Advanced calibration techniques for data acquisition and measurement

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Abstract

Digital calibration techniques exploit the growing signal processing power of digital systems to correct the impairments of analog, mixed-signal and radiofrequency systems. Digital calibration is a generalization of equalization, which can be considered a form of calibration in which linear phenomena are corrected via digital linear filters. Digital calibration can be applied to linear and nonlinear systems, single-channel and multi-channel (time-interleaved) systems, and can help improve analog figures of merits for analog-to-digital converters, mixers, power amplifiers, analog filters, or entire systems such as receivers and beamformers. This work describes the main techniques and issues of digital calibration.

1. Introduction

Data acquisition systems process analog or radiofrequency signals to obtain a digital representation of the input signal. For instance, in a homodyne receiver, shown in Fig. 1, a signal of bandwidth B_W around a carrier frequency f_C is downconverted to obtain its complex envelop of bandwidth $B_W/2$, which can be sampled without loss of information at a sampling frequency $f_S \geq B_W$ and quantized with increasing accuracy into a word of N_B bits. Each component in the receiver chain, mixers, filters, amplifiers and analog-to-digital converters (ADCs), introduce noise and distortions on the input signal, altering its behavior and reducing system performance, be it its resilience to jammers and interferers, the data link's bit error rate, etc.

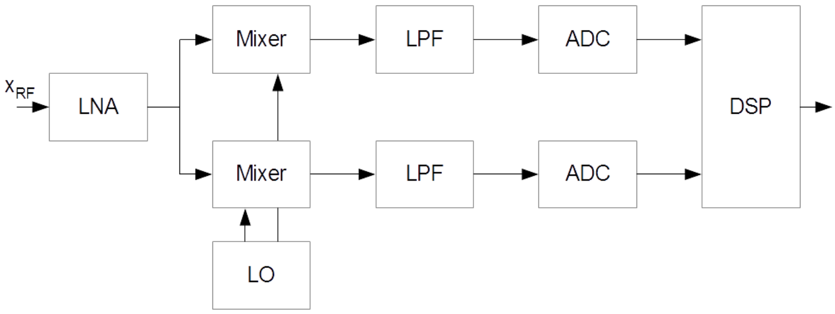

Fig.1. Architecture of homodyne receiver. LNA is the low-noise amplifier, LPF the lowpass filter, ADC the analog-to-digital converter, DSP the digital signal processing section, and LO the local oscillator.

There are two main classes of impairments in analog and radiofrequency circuits: deterministic and stochastic errors. Deterministic errors are functions of the input signal (which may or may not include interferers, for instance in a radar receiving a strong clutter return) and can be described as a function of the input $x(t)$, depending on a vector of unknown parameters θ, which provides the output $y(t)$:

$$y(t) = f(x(t), \theta) \quad (1)$$

This model is general because it can include all sorts of deterministic effects, linear and nonlinear, and with or without memory. The parameter vector can model process variables like CMOS transistors' threshold voltages (which have a certain spread over their nominal value) or environmental variables (such as ambient temperature). Stochastic errors are unpredictable and depend on random events, so that they are not function of the signal and cannot be represented as in (1). Additive noise can be written as an additive term, while other stochastic impairments such as jitter can be written as a random modulation of the amplitude and delay of the input waveform. Noise is unpredictable, though in principle correlated noise can be partially predicted and thus reduced, and it is not of interest for digital calibration, whose purpose is to correct deterministic errors. However, calibration can improve noise behavior, as shown in the following.

Deterministic errors are predictable if the function $f(\cdot)$ is known. Digital calibration techniques attempt to estimate and invert this function (for each realization of the parameter vector) to reconstruct the input signal $x(t)$ from the output of the system $y(t)$. Calibration is called "digital" because it operates on the sampled output $y[n] \equiv y(nT_S)$, where $T_S = 1/f_S$, to obtain a digital representation of the input $x[n] \equiv x(nT_S)$. Because the input signal fulfils the Nyquist condition, as its bandwidth is by hypothesis lower than half the sampling frequency, it is possible to operate in the discrete-time domain without loss of information, except for quantization noise in the ADC and stochastic effects which cannot be corrected.

