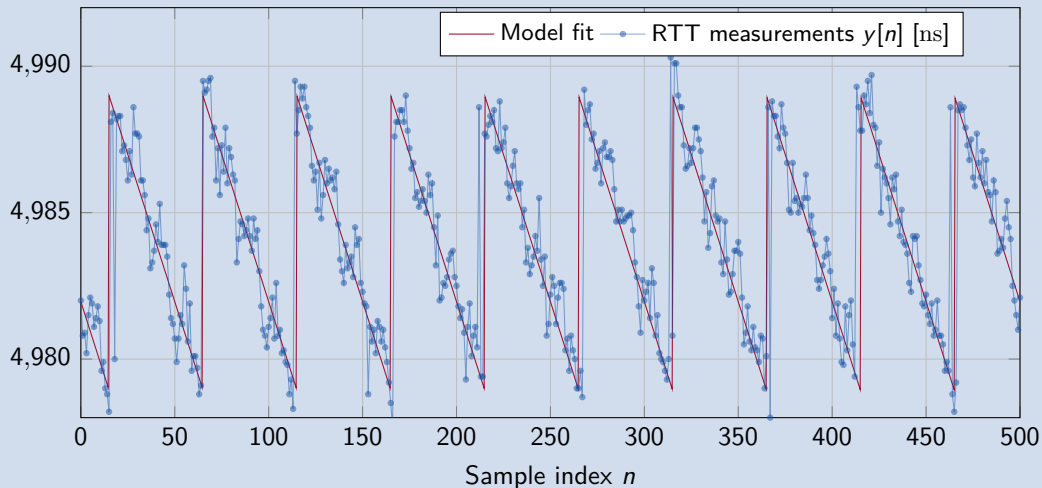


$$y_{\text{det}}[n] = \delta_0 + \delta_{\leftrightarrow} + \Delta_n, \text{ with } \delta_{\leftrightarrow} = \delta_{\rightarrow} + \delta_{\leftarrow} \approx 2\delta_{\rightarrow}, \text{ and}$$

$$\Delta_n = T_S \left(1 - \text{mod}_1 \left[T_S f_d n + \frac{\delta_{\rightarrow}}{T_S} + \frac{\phi_S}{2\pi} \right] \right), \text{ with } f_d = \frac{1}{T_S} - \frac{1}{T_M}.$$

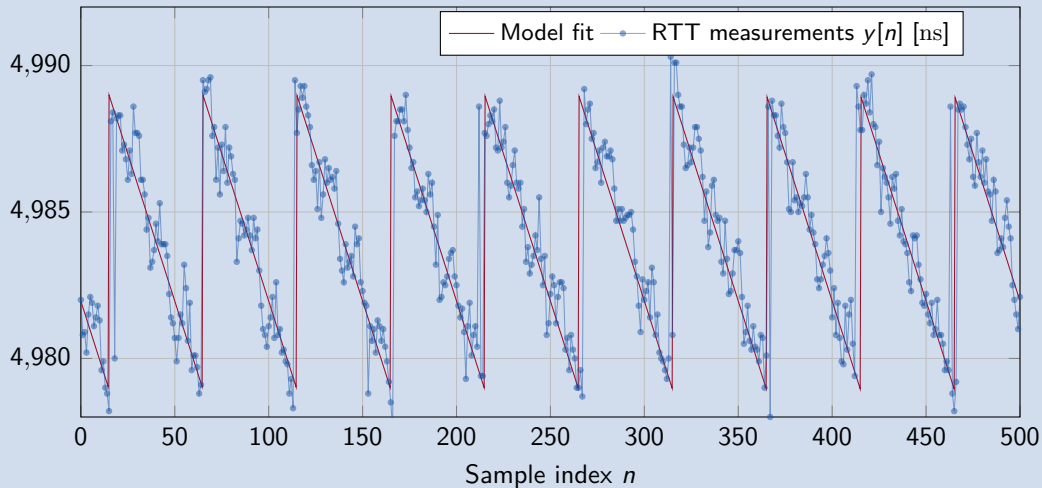
Introduction to the sawtooth model (III)

$$y_{\text{det}}[n] = \delta_{\leftrightarrow} + \delta_0 + T_S \left(1 - \text{mod}_1 \left[T_s f_d n + \frac{\delta_{\rightarrow}}{T_S} + \frac{\phi_S}{2\pi} \right] \right)$$



Introduction to the sawtooth model (III)

$$Y[n] = \alpha + W[n] + \psi \bmod_1(\beta n + \gamma + V[n]), \text{ with } W[n] \text{ and } V[n] \text{ AWGN.}$$



