ROBUST LOW COMPLEXITY DIGITAL SELF INTERFERENCE CANCELLATION FOR MULTI CHANNEL FULL DUPLEX SYSTEMS

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ABSTRACT

Self interference in a communications system occurs when there is electromagnetic coupling between the transmission (TX) and reception (RX) radio frequency (RF) chains or antennas. This coupling degrades the system's RX sensitivity to incoming signals. In this paper a low complexity technique for self interference cancellation in multi channel systems is presented. In this scenario, multiple carriers at overlapping arbitrary bandwidths and powers are simultaneously received and transmitted by the system. Traditional algorithms for self-interference mitigation based on Recursive Least Squares (RLS) and Least Mean Squares (LMS), fail to provide sufficient rejection since the incoming signal is not spectrally white, which is critical for their performance. The proposed algorithm mitigates the interference by modeling the incoming multi carrier signal as an Auto-Regressive (AR) process and jointly estimates the AR parameters and self interference. The resulting algorithm can be implemented using a low complexity architecture comprised of only two RLS modules. The main advantage of the proposed technique over RLS and LMS is the robustness to the spectrum of arbitrary incoming signals and improved rejection levels of over 10dB. All of this is achieved while not compromising on low latency constraints.

1. INTRODUCTION

Full duplex communications has the potential to improve the spectral efficiency of wireless communications and become a significant driver of future 5G communication systems. In full duplex communications, the transmitter and receiver share the same frequency band, thus theoretically increasing the spectral efficiency by a factor of two. However, RF coupling between TX and RX causes self interference which is added to the signals incoming to the RX. This effect can also happen in Frequency Division Duplex (FDD) communications, when the TX's Power Amplifier (PA) is close to saturation and intermodulation (IMD) components of the transmission leak to the RX frequency band of interest. We denote the signals incoming from users as Uplink (UL) and the system's transmission as Downlink (DL).

There are several approaches to counter the effect of self interference, they are generally composed of two steps. Firstly, analog domain mitigation (antenna nulling or sharp analog filters) reduces the interference to a level which does not saturate the Analog to Digital Converter (ADC). Next, digital signal processing algorithms counter the residual noise. A comprehensive summary on solutions and algorithms in both analog and digital domains can be found in [1, 2, 3].

Digital domain cancellation can be generally divided to two categories: ones using auxiliary path ADC [4] and those which do not [5]. The signal after Digital to Analog Converter (DAC), in the TX RF path, passes through a PA and other active devices which can create non linear IMD's which are hard to model. The auxiliary ADC, sampling the signal as close as possible to the TX antenna, records an accurate replica of the TX signal, which can later be used for leakage filter estimation. Solutions which do not use an auxiliary ADC and thus save hardware cost, usually use some sort of polynomial approximation of the PA's IMD's.

In [4] an auxiliary receiver measures the DL's frequency response and a Least Squares (LS) estimation is performed to recover the leakage filter in frequency domain. Next, the filter is used to cancel out the self-interference signal. In [5] there is no auxiliary ADC path and modeling of the IMD is proposed using 2nd-order nonlinear terms. A training sequence is transmitted by the system when there is no RX reception and the self interference filter is estimated using LS. This assumption is not useful in practice, since the users can transmit at any time, in particular in cellular communications.

Most algorithms for digital domain cancellation use RLS or LMS since these algorithms have low computational complexity and they perform fairly well when the UL and DL are spectrally white. In fact, performance of LS, RLS and LMS will be as good as Maximum Likelihood (ML) only when the UL is either spectrally white or its power is significantly lower than the self interference. However, in practical application and in particular multi channel communications, multiple carriers at arbitrary bandwidths and power levels coexist at the UL thus its spectrum is non-white and its power might be comparable to the leakage.

In this paper we propose a novel algorithm for interference cancellation which is more robust to the spectrum shape of the DL and UL than RLS, LMS and LS. The algorithm is based on the observation that the UL signal can be modeled as an AR process. Based on this, we devise a self interference cancellation algorithm utilizing the special characteristics of the AR process. In subsequent sections, we will show simulations of scenarios where LS, RLS and LMS fail to provide sufficient interference rejection, while our novel algorithm provides dramatically better interference rejection.

2. SYSTEM MODEL

In this section we describe the mathematical model for our system. Suppose we have a cellular base station (BS) and in order to demodulate the UL, the BS needs to remove the interference created by its DL. We denote the discrete time domain DL signal as $x[n]$.

