RECEIVER DESIGN AND AGC OPTIMIZATION WITH SELF INTERFERENCE INDUCED SATURATION

Chandan Kumar Sheemar, Dirk Slock

EURECOM, Sophia-Antipolis, France, Email:{sheemar,slock}@eurecom.fr

ABSTRACT

In-band Full Duplex (FD) is a wireless communication technology which has the potential to transmit and receive simultaneously in the same frequency band. Self-interference cancellation (SIC) is the key enabler to achieve FD operation. As the SI is severe, some SIC is required at the antenna level and in the analog domain before analog to digital converter (ADC) in the receiver chain because the ADC has only a limited dynamic range. Here we consider deliberately scaling up the received signal, provoking ADC saturation due to the SI signal. This leads to missing samples which we propose to reconstruct under the assumptions that the receive signal of interest is a low pass bandlimited signal with known spectrum (mask), oversampling and (perfect) digital SIC after the ADC. The missing samples are estimated by fixed lag Kalman smoothing. More upscaling leads to fewer available samples but with less quantization noise. Hence an optimum compromise arises. We provide an approximate resulting MSE analysis based on large random matrix theory, replacing randomly selected Fourier transform vectors by vectors of i.i.d. variables. Simulation results show the improvement in reconstruction Signal to Noise Ratio (RSNR) and the optimal compromise behavior.

***Index Terms*—** Full Duplex, Missing samples, Saturated samples, Saturation, Signal recovery, Fixed lag Kalman smoothing.

1. INTRODUCTION

Ongoing evolution in wireless communication systems is subject to tremendous growth for the number of users in a limited wireless spectrum. Full duplex (FD) systems theoretically double the spectral efficiency [1–4], hence very prominent to overcome the saturation of available spectrum. To achieve FD operation, the self-interference (SI) signal needs to be subtracted from the total receive (Rx) signal to allow proper reception. SI signal power is around 110 dB higher compared to the Rx signal of interest and its cancellation is not an easy task. This is mainly due to the nonlinearities present in the transmit (Tx) and Rx chains, which lead to inaccurate SI channel estimate and limit the SI cancellation (SIC) capabilities.

However, continuous advancement in SIC techniques at the antenna level, in the analog and digital domain has made FD operation feasible [5–7]. The first ever WiFi FD system was presented in [1], later extended to the MIMO case in [2]. Multiple solutions since then have been proposed to push the limits of SIC to make FD operation feasible also at the high Tx power scenarios. Beamforming based techniques have also been proposed to improve the performance of SIC [8–11]. Complexity of the analog SIC stage was a major challenge to deploy FD in massive MIMO scenarios, but recently a solution based on hybrid SIC has been proposed, which decreased its complexity considerably [12].

Besides the nonlinearities, also the limited dynamic range (LDR) of analog to digital converters (ADCs) can limit the performance of a FD system. Saturation of converters in Rx chains limits the correct adaption of digital SIC (DSIC) stage to mimic the SI signal with opposite sign. Moreover, we also loose the Rx signal of interest for the duration of saturation. In [13, 14], the authors claim that saturation of ADCs is a major bottleneck for FD systems, which is preventing us to benefit from their full potential. The first analysis of residual SI for a FD MIMO-OFDM system which took into account the LDR model was presented in [15]. Recently, we analyzed the performance of a multistage/hybrid beamforming for an OFDM FD backhaul system by using the LDR model [16]. Though all the other critical challenges to achieve FD operation have been well tackled by the researchers, the possibility to reconstruct saturated/missing samples has not been yet taken into account. So the work we present here considers for the first time ever this possibility to achieve higher gains. To avoid saturation, one existing solution is the automatic gain control (AGC) which scales down the total signal to fit it into the LDR of converters. But, this solution preserves only few quantization levels for the Rx signal of interest and hence increases the quantization noise (QN). Recently, an alternative FD transceiver structure to discard the saturated samples based on non uniform sampling and zero crossing of the SI signal for an OFDM system has been proposed [17]. In contrast to their approach, our approach is more appealing as it doesn't require additional hardware as in [17] and applicable to FD systems equipped with classical ADCs having uniform samplers.

