WIDELY LINEAR CLMS BASED CANCELATION OF NONLINEAR SELF-INTERFERENCE IN FULL-DUPLEX DIRECT-CONVERSION TRANSCEIVERS

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ABSTRACT

An augmented nonlinear complex LMS (ANCLMS) algorithm is proposed to adaptively mitigate both the linear and nonlinear self-interference (SI) components in a full-duplex direct-conversion transceiver (DCT). A data prewhitening scheme, which exploits the known SI signal distributions, is also adopted to accelerate the convergence. Theoretical mean and mean square performance evaluations of the proposed SI canceller are performed and fully support the proposed approach. Computer simulations on wireless local area network (WLAN) standard compliant waveforms in practical full-duplex (FD) direct-conversion transceiver settings support the analysis.

Index Terms— Full-duplex communications, power amplifier (PA) distortion, I/Q imbalances, self-interference cancellation, augmented nonlinear complex LMS (ANCLMS)

1. INTRODUCTION

The full-duplex (FD) technology [1], which aims to obtain a doubled radio-link data rate by transmitting and receiving simultaneously and bidirectionally at the same center frequency, has drawn plenty of attention in recent years. The minimisation of self-interference (SI), that is, the strong transmit signal coupled into the receiver (Rx) path, is the key issue in the design of a FD transceiver. Successful experimental demonstrations [2, 3] have opened the possibilities for a practical realization of FD technology on the backhaul sides, and in recent years, more attention has been paid to the design of mobile-scale FD devices [4, 5], in which the direct-conversion architecture is of particular attraction due to its small-size, low-cost and low-energy consumption nature. However, this simple architecture introduces inherent hardware nonidealities, such as power amplifier (PA) nonlinearity, I/Q imbalances and phase noise, which deteriorate the SI cancellation performance in a FD direct-conversion transceiver (DCT).

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In order to maintain a sufficient amount of post-cancellation signal-to-noise-plus-interference-ratio (SNIR), it is suggested that the mitigation of SI is firstly performed at the radio frequency (RF) end, where a further digital cancellation procedure is adopted to mitigate the SI residual, as well as other nonidealities, such as I/Q imbalances and phase noise. This facilitates both channel estimation and signal detection in the baseband. To this end, a widely linear digital SI canceller was developed in [4], where the original transmit SI and its self-image interference, which arises due to the I/Q imbalances in the DCT [6–8], are jointly mitigated through a least-squares model fitting. In [5], the augmented complex least mean square (ACLMS) adaptive filtering algorithm [9, 10] was employed in a DSP-assisted analog SI cancellation process, and its theoretical performance was addressed.

However, due to model simplicity, the approaches in [4,5] were not able to achieve an optimal solution when PA distortion became dominant at the RF end of FD DCTs. To this end, we first propose an augmented nonlinear CLMS (ANCLMS) method for a joint cancellation of both the linear and nonlinear SI components, as well as their image components, by virtue of a widely-nonlinear model fitting. Next, to alleviate its potential slow convergence due to the high eigenvalue spread within the input covariance matrix when the nonlinear SI components are involved, we further equip the method with a data prewhitening framework. This is achieved by exploiting the special advantage of the FD mode, namely that the transmitted SI signal is inherently known to the receiver. The SI cancellation capability of the proposed approach is validated by rigorous mean and mean square performance analyses and through representative simulation.

2. WIDELY-NONLINEAR MODELING OF FD DCTS

Within the FD DCT, the SI signal $x(n)$, along with its image SI and nonlinear components is produced respectively by the IQ mixer and PA couple into to the receiver path. After the analog SI cancellation at the RF end, the observed signal $d(n)$ in the baseband can be expressed in a vectorized form [4]

$$d(n) = \mathbf{h}^{\mathrm{o}H}\mathbf{x}(n) + \mathbf{g}^{\mathrm{o}H}\mathbf{x}^{*}(n) + \mathbf{h}_{\mathrm{IMD}}^{\mathrm{o}H}\mathbf{x}_{\mathrm{IMD}}(n) + \mathbf{g}_{\mathrm{IMD}}^{\mathrm{o}H}\mathbf{x}_{\mathrm{IMD}}^{*}(n) + v(n) + q(n) \quad (1)$$