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- ▶ Model derivation
- ▶ Estimation theoretic analysis
- ▶ Conditions for identifiability
- ▶ Exhaustive empirical results
- ▶ DOI: 10.1109/OJSP.2020.2978762

Clock Synchronization Over Networks: Identifiability of the Sawtooth Model

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ABSTRACT In this paper, we analyze the two-node joint clock synchronization and ranging problem. We focus on the case of nodes that employ time-to-digital converters to determine the range between them precisely. This specific design choice leads to a sawtooth model for the captured signal, which has not been studied before from an estimation theoretic standpoint. In the study of this model, we recover the basic conclusion of a well-known article by Florin, Graham, and Kumar (a clock synchronization. More importantly, we discover a surprising identifiability result on the sawtooth signal model: such improves the theoretical condition of the estimation of the phase and offset parameters. To complete our study, we provide performance references for joint clock synchronization and ranging using the sawtooth signal model by presenting an extensive simulation study on basic estimation strategies under different realistic conditions. With our contributions in this paper, we enable further research in the estimation of sawtooth signal models and pave the path towards their industrial use for clock synchronization and ranging.

INDEX TERMS Clock synchronization, ranging, identifiability, sawtooth model, sensor networks, round-trip time (RTT).

1. INTRODUCTION

Clock synchronization across a deployed network is a pervasive and long-standing challenge [1]–[6]. Furthermore, next-generation technologies such as 5G require more accurate synchronization between base stations through a backhaul channel is fundamental to maintain frame alignment and per-packet latency among neighboring cells, and has been identified as a crucial requirement for distributed beamforming, interference alignment, and user positioning [7]–[11]. In radio-frequency technology [9], accurate clock synchronization between the sparse chips that form an array is critical, and in active-ranging 3-dimensional cases [10], [11], it results in low-cost wide-spectrum ultra-short ultra-wideband

(UWB) pulses, increasing both the angular and depth resolution of the captured signals. In wireless sensor networks [12], [13], synchronization is critical to data fusion, channel-sharing, coordinated scheduling [14], [15], and distributed control [2] and is) in distributed database solutions that provide central consistency, clock synchronization accuracy regulates latency, throughput, and performance [5]. Consequently with this wide range of applications, theoretical insights on the fundamental limitations of clock synchronization over networks are likely to have radical implications in a number of fields. In [16], Florin, Graham, and Kumar established the fundamental limitations of the clock synchronization problem in an idealized scenario. Particularly, given a network of nodes with non-zero offset clocks,

Cramér-Rao Lower Bounds of an unwrapped / linear model

Our model is not differentiable, so one can not define the CRLBs.

$$Y[n] = \delta_{\leftrightarrow} + \delta_0 + W[n] + T_S \left[1 - \text{mod}_1 \left(T_s f_d n + \frac{\delta_{\rightarrow}}{T_S} + \frac{\phi_S}{2\pi} + V[n] \right) \right]$$

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We work on an unwrapped / linearized model $Z[n]$,

$$Z[n] = \delta_0 + \frac{\delta_{\leftrightarrow}}{2} + T_S \left(1 - \frac{\phi_S}{2\pi} \right) - T_S T_s f_d n + U[n],$$

with $U[n]$ a white Gaussian process such that $U[n] \sim \mathcal{N}(0, \sigma^2)$ with $\sigma^2 = \sigma_w^2 + T_S^2 \sigma_v^2$.

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Caveats of the approach

- Not the same model (but provides a linearized intuition)

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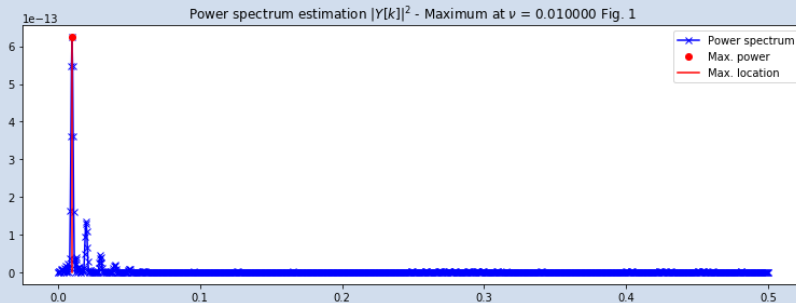
Caveats of the approach

- ▶ Not the same model (but provides a linearized intuition)
- ▶ Non-identifiability of ϕ_S and δ_{\leftrightarrow} (but we can suppose we know the respective other when deriving the lower bound)
- ▶ Dependence of σ^2 on $f_d = \frac{1}{T_S} - \frac{1}{T_M}$ (but that is covered by standard results)

Estimation - Periodogram and correlation peaks (PCP)