Fig. 2 explains the process of digital calibration. The uncalibrated output signal $y[n]$ is processed by a digital system which produces the calibrated output $z[n]$, which is forced to be as close as possible to the input signal $x[n]$, except for stochastic errors and residual modeling errors. The digital processing section performs an operation $z[n] = g(y[n], \theta^S)$, which can be linear or nonlinear, and with or without memory, depending on a set of estimated parameters θ^S. All the possible realizations of the system model $f(x[n], \theta)$ should be corrected by the correction model $g(y[n], \theta^S)$, if the parameter set is correctly estimated ($\theta^S \approx \theta$) and if the correction model is the inverse of the system model: $g(f(x[n], \theta), \theta) \approx x[n]$.

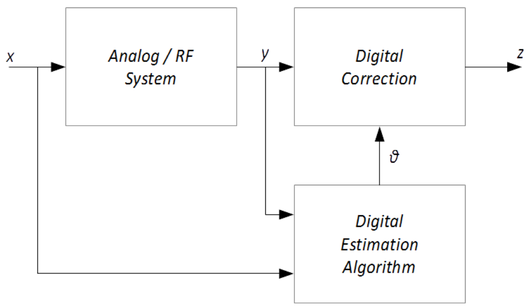

Fig. 2. The idea of digital calibration: (analog) system model cascaded with (digital) correction model.

Because only deterministic errors are calibrated, system performance is limited by noise when the model is sufficiently accurate and is correctly estimated. Hence, noise sets an upper limit on performance. When distortions dominate noise, there is a clear advantage in terms of accuracy in performing calibration. Furthermore, often distortion terms are concentrated in narrow bands, while noise is about evenly spread throughout the Nyquist band, so that even small deterministic narrowband errors can be observed in the uncalibrated output spectrum amidst a stronger wideband noise background. Digital calibration can improve the performance of such systems (in ADCs, narrowband errors influence the Spurious Free Dynamic Range, or SFDR, while all the error sources together influence the Signal-to-Noise-and-Distortion Ratio, or SNDR: in this case, digital calibration improves SFDR even if SNDR is not improved, because it is dominated by SNR).

Some errors are stationary and others are time-varying. This implies that θ can be a function of the time index n, at least to some extent. Time-varying errors can be due to environmental variations, but also device aging or the system's configuration (i.e., the orientation of a mobile receiver). Fast time-varying errors can be corrected only if the estimation of $\theta[n]$ is fast enough to ensure that $\theta^S[n] \approx \theta[n]$ at all times. This means that calibration needs to be in real time, through the use for instance of adaptive filters. When calibration is performed when the system is up and running, it is called "background" calibration, and estimation of θ is performed in the presence of the useful signal $x[n]$, which acts as nuisance for the estimation process. Otherwise, when estimation is performed in the absence of the useful but unknown signal, and possibly by injection of a known test signal, it is called "foreground" calibration. Time-varying errors require background calibration, while in principle foreground calibration can be used for stationary errors, or for time-varying errors which vary slow enough that they can be assumed constant between two consecutive estimations.

The process of digital calibration can thus be conceptualized in three separate steps. Modeling is the specification of a model for correcting the impairments of the system to be calibrated. This is a theoretical – paper and pencil – step which takes into account the structure of the system and the properties of the analog impairments to specify a parametric class of functions $g(y[n], \theta)$ which can be used to calibrate the system. Estimation is the identification of the error parameters θ, and can be performed in the background or in foreground depending on the type of estimation strategy. Correction is the computation, in real time, of the correction function $g(y[n], \theta^s)$ to obtain the calibrated output. Of these steps, only the last one always needs to be performed in real time, and requires actual digital resources, while the second step may or may not be performed in real time in the case of background calibration.

Equalization can already be considered a form of digital calibration, in that an output signal $y[n]$ obtained by linear filtering of an input signal $x[n]$ is digitally filtered to obtain a combined frequency response without linear distortions, i.e., with flat gain and linear phase response. This is an example of linear impairments with linear effects which are corrected via a linear model.

In inherently nonlinear systems, such as ADCs, linear errors can have nonlinear effects. For instance, linear gain errors in the stages of a pipeline ADCs [1-5] give rise to distortions, which can be corrected by estimating the gain of the stages and taking into account the estimated gain to correct the output of the ADC. The same problem occurs in multi-channel systems, such as time-interleaved ADCs [6-11] or I/Q mixers [12-13], where mismatches between nominally identical parallel channels cause nonlinearities in the form of aliasing distortions, i.e., spectral copies of the input signal translated in frequency by multiples of $2\pi/M$, where M is the number of channels.

