Realtime Software Defined Self-Interference Cancellation Based on Machine Learning for In-Band Full Duplex Wireless Communications

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Abstract—The key enabling technology to in-band full duplex wireless is the self-interference cancellation. This paper proposes a realtime software defined digital self-interference cancellation based on machine learning. The contributions of this work include: (1) a digital self-cancellation scheme that approaches to the limit of the hardware, and (2) an open software defined cancellation framework that supports the realtime cancellation using machine learning algorithms with synchronized iterative training and prediction. This solution is implemented and evaluated on a software defined radio testbed. It results in performance of 50 dB in digital cancellation, which is close to the hardware limit and significantly outperformed available literature digital cancellation solutions. It also demonstrates stable performance across spectral band.

I. Introduction

Generally, today wireless RF works in half duplex (FD) mode. That means, on a single channel, transmission and receiving cannot happen simultaneously. FD radio yields many limitations to the protocols and architectures of wireless communications and networks, such as media access control(MAC), bit rate adaptation and interference of symbols. In contrast, in band full duplex(IBFD) wireless offers many promising features: in the physical layer, it is likely to double the spectrum efficiency; in the MAC layer, it shows potentials to solve some existing half-duplex wireless problems, such as hidden terminal problems, loss of throughput due to transmission congestion, unfairness while in star or mesh network topologies, and large delays caused by receiving and transmission strategues [1]. Additionally, IBFD wireless relay can significantly improve the network throughput and coverage.

Although IBFD has a promising future, the most difficult challenge to enable IBFD is the *self-interference* that is defined by the transmitted signal power to the simultaneously received signal at the wireless interference of a wireless node. A few years ago, it was believed that the transmission and reception of signals on the same channel, namely IBFD, is impossible in practice [2]. The tremendous potential benefits of IBFD have however attracted many researchers to explore various such wireless solutions as that they can reduce or mitigate self-interference. Conceptually, if a wireless node can cancel its own transmitted signal in its receiver circuit, then what it transmits will not have impact on what it receives at the same time. As a result, it can transmit and receive simultaneously, namely achieving IBFD.

In this paper, we target the most difficult challenge of IBFD, *self-interference cancellation*. We propose a realtime solution that employs machine learning and achieves the best ever performance in digital self-cancellation in real world with a software defined radio (SDR) implementation. This work answers two questions: (1) how to exploit machine learning to *adaptively* cancel self-interference in IBFD? and (2) how to achieve the iterative parameter update for machine learning cancellation models in realtime wireless communications?

In the rest of this paper, Section II provides a brief research background and literacy of IBFD wireless and self-cancellation. Then Section III describes current problems in self-interference cancellation in propagation, analog and digital domains. Section IV next presents our solutions to cancel self-interference, including a traditional method as well as a machine learning based scheme, and followed by Section V showing our experiment performance on a USRP SDR testbed. Finally the paper is concluded by Section VII.

II. Background

The first experiment about IBFD wireless on a narrow band was reported in 1998 [3]. Since then, Researchers at Stanford [4] has designed a solution that combines analog signal inversion cancellation and digital cancellation and achieved 73 dB self interference reduction. Rice university [5] has used off-the-shelf MIMO radios for full duplex and presented the experimental results of three cancellation mechanisms. These mechanisms are a different mixture of analog and digital cancellations in narrow-band with a bandwidth of 625 KHz. Askar *et al.* use an extra transmit chain to create an additional signal, which is then added at the receiver RF front end [6]. Their experiment results show that the nonlinear method achieves slightly better performance compare to linear one, with 50 dB self-interference power cancelled, while the linear solution cancels 47 dB in the same scenario. Researcher at Stanford has designed another full duplex single antenna node [7], which achieves 110 dB self-interference cancellation totally by employing a dynamic adaption of analog cancellation and eliminating the residual power in digital domain, thus it cancels both linear and non-linear components. A similar digital cancellation was already attempted in [4], which uses

an FIR filter to simulate the channel and cancels the self-interference.

III. Research Problems

Prior self-interference cancellation solutions deal with three domains, propagation domain, analog domain and digital domain. Each domain cancellation has some problems.

A. Antenna Cancellation Problem

Propagation domain cancellation aims to cancel the self-interference power in the air or wireless channel by using multiple antennas. Typically it uses two transmission antennas and one receiving antenna at one full duplex node, where two transmission antennas are placed at specific positions, at ℓ and $\ell + \frac{\lambda}{2}$ from the receiving antenna (λ is the wave length of the operation frequency), which allows the transmitted signals to mix π out of phase and hence to cancel each other at the receiver. The problem is the cancellation performance is restricted by the perfect transmission power estimate. In other words, it requires that Tx1 and Tx2 antennas have perfect placement so that the inversed phase signals reached at Rx antenna with the same power. Moreover, it results in a large area adversarily effected, called nulling area [1], where the received power would be lower than normal situations.

