Adaptive Cancellation of Nonlinear Self-Interference in Wireless Full-Duplex: Cascaded Spline-Interpolated Methods

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Abstract—This article studies advanced digital self-interference (SI) cancellation algorithms for wireless full-duplex (FD) transceivers. While the majority of works in this area consider linear SI models and corresponding cancellation algorithms, we take also both the transmitter (TX) and receiver (RX) nonlinearities into account. Specifically, we develop a Hammerstein-Wiener type of digital SI cancellation system where the two involved nonlinearities are efficiently implemented through spline-interpolated look-up tables (LUTs). Also, adaptive parameter estimation solutions are pursued and discussed, and comprehensive cancellation performance examples and processing complexity comparisons are provided. The obtained results show that taking both the TX and RX nonlinearities into account in the digital cancellation stage can be beneficial, particularly when the TX power amplifier is operating close to saturation and when the RF isolation and RF cancellation prior to the RX low-noise amplifier (LNA) is limited, such that also the LNA is distorting the SI waveform.

Index Terms—Self-interference, spline interpolation, in-band full-duplex, cancellation, look-up table, adaptive, nonlinear distortion

I. INTRODUCTION

The potential of full-duplex technology has been demonstrated by several research groups [1]–[5], but much more implementation-oriented research is needed to fulfill the potential. In theory, full-duplex is capable of doubling the spectral efficiency of a wireless communication system by transmitting and receiving information simultaneously at the same frequency channel. The resulting data rate increase is particularly sought within the heavily congested ultra high frequency (UHF) radio frequency spectrum, since full-duplex operation does not require any additional bandwidth.

Although full-duplex may be a key technology for future wireless networks, also new challenges appear. A particular challenge is the inevitable self-interference (SI), which can be more than 100 dB stronger than the weak desired signal at the receiver input [6]. The SI is caused by the own transmit signal which is leaked back to the full-duplex receiver, overlapping the desired received signal both temporally and spectrally. Any full-duplex device must be capable of suppressing it in order to operate properly, and many coexisting techniques are typically used, as shown in the transceiver block diagram in Fig. 1. The digital cancellation stage is the last cancellation stage, with the aim of reducing the SI level below the noise floor, by accurately modeling and accounting for the coupling channel effects [5], [7]. Since any full-duplex device must perform the SI cancellation, it is key to explore ways of minimizing the involved computational complexity, while at the same time provide the required SI cancellation.

In this paper, we propose a Hammerstein-Wiener type of digital SI cancellation system which utilizes spline-interpolated look-up tables (LUTs) [7], [8] to efficiently model the two involved nonlinearities in the cascaded model. Both nonlinearities aim at modelling the transmit (TX) power amplifier (PA) and the receiver (RX) low noise amplifier (LNA), thus taking into account both the TX and RX path effects. Spline modeling allows for significant complexity reduction when compared to classical models, as already discussed in our earlier work [7]. Additionally, adaptive parameter estimation solutions, based on the steepest gradient-descent, are derived and discussed for each involved parameter. A detailed complexity analysis is also presented to assess the complexity-performance trade-offs of the presented models.

Then, extensive RF cancellation results at 28 GHz (5G NR band n257 [9]), utilizing a state-of-the-art 64-element active antenna array and 5G NR like OFDM waveforms, are reported and analyzed, incorporating standard-compliant channel bandwidths of 100 and 400 MHz. The classical Wiener and Hammerstein models, where the instantaneous nonlinearity is also implemented with spline-interpolated LUTs, are also measured and reported as a reference. The obtained cancellation results, together with the provided detailed complexity analysis, demonstrate the favorable performance-complexity
trade-off of the proposed model.

The rest of this article is organized as follows. In Section II, the proposed Hammerstein-Wiener model is described, along with the derived adaptive parameter update learning equations. Section III presents a detailed complexity analysis of the proposed algorithm, in terms of real multiplications per sample. After this, the cancellation performance of the proposed and reference models is evaluated and compared in Section IV, with real RF measurements. Finally, Section V concludes and summarizes the main findings of this paper.