The most complex case is that of nonlinear impairments, such as amplifiers' nonlinearities [14] caused by the nonlinear characteristic of active semiconductor devices, which cause nonlinear effects. In this case, models become more complex, parameter estimation may become harder, and the required digital processing power to compute the correction function grows with the complexity of the model. This type of distortions occurs for instance in power amplifiers and active filters. Nonlinear effects have an inherent spectral growth effect because nonlinearities in the time domain, such as $x^p[n]$ polynomial terms, become a $p-1$-fold self-convolution of the spectrum $X(\omega)$, which causes the bandwidth of the resulting signal to grow. Fig. 3 shows spectral regrowth of a signal with rectangular spectrum through a nonlinearity of the second order. The output of analog nonlinearities often no longer fulfil the Nyquist condition, and obtaining models of the analog nonlinearity in the discrete-time domain must take into account aliasing effects which do not occur in the analog domain.

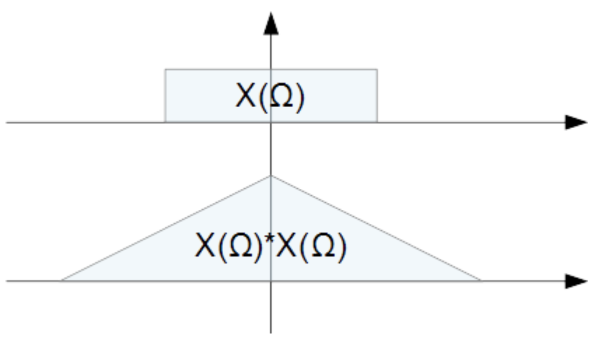

Fig. 3. Spectral regrowth through a second-order nonlinearity.

Section 2 recasts the common problem of equalization as a form of digital calibration. Section 3 describes the effect of linear (gain) errors on the behavior of inherently nonlinear systems such as pipeline ADCs.

Section 4 describes the onset of aliasing distortions in multichannel systems such as I/Q mixers and time-interleaved ADCs. Section 5 is about nonlinear calibration of nonlinear impairments, and describes the main modeling, identification and correction issues in this kind of calibration techniques. Section 6 summarizes the benefits of digital calibration for nonlinear systems, taking a system-level view of the issue. Section 7 concludes.

2. Equalization as digital calibration

In equalization problems, the system model $f(x[n],\theta)$ is an analog linear filter with unknown parameters θ which usually takes into account the response of the communication channel, and the correction model $g(y[n],\theta)$ is a digital linear filter, usually a FIR filter, which is chosen so that $g(f(x[n],\theta),\theta^s) = g[n,\theta^s] * f[n,\theta^s] * x[n] \approx Gx[n-\tau]$. The cascading of linear systems is performed by convolution (operator $*$) and the result has flat gain G and linear phase $-\omega\tau$ in the discrete-time angular frequency ω, which corresponds to absence of linear distortions.

If the input signal is Nyquist at the sampling frequency $f_S \equiv 1/T_S$ of the system, it is equivalent to work in the analog or discrete-time domains, as it is possible to work on $x(t)$ or on $x[n] \equiv x(nT_S)$ interchangeably. The system $f(x(t),\theta)$ is an analog filter, but can also be modelled in the discrete-time domain because the output of a linear filter with a Nyquist input signal is also a Nyquist signal:

$$y(t) = f(x(t),\theta) \equiv f(t,\theta) * x(t) \leftrightarrow y[n] = f[n,\theta] * x[n] \tag{2}$$

$f(t,\theta)$ is the impulse response of the system in the analog domain, and $f[n,\theta]$ is the impulse response of the system in the discrete-time domain. Both depend on a vector of unknown parameters θ.

The correction model operates in the digital domain and the goal is to obtain a discrete-time impulse response $g[n,\theta^s]$ so that:

$$\theta^s \approx \theta \rightarrow z[n] = g[n,\theta^s] * y[n] \approx Gx[n-\tau] \tag{3}$$

If the impulse response (or equivalently the frequency response) of the system is correctly identified, it is thus possible to design a correction digital filter g which removes linear distortions caused by f so that the cascaded filter $f * g$ has flat gain and linear phase.

