Self Interference Mitigation for Full Duplex Systems

Shachar Shayovitz and Dan Raphaeli

Tel Aviv University

Presented in IEEE SSP 2018

June 20, 2018

Full Duplex can potentially increase capacity by 2!

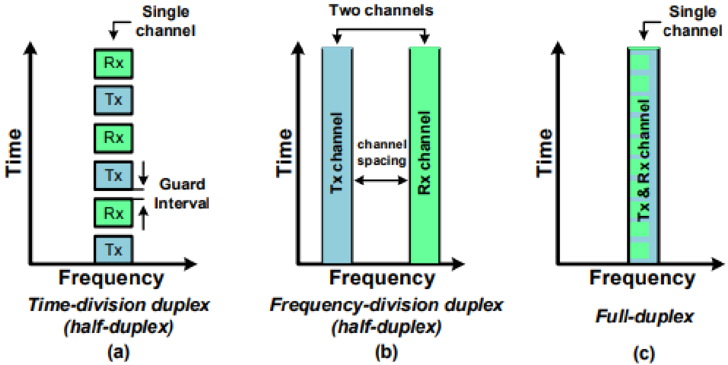
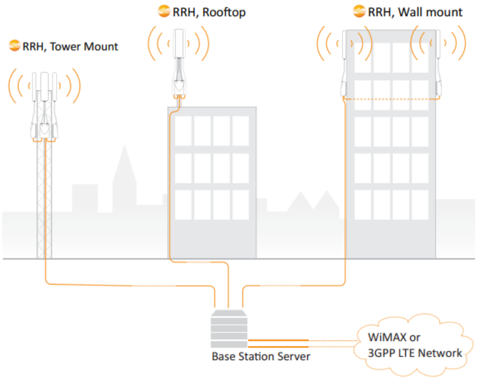


Figure: From "RF Self-Interference Cancellation for Full-Duplex" by van Liempd et al 2014

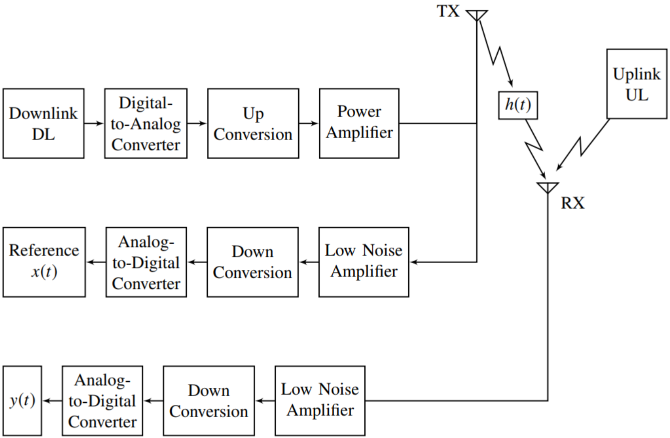
Use Case: Remote Radio Head System



Use Case: Remote Radio Head System

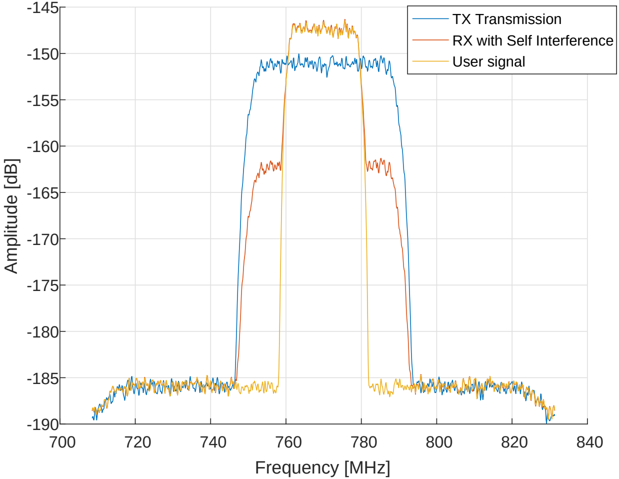
- Future 5G systems may use the oblivious approach which constructs universal relaying components serving many diverse users and operators (multi channel wide band)
- It is not dependent on a priori knowledge of the modulation method and coding (SW configurable)
- Need to be low cost and light weight (minimal HW, all digital computation)
- This approach might benefit systems used in cloud communication (CRAN)

