Non-linear self-interference cancellation on base of mixed Newton method

Graduate student Degtyarev Alexander Andreevich
Supervisor: DSc, Dvorkovich Alexander Viktorovich
Scientific consultant: PhD, Bakhurin Sergey Alexeyevich

MIPT
Department of Multimedia Technologies and Telecommunications

2023-11-23

Contents

Topic relevance

Requirements:

- Effective resources arrangement among users
- Networks with high reliability, low latency, and high data rates

In-band full-duplex technology (IBFD) provides:

- Efficient exploitation of the spectrum, by frequency bandwidth sharing between transmitter and receiver

IBFD systems suffer from undesired self-interference at the receivers path

Self-interference cancellation (SIC) issue

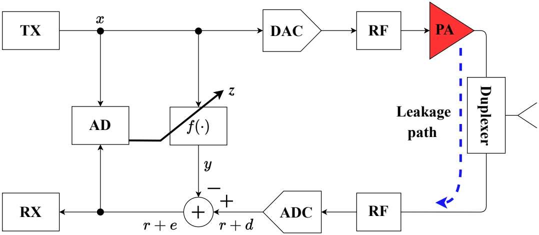


Figure: Full-duplex transceiver simplified scheme {Degtyarev A., draw.io}

- RF-chipset integral implementation and isolation issues → TX leakage to RX
- TX signal **x** is distorted in non-linear components (PA, Duplexer) and TX-RX leakage path
- SIC is an interference identification task:

$$\mathcal{J}(\mathbf{h}) = \mathbb{E}\Big(|\mathbf{r} + \mathbf{d} - \mathbf{y}|\Big)^2 \to \min_{\mathbf{h}}, \qquad (1)$$

Non-linear interference model

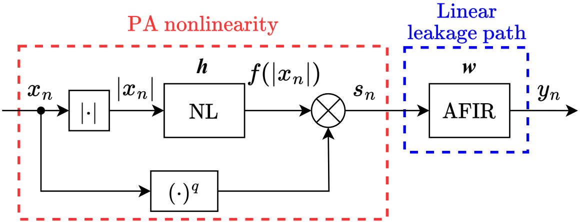


Figure: Hammerstein model {Degtyarev A., draw.io}

- Behavioral Hammerstein model describes interference creation physical process $\rightarrow$ low-complexity
- Hammerstein model output sample:

$$y_n = \sum_{m=-D}^{D} w_m \sum_{k=0}^{P-1} h_k x_{n-m} NL(|x_{n-m}|), \qquad (2)$$

$w_m \in \mathbb{C}$, $h_k \in \mathbb{C}$ – FIR and NL adaptive parameters.

Introduction to mixed Newton method

- Mixed Newton method (MNM) – second order method:

$$\mathbf{z}_{k+1} = \mathbf{z}_k - \mu_k(\mathbf{H}_{\mathbf{z},\mathbf{z}^*}J)^{-1}(D_{\mathbf{z}^*}J)^T, \quad (3)$$

$\mathbf{z}^T = (\mathbf{h}^T\mathbf{w}^T) \in \mathbb{C}^{1\times K}$ – parameter vector, $J = \mathbf{e}^H\mathbf{e}$ – MSE.

- For holomorphic error $\mathbf{e} = \mathbf{d} - \mathbf{y}$: $D_{\mathbf{z}^*}\mathbf{e} = \mathbf{0}$, mixed hessian and gradient are expressed through jacobian:

$$\mathbf{H}_{\mathbf{z},\mathbf{z}^*}J = (D_{\mathbf{z}}\mathbf{y})^H D_{\mathbf{z}}\mathbf{y};\ (D_{\mathbf{z}^*}J)^T = (D_{\mathbf{z}}\mathbf{y})^H\mathbf{e} \quad (4)$$