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

$$\underline{y} = X\underline{h} + \underline{s} \tag{1}$$

Where $\underline{s}$ is the UL modeled as a size N proper complex Gaussian vector, $\underline{h}$ is the self-interference filter of length M and 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).

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

$$\hat{\underline{s}} = \underline{y} - X\hat{\underline{h}} \tag{2}$$

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

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

$$\log\left(p(\underline{y}|\underline{h};\Sigma)\right) \propto -\log(\det\Sigma) - \left(\underline{y} - X\underline{h}\right)^{\star}\Sigma^{-1}\left(\underline{y} - X\underline{h}\right) \tag{3}$$

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

If Σ was known *a-priori*, then maximization of (3) would reduce to a closed form solution (Weighted Least Squares (WLS)). Moreover, if $\underline{s}$ was an i.i.d vector, then the LS and RLS solutions would yield the same performance as ML.

However, $\underline{s}$ has unknown statistics since it is the combination of all the active users in a given cell sector. All users are transmitting in different band-widths, center frequencies and power levels, in various formats like LTE, GSM and CDMA.

3.1. Stochastic Modeling of the UL

In the multi channel scenario, the UL signal is comprised of multiple carriers with different bandwidths and power levels. For example, several LTE and CDMA carriers from multiple users. Therefore, the UL is clearly not spectrally white and thus RLS and LMS will have a significant performance loss compared to ML that maximizes (3).

Since the objective is to maximize (3), then the UL's PSD, assuming the UL is Wide Sense Stationary (WSS), is of interest. The Auto-Regressive Moving Average (ARMA) model defines a dense set in the class of all continuous PSDs according to section 3.2 in [6]. These processes are modeled as the output of a stable LTI system with zero mean white Gaussian input, where the frequency response of the system can be written as a division of two polynomials. Therefore, the second order statistics of an ARMA process can approximate most well-behaved WSS processes and in particular the UL.

However, ARMA processes are harder to work with than AR. Fortunately, causal and invertible ARMA processes can be written as AR process of infinite order [7]. Therefore, we suggest to approximate the UL signal $\underline{s}$, as a complex valued autoregressive process of order p.

$$s[n] = \sum_{k=1}^{p} g_k s[n-k] + u[n] \tag{4}$$

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.

Equivalently, (4) can be written in matrix form,

$$\underline{u} = W\underline{s} \tag{5}$$

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

$$W = \begin{pmatrix} 1 & -g_1 & -g_2 & \dots & -g_p & 0 & 0 & \dots & 0 \\ 0 & 1 & -g_1 & -g_2 & \dots & -g_p & 0 & \dots & 0 \\ \dots & \dots & \dots & \dots & \dots & \dots & \dots & \dots & \dots \\ 0 & 0 & 0 & 0 & \dots & 0 & 0 & 1 & -g_1 \\ 0 & 0 & 0 & 0 & \dots & 0 & 0 & 0 & 1 \end{pmatrix} \tag{6}$$

We notice that due to (5), the matrix Σ can be written as,

$$\Sigma = \mathbb{E}\left((W^{-1})^{\star}\underline{u}\underline{u}^{\star}W^{-1}\right) \tag{7}$$

Since $\underline{u}$ is an i.i.d vector, the inverse is

$$\Sigma^{-1} = \frac{W^{\star}W}{\sigma_u^2} \tag{8}$$

We propose to use a Generalized Likelihood Ratio (GLRT) approach for solving the ML problem. We will find the vector

$\underline{g}$ which maximizes (3), and use it to compute the posterior. Equivalently, we can look at this approach as jointly maximizing (3),

$$\underline{\hat{h}}, \underline{\hat{g}} = \arg\max_{\underline{h},\underline{g}} p(\underline{y}|\underline{h}; W) \tag{9}$$

4. ALTERNATING MINIMIZATION ALGORITHM

In this section, an algorithm which approximately solves the ML problem defined in (9) is proposed. 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 on a joint solution for both filters.