Remote Radio Head Block Diagram



Note: Aux path may be optional

Self Interference - Spectrum of DL signal masking the UL signal



Self Interference Mitigation

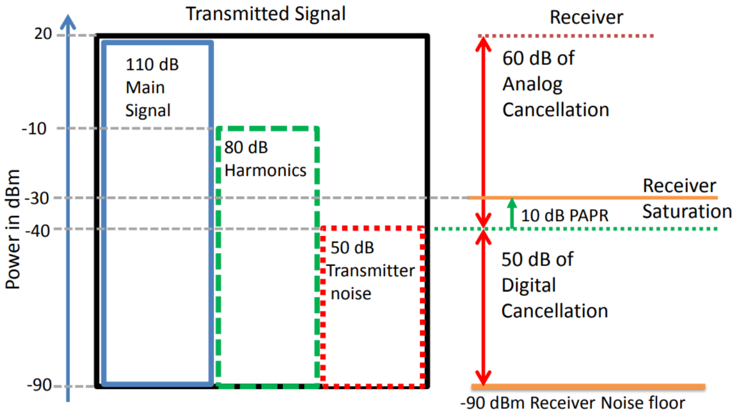
Why cancel interference at the RRH?

- It is preferable to remove the interference as close as possible to the antenna, in order to avoid over-modeling of PA IMD and tracking issues.
- At the Base Band Unit (BBU), several fibers connect and the interferences add up casuing higher noise floor.
- No need to pass the reference to the BBU too.

Current Solutions

- Half duplex (IMD issues) - Sharp analog filters
- Full Duplex - RLS and LMS at the RRH

Rejection Target



System Model

We describe the signal received in the RX after ADC as,

$$\underline{y} = X\underline{h} + \underline{s}$$

- $\underline{s}$ is the UL modeled as a size N proper complex Gaussian vector
- $\underline{h}$ is the self-interference filter of length M
- X is an NxM tall Toeplitz matrix ($N \gg M$) with $X_{ij} = x[i+j]$ for $0 \leq i < N$ and $0 \leq j < M$. The matrix multiplication $X\underline{h}$, is the equivalent of convolving the DL with an FIR filter: $\underline{h}$ (neglecting boundary effects).

Maximum Likelihood Estimation of the self Interference Filter

Our main objective is to recover the UL signal - $\underline{s}$, from the RX ADC measurements $\underline{y}$ and TX signal X.

Interference Removal

We propose to use an ML estimation of the self interference filter $\underline{\hat{h}}$ and subtract it from $\underline{y}$.

$$\underline{\hat{s}} = \underline{y} - X\underline{\hat{h}}$$

where $\underline{\hat{s}}$ and $\underline{\hat{h}}$ are the estimations of the UL and the self interference filter respectively.

Maximum Likelihood Estimation of the self Interference Filter

The ML solution for the leakage filter finds the vector $\underline{h}$ which maximizes the log likelihood function,

$$\log\left(p(\underline{y}|\underline{h};\Sigma)\right) \propto -\log(\det\Sigma) - \left(\underline{y} - X\underline{h}\right)^{\star}\Sigma^{-1}\left(\underline{y} - X\underline{h}\right)$$

where Σ is the covariance matrix of the vector $\underline{s}$ and $()^{\star}$ is the matrix conjugate transpose operator.

Known Solutions

Algorithm	Complexity	Optimal (ML)	Online	Adaptive
LS	High	Need white UL	No	No
RLS	Medium	Same as LS	Yes	Yes
LMS	Low	Need white UL,DL	Yes	Yes

Problem

- If Σ was known *a-priori*, then ML would reduce to a closed form solution (Weighted Least Squares (WLS)).
- In the multi channel scenario, the UL signal is comprised of multiple carriers with different bandwidths and power levels.
- $\underline{s}$ has unknown statistics.
- UL is clearly not spectrally white and thus RLS and LMS will have a significant performance loss compared to ML

Modeling UL as AR process

- ML depends on Σ, thus only the UL's PSD is of interest.
- ARMA models define a dense set in the class of all continuous PSDs
- The second order statistics of an ARMA process can approximate most well-behaved WSS processes and in particular the UL.
- Causal and invertible ARMA processes can be written as AR process of infinite order.
- We suggest to approximate the UL signal $\underline{s}$, as a complex valued autoregressive process of order p.

Modeling UL as AR process

AR Process

$$s[n] = \sum_{k=1}^{p} g_k s[n-k] + u[n]$$

where $\underline{g}$ is an unknown vector of size p
$u[n]$ is a circularly-symmetric complex normal i.i.d process with zero mean and variance σ_u^2.

The choice of p determines the approximation's accuracy, and it effects the model's frequency selectivity.