3. Linear errors with nonlinear effects in ADCs

Fig. 4 shows the architecture of a pipeline ADCs with 1-bit stages. Each stage, called multiplying DAC (MDAC), has an analog input x_i, an analog output y_i, and a digital output $D_i = \{-1,1\}$. The input is normalized to be in the interval $[-1,1]$, and so by construction is the output, because each stage is described by the equations:

$$\begin{cases} y_i = 2x_i - D_i \\ D_i = \operatorname{sign} x_i \end{cases} \tag{4}$$

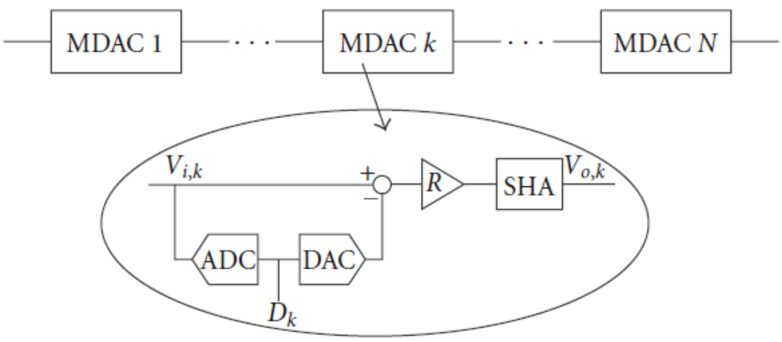

Fig. 4. Architecture of a pipeline ADC with single-bit MDAC stages.

Because the stages are cascaded, $x_i = y_{i-1}$, for $i = 2, \dots, N_S$, where N_S is the number of stages, and $x_1 = V_{in}$. It can be easily proven by substitution that:

$$y_{N_S} = 2^{N_S} V_{in} - \sum_{i=1}^{N_S} 2^{N_S - i} D_i \tag{5}$$

Noticing that the output of each stage is bounded between -1 and 1, that the output of the last stage is not processed by any other stage and so is unknown, and that its best estimate is 0 because of symmetry, we have:

$$\begin{cases} V_{in} = \frac{y_{N_S}}{2^{N_S}} + \sum_{i=1}^{N_S} \frac{D_i}{2^i} \approx \sum_{i=1}^{N_S} \frac{D_i}{2^i} \\ \left|\frac{y_{N_S}}{2^{N_S}}\right| \leq \frac{1}{2^{N_S}} \end{cases} \tag{6}$$

The pipeline ADC can reconstruct the input waveform by means of the digital outputs D_i, and the reconstruction error $\frac{y_{N_S}}{2^{N_S}}$ is bounded in the interval $\left[-\frac{1}{2^{N_S}}, \frac{1}{2^{N_S}}\right]$ and vanishes to zero as the number of pipelined stages increases.

The problem arises when the gain of each stage is not known [1-5], for instance if, because of linear errors, the input-output relation of each stage becomes, for some $-1 \ll \epsilon_i \ll 1$:

$$\begin{cases} y_i = 2x_i - (1 + \epsilon_i) D_i \\ D_i = \operatorname{sign} x_i \end{cases} \tag{7}$$

In this case, the reconstruction formula $V_{in} \approx \sum_{i=1}^{N_S} \frac{D_i}{2^i}$ gives rise to errors proportional to $\epsilon_i D_i$:

$$V_{in} = \frac{y_{N_S}}{2^{N_S}} + \sum_{i=1}^{N_S} \frac{(1+\epsilon_i) D_i}{2^i} \approx \sum_{i=1}^{N_S} \frac{(1+\epsilon_i) D_i}{2^i} \approx \sum_{i=1}^{N_S} \frac{D_i}{2^i} + \sum_{i=1}^{N_S} \epsilon_i \frac{D_i}{2^i} \tag{8}$$

Because D_i are nonlinear functions of the input signal, distortions arise when the gain errors are different from zero. However, if the gain errors are not zero but are known, it is possible to compute (8) directly, and reconstruct the input signal exactly, except for the term in y_{N_S} and the residual calibration error due to inaccurate estimations of the gain errors. Of course, also stochastic errors are not corrected by this process.

Pipeline ADCs with poor SFDR and THD can thus be made more accurate if a technique to estimate the gain errors is found, provided that gain errors dominate distortions and the estimation process is sufficiently accurate. Background calibration techniques exist for this kind of problems [1, 4-5], including errors due to memory effects [3] in which the output also depends (linearly) on the previous history of the signal.

A fundamental problem with background calibration is that the error terms to be estimated, $\epsilon_i D_i$, have very low power with respect to the input signal. In a pipeline ADC with $THD = -40dB$, for instance, gain errors are about 40dB below the signal. To improve linearity to -80dB, the gain errors must be estimated with an accuracy of 40dB, and estimation is performed with a nuisance input signal 80dB above the required estimation accuracy. This problem has been greatly reduced with split-ADC techniques [4-5], and with other techniques based on spectral separation [1] of the signal and error terms to allow faster estimation.