Note that, $\det A^{-1} = \frac{1}{\det A}$, therefore (3) becomes,

$$\log\left(p(\underline{y}|\underline{h}; \Sigma)\right) \propto \log(\det W^\star W) - \left(\underline{y} - X\underline{h}\right)^\star \frac{W^\star W}{\sigma_u^2} \left(\underline{y} - X\underline{h}\right) \tag{10}$$

Since W is a matrix with ones across its main diagonal and assuming large enough vectors (neglecting boundary effects), $\det W = 1$. Moreover, $\det W^\star W = \det W^\star \det W$, Thus $\det W^\star W = 1$

$$\underline{\hat{h}}, \underline{\hat{g}} = \arg\min_{\underline{h},\underline{g}} \left(\underline{y} - X\underline{h}\right)^\star W^\star W \left(\underline{y} - X\underline{h}\right) \tag{11}$$

We minimize (11) using alternating minimization [8]. That is, we set $\underline{h}^{k=0}$ and $\underline{g}^{k=0}$ to some initial values, where k is the iteration index for the alternating minimization. Then we fix $\underline{h}^k$ and perform a minimization for $\underline{g}^{k+1}$. Then we fix $\underline{g}^{k+1}$ to the new value and minimize according to $\underline{h}^{k+1}$. We repeat this procedure until the difference between estimated filters in subsequent iterations is smaller than a predefined value.

4.1. Minimization over the self interference filter

We use the previous estimation of the AR filter taps, $\underline{g}^k$ which define the matrix W_k and minimize (11) over the vector $\underline{h}$.

$$\underline{h}^{k+1} = (X^\star W_k^\star W_k X + \lambda_h I_M)^{-1} X^\star W_k^\star W_k \underline{y} \tag{12}$$

where I_M is an M by M identity matrix and λ_h is a regularization factor added to increase robustness of the estimation.

Note that (12) is the WLS solution to the ML problem, when the covariance matrix is known. 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.

4.2. Minimization over the whitening filter

In the second step of each iteration, we use the previous estimation of the self interference filter, $\underline{h}^k$ and minimize (11) over the vector $\underline{g}$.

We define the following residual vector:

$$\underline{e}_k = \underline{y} - X\underline{h}^k \tag{13}$$

Plugging (13) into (11)

$$\underline{g}^{k+1} = \arg\min_{\underline{g}} \left\|W\underline{e}_k\right\|^2 \tag{14}$$

Since W is a Toeplitz matrix dependent on $\underline{g}$ and the matrix multiplication in (14) is equivalent to a convolution between $[1, -\underline{g}]$ and $\underline{e}_k$, we can rewrite (14) as,

$$\underline{g}^{k+1} = \arg\min_{\underline{g}} \left\|E_k \begin{pmatrix} 1 \\ -\underline{g} \end{pmatrix}\right\|^2 \tag{15}$$

where E_k is a Toeplitz matrix defined as,

$$E_k = \begin{pmatrix} e_k(N) & e_k(N-1) & \dots & e_k(N-p) \\ e_k(N-1) & e_k(N-2) & \dots & e_k(N-(p+1)) \\ \dots & \dots & \dots & \dots \end{pmatrix} \tag{16}$$

where $e_k(i)$ is the i'th element in the vector $\underline{e}_k$.

Plugging (16) into (15) and re-arranging we get,

$$\underline{g}^{k+1} = \arg\min_{\underline{g}} \left\|\underline{e}_k - \tilde{E}_k \underline{g}\right\|^2 \tag{17}$$

where $\tilde{E}_k$ is defined as,

$$\tilde{E}_k = \begin{pmatrix} e_k(N-1) & e_k(N-2) & \dots & e_k(N-p) \\ e_k(N-2) & e_k(N-3) & \dots & e_k(N-(p+1)) \\ \dots & \dots & \dots & \dots \end{pmatrix} \tag{18}$$

We notice that (17) can be solved using LS and the solution is,

$$\underline{g}^{k+1} = (\tilde{E}_k{}^\star \tilde{E}_k + \lambda_g I_M)^{-1} \tilde{E}_k{}^\star \underline{e}_k \tag{19}$$

where λ_g is a regularization factor added to increase robustness of the estimation.

We notice that (19) is equivalent to the Yule-Walker solution for the AR parameters estimation.

5. LOW COMPLEXITY RLS IMPLEMENTATION

The algorithm derived above works on a batch but can be made sequential. Since all the minimizations above can be described as LS problems, we can convert them to RLS and thus provide a sequential, real time solution. Note that this solution is approximate, since LS estimation is done in each of the iterations we described in the previous section.