where $\mathbf{x}(n) = [x(n), x(n-1), \ldots, x(n-M+1)]^T$ is of length M, and the SI component $x(n)$ is considered to be a proper Gaussian process with zero-mean and variance σ_x^2 [11, 12], e.g., a wideband OFDM waveform, and is inherently known to the receiver. The vector $\mathbf{x}_{\text{IMD}}(n) = [x_{\text{IMD}}(n), x_{\text{IMD}}(n-1), \ldots, x_{\text{IMD}}(n-N+1)]^T$ is of length N, the element of which, $x_{\text{IMD}}(n)$ is the nonlinear third-order intermodulated (IMD) SI component caused by PA distortion, defined as $x_{\text{IMD}}(n) = k_{\text{TIQ}}^{3/2} |x(n)|^2 x(n)$, where k_{TIQ} is the transmitter mixer gain. Observe that $x_{\text{IMD}}(n)$ is also zero-mean proper, whose variance can be obtained using the Gaussian fourth order moment factorizing theorem as $\sigma_{x_{\text{IMD}}}^2 = E[|x_{\text{IMD}}(n)|^2] = 6k_{\text{TIQ}}^3\sigma_x^6$. In order to precisely describe the prominent nonidealities in the circuit, the M-tap filters $\mathbf{h}^{\text{o}}$ and $\mathbf{g}^{\text{o}}$ are used to represent the end-to-end system impulse responses, which incorporate the effects of the frequency-dependent I/Q imbalances [13], PA memory and residual of RF cancellation in the transmit-receiver chain, for the SI component $\mathbf{x}(n)$ and its image $\mathbf{x}^*(n)$, respectively. Similarly, for the IMD SI components $\mathbf{x}_{\text{IMD}}(n)$ and $\mathbf{x}_{\text{IMD}}^*(n)$, we use $\mathbf{h}_{\text{IMD}}^{\text{o}}$ and $\mathbf{g}_{\text{IMD}}^{\text{o}}$ to present the associated end-to-end system coefficients, respectively. The thermal noise and the quantization noise are respectively denoted by $v(n)$ and $q(n)$, and are assumed to be proper white Gaussian processes with the respective variances σ_v^2 and σ_q^2, independent of those linear and nonlinear SI components. From (1), the aim of a digital SI canceller is to ensure a sufficient level of signal-to-noise-plus-interference ratio (SNIR) by achieving accurate estimates of the system coefficients $\mathbf{h}^{\text{o}}$, $\mathbf{g}^{\text{o}}$, $\mathbf{h}_{\text{IMD}}^{\text{o}}$ and $\mathbf{g}_{\text{IMD}}^{\text{o}}$.

3. PROPOSED DATA PREWHITENING ASSISTED ANCLMS BASED SI CANCELLER

The approaches in [4, 5] consider the IMD SI components as part of the overall noise. However, a more natural and optimal SI canceller should employ the widely linear auto-regressive model in (1) which is augmented with the nonlinear SI terms, particularly when the transmit power is high. For the compactness of analysis, we first reinterpret this model in the augmented manner, to give

$$d(n) = \mathbf{w}^{\text{o}H}\mathbf{x}_a(n) + v(n) + q(n) \tag{2}$$

where $\mathbf{x}_a(n)$ is a $(2M+2N)\times 1$ augmented vector of nonlinear SI, defined as $\mathbf{x}_a(n) = [\mathbf{x}^T(n), \mathbf{x}_{\text{IMD}}^T(n), \mathbf{x}^H(n), \mathbf{x}_{\text{IMD}}^H(n)]^T$ and $\mathbf{w}^{\text{o}} = [\mathbf{h}^{\text{o}T}, \mathbf{h}_{\text{IMD}}^{\text{o}T}, \mathbf{g}^{\text{o}T}, \mathbf{g}_{\text{IMD}}^{\text{o}T}]^T$ is the vector of corresponding $(2M+2N)\times 1$ overall end-to-end system coefficients of the FD DCT. Similar to the augmented CLMS (ACLMS) based SI canceller in [5], we here aim to estimate the set of system parameters $\mathbf{w}^{\text{o}}$ according to the minimization of the standard mean square error (MSE) cost function $J(n)$, defined as