B. Analog Cancellation Problem

In traditional analog cancellation, another transmission chain is added inside the wireless interface at a full duplex node, which feeds a copy of the transmitted signal to the receiving chain, and thus cancels the self-interference in the analog domain.

Because the transmitted signal in real world has multipath effect, the receiver will receive a linear combination of different delayed copies of the original transmitted signal as shown in formula 1.

$$y(t) = \sum_i a_i(t)x(t - \tau_i(t)) \tag{1}$$

Where $a_i(t)$ means attenuation in i-th route, it depends on different SNR in various channel, $\tau_i(t)$ is delay in i-th route. As can be observed from this formula, the received linear component attenuation only related to time delay or phase delay and amplitude attenuation.

This linear combination is clearly different from the original transmitted signal. Therefore, the internal fed transmitted signal through the added chain needs to be adjusted to match the received signal so that linear combination self-interference can be cancelled. The problem is visited by a prior work [4] that uses a Qhx220 chip to vary the gain for in-phase and quadrature components. However Qhx220 has fix delays and the delays in both components were not considered by the authors.

C. Digital Cancellation Problem

Since we know what we transmit and what we receive in digital bits, we can subtract the transmitted signal from the received data directly in digital domain. Researchers have showed that the analog-to-digital converter (ADC) dynamic range limits the performance of digital cancellation [8]. Considering a typical ADC range of 14 bits and possible noises of 2 bits, the ADC dynamic range follows Equation 2.

$$range = 20 \lg(\frac{max}{min}) = 20 \lg(\frac{2^{12}}{1}) \tag{2}$$

The range calculated above is 72.25 dB, which means, when the transmitted signal power is 20 dBm in most cases, if we can subtract the transmitted signal completely from the receive signal, the residual power of the transmitted signal will still be 52.25 dBm. Unfortunately, literature digital cancellation solutions can only cancel 20-25 dB [9] [10] [1], far away from the limitation. Thus digital cancellation has a large potential for improvement. **Our key innovation in this paper is to use machine learning methods for highly effective digital cancellation solutions**.

1) Transmission and Receiving Data Mismatch: In digital domain, signals are sampled at specific rates. Digital cancellation requires that the transmitted digital signal passing through DAC to the emitting antenna has to be sampled at the same rate as the received analog signal will be sampled. If the transmission sample rate in the cancellation chain differs from the receiving ADC sample rate, the cancelling transmission data will mismatch the received data, which is a common problem in digital cancellation.

2) Real-time Iterative Cancellation: In machine learning, training and loading are two separate processes, but the iterative self-interference cancellation with machine learning requires both processes have information exchanged. It is quite challenging for two chronologically separated processes to exchange information while meeting the real-time requirement demanded by wireless communications. Moreover, a machine learning full duplex node has to update the trained parameters each time and load the new trained parameters. Even the most advanced software defined radio platform USRP GNU-Radio available today is lack of the architecture to support the synchronized training and loading. Thus a new design of the architecture is required to support machine learning cancellation solutions.

IV. Machine Learning Based Digital Cancellation Solution

Since it is extremely difficult for the self-interference cancellations in propagation and analog domains to reach expected performance, and the limitation of the ADC dynamic range is far for the literature digital cancellation solutions to reach, we design a machine learning based solution to reach the capacity in digital cancellation.

The key of the proposed solution is to estimate the self-interference signals with machine learning algorithms. Whatever are transmitted, we can use machine learning models, e.g.

Tensorflow graphs, to predict the interference digital signal, and then add the negative copy of the predicted signal to the received mixture signal to cancel the self-interference samples. This section details our design and the challenges addressed by our design.