$Y[n] = \alpha + W[n] + \psi \bmod_1(\beta n + \gamma + V[n])$, with $\psi < 0$ known when β is known

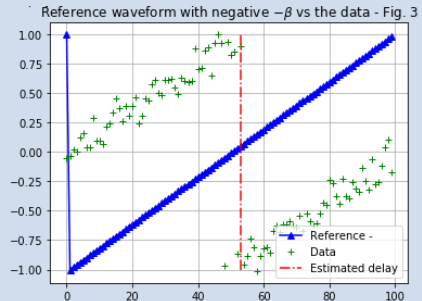
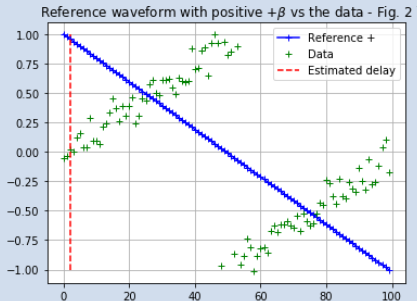
- Estimate $|\beta|$ as the highest peak in the periodogram of the $L - 1$ -times zero-padded, zero-mean data, i.e., $|\hat{\beta}| = \arg \max_k |\text{DFT}_{NL}(\tilde{y}[n])[k]|^2 / (NL)$



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$$Y[n] = \alpha + W[n] + \psi \bmod_1(\beta n + \gamma + V[n]), \text{ with } \psi < 0 \text{ known when } \beta \text{ is known}$$

- ▶ Generate two single-period templates $p_{\pm}[n]$ for $\pm\beta$ and circularly correlate them with the first period of the max-normalized zero-mean data
- ▶ Estimate the sign of β by the largest correlation and the phase γ from the index at which it happens, i.e., $\hat{\gamma} = \bmod_1(\hat{\beta} n^{\text{opt}})$



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- ▶ Estimate ψ through its known relation with β , and α by the closed-form minimum prediction mean squared error solution assuming $\hat{\beta}$, $\hat{\psi}$ and $\hat{\gamma}$ are correct, i.e.,

$$\hat{\alpha}_{\hat{\beta}, \hat{\gamma}} = \sum_{n=0}^{N-1} y[n] - \sum_{m=0}^{N-1} \hat{\psi}_{\hat{\beta}} \bmod_1[\hat{\beta} m + \hat{\gamma}].$$

Estimation - Grid Search, either local (LGS), or global (GGS)

Define a grid $\mathcal{G} \times \mathcal{B}$ in $[-\frac{1}{2}, \frac{1}{2}) \times [0, 1)$, and estimate the point in the grid that minimizes the prediction mean squared error, i.e.,

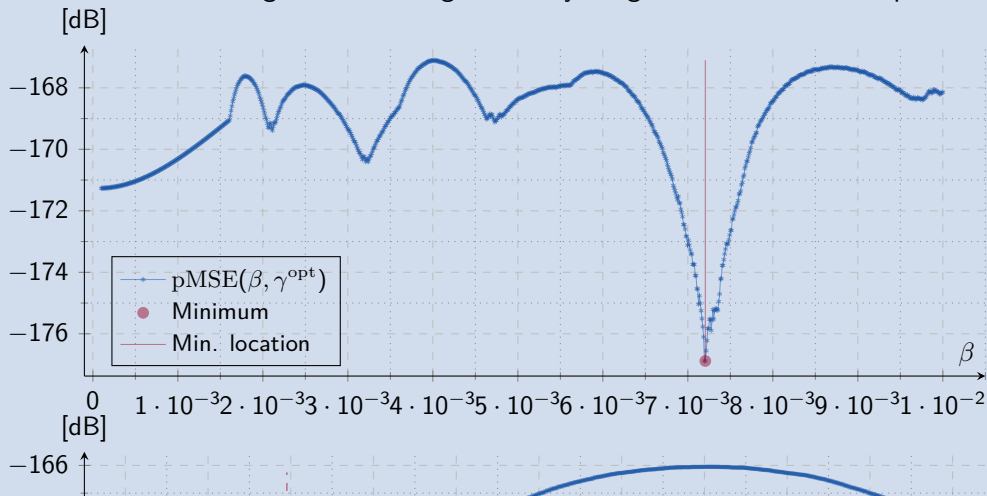
$$\min_{(\beta, \gamma) \in \mathcal{G} \times \mathcal{B}} \left\{ \sum_{n=0}^{N-1} \left(y[n] - \hat{\alpha}_{\beta, \gamma} - \hat{\psi}_{\beta} \bmod_1[\beta n + \gamma] \right)^2 \right\},$$

where $\hat{\alpha}_{\beta, \gamma}$ is the closed form solution as above, and $\hat{\psi}_{\beta}$ is the known amplitude given the frequency.