$$J(n) = E[|e(n)|^2] = E[e(n)e^*(n)] \tag{3}$$

where $E[\cdot]$ is the statistical expectation operation and $e(n)$ is the instantaneous output error, given by

$$e(n) = d(n) - \mathbf{w}^H(n)\mathbf{x}_a(n) \tag{4}$$

in which the weight vector $\mathbf{w}(n)$ can be updated in the sense of gradient descent least mean square as

$$\mathbf{w}(n+1) = \mathbf{w}(n) + \mu e^*(n)\mathbf{x}_a(n) \tag{5}$$

where μ is the step-size.

Although the proposed SI canceller, referred to as augmented nonlinear CLMS (ANCLMS), is optimal in the sense of model fitting. It may suffer from a slow convergence due to the potential high eigenvalue spread of its input covariance matrix when the higher order nonlinear SI components are strong. This becomes clear when we examine at the augmented covariance matrix $\mathbf{R}_a$, expressed as

$$\mathbf{R}_a = E[\mathbf{x}_a(n)\mathbf{x}_a^H(n)] = \begin{bmatrix} \mathbf{R}_{a0} & \mathbf{0} \\ \mathbf{0} & \mathbf{R}_{a0} \end{bmatrix} \tag{6}$$

where

$$\mathbf{R}_{a0} = E[\mathbf{x}_c(n)\mathbf{x}_c^H(n)] = \begin{bmatrix} \sigma_x^2\mathbf{I}_M & \mathbf{\Omega}^T \\ \mathbf{\Omega} & 6k_{\text{TIQ}}^3\sigma_x^6\mathbf{I}_N \end{bmatrix}$$

$$\mathbf{\Omega} = [\ \mathbf{R}_d \quad \mathbf{0}_{N\times(M-N)}\ ]$$

$$\mathbf{R}_d = E[\mathbf{x}_d(n)\mathbf{x}_{\text{IMD}}^H(n)] = 2k_{\text{TIQ}}^{3/2}\sigma_x^4\mathbf{I}_N$$

in which $\mathbf{x}_c(n) = [\mathbf{x}^T(n), \mathbf{x}_{\text{IMD}}^T(n)]^T$, and $\mathbf{x}_d(n) = [x(n), x(n-1), \ldots, x(n-N+1)]^T$.

Remark 1: Owing to higher-order moments of the SI signal $x(n)$ involved in (6) due to the nonlinear SI components, the eigenvalue spread of $\mathbf{R}_a$ becomes large when transmit power σ_x^2 increases. On the other hand, since $x(n)$ is inherently known to the receiver due to the full-duplex transmission mode, we are able to improve its slow convergence by using a simple data prewhitening scheme.

By using the standard eigenvalue decomposition of $\mathbf{R}_a$, we have $\mathbf{R}_a = \mathbf{U}\mathbf{\Lambda}\mathbf{U}^H$, where $\mathbf{U}$ is a unitary matrix and $\mathbf{\Lambda} = \text{diag}\{\lambda_1, \lambda_2, \ldots, \lambda_{2M+2N}\}$ is a diagonal matrix comprising of the eigenvalues of $\mathbf{R}_a$. Now, before performing the digital SI cancellation procedure, a whitened input vector $\mathbf{x}_p(n)$ can be constructed as $\mathbf{x}_p(n) = \mathbf{\Phi}\mathbf{x}_a(n)$, where $\mathbf{\Phi} == [\mathbf{\Lambda}]^{-\frac{1}{2}}\mathbf{U}^H$. This yields the data prewhitening assisted ANCLMS (DPA-ANCLMS), which can be summarized as

$$\mathbf{w}_p(n+1) = \mathbf{w}_p(n) + \mu e_p^*(n)\mathbf{x}_p(n) \tag{7}$$

where the estimation error $e_p(n)$ is given by

$$e_p(n) = d(n) - \mathbf{w}_p^H(n)\mathbf{x}_p(n) \tag{8}$$

and $\mathbf{w}_p(n) = \mathbf{\Phi}^{-H}\mathbf{w}_a(n)$.