We propose to deliberately scaling up the total Rx signal before the ADC, which of course leads to have more saturated samples but reduces QN on the available samples as well. Missing samples are then reconstructed according to their linear minimum mean square error (LMMSE) estimate by fixed lag Kalman smoothing. For the state of the art on the LMMSE estimation of missing samples, we refer to [18]. In this work, we deal only with the case of real signals but in principle our approach should be applied to both I and Q branches. Here we assume that the available samples are SI free, but ideally the joint optimization of DSIC stage and reconstructing of missing samples should be considered. Classical LMMSE estimation techniques requiring matrix inversions, may not be feasible when the dimensions increase. Our fixed lag Kalman smoothing approach to reconstruct missing samples in a FD system is more appealing, being computationally very efficient, as it is a recursive approach.

1.1. Contributions of this paper

- For the first time ever, we consider the possibility to reconstruct missing samples in a FD system by deploying Fixed lag Kalman smoothing, which leads to significant performance

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improvement.

- We provide an approximate resulting MSE expression based on large random matrix theory as a function of the available fraction of samples β. Also, the link between β and saturation point Δ of an ADC is established.
- Simulation results demonstrate that when the signal to be reconstructed is upsampled of factor $1/\alpha$, then missing samples can be reconstructed with small β.

Notation: In this paper, boldface lower-case and upper-case characters denote vectors and matrices, respectively. The operators $\mathbf{E}\{\cdot\}, \mathbf{tr}\{\cdot\}, (\cdot)^{\mathbf{H}}, (\cdot)^{\mathbf{T}}, \Pr(\cdot)$ denote expectation, trace, Hermitian transpose, transpose and probability, respectively.

2. SYSTEM MODEL

We consider the scenario consisting of a FD system with single Tx and Rx antenna, which is serving only one user. Let x be the signal transmitted from its user and y be its received version. We assume that x is generated according to an autoregressive (AR) process of order M, so at time k its sample can be written as

$$x_k = -a_1 x_{k-1} - a_2 x_{k-2} - .... - a_M x_{k-M} + z \quad (1)$$

where $z \sim \mathcal{N}(0, \sigma_z^2)$ is an independent noise term driving the AR process. We further assume that x is a bandlimited signal with a known low pass specturm $S_{x,x}(f)$ and upsampled of factor $1/\alpha$, where α is a rational number. We further assume perfect SIC for the fraction of available samples β, so we are ignoring the nonlinearities of Tx and Rx chain. At the receiver side, the measurement equation for non saturated sample of x at time k can be written as

$$y_k = x_k + v_k \quad (2)$$

where v_k denotes the granular QN. Let δ and b denote the quantization step size and the number of bits of an ADC. Then, v_k is uniformly distributed in $[-\delta/2, \delta/2]$ with variance σ_v^2 and connected to Δ by $\delta = \Delta/2^{(b-1)}$, where b denotes the number of bits. Missing samples are denoted with y'_k and their measurement equation can be written as

$$y'_k = x_k + v_k + s_k \quad (3)$$

where s_k denotes saturation noise. For y'_k, s_k dominates and has variance $\sigma^2_{s_k} >> \sigma^2_{v_k}$. It is easy to identify the positions of missing samples as $y'_k = \pm\Delta$. So, also the position of missing samples are well known and we discard these values by replacing them with zeros. Our Rx signal obeys (1) and the coefficients of this AR process can be estimated by using the following equation