**Notation used in this paper**

In this paper, vectors are represented with boldface lowercase letters. By default, all vectors consist of complex-valued elements represented as columns vectors (i.e., $\mathbf{x} \in \mathbb{C}^{N \times 1} = [x_0 \ x_1 \ \cdots \ x_{N-1}]^T$). Matrices are expressed with boldface capital letters (i.e., $\mathbf{A} \in \mathbb{C}^{N \times M}$). Ordinary transpose of vectors is represented as $(\cdot)^T$. Moreover, the complex conjugate, absolute value, and floor operator are denoted by $(\cdot)^*$, $|\cdot|$, and $\lfloor \cdot \rfloor$, respectively.

**II. SPLINE-BASED HAMMERSTEIN-WIENER MODEL**

In this section, we study the spline-based Hammerstein-Wiener model (denoted here as SPHW), a block-oriented system that serially connects elementary linear and nonlinear blocks to ideally model a system whose structure is alike [10], [11]. The SPHW method has two nonlinear blocks and a linear finite impulse response (FIR) filter block connected in between, as illustrated in Fig. 2. In this work, the nonlinear blocks are implemented with an injection-based uniform spline interpolated LUT, and the linear block is implemented as an FIR filter. In the context of in-band full-duplex, and following the nomenclature used in Fig. 1, the LUT-based nonlinear elementary blocks model the nonlinear responses of the TX PA and the RX LNA, and the FIR filter models the multipath channel response. The output signal of the model is then the estimated SI signal, denoted as $y[n]$. The digital SI canceller (DSIC) will subtract this perturbation from the received signal, $d[n]$, in order to suppress its interfering effect. The SPHW structure and the spline interpolated LUTs are adopted due to its inherent low complexity, while they still achieve excellent levels of SI cancellation, as demonstrated in later sections.

**A. SI Regeneration and Cancellation**

Following the serial order described above, and making reference to Fig. 2, the regenerated SI signal, $y[n]$, is obtained as follows.

First, a preceding nonlinear block is considered, providing the output signal $l[n]$. The spline interpolated LUT scheme divides the input magnitude, $|x[n]|$, in $C$ regions. Each region is modelled with a spline polynomial of order $P$. The characterization of the regions is given through the index, abscissa, and ordinate vector local parameters, which constitute the basis for the spline interpolation scheme [12], and read

$$i_n = \left\lfloor \frac{|x[n]|}{\Delta_x} \right\rfloor + 1,$$

$$u_n = \frac{|x[n]|}{\Delta_x} - (i_n - 1),$$

$$\mathbf{u}_n \in \mathbb{R}^{(P+1) \times 1} = [u_{n}^{P} \ u_{n}^{P-1} \ \cdots \ 1]^T,$$

where $\Delta_x$ represents the region spacing. According to this definition, $i_n$ corresponds to the region number, and $u_n$ is the normalized value within each spline region.

Once the region parameters are characterized from the input sample, the injection-based interpolation scheme can be applied to obtain the output value, $l[n]$, as

$$l[n] = x[n] \mathbf{\Psi}_n^T (1 + \mathbf{c}_n).$$

Here, $1 \in \mathbb{R}^{C \times 1}$ is a vector of all ones, $\mathbf{c}_n \in \mathbb{C}^{C \times 1}$ contains the complex LUT control points used in the interpolation scheme, and the vector $\mathbf{\Psi}_n \in \mathbb{C}^{C \times 1}$ contains nonzero values starting from index $i_n$, such that only the appropriate control points are selected as weights for the interpolation scheme (i.e. $(c_{i_n}, c_{i_n+1} \cdots c_{i_n+P})$). It is formally defined as

$$\mathbf{\Psi}_n \in \mathbb{C}^{C \times 1} = [0 \ \cdots \ u_n^{P} \ \mathbf{B}_p \ 0 \ \cdots \ 0]^T,$$

where $\mathbf{B}_p \in \mathbb{R}^{(P+1) \times (P+1)}$ corresponds to the spline basis matrix, which depends on the considered spline order, and can be found in, for instance, [8], [13].

It is worth noting that the injection-based scheme, in combination with the spline interpolated LUT, allows for two main things. First, the gain ambiguities between the linear and nonlinear cascaded blocks are effectively removed. Second, the dynamic range of the LUT control point vector is reduced, requiring less bits and thus making fixed-point implementations more efficient [14].