4. PERFORMANCE ANALYSIS

In this section, rigorous performance evaluations of the proposed DPA-ANCLMS SI canceller are conducted in the mean and mean square sense.

4.1. Mean Convergence Analysis

Note that after the data prewhitening procedure, the overall optimal system coefficients become $\mathbf{w}_p^{\mathrm{o}} = \mathbf{\Phi}^{-H}\mathbf{w}^{\mathrm{o}} = \mathbf{\Lambda}^{\frac{1}{2}}\mathbf{U}^H\mathbf{w}^{\mathrm{o}}$. Now, upon introducing the $(2M+2N)\times 1$ weight error vector

$$\widetilde{\mathbf{w}}_p(n) = \mathbf{w}_p^{\mathrm{o}} - \mathbf{w}_p(n) \tag{9}$$

the output error $e_p(n)$ in (8) becomes

$$e_p(n) = v(n) + q(n) - \widetilde{\mathbf{w}}_p^H(n)\mathbf{x}_p(n) \tag{10}$$

and hence from (7), we have

$$\begin{aligned}\widetilde{\mathbf{w}}_p(n+1) \\ =[\mathbf{I}-\mu\mathbf{x}_p(n)\mathbf{x}_p^H(n)]\widetilde{\mathbf{w}}_p(n)+\mu[v^*(n)+q^*(n)]\mathbf{x}_p(n)\end{aligned} \tag{11}$$

Upon taking the expectation $E[\cdot]$ on both sides of (11) and using the standard independence assumptions among the input $\mathbf{x}_p(n)$, the thermal noise $v(n)$, and the quantization noise $q(n)$ [10,14], we arrive at $E[\widetilde{\mathbf{w}}_p(n+1)] = (1-\mu)E[\widetilde{\mathbf{w}}_p(n)]$, and hence, the step-size μ which guarantees convergence of the proposed DPA-ANCLMS for an asymptotically unbiased estimation should satisfy $0 < \mu < 2$.

4.2. Mean Square Convergence Analysis

Again by using the standard independence assumptions from (10), the MSE $J_p(n)$ can be evaluated as

$$J_p(n) = E[|e_p(n)|^2] = \mathrm{Tr}[\mathbf{K}_p(n)] + \sigma_v^2 + \sigma_q^2 \tag{12}$$

where $\mathbf{K}_p(n) = E[\mathbf{w}_p(n)\mathbf{w}_p^H(n)]$ is the weight error covariance matrix and $\mathrm{Tr}[\cdot]$ the matrix trace operation. Now, by multiplying both sides of (11) with $\mathbf{w}_p^H(n)$, and taking the statistical expectation operation $E[\cdot]$, the evolution of $\mathbf{K}_p(n)$ becomes

$$\begin{aligned}\mathbf{K}_p(n+1) = \mathbf{K}_p(n) + \mu^2(\sigma_v^2+\sigma_q^2)\mathbf{I}_{2M+2N} - 2\mu\mathbf{K}_p(n) \\ +\mu^2 E[\mathbf{x}_p(n)\mathbf{x}_p^H(n)\widetilde{\mathbf{w}}_p(n)\widetilde{\mathbf{w}}_p^H(n)\mathbf{x}_p(n)\mathbf{x}_p^H(n)]\end{aligned} \tag{13}$$

Upon using the Gaussian fourth order factorizing theorem [10,14,15] on the fourth term on the right hand side (RHS) of (13), we have

$$\begin{aligned}&E[\mathbf{x}_p(n)\mathbf{x}_p^H(n)\widetilde{\mathbf{w}}_p(n)\widetilde{\mathbf{w}}_p^H(n)\mathbf{x}_p(n)\mathbf{x}_p^H(n)] \\ &= \mathbf{K}_p(n) + \underbrace{\mathbf{P}_p\mathbf{K}_p^T(n)\mathbf{P}_p}_{\mathbf{K}_p'(n)} + \mathrm{Tr}[\mathbf{K}_p(n)]\mathbf{I}\end{aligned} \tag{14}$$

where the complementary covariance matrix [15,16]

$$\mathbf{P}_p = E[\mathbf{x}_p(n)\mathbf{x}_p^T(n)] = \begin{bmatrix} \mathbf{0} & \mathbf{I} \\ \mathbf{I} & \mathbf{0} \end{bmatrix}$$