$$\begin{bmatrix} r_{x,x}(0) & r_{x,x}(1)\ldots & r_{x,x}(M) \\ r_{x,x}(1) & \ddots \quad \ldots & \vdots \\ \vdots & \ddots \quad \ldots & r_{x,x}(1) \\ r_{x,x}(M) & \ldots \quad \ldots & r_{x,x}(0) \end{bmatrix} \begin{bmatrix} 1 \\ a1 \\ \vdots \\ a_M \end{bmatrix} = \begin{bmatrix} \sigma_z^2 \\ 0 \\ \vdots \\ 0 \end{bmatrix}, \quad (4)$$

where $r_{x,x}(\cdot)$ is the correlation sequence of x obtained by inverse DFT of the low pass spectrum $\mathbf{S}_{xx}(f)$, which is assumed to be known at the Rx side. The system of equations (4) is known as Yule-Walker equations and by scaling all the elements by σ_z^2, it can be rewritten as

$$\mathbf{R}_{M+1}\ \mathbf{a} = \mathbf{e}_1 \quad (5)$$

where $\mathbf{R}_{M+1}$, $\mathbf{a}$ and $\mathbf{e}_1$ are the matrix of correlation sequence, vector of AR coefficients and the first standard basis vector, respectively. Now $\mathbf{a}$ can be obtained as $\mathbf{a} = \mathbf{R}_{M+1}^{-1}\mathbf{e}_1$, from which we can recover the coefficients of (1) as $[1, -a1, -a2, ..., -a_M]^T = \mathbf{a}^T/\mathbf{e}^T\mathbf{a}$. Also Levinson's algorithm can be used to solve (4), which is a recursive approach, has complexity $\mathcal{O}(M^2)$ and it further provides an accurate estimate of σ_z^2.

Kalman's filter equations are very appealing to the case in which unknown parameters that we wish to estimate follow a state space model. These unknowns are estimated by minimizing the mean square error (MSE). It consists in following a series of steps at each time instant to predict the future state by performing LMMSE prediction, based on the so called Gauss-Markov model. Then Kalman gain is evaluated based on the estimation error and measurement covariance matrices and its objective is to correct the a priori estimate. Correction of the state estimate at time k consists in summing to the a priori estimate, a factor consisting of the Kalman gain K_k multiplying innovation, which is a difference between the measured value and the a priori estimate. Kalman gain varies from $[0, 1]$ and it is 0 when the measurements are very noisy and innovation is not taken into account at all. It assumes value 1 when the measurement can provide perfect information to update the a priori estimate by summing up directly the innovation. Finally, LMMSE is achieved with minimum prediction MSE multiplying $(1 - K_k)$. For the state of the art on Kalman Filtering and the state space model, we refer the reader to [19].

As we are interested in also smoothing our estimates of missing samples, we leverage fixed lag Kalman smoothing with lag $L << N$, where N is the total number of samples. So to estimate the sample at time k, measurements up to time $k + L$ are taken into account. The state space model for the fixed lag Kalman smoothing can be written as

$$\mathbf{x}_k = \mathbf{H}\mathbf{x}_{k-1} + \mathbf{e}_1 z \quad (6)$$

$$\mathbf{y}_k = \mathbf{A}(\mathbf{x}_k + \mathbf{v}_k + \mathbf{s}_k) \quad (7)$$

where $\mathbf{x}_k$ is the $L \times 1$ state vector at time k, $\mathbf{v}_k$ is the granular quantization noise state vector, $\mathbf{A}$ is the $L \times L$ state observation matrix, $\mathbf{y}_k$ is the observed state at time k, $\mathbf{e}_1 z$ is noise of the AR process, $\mathbf{s}_k$ is the saturation noise state vector with non zero elements only for saturated samples, $\mathbf{H}$ is the $L \times L$ state space matrix with its first row $[-a_1, .., -a_M\ \mathbf{0}]$, its left lower block is an identity of size $L-1$ denoted with $\mathbf{I}_{L-1}$ and its L-th column is made of all zeros. We denote with $\hat{\mathbf{x}}_k^-$ and $\hat{\mathbf{x}}_k^+$ the a priori and posteriori estimate of the state $\mathbf{x}_k$, with $\mathbf{R}^{k-}_{\tilde{x}\tilde{x}}$ and $\mathbf{R}^{k+}_{\tilde{x}\tilde{x}}$ the a priori and posteriori error covariance matrices and with $\mathbf{Q}_k$ the measurement covariance matrix.