A. Platform

Our proposed solution is based on GNURadio SDR and USRP X310 platform. The architecture block diagram is shown as in Figure 1. The machine learning platform is based on Google Tensorflow, which is implemented by us into GNURadio.
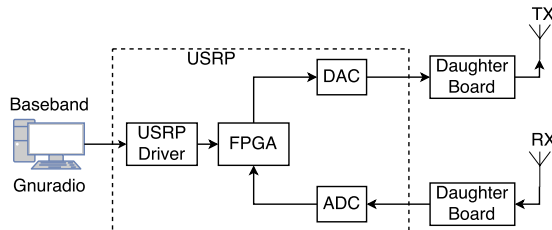

Fig. 1. Our Experiment Platform Structure

B. Interpolation

In our solution, the first challenge is to solve the data mismatch as discussed in Section III-C1. In digital domain, all data can be collected at the node. Since what is transmitted is known and what is received is also known in digital domain, it is feasible to collect the training data. Assuming we send 150k sine waves and the sample rate is set to 1.5M, theoretically, 10 values will be sampled during one sine wave period. This can be exactly performed for the transmission signal emulation in *software*. However, the received signal is not sampled strict by 1.5M due to the imperfection of the *hardware*. For example, in our USRP X310 platform, every three periods will lose one sample, causing the transmitted data does not synchronize to its corresponding received data. This issue is illustrated in top diagram of Figure 2 where the square points are what we transmit and the circle points are what we receive in digital domain. From the top digram, during three periods, there are 31 square points while there are only 30 circle points. In the proposed machine learning solution, the training source is the transmitted data, and the labels are the receive data. So, if a source cannot match its label, the training will rapidly overfit and incur a large loss that significantly hurts the accuracy and performance of the results. To solve this problem, we employ an interpolation algorithm to insert a point in the received data so that the number of transmitted data matches the number of received data. As shown in the bottom diagram of Figure 2, after the interpolation, inter-symbol interference is eliminated and each transmitted signal matches to a receive signal.

C. Model Selection

After the training data is pre-processed, our solution uses a multi-Linear model to predict the output as in Equation 3. Here both the received signal $y(n)$ and the transmitted signal $x(n)$ are complex data, and b can be divided to a real part and an imaginary part. The model parameters W and b are to
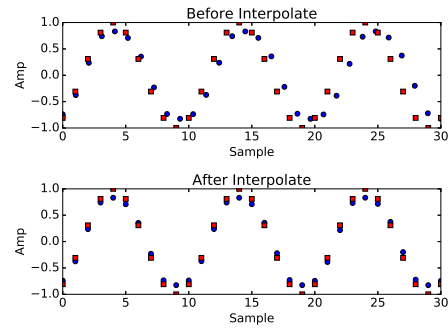

Fig. 2. Before and after interpolate

be iteratively estimated through the machine learning training process.

$$\begin{bmatrix} y(n) \\ y(n+1) \\ \vdots \\ \vdots \\ y(n+k) \end{bmatrix} = \begin{bmatrix} W_{11} * x(n) \\ W_{21} * x(n+1) \\ \vdots \\ \vdots \\ W_{k1} * x(n+k) \end{bmatrix} + \begin{bmatrix} b_{11} \\ b_{21} \\ \vdots \\ \vdots \\ b_{k1} \end{bmatrix} \quad (3)$$

This model feeds k values each time and generates the output $y(n)$, where k is defined as $\frac{sample\ rate}{transmission\ rate}$ (in our case, $k = \frac{1.5M}{150k} = 10$). In machine learning, we only focus on the relation between the predicted output $y(n)$ and its corresponding label, namely the actual received data label. To decrease the loss (deviation) between them, thus improve the prediction accuracy, since $y(n)$ only relates to $x(n)$, W and b are trained in this scheme. Each sample in one period may have different W and b.

We compare the output $y(n)$ to its label, and use the following loss function in machine learning:

$$loss = \frac{\sqrt{(y_{real} - y_{predict})^2}}{samples} \quad (4)$$

Here y_{real} is the label data — the actual received, and $y_{predict}$ is $y(n)$ predicted data. Both y_{real} and $y_{predict}$ have in-phase and quadrature parts.

1) Real-time Training Loading Scheme: Wireless communication requires a self-interference cancellation scheme be realtime. Because, the training of machine learning models works upon multiple iterations, our design makes sure of the realtime updates between iterations. Our real-time cancellation solution updates the feeding process and loading process at same time, so that the machine learning model parameters can be updated continually.
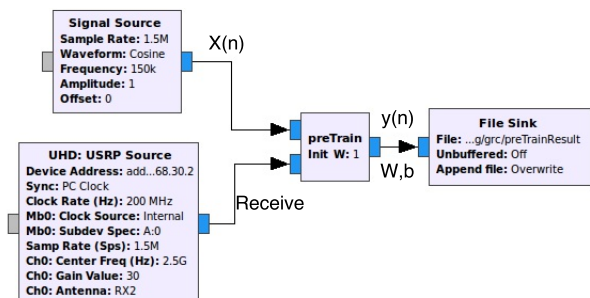