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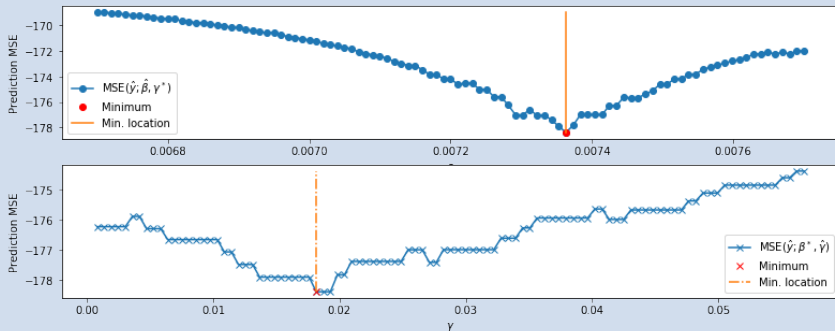
- $\mathcal{G} \times \mathcal{B}$ can be chosen global, resulting on a very irregular function landscape



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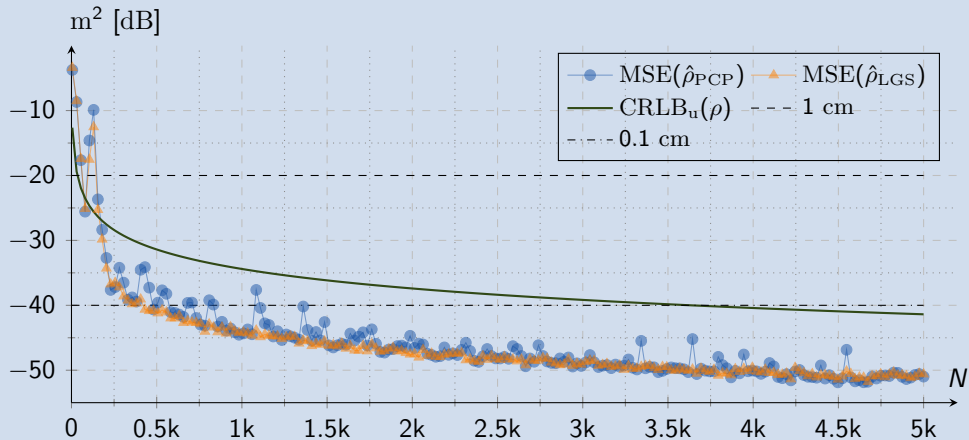
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- ▶ $\mathcal{G} \times \mathcal{B}$ can be chosen global, resulting on a very irregular function landscape
- ▶ or local, around the result of PCP, where smoother behavior is expected and better estimates are likely due to a finer gridding if the PCP was close to the right solution



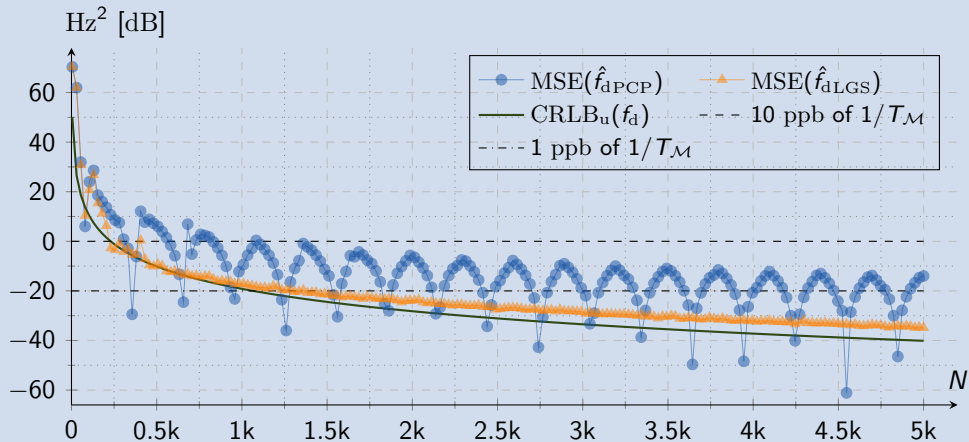
Empirical results

300 Monte Carlo repetitions, $f_d = 73$ Hz, $\phi_S = 3\pi/4$, $\delta_{\leftrightarrow} = 2\rho/c$, $\rho = 2$ m, $1/\sigma_v^2 = 40$ dB, $\psi^2/\sigma_w^2 = 20$ dB, $T_M = 10$ ns, $T_s = 0.1$ ms, and $\delta_0 = 5$ μ s.



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