The LMMSE estimates of missing samples with fixed lag Kalman smoothing can be obtained by iterating algorithm 1. The smoothed LMMSE estimate of sample x_k can be found in the $L-$th element of the state vector $\mathbf{x}_{k+L}$ and the minimum mean square error is contained in $\mathbf{R}^{(k+L)+}_{\tilde{x}\tilde{x}}(L, L)$.

Algorithm 1 Fixed lag Kalman smoothing

Initialize $\mathbf{x}_0^+ = E[\mathbf{x}_0]$ and $\mathbf{R}^{0+}_{\tilde{x}\tilde{x}} = E[(\mathbf{x}_0 - \hat{\mathbf{x}}_0^+)(\mathbf{x}_0 - \hat{\mathbf{x}}_0^+)^T]$
for $k = 1, ..., N$, where N denotes the total samples of x

1. $\mathbf{R}^{k-}_{\tilde{x}\tilde{x}} = \mathbf{H}\mathbf{R}^{k-1+}_{\tilde{x}\tilde{x}}\mathbf{H}^T + \mathbf{e}_1\mathbf{Q}_{k-1}$
2. $\mathbf{K}_k = \mathbf{R}^{k-}_{\tilde{x}\tilde{x}}\mathbf{A}_k^T(\mathbf{A}\mathbf{R}^{k-}_{\tilde{x}\tilde{x}}\mathbf{A}^T + \mathbf{R}_k)$
3. $\hat{\mathbf{x}}_k^- = \mathbf{H}\hat{\mathbf{x}}_{k-1}^-$
4. $\hat{\mathbf{x}}_k^+ = \hat{\mathbf{x}}_k^- + \mathbf{K}_k(\mathbf{y}_k - \mathbf{A}\hat{\mathbf{x}}_k^-)$
5. $\mathbf{R}^{k+}_{\tilde{x}\tilde{x}} = (\mathbf{I}_L - \mathbf{K}_k\mathbf{A})\mathbf{R}^{k-}_{\tilde{x}\tilde{x}}$

end

3. MSE LARGE SYSTEM ANALYSIS

In this section, we derive analytically the approximate resulting MSE as a function of the fraction of available samples β. Our derivation is based on the properties of trace operator, random matrix theory, cyclic permutation, circulant matrix approximation and partially on the expressions derived in [20]. At the end, we also establish the link between β and saturation point Δ of an ADC.

The error correlation matrix for the LMMSE estimation can be written as

$$\mathbf{R}_{\tilde{x}\tilde{x}} = \mathbf{R}_{\mathbf{xx}} - \mathbf{R}_{\mathbf{xx}}\mathbf{A}^H(\mathbf{A}\mathbf{R}\mathbf{y}\mathbf{y}\mathbf{A}^H)^{-1}\mathbf{A}\mathbf{R}_{\mathbf{xx}}, \tag{8}$$

where $\mathbf{A}$ now becomes a $K \times N$ matrix which selects K non saturated samples from the total of N received samples to achieve $\beta = K/N$, $\mathbf{R}_{\mathbf{yy}} = \mathbf{R}_{xx} + \sigma_v^2\mathbf{I}$ and $\mathbf{R}_{xx}$ are the correlation matrix of the received and transmitted signal. $\mathbf{R}_{xx}$ is a Toepliz matrix and can be approximated as a circulant matrix $\mathbf{R}^c_{\mathbf{xx}}$, which can be written as