For a better understanding of (14), we first decompose $\mathbf{K}_p^T(n)$ into four block matrices according to its augmented nature, given by

$$\mathbf{K}_p(n) = \begin{bmatrix} \mathbf{K}_{pa}(n) & \mathbf{K}_{pb}(n) \\ \mathbf{K}_{pc}(n) & \mathbf{K}_{pd}(n) \end{bmatrix} \tag{15}$$

In this way, the second term $\mathbf{K}_p'(n)$ on the RHS of (14) now becomes

$$\mathbf{K}_p'(n) = \mathbf{P}_p\mathbf{K}_p^T(n)\mathbf{P}_p = \begin{bmatrix} \mathbf{K}_{pd}^T(n) & \mathbf{K}_{pb}^T(n) \\ \mathbf{K}_{pc}^T(n) & \mathbf{K}_{pa}^T(n) \end{bmatrix} \tag{16}$$

By comparing (16) with (15), we find that all four block matrices of $\mathbf{K}_p(n)$ are transposed in $\mathbf{K}_p'(n)$, and that the diagonal matrices $\mathbf{K}_{pa}(n)$ and $\mathbf{K}_{pd}(n)$ are swapped.

The third term $\mathrm{Tr}[\mathbf{K}_p(n)]\mathbf{I}$ on the RHS of (14) can be further decomposed as

$$\mathrm{Tr}[\mathbf{K}_p(n)]\mathbf{I} = \mathbf{1}_{2M+2N}\mathbf{1}_{2M+2N}^T\boldsymbol{\kappa}_p(n) \tag{17}$$

where $\mathbf{1}_{2M+2N}$ denotes a $(2M+2N)\times 1$ unit vector and $\boldsymbol{\kappa}_p(n)$ is a $(2M+2N)\times 1$ vector, whose entries are the diagonal elements of $\mathbf{K}_p(n)$, that is, the variances of the weight error coefficients, defined as

$$\begin{aligned}\boldsymbol{\kappa}_p(n) &= \left[E[|\widetilde{w}_1(n)|^2], E[|\widetilde{w}_2(n)|^2], \ldots, E[|\widetilde{w}_{2M+2N}(n)|^2]\right]^T \\ &= [\boldsymbol{\kappa}_{p1}^T(n), \boldsymbol{\kappa}_{p2}^T(n)]^T\end{aligned} \tag{18}$$

where $\boldsymbol{\kappa}_{p1}(n)$ and $\boldsymbol{\kappa}_{p2}(n)$ are both $(M+N)\times 1$ sub-vectors, which respectively contain the first half and the second half of the weight error variances. Based on the matrix structure relationship between $\mathbf{K}_p(n)$ and $\mathbf{K}_p'(n)$, the vector of the diagonal elements of $\mathbf{K}_p'(n)$, that is, $\boldsymbol{\kappa}_p'(n)$, can be achieved by shifting cyclically each entry in $\boldsymbol{\kappa}_p(n)$ by $M+N$, so that

$$\begin{aligned}\boldsymbol{\kappa}_p'(n) &= \left[E[|\widetilde{w}_{M+N+1}(n)|^2], \ldots, E[|\widetilde{w}_{2M+2N}(n)|^2],\right. \\ &\qquad \left. E[|\widetilde{w}_1(n)|^2], \ldots, E[|\widetilde{w}_{M+N}(n)|^2]\right]^T \\ &= [\boldsymbol{\kappa}_{p2}^T(n), \boldsymbol{\kappa}_{p1}^T(n)]^T\end{aligned} \tag{19}$$