Fig. 3. The preTrain diagram

To support this realtime training, our solution designs three customized out of tree (OOT) modules in GNURadio: *pre-Train*, *Train* and *Load* modules. Flowchart 4 shows the architecture of the iterative realtime machine learning cancellation. At the very beginning, the *preTrain* module shown as figure 3 is triggered. After we feed our received signals and our transmitted signals $X(n)$, it generates the initial values of W and b, and a new Tensorflow graph. After that, the *Train* module will collect the received signals in real time. In each iteration, the *Train* module inherits the prior values of W and b. At the end of each iteration, the *Train* module saves the graph for the next iteration. The *Train* module also updates the trained W and b matrices. The *Load* module predicts the emulated self-interference data, which is used to cancel the self-interference in the received data.
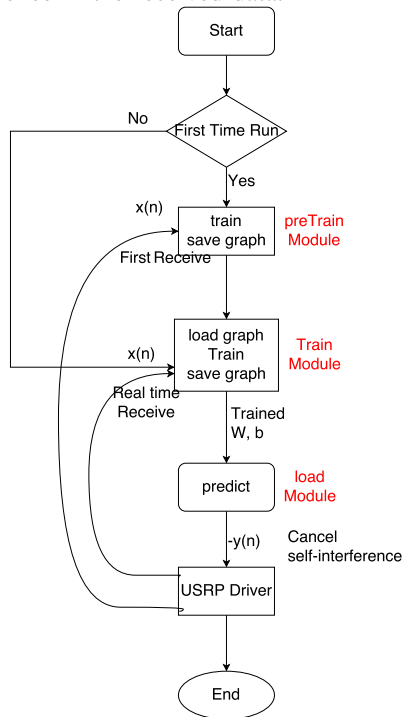

Fig. 4. The training flow graph

V. PERFORMANCE EVALUATION

We implemented the proposed realtime machine learning digital cancelation solution into the open source GNURadio package and have evaluated its performance on a SDR platform in the real world.

A. Experiment Settings

Our SDR evaluation testbed consists of two USRP X310 nodes connected via 10 Gbps cables to a control host running the GNURadio package with our solution implemented. The UBX RF daughter-boards of the USRP X310 nodes can support the frequency from 10MHz to 6GHz. GNURadio generates digital signals and pass the signals to the FPGA inside the X310 node through the USRP driver, and after ADC, the daughter board knows what signals to transmit. Thus we can transmit customized signals and know the signals existing in real world and received. The daughter board receives the

signal and converts to digital domain. At a USRP X310 node, the self-interference happens in the wireless channel between the TX and RX antennas. In experiments, one USRP X310 node works in IBFD mode: it transmits 150k sine waves while it is receiving its self-interference. The carrier frequency is configured to 2.5 GHz.

In the machine learning model, we set the learning rate as 0.01 and the training epoch as 300. Gradient descent function is used to train the matrices of W and b in real and imaginary components.

B. Cancellation Effectiveness

We plot the cancellation performance in Figure 5. The vertical axes of these diagrams refer to the normalized power in mW and the horizontal axes show signal data points. The first diagram from the left shows the real part of our transmitted signal real part. Each time our solution feeds 8192 digital data (the MTU size of USRP). We pick 470 points from the 150k sine signal data, and the sampling rate is 1.5M. The second diagram from the left plots the real part of the received self-interference. As can be seen, some of them are effected by the channel and the value fluctuates randomly. The third diagram from the left is the predicted self-interference by our solution. The trained W and b with real part adjust the original $x(t)$. Each time we train 300 epochs until the loss decreased to 0.000001 before the W and b are loaded to predict the self-interference. The right diagram shows the cancellation result after the received self-interference subtracts the predicted self-interference. As can be observed, most of signals can be fully cancelled.

C. Performance Comparison

We have conducted experiments to compare our solution with other digital cancellation solutions in the literature. Figure 7 shows the performance comparison between our proposed machine learning digital cancelation solution and literature digital cancelation solutions. With the proposed solution, we can cancel more than 50 dB self-interference. As it shows, our solution results in significantly better performance in self-interference cancellation. Since we have designed an open general real-time training self-cancellation framework, any neural network graph can be employed on this framework. As a result, the combination of AI and SDR will provides more opportunities.