$$\mathbf{R}^c_{\mathbf{xx}} = \frac{1}{N}\mathbf{F}^H\mathbf{D}\mathbf{F}, \tag{9}$$

where $\mathbf{D}$ is the DFT of the finite correlation sequence of (4), $\mathbf{F}$ denotes the DFT of size N and also $\mathbf{F}^{-1} = \mathbf{F}^H$ is true. We assume that $\mathbf{A}$ performs random sub-selection of the samples to achieve β and approximate $\mathbf{A}\mathbf{F}^H \sim \mathbf{S}$, a $K \times N$ matrix with elements $s_{i,j} \sim \mathcal{N}(0, 1)$. This approximation can be introduced because $\mathbf{A}$ performs random subset selection of samples to achieve β. This fraction is strictly related to the commulative distribution of $\mathbf{A}$ as the DFT matrix has unit magnitude and different phase terms. $\mathbf{A}$ selects its K rows randomly and therefore $\mathbf{A}\mathbf{F}^T$ can be seen as a random set of orthonormal columns. By taking the elements pairwise, the average norm of $\mathbf{S}$ (if divided by N) as $N \to \infty$ goes to one, the inner product between two rows goes to zero and the inner product between two elements goes to 0 as it has independent variables. By taking into account the aforementioned approximations, we can rewrite (8) as follows

$$\mathbf{R}_{\tilde{x}\tilde{x}} = \mathbf{F}^{-1}\mathbf{D}\mathbf{F} - \mathbf{F}^{-1}\mathbf{D}\mathbf{S}^H(\mathbf{S}\mathbf{D}\mathbf{S}^H + N\sigma_v^2\mathbf{I})^{-1}\mathbf{S}\mathbf{D}\mathbf{F}. \tag{10}$$

By applying the trace operator and dividing everything by N, we have

$$\frac{tr(\mathbf{R}_{\tilde{x}\tilde{x}})}{N} = tr(\frac{\mathbf{F}^{-1}\mathbf{D}\mathbf{F}}{N} - \frac{\mathbf{F}^{-1}\mathbf{D}\mathbf{S}^H}{N}(\mathbf{S}\mathbf{D}\mathbf{S}^H + N\sigma_v^2\mathbf{I})^{-1}\mathbf{S}\mathbf{D}\mathbf{F}). \tag{11}$$

Now, using the property of trace operator which allows cyclic permutation, $\mathbf{F}\mathbf{F}^{-1}$ becomes identity in both of the terms of the MSE expression. Hence, (11) can be further simplified as

$$\frac{tr(\mathbf{R}_{\tilde{x}\tilde{x}})}{N} = tr(\frac{\mathbf{D}}{N} - \frac{\mathbf{D}\mathbf{S}^H}{N}(\mathbf{S}\mathbf{D}\mathbf{S}^H + N\sigma_v^2\mathbf{I})^{-1}\mathbf{S}\mathbf{D}). \tag{12}$$

By applying the matrix inversion lemma, we can simplify the $()^{-1}$ term in (12) as

$$\mathbf{S}^H(N\sigma_v^2\mathbf{I} + \mathbf{S}\mathbf{D}\mathbf{S}^H)^{-1} = \mathbf{D}^{-1}(\frac{1}{N\sigma_v^2}\mathbf{S}^H\mathbf{S} + \mathbf{D}^{-1})\frac{\mathbf{S}^H}{N\sigma_v^2}, \tag{13}$$

which allows us to rewrite (12) as

$$\begin{aligned}\frac{MSE}{N} &= \frac{1}{N}tr(\mathbf{D}) - \frac{1}{N}tr((\mathbf{S}^H\mathbf{S} + N\sigma_v^2\mathbf{D}^{-1})^{-1}\mathbf{S}^H\mathbf{S}\mathbf{D}) \\ &= \sigma_v^2 tr((\mathbf{S}^H\mathbf{S} + N\sigma_v^2\mathbf{D}^{-1})^{-1}).\end{aligned} \tag{14}$$