- For holomorphic error $\mathbf{e}$ method repulses from saddle points.
- Computational complexity defined by hessian calculation and inversion:

$$\chi_{\text{MNM}} = \mathcal{O}(K^3 + K^2N) \quad (5)$$

Experimental setup

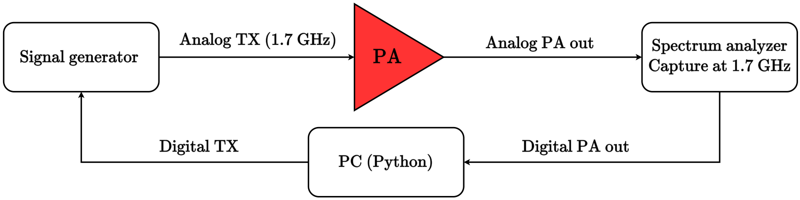
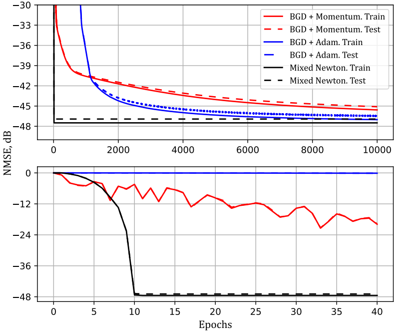


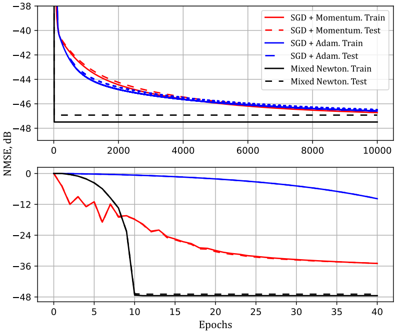
Figure: Testbench {Degtyarev A., draw.io}

- TX – QAM modulated OFDM signal, 60 MHz bandwidth, 480 MHz sample rate
- Average PA output power 20 dBm
- Leakage path is simulated by digital FIR
- Hammerstein model: NL – polynomial order 8, FIR – 45 taps

Learning curves



(a) BGD with Momentum, BGD with Adam and MNM learning curves on train and test data sets



(b) SGD with Momentum, SGD with Adam and MNM learning curves on train and test data sets

- Mixed Newton achieves final performance in ∼30 epochs, comparing to gradient-based methods (∼10000 epochs)

Algorithm performance

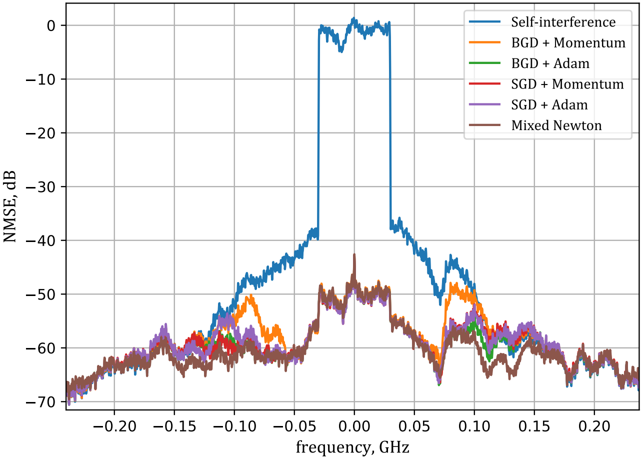


Figure: Power spectral densities of initial and suppressed interference. Signal power distribution along the frequency {Degtyarev A., Python}

Convergence speed comparison

Table: Performance and convergence speed comparison

Algorithm	**BGD Moment.**	**BGD Adam**	**SGD Moment.**	**SGD Adam**	**MNM**
Epoch number	10000	10000	10000	10000	30
Time per epoch, 10^{-2} **s**	3.8	4.0	3.7	4.1	21
Total elapsed tims, s	380	403	386	412	6.2
NMSE, dB	-45.1	-46.7	-46.6	-46.5	-46.9

- MNM step is $\sim$5 times longer comparing to gradient methods
- Total convergence time decreased significantly

Conclusions and further work

- Total training time is decreased to 6 s comparing to 380 s for gradient-based methods to achieve $\sim$46.5 dB suppression
- Mixed Newton requires high memory and computation resources due to hessian calculation and inversion
- Mixed Newton can be modified by inverse hessian (or diagonal) estimation to reduce required resources
- Application of modified version to complex-valued NN structures