The signal $l[n]$ is then carried through the linear block, implemented as a FIR filter. Its output can be directly written as

$$s[n] = \mathbf{w}_n^T \mathbf{l}_n,$$

where $\mathbf{w}_n \in \mathbb{C}^{M \times 1} = [w_0 \ w_1 \ \cdots \ w_{M-1}]^T$ are the FIR filter coefficients, and $\mathbf{l}_n \in \mathbb{C}^{M \times 1} = [s[n] \ s[n-1] \ \cdots \ s[n-M+1]]^T$ is the signal regression of $l[n]$.

Finally, the obtained signal $s[n]$ is passed through the second nonlinear block. The process is the same as presented above, but considering now a spline order $K$, and number of created regions $Q$. Mimicking the expressions presented in (1), (2), (3), (5), but considering $s[n]$ as the input signal, the interpolation scheme is built, and the model output signal, $y[n]$, is obtained as

$$y[n] = s[n] \mathbf{\Phi}_n^T (1 + \mathbf{q}_n),$$

where $\mathbf{q}_n \in \mathbb{C}^{Q \times 1}$ corresponds to the second LUT control point vector, and $\mathbf{\Phi}_n \in \mathbb{R}^{Q \times 1}$ is defined in the same way as in (5).
It is noted that different parametrization (spline order and number of regions) can be used in each individual nonlinearity. This can be useful if one of the amplifiers exhibits deeper nonlinear effects than the other. The parametrization can be consequently increased or decreased accordingly to optimize performance and/or complexity.

Finally, once the SI signal $y[n]$ is regenerated, it can be suppressed in the final digital cancellation stage by subtracting it from the received signal (i.e., $d[n] - y[n]$).

### B. Learning Updates

In order to estimate and track the involved parameters in the SPHW unknown system, three different learning rules are derived to adapt each of the considered parameters (i.e., $c_n$, $w_n$, and $q_n$). Firstly, let us denote the error signal used in the estimation as

$$e[n] = d[n] - y[n], \quad (8)$$

where $d[n]$ denotes the received signal the digital canceller aims at suppressing, and $y[n]$ is the SI regeneration obtained in the previous section. At this point, the problem lies in obtaining the mathematical formulation that minimizes $e[n]$, for each parameter. To this end, we utilize the least mean square (LMS) gradient-based adaptation, in which the parameters are adapted following the negative steepest descent direction of the cost function, given by the gradient. The cost function depending on $c_n$, $w_n$, $q_n$, can be defined, in turn, as

$$J(c_n, w_n, q_n) = e[n]e^*[n]. \quad (9)$$

At this point, three assumptions can be made regarding the cascaded structure of the SPHW model:

- The first nonlinearity, $c_n$, depends on the FIR filter and second nonlinearity.
- The FIR filter, $w_n$, depends on the second nonlinearity, but not on the first.
- The second nonlinearity, $q_n$, does not depend on the first nonlinearity nor the FIR filter.

Taking these assumptions into account, the general form of the learning rule for the first nonlinearity, $c_n$, can be written as

$$c_{n+1} = c_n - \mu_c \nabla c_n J(c_n, w_n, q_n), \quad (10)$$

where $\mu_c$ is the learning rate for the update, and $\nabla \cdot$ refers to the complex gradient. Making use of elementary differentiation rules, the derivative with respect $c_n$, keeping the other parameters fixed, can be calculated as

$$\frac{\partial J(c_n, w_n, q_n)}{\partial c_n} = e[n] \frac{\partial e^*[n]}{\partial c_n} + e^*[n] \frac{\partial e[n]}{\partial c_n} = -e[n] \frac{\partial s^*[n]\Phi_n^T(1 + q_n^*)}{\partial c_n} + 0$$

$$= -e[n] \Phi_n^T \Sigma_n \Phi_n^T (1 + q_n^*), \quad (11)$$

where $X_n \in \mathbb{C}^{M \times M} = \text{diag}(x[n], x[n-1], \ldots, x[n-M+1])$, and $\Sigma_n = (\Psi_{n-1} \Psi_{n-1} \cdots \Psi_{n-M+1})^T$. Additionally, it is assumed that the rate of change of $c_n$ over the span of the filter length $M$ is negligible, i.e., $c_n \approx c_{n+M}$. This assumption is made considering the small value of $\mu_c$.