By using (8)-(14) from [20], for $s_{i,j}$ being iid, (14) can be written as

$$\frac{MSE}{N} = e\,\sigma_v^2 = \frac{1}{N}tr((\frac{K}{N}\frac{1}{1+e}\mathbf{I}_N + \sigma_v^2\mathbf{D}^{-1})^{-1}), \tag{15}$$

which yields

$$e\,\sigma_v^2 = \frac{1}{N}\sum_i^N \frac{1}{\frac{K}{N}\frac{1}{1+e} + \frac{\sigma_v^2}{d_i}}. \tag{16}$$

For the ideal low pass bandlimited spectrum case, fraction α of the N d_i values are $d_i = d$. By taking the inverse DFT of the spectrum of x, we get

$$\sigma_x^2 = \frac{1}{N}\alpha N d, \tag{17}$$

and for exact bandlimited spectrum it equals fraction α of the (over)sampling frequency. Therefore, $\frac{1}{\alpha}$ denotes the oversampling factor, which implies $d = \sigma_x^2/\alpha$ and $\rho = \sigma_x^2/\sigma_v^2$ is the signal-to-noise-ratio (SNR). By using the previous results, we can rewrite (16) as

$$e\,\sigma_v^2 = \alpha\frac{1}{\frac{K}{N}\frac{1}{1+e} + \frac{\alpha}{\rho}}. \tag{18}$$

It implies

$$\frac{K}{N}\frac{e}{1+e} + \frac{\alpha}{\rho}e = \frac{\alpha}{\sigma_v^2}, \tag{19}$$

which can be rearranged as

$$\beta e + \frac{\alpha}{\rho}(e + e^2) - \frac{\alpha}{\sigma_v^2}(1 + e) = 0. \tag{20}$$

By multiplying with ρ and dividing by α we get

$$\frac{\rho\beta}{\alpha}e + e + e^2 - \frac{\rho}{\sigma_v^2}(1 + e) = 0, \tag{21}$$

which leads to the following expression

$$e^2 + (1 + \frac{\rho\beta}{\alpha} - \frac{\rho}{\sigma_v^2})e - \frac{\rho}{\sigma_v^2} = 0, \tag{22}$$

and finally by solving for e we get

$$e = \frac{1}{2}\left[-(1 + \frac{\rho\beta}{\alpha} - \frac{\rho}{\sigma_v^2}) + \sqrt{(1 + \frac{\rho\beta}{\alpha} - \frac{\rho}{\sigma_v^2})^2 + \frac{4\rho}{\sigma_v^2}}\right]. \tag{23}$$

Under the assumptions that x_k, v_k and the SI signal follow Gaussian distribution and s_k has the dominant contribution, the fraction of available samples β can be linked to Δ as

$$\begin{aligned}&\beta = P(|y'_k| < \Delta) = 1 - P(|y'_k| \geq \Delta) = 1 - 2P(y'_k \geq \Delta) \\ &= 1 - 2(1 - P(y'_k \leq \Delta)) = 2P(y'_k \leq \Delta) - 1 = 2F'_y(\Delta) - 1\end{aligned} \tag{24}$$

where $F'_y(\cdot)$ is the CDF of y'_k. Now $F_{y'}(.) = F_{s+x+v}(.) \approx F_{s+x}(.) \approx F_s(.)$ where $F_s(.)$ is the CDF of a Gaussian random variable with zero mean and variance σ_s^2. So under the assumption that s_k is Gaussian, we can finally conclude that $\beta = 2F_s(\Delta) - 1$.