Moreover, (12) and (19) incorporate the regularization terms in the LS solution, to improve robustness to low power DL scenarios. These terms depend on the power difference between the UL and DL and are fine tuned until adequate performance is reached. The canonical form of RLS employs the matrix inversion lemma to avoid explicit inversion of the correlation matrix. However, regularization essentially creates a full rank matrix and excludes the use of the matrix inversion lemma. Therefore, in order to incorporate these terms in RLS, we used the algorithm presented in [9], which finds the matrix inverse using a line search and is essentially an approximation of RLS, denoted as RLS-DCD.

RLS-DCD is a low complexity implementation of RLS whose number of real multipliers is linear with the filter's length. In [10] there is also an FPGA implementation of this algorithm which shows its real world value and applicability. Since RLS-DCD has linear computational complexity, then also our algorithm is linear with the sizes of the two filters. This concludes that the computational complexity of our approach is much better than RLS which is quadratic with the filter size.

The proposed algorithm, which we denote as JWRLS-DCD (Joint Whitening RLS - DCD) can be summarized as follows: the DL and UL signals go through a whitening filter $1 - \underline{g}$ and then fed to an RLS-DCD module which produces an estimate of the self interference filter. In parallel, the reference is convolved with the self interference filter estimate and subtracted from the UL, which produces an estimate of the UL without interference. This output is delayed by one sample and sent to another RLS-DCD module which estimates the UL's covariance which is basically the whitening filter.

6. SIMULATION RESULTS

In this section, the proposed algorithm's performance is analyzed using a simulation. DL and UL signals were generated by colored Gaussian processes with variable power levels and bandwidths. Next, in order to simulate the PA's response, non linearity was introduced to the DL using a Hammerstein-Weiner model [11]. For simplicity, the non linear DL was filtered using an attenuator to simulate the RF leakage filter. Finally, the self interference was added to the UL which was then inputted to our algorithm. Note that JWRLS-DCD used 24 taps for both filters $\underline{g}$ and $\underline{h}$. All the other algorithms used 24 taps for their filter estimation.

We have examined two full duplex scenarios: The first scenario comprises of two narrow band UL signals with equal power and a wide band DL signal. In Fig. 1, we can see the UL with and without interference, JWRLS-DCD, RLS, LS and LMS. We can see that JWRLS-DCD produces an output with better rejection of the interference than all the other algorithms, some areas are even 10dB better.

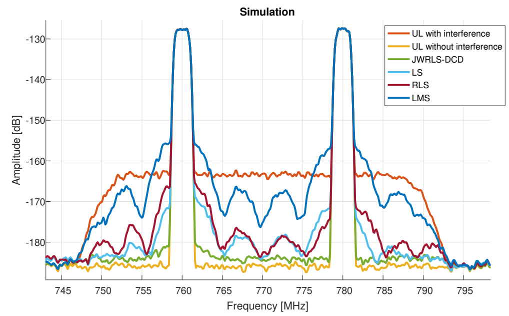

Fig. 1. Rejection performance of JWRLS-DCD for two narrow-band UL with wide-band DL in full duplex.

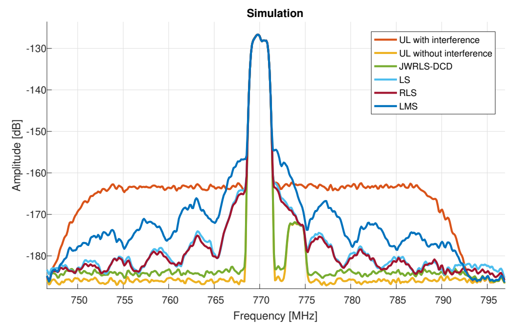

Fig. 2. Rejection performance of JWRLS-DCD in full duplex near far scenario.

The second scenario we have examined is the near-far situation, where there are two UL signals, one with higher power and another with lower power, simulating a close proximity user and a distant user. The challenge here is to remove the self interference well enough so that the lower power UL is observable and not corrupted by estimation noise around the strong UL. We can see in Fig. 2 that JWRLS-DCD performs significantly better than RLS and the low power UL is clearly observable, while the other algorithms do not succeed in this test.

7. CONCLUSIONS

In this paper, an innovative algorithm for mitigating self interference which exists in full duplex communication systems was presented. The main novelty is the AR modeling of the UL, which enabled the development of an algorithm which has lower computational complexity than RLS and LS while having rejection performance much better than LS, RLS and LMS.

8. REFERENCES

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