Therefore, the final expression for the learning rule of $c_n$ reads

$$c_{n+1} = c_n + \mu_c e[n] \Sigma_n^T X_n^* w_n^* \Phi_n^T (1 + q_n^*). \quad (12)$$

Secondly, the learning rule for the FIR filter, $w_n$, can be expressed as

$$w_{n+1} = w_n - \mu_w \nabla w_n J(c_n, w_n, q_n), \quad (13)$$

where $\mu_w$ is the learning rate. Again, by obtaining the derivat-
TABLE I: Computational complexity in terms of real multiplications per sample of the SPHW model, as a function of the modelling parameters $P$, $K$, $M$, and $\tau$. In the third column, a numerical example is presented, when $P = 3$, $K = 3$, $M = 76$, and $\tau = 5$.

<table>
<thead>
<tr>
<th>Operation</th>
<th>Symbolic real multiplications</th>
<th>Numerical real multiplications</th>
</tr>
</thead>
<tbody>
<tr>
<td>Model identification</td>
<td></td>
<td></td>
</tr>
<tr>
<td>$l[n]$</td>
<td>$P^2 + 4P + 8 + \sqrt{P}$</td>
<td>29</td>
</tr>
<tr>
<td>$s[n]$</td>
<td>$4M$</td>
<td>304</td>
</tr>
<tr>
<td>$y[n]$</td>
<td>$K^2 + 4K + 8 + \sqrt{K}$</td>
<td>29</td>
</tr>
<tr>
<td>Total</td>
<td>$P^2 + K^2 + 4P + 4K + 4M + 16 + 2\sqrt{M}$</td>
<td>362</td>
</tr>
<tr>
<td>Coefficient update</td>
<td></td>
<td></td>
</tr>
<tr>
<td>$q_{n+1}$</td>
<td>$2K + 8$</td>
<td>14</td>
</tr>
<tr>
<td>$w_{n+1}$</td>
<td>$K^2 + 3K + 6M + 15 + \text{div}$</td>
<td>489</td>
</tr>
<tr>
<td>$c_{n+1}$</td>
<td>$4P + 2P \tau + 6\tau + 10$</td>
<td>82</td>
</tr>
<tr>
<td>Total</td>
<td>$4P + 2P \tau + 6\tau + K^2 + 5K + 6M + 33 + \text{div}$</td>
<td>585</td>
</tr>
<tr>
<td>Total per iteration</td>
<td>$P^2 + 8P + 2P \tau + 6\tau + 2K^2 + 9K + 10M + 49 + \text{div} + 2\sqrt{M}$</td>
<td>947</td>
</tr>
</tbody>
</table>


In this section, we study the computational complexity involved in the proposed SPHW method. Together with the experimental results presented in the next section, it will allow to assess the performance-complexity trade-off of the SPHW model.

In this paper, the computational complexity is divided in two stages, cancellation and coefficient update, and it is presented in terms of real multiplications per sample. Real multiplications constitute a critical metric for digital signal processing (DSP) implementations, while additions are essentially free [15]. For the analysis, it is assumed that one complex multiplication costs 4 real multiplications, and one complex-real multiplication is calculated with 2 real multiplications.

Table I presents the symbolic computational complexity expressions as a function of the spline order, $P$ (first nonlinear block), and $K$ (second nonlinear block), and as a function of the FIR filter memory taps, $M$. Additionally, a complexity reduction method in the learning update of $c_n$ is proposed in order to ease the coefficient update. This method is formulated by considering the additional parameter $\tau$, which truncates the time dimension of $\Sigma_n$ (row dimension), by only considering a specific number of past samples in the update. This process is motivated as follows. $\Sigma_n$ is usually a big matrix if $M$ is large, however, the most significant memory taps contributing to the learning update are usually the most recent ones, thus by selecting only these, the computational complexity can be greatly reduced, while the cancellation performance is almost not affected. Note that if $\tau = M$, no approximation is done.