4. SIMULATION RESULTS

In this section, we present simulation results to evaluate the performance of fixed lag Kalman smoothing to reconstruct missing/saturated samples. We consider a FD system equipped with a single Tx and Rx antenna, which receives a real signal form its only user and has an ADC in its Rx chain with uniformly quantized dynamic range. For evaluation purpose, we consider ADCs with resolution of $8, 10$ and 12 bits to see the variation in reconstruction performance. We assume that the SI signal has the same characteristics of x, except the power. We assume also that after the analog SIC stage a residual of 50 dB is left, to be taken care of in the baseband. At the input of the ADC, we deliberately scale up the signal consisting of residual SI and x, by letting it saturate with an AGC to change β. Available samples change as a function of n, which is linked to the saturation point as $\Delta = 2^n\sigma_x$. We also assume perfect SIC for the non saturated samples, so we are ignoring the nonlinearities of the Tx and Rx chain. We further also assume that Rx signal is upsampled of factor $1/\alpha = 4$ and its spectrum $S_{x,x}(f)$ at the Rx side to be known.

The fixed lag Kalman smoothing initializes at time instant $L+1$ and by choosing $L = 20$ we assume that $\mathbf{x}_L$ is known in a noisy form (only QN). We generate the Rx signal of length $N = 1000$ with variance $\sigma_x^2 = 1$ according to an AR process of order $M = 10$, which has a perfect lowpass spectrum $S_{x,x}(f)$. At the Rx side, as $S_{x,x}(f)$ is supposed to be known, its inverse DFT is calculated to get the correlation sequence of size $M+1$ which appears in (4). Then, the AR coefficients and σ_z^2 driving the process are estimated by using the Levinson's algorithm. For the SI signal, we assume that it has the same spectrum, same length and generated using the same AR coefficients of x, but with different variance σ_s^2. Figure 1 shows β as a function of n, which varies with step size 0.5. We define the signal-to-noise-ratio as SNR$= \sigma_x^2/\sigma_v^2$. To evaluate the reconstruction performance, we define reconstruction SNR (RSNR) as $= \sigma_x^2/MSE$. For fixed lag Kalman smoothing with lag L, the MSE for each sample at time k is obtained by averaging over the (L, L)-th element of the posteriori error covariance matrix $\mathbf{R}_{\tilde{x}\tilde{x}}^{(k+L)+}$.

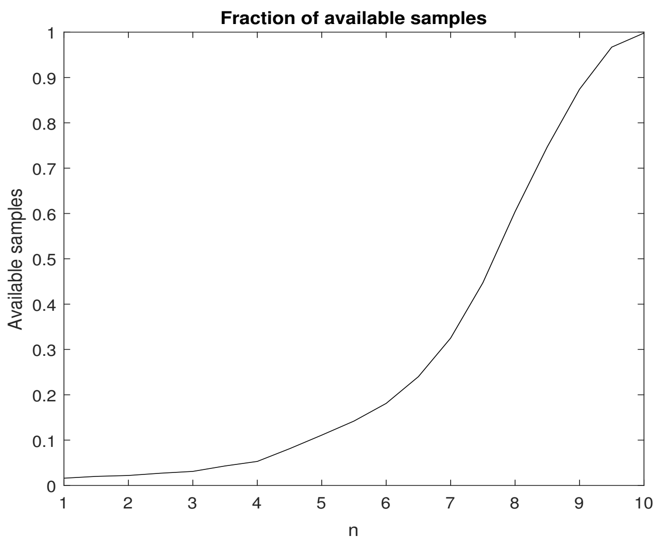

Fig. 1. Fraction of available samples as a function of n.