D. Spectral Stability

Figure 6 shows our digital cancellation performance across the spectrum band centered on 2.5 GHz. The blue line is the received signal power, and the red line is the power after our cancellation. As can be observed, the cancellation is very stable across the spectral band. There is nearly 50 dB self-interference cancelled at 2500.150MHz. Although the result may vary as the transmitted signal changes, the proposed machine learning scheme is inherently adaptive to any change due to its training and adjusting proper parameters to cancel the self-interference in digital domain.
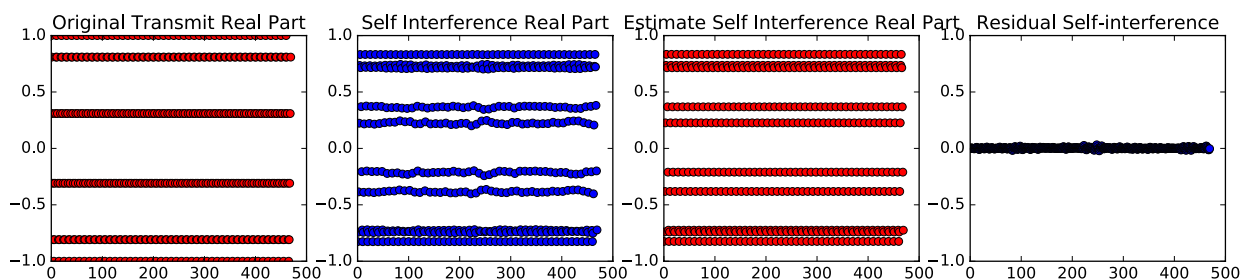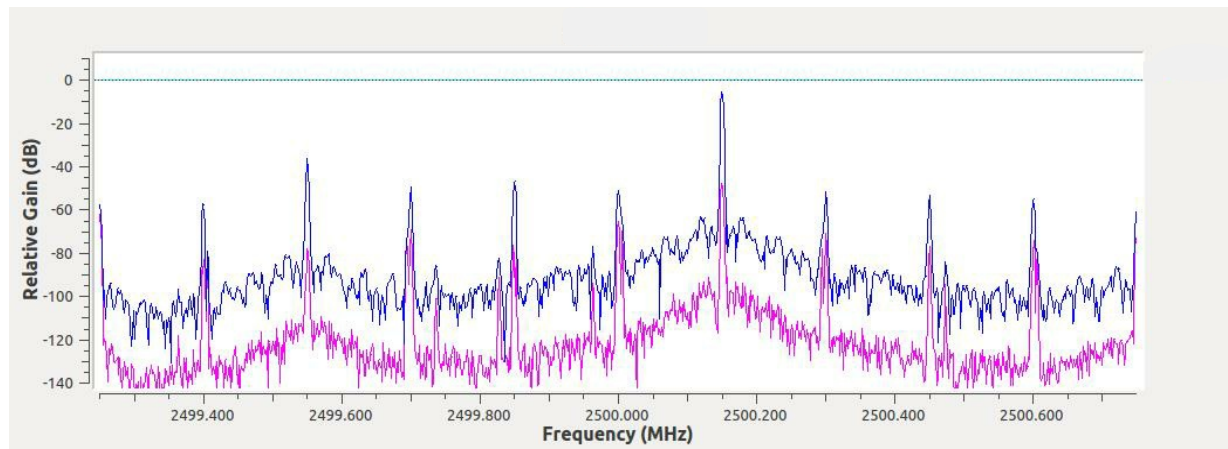
Fig. 5. Cancellation Effectiveness

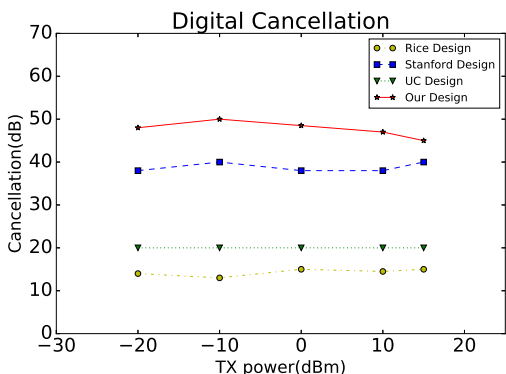
Fig. 6. Cancellation Stability Across Spectral Band

Fig. 7. Performance Comparison

VI. Conclusion

In this paper, we present a digital self-interference cancellation solution for in-band full duplex wireless communication and networking. This solution is based on machine learning and thus it does not need any knowledge of the wireless channel and is adaptive to any wireless environment. This solution is implemented into GNURadio and has been extensively evaluated with USRP X310 SDR nodes in real world. Its performance approaches to the limit of the hardware and outperforms the digital cancellation solutions in literature.

VII. Acknoledgement

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