Finally, the learning rule for the second nonlinearity, $c_n$, can be expressed as

$$q_{n+1} = q_n - \mu_q \nabla_{q_n} J(c_n, w_n, q_n),$$

where $\mu_q$ is the learning rate. Differentiating with respect $q_n$, we obtain

$$\frac{\partial J(c_n, w_n, q_n)}{\partial q_n} = e[n] \frac{\partial e[n]}{\partial q_n} + e^*[n] \frac{\partial e[n]}{\partial q_n} = -e[n] \Phi^T_n (1 + q_n) + 0 = -e[n] s^*[n] \Phi_n.$$  

And thus, the final learning rule reads

$$q_{n+1} = q_n + \mu_q e[n] s^*[n] \Phi_n.$$  

These learning equations can thus be executed iteratively to track possible dynamic changes in the system, or kept fixed if the system is expected to remain static.
A. Measurement Setup

In order to evaluate the cancellation performance of the proposed SPHW, the mmW RF test setup presented in Fig. 3 has been utilized. The proposed setup consist on the following elements. First, and arbitrary waveform generator (AWG) is utilized to generate the transmit I/Q data, which is then upconverted to 28 GHz and pre-amplified in order to facilitate a sufficiently high saturation power in the TX array. Then, the signal is transmitted over-the-air (OTA) by an Anokiwave AWMF-0219 active antenna array (3), metallic reflector to generate the coupling SI (4), horn antenna as receiver (5), AD HMC1040LP3CE LNA (6), and Keysight UXR0402AP digitizer (7).

B. BW 100 MHz Digital Cancellation Results

This section evaluates the digital cancellation performance over a signal bandwidth of 100 MHz. The generated signal is a 3GPP 5G new radio (NR) Release-15 frequency range 2 (FR-2) compliant OFDM waveform, with 120 kHz subcarrier spacing (SCS) and 66 allocated resource blocks (RBs). This configuration maps to the aforementioned signal bandwidth of 100 MHz [9]. Additionally, the initial peak-to-average power ratio (PAPR) of the digital waveform is 9.5 dB, when measured at the 0.01% point of the instantaneous PAPR complementary cumulative distribution function (CCDF), and is then limited to 7 dB through iterative clipping and filtering. An additional time-domain window is also applied to suppress the inherent OFDM signal sidelobes.

The parametrization chosen for the SPHW model is \( P = K = 3, C = Q = 7 \) for the spline order and LUT size, and \( M_{\text{pre}}/M_{\text{post}} = 25/50 \) for the pre-cursor and post-cursor memory taps in the FIR filter. Additionally, the spline-based Wiener (SPW) and Hammerstein (SPH) models, configured with \( K = 3, Q = 7 \) (SPW), \( P = 3, C = 7 \) (SPH), and \( M_{\text{pre}}/M_{\text{post}} = 25/50 \), have also been measured and presented for reference. The experimental results are then presented in Fig. 4, and summarized in Table II. It can be seen that the best SI cancellation performance is obtained with the proposed SPHW model (32 dB), followed by the SPH model (26 dB), and finally by the SPW model (22 dB). This result can be explained as follows. The SPHW approach has richer modeling capabilities than the other two models, as it includes two instantaneous nonlinear functions in its cascaded structure, which successfully model the behavior of both TX PA and RX LNA. Secondly, the inherent cascaded structure of the SPH approach is able to successfully model the TX antenna array, which is the predominant source of nonlinear distortion in this system. Finally, the SPW approach is not fully capable of modeling the distortion injected by the antenna array, due to its cascaded structure, thus providing a somewhat more degraded cancellation performance.

Finally, it can be seen from Fig. 4b that the convergence speed is reduced when considering the SPHW approach, compared to SPW or SPH. The former model has an increased number of parameters to be estimated, thus it takes more iterations to reach the final steady-state.

C. BW 400 MHz Digital Cancellation Results

The second experiment further pushes the performance boundaries by considering an increased signal bandwidth of 400 MHz. The generated FR-2 NR signal has now 264 allocated RBs, while the SCS and PAPR remain the same as before, thus yielding a bandwidth of 400 MHz [9].