The reconstruction performance is shown in Fig. 2, which clearly exhibits the optimal compromise between QN and $\beta(n)$, resulting to be different for different ADCs. It may worth mentioning that because of the initialization condition, state at time L to be perfectly known, the LMMSE estimates of missing samples with very small β tends to still give a positive RSNR (in dB). This occurs because the saturated samples from time $L+1$ onwards are estimated according to the AR model (1) and for $n \in [1, 6]$ only very few innovations are taken into account to update the a priori estimates.This leads to have almost the same reconstruction performance for $n \in [1, 6]$, even with ADCs with different resolution as the available samples occupy the whole LDR and the effect of QN is negligible. For $n > 6$, when more than 25% (upsampling of factor 4) becomes available then more and more innovations are taken into account to improve the performance. However as the QN also start to become non negligible and it is different for ADCs with different resolution, the reconstruction performance also varies. It is worth emphasizing that the initial condition for which we suppose the state at time L to be known, represents the case in which saturation may occurs due to instantaneous SI power increase, but before that we still have some non saturated samples available, which we can use to estimate the saturated samples. Initializing the estimation process with no knowledge of available samples leads to different MSE for the three ADCs considered when $n \in [1, 6]$ and results to be the same for $n > 6$.

It is clearly visible from Fig. 2 for the case of 8 bit ADC that RSNR is equal to SNR when only 25% $(1/\alpha = 4)$ of the non saturated samples are available. For each ADC considered, there exits a different optimum point leading to RSNR*. This point represents the optimum compromise between β and QN, which allows to achieve higher gains for FD systems. It is evident from Fig. 2 that, as the resolution increases, the QN variance decreases and therefore to achieve RSNR* (higher than SNR) more and more fraction of available samples are needed. The tuning of AGC should be done to make sure that we receive the optimum fraction of available samples β^* at the receiver side to reconstruct the missing samples.

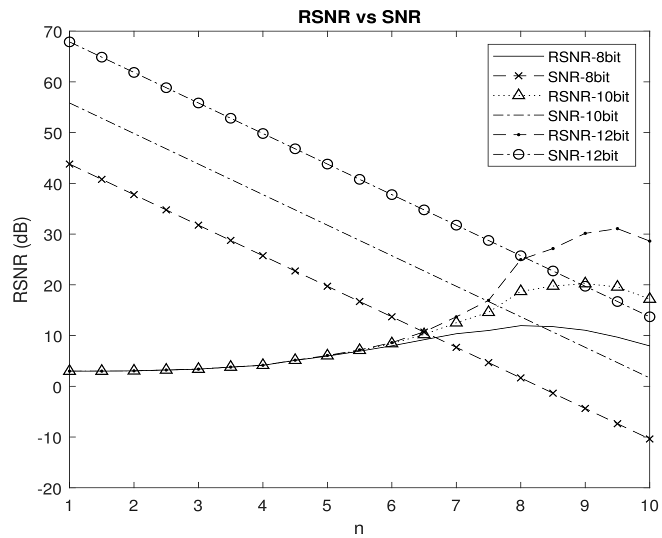

Fig. 2. Reconstruction SNR for $8, 10$ and 12 bit ADCs as a function of n

5. CONCLUSION

Saturation of ADCs in the Rx chains is a major bootleneck of FD systems. Tuning with AGC has been used so far to avoid saturation, but it is based on scaling the total Rx signal (residual SI and Rx signal of interest) completely to fit it into the LDR of ADCs. This leads to preserve very few quantization levels for the signal of interest and hence increases QN. In this work, for the first time ever we considered the possibility to reconstruct saturated samples according to their LMMSE estimate by using fixed lag Kalman smoothing. To leverage our approach, we assume that the signal to be reconstructed follows an AR model, its upsampled and its spectrum to be perfectly known at the receiver side. We deliberately provoke saturation which leads to have fewer available samples but with very less quantization noise. Simulation results show that saturated samples can be reconstructed very well if the assumptions mentioned above are met. Also, the optimum compromise between the fraction of available samples and QN is evident, which results to be different for ADCs.

Future work direction of our proposed approach may consider its extension to the multi-user MIMO case, possibly exploiting the OFDM signal model. Moreover, in principle also digital SIC stage should be adapted as the SI channel estimation results to be erroneous due to saturated samples. Therefore, one further direction would be the joint optimization of DSIC stage and AGC.

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