Modeling UL as AR process

In matrix form,

$$\underline{u} = W\underline{s}$$

where W is a square Toeplitz whitening matrix with dimension N, which is the size of vectors $\underline{u}$ and $\underline{s}$

$$W = \begin{pmatrix} 1 & -g_1 & -g_2 & \dots & -g_p & 0 & 0 & \dots & 0 \\ 0 & 1 & -g_1 & -g_2 & \dots & -g_p & 0 & \dots & 0 \\ \dots & \dots & \dots & \dots & \dots & \dots & \dots & \dots & \dots \\ 0 & 0 & 0 & 0 & \dots & 0 & 0 & 1 & -g_1 \\ 0 & 0 & 0 & 0 & \dots & 0 & 0 & 0 & 1 \end{pmatrix}$$

The matrix Σ can be written as,

$$\Sigma^{-1} = \frac{W^\star W}{\sigma_u^2}$$

Joint Minimization

Therefore ML reduces to joint minimization of,

$$\underline{\hat{h}}, \underline{\hat{g}} = \arg\min_{\underline{h}, \underline{g}} \left(\underline{y} - X\underline{h}\right)^{\star} W^{\star} W \left(\underline{y} - X\underline{h}\right)$$

- Since the optimization is also done on the covariance's parameters, the problem does not have a simple closed form solution and a unique algorithm is developed.
- We use alternating minimization of the likelihood function and converge to a joint solution for both filters.

Alternating Minimization - Step 1

- Assuming known AR filter, then the covariance matrix is known.
- The ML problem becomes a conventional WLS problem.
- This result has the following interpretation: passing the DL and UL signals through a whitening filter and performing LS estimation of the self interference filter.

- In the second step of each iteration, we use the previous estimation of the self interference filter, $\underline{h}^k$ and minimize over the vector $\underline{g}$.
- We define the following residual vector:

$$\underline{e}_k = \underline{y} - X\underline{h}^k$$

- Thus the ML reduces to,

$$\underline{g}^{k+1} = \arg\min_{\underline{g}} \left\| W\underline{e}_k \right\|^2$$

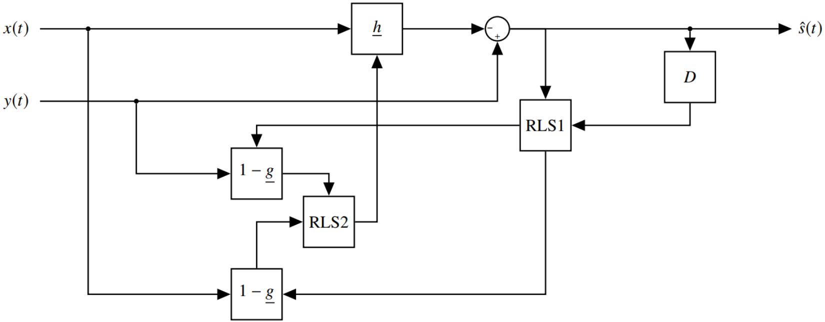
Alternating Minimization - Step 2

The resulting objective becomes,

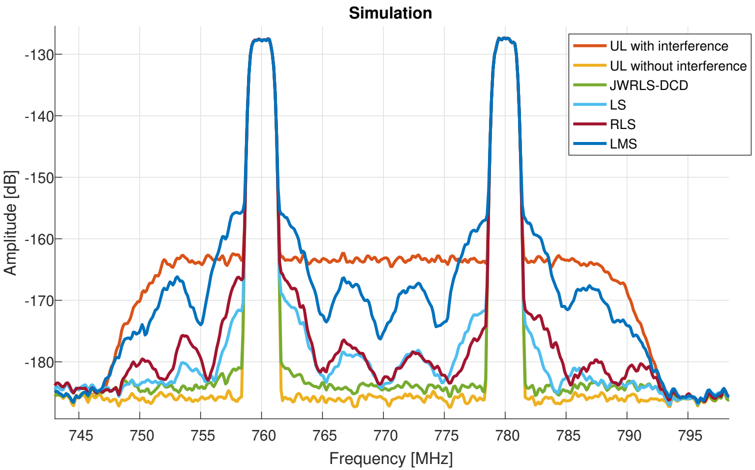
$$\underline{g}^{k+1} = \arg\min_{\underline{g}} \left\| \underline{e}_k - \begin{pmatrix} e_k(N-1) & e_k(N-2) & \dots & e_k(N-p) \\ e_k(N-2) & e_k(N-3) & \dots & e_k(N-(p+1)) \\ \dots & \dots & \dots & \dots \end{pmatrix} \underline{g} \right\|^2$$

We notice that this is equivalent to the Yule-Walker problem for the estimation of AR parameters (solved by LS)

JWRLS Block Diagram



Two Strong Users



Near Far Scenario