In this experiment, the parametrization chosen for the SPHW model is \( P = K = 3, C = Q = 7 \) for the spline order and LUT size, and \( M_{\text{pre}}/M_{\text{post}} = 25/60 \) for the pre-cursor and post-cursor memory taps in the FIR filter. The SPW and SPH models have also been measured for reference, configured with \( K = 3, Q = 7 \) (SPW), \( P = 3, C = 7 \) (SPH), and \( M_{\text{pre}}/M_{\text{post}} = 25/60 \). The overall memory of the models have been increased to better model the wider SI coupling channel. The obtained results are then presented in Fig. 5, and summarized in Table III. The proposed SPHW model is capable of obtaining the best SI cancellation (29 dB), followed by the SPH approach (25 dB), and finally by
the SPW scheme (18 dB). Similar observations to those of the previous experiment can be drawn. Since the SPHW model takes into account both TX and RX nonlinearities, it is capable of achieving an enhanced cancellation performance, while the SPW and SPH models, only considering either the TX or RX nonlinearity, lie somewhat behind.

It is also noted that the convergence speed of the SPHW approach is somewhat slower compared to SPW or SPH, as seen from Fig. 5b, since the model has a greater number of parameters to be updated.

V. CONCLUSIONS

In this article, we proposed a novel digital self-interference canceller for in-band full-duplex devices. The proposed model was a Hammerstein-Wiener type of system such that both TX and RX nonlinearities can be taken into account. Specifically, the instantaneous nonlinearities in the model were implemented through spline-interpolated look-up tables. Efficient adaptive parameter estimation solutions, based on the steepest gradient-descent algorithm, were also presented and discussed. Moreover, a detailed complexity analysis of the proposed model was reported, in terms of real multiplications per sample. Then, comprehensive RF measurements showing the cancellation performance of the proposed model were presented and compared to other existing solutions. The obtained results showed that taking both TX and RX nonlinearities into account can be beneficial, particularly when the TX power amplifier is operated close to saturation, and when the RF isolation and RF cancellation cannot provide sufficient SI cancellation, such
TABLE II: The RF measurement and model parameters in the DSIC experiment 1. The complexity in the cancellation and parameter update stages is presented in the last two columns, in terms of real multiplications per sample.

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</thead>
<tbody>
<tr>
<td>Transmit waveform</td>
<td>100 MHz NR OFDM @ 28 GHz</td>
<td>SPW DSIC</td>
<td>- / -</td>
<td>25 / 50</td>
<td>3 / 7</td>
<td>23 dB</td>
<td>333</td>
<td>503</td>
</tr>
<tr>
<td>EIRP</td>
<td>43 dBm</td>
<td>SPH DSIC</td>
<td>3 / 7</td>
<td>25 / 50</td>
<td>- / -</td>
<td>26 dB</td>
<td>333</td>
<td>384</td>
</tr>
<tr>
<td>Received power (d[n])</td>
<td>11 dBm</td>
<td>SPHW DSIC</td>
<td>3 / 7</td>
<td>25 / 50</td>
<td>3 / 7</td>
<td>32 dB</td>
<td>362</td>
<td>585</td>
</tr>
</tbody>
</table>

TABLE III: The RF measurement and model parameters in the DSIC experiment 2. The complexity in the cancellation and parameter update stages is presented in the last two columns, in terms of real multiplications per sample.

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</thead>
<tbody>
<tr>
<td>Transmit waveform</td>
<td>400 MHz NR OFDM @ 28 GHz</td>
<td>SPW DSIC</td>
<td>- / -</td>
<td>25 / 60</td>
<td>3 / 7</td>
<td>18 dB</td>
<td>373</td>
<td>563</td>
</tr>
<tr>
<td>EIRP</td>
<td>43 dBm</td>
<td>SPH DSIC</td>
<td>3 / 7</td>
<td>25 / 60</td>
<td>- / -</td>
<td>25 dB</td>
<td>373</td>
<td>424</td>
</tr>
<tr>
<td>Received power (d[n])</td>
<td>11 dBm</td>
<td>SPHW DSIC</td>
<td>3 / 7</td>
<td>25 / 60</td>
<td>3 / 7</td>
<td>29 dB</td>
<td>402</td>
<td>645</td>
</tr>
</tbody>
</table>

that also the LNA is distorting the SI waveform. All in all, the obtained results, together with the complexity analysis, indicated a very favorable performance-complexity trade-off of the proposed spline-based Hammerstein-Wiener model.

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