Then, based on (13), the evolution of the weight error variance vector $\boldsymbol{\kappa}_p(n)$ becomes

$$\underbrace{\begin{bmatrix} \boldsymbol{\kappa}_{p1}(n+1) \\ \boldsymbol{\kappa}_{p2}(n+1) \end{bmatrix}}_{\boldsymbol{\kappa}_p(n+1)} = \mathbf{F}_\mu \underbrace{\begin{bmatrix} \boldsymbol{\kappa}_{p1}(n) \\ \boldsymbol{\kappa}_{p2}(n) \end{bmatrix}}_{\boldsymbol{\kappa}_p(n)} + \mu^2(\sigma_v^2+\sigma_q^2)\mathbf{1}_{2M+2N} \tag{20}$$

where

$$\begin{aligned}\mathbf{F}_\mu = &\begin{bmatrix} (1-2\mu+\mu^2)\mathbf{I}_{M+N} & \mu^2\mathbf{I}_{M+N} \\ \mu^2\mathbf{I}_{M+N} & (1-2\mu+\mu^2)\mathbf{I}_{M+N} \end{bmatrix} \\ &+\mu^2\mathbf{1}_{2M+2N}\mathbf{1}_{2M+2N}^T\end{aligned} \tag{21}$$

In order for the recursion in (20) to converge, all the eigenvalues of the transition matrix $\mathbf{F}_\mu$ must be less than unity [14,15,17]. Now, by solving $\det[\mathbf{F}_\mu - \gamma_i\mathbf{I}_{2M+2N}] = 0$, where $\det[\cdot]$ is the matrix determinant operation, and after a few manipulations, we arrive at

$$\gamma_1 = 1-2\mu, \quad \gamma_2 = 1-2\mu+2\mu^2,$$
$$\gamma_3 = 1-2\mu+2(M+N+1)\mu^2$$

where the algebraic multiplicities of γ_1, γ_2 and γ_3 are respectively $M+N$, $M+N-1$ and 1. Since $\gamma_3 > \gamma_2 > \gamma_1$, the convergence of $\boldsymbol{\kappa}_p(n)$, and hence, the MSE $J_p(n)$ in (12), is satisfied if $\gamma_3 < 1$, to yield

$$0 < \mu < 1/(M+N+1) \tag{22}$$

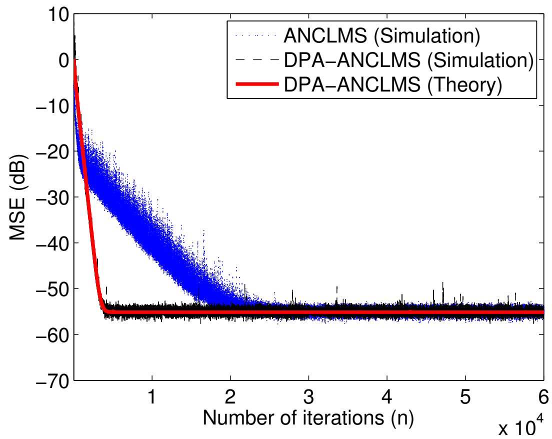

Fig. 1. Comparison of the transient MSE performances of ANCLMS and DPA-ANCLMS based SI cancellers.

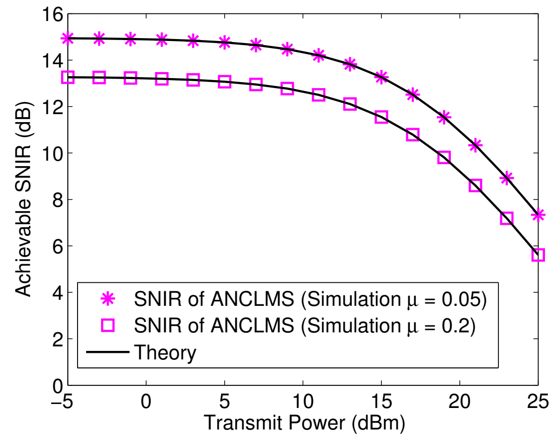

Fig. 2. Comparison of the theoretical and simulated steady-state mean square performances, in terms of achievable SNIRs, of DPA-ANCLMS based SI canceller.

4.3. Steady State Analysis

Assume that step-size μ is chosen such that the mean square stability of the proposed DPA-NACLMS based SI canceller is guaranteed, and consider $n \to \infty$ in (12), so that the steady-state MSE $J_p(\infty)$ can be evaluated as

$$J_p(\infty) = \mathbf{1}_{2M+2N}^T \boldsymbol{\kappa}_p(\infty) + \sigma_v^2 + \sigma_q^2 \tag{23}$$

where, based on (20), $\boldsymbol{\kappa}^a(\infty)$ can be derived as

$$\boldsymbol{\kappa}_p(\infty) = \mu^2(\sigma_x^2 + \sigma_q^2)(\mathbf{I}_{2M+2N} - \mathbf{F}_\mu)^{-1}\mathbf{1}_{2M+2N} \tag{24}$$

Upon substituting (24) into (23), we arrive at

$$J_p(\infty) = (\sigma_v^2 + \sigma_q^2)\{1 + 2\mu^2(M+N) + \mu^2 \mathrm{Tr}[\mathbf{F}_\mu^{-1}\mathbf{1}_{2M+2N}\mathbf{1}_{2M+2N}^T]\} \tag{25}$$

The achievable signal-to-noise-plus-interference ratio (SNIR), defined as the relative power ratio between the received signal of interest $x_{\mathrm{SOI}}(n)$ and the residual SI $e_p(n)$ [4], of the proposed DPA-ANCLMS based SI canceller can be evaluated as $\mathrm{SNIR} = p_{\mathrm{SOI}}/J_p(\infty)$, where p_{SOI} is the power of the $x_{\mathrm{SOI}}(n)$.

5. SIMULATIONS

Simulations were conducted in the MATLAB programming environment to verify the benefits of the proposed DPA-ANCLMS based digital SI canceller for FD DCTs in the presence of PA nonlinear distortion and frequency-dependent IQ imbalances. The simulated waveforms of the transmit SI $x(n)$ and the received signal of interest $x_{\mathrm{SOI}}(n)$ were considered to be generated from wireless LAN (WLAN) 802.11 standards compliant OFDM transmission systems. The analog SI attenuation of the FD DCT was considered at the level of 50 dB, and the cancellation error was subject to a 3-tap static Rayleigh distribution [18]. The frequency-dependent transmitter and receiver I/Q imbalance were both modeled as 2-tap static FIR filters [13], so that $M = 5$ and $N = 4$. The powers of the thermal noise $v(n)$ and the quantization noise $q(n)$ were respectively $\sigma_v^2 = -48$ dBm and $\sigma_q^2 = -60$ dBm. Typical values for other system parameters were chosen according to the specifications in [4].

Fig. 1 shows the theoretical convergence behavior of $J_p(n)$, evaluated by using (12) and (13), when DPA-ANCLMS with a step-size $\mu = 0.05$ was applied for a digital SI attenuation on the considered FD DCTs. It accurately describes the empirical MSE evolution in both the transient and steady-state stages. We also observed that the prewhitening scheme enabled a speed up in the convergence due to the stabilized eigenvalue spread in the transformed input covariance matrix, e.g., the original ANCLMS required 25000 iterations to converge, while it took 3000 iterations for DPA-ANCLMS. In Fig. 2, the digital SI cancellation performances of DPA-ANCLMS, measured in terms of the achievable SNIRs, were investigated against different levels of the transmit powers. Observe the excellent agreement between the simulated results and their theoretical evaluations. Fig. 2 also reveals that a smaller step-size μ enabled better performance for the proposed digital SI canceller but this was achieved at a cost in convergence speed.

6. CONCLUSIONS

We have introduced a data prewhitening assisted augmented nonlinear complex least-mean-square based digital self-interference (SI) canceller for full-duplex direct-conversion transceivers in the presence of PA distortion and frequency-dependent I/Q imbalances. This has been achieved by using a widely-linear model fitting and exploiting the known statistics of the SI signal to accelerate its iterative mitigation process. The SI cancellation capabilities of the proposed model have been rigorously justified in both the transient and steady-state stages. Simulations on wireless local area network standard compliant waveforms support the analysis.

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