4. Linear errors with nonlinear effects in multichannel architectures

Many electronic systems assume the presence of two or more nominally identical channels which operate on the same input. For instance, complex mixers [12-13] extract the in-phase and quadrature components of a radiofrequency signal by mixing it with a quadrature signal at the carrier frequency f_C, i.e., by multiplying the input signal by $\cos 2\pi f_C t$ and $\sin 2\pi f_C t$. Errors arise when the two sinusoidal signals have different amplitude and their phases are not in perfect quadrature.

Fig. 5 shows a two-channel time-interleaved system. Time-interleaving is used to increase the overall sampling frequency (but not the bandwidth) of an ADC by using multiple ADCs in parallel, used in time-interleaved fashion [6-11]. The first ADC digitizes the even samples of the input signal, and the second the odd samples. Combining the two ADCs' outputs it is possible to reconstruct the input signal, as both the even and odd samples are known.

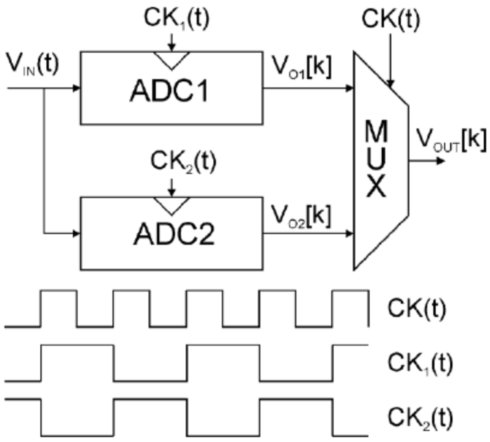

Fig. 5. 2-channel time-interleaved ADC with clocking scheme.

It is however assumed that the two channels have identical offsets and gain, and that the clock timing is perfectly spaced by one sampling period, so that the first ADC's output is $x[2n]$ and the second ADC's output is $x[2n+1]$. If the two ADCs have mismatches, i.e., there are offset, gain or timing differences, reconstruction produces aliasing. Consider for instance the first ADC to have unitary gain and the second ADC to have a gain $1+\epsilon_G$. The two ADCs' outputs are $x[2n]$ and $(1+\epsilon_G)x[2n+1]$. There is thus a periodic gain modulation superposed on the signal, and gain modulation produces distortions. The output of the time-interleaved ADC can be written as:

$$y[n] = x[n] + \epsilon_G \frac{(1-(-1)^n)}{2} x[n] = \left(1+\frac{\epsilon_G}{2}\right) x[n] - \frac{\epsilon_G}{2}(-1)^n x[n] \tag{9}$$

The term $(-1)^n x[n] \equiv e^{j\pi n} x[n]$ is, by the modulation theorem of the discrete-time Fourier transform, the input signal translated in frequency by π, i.e., by $f_S/2$. An input sinusoid with unitary amplitude and zero phase at a frequency f_{in} is thus observed at the output of the time-interleaved ADC as two sinusoids, one of amplitude $\left(1+\frac{\epsilon_G}{2}\right)$ at the correct frequency f_{in}, and the other of amplitude $-\frac{\epsilon_G}{2}$ at the aliasing frequency $\frac{f_S}{2} - f_{in}$. The aliasing tone is nonlinear distortion, because no linear system can produce outputs at frequencies different from those of the input signal, but the source of the distortion is linear (a gain error).

Digital calibration of multichannel systems, for instance time-interleaved and asynchronous time-interleaved ADCs and I/Q mixers, estimates the mismatches (offset, gain, timing, bandwidth…) between the channels and remove the aliasing terms. If for instance the gain error term ϵ_G is estimated, it is sufficient to scale the output of the second ADC by $1+\epsilon_G$ to remove the aliasing term at the output.

5. Calibration of nonlinear errors

The most complex applications of digital calibration are related to nonlinear impairments [15-18]. All devices, especially active ones, are nonlinear, and they behave as linear systems only within a certain range and with a certain level of accuracy. Nonlinear effects are usually modeled with nonlinear functions of the input signal, for instance polynomials. There is no general model for nonlinear effects, and many different models can be conceived. Some models have no memory and only depend on the instantaneous value of the input, others have memory and depend on the history of the input signal.

Equation (10a) is an example of memoryless polynomial of order up to P, which is the simplest model for nonlinearities. It has no memory and has poor accuracy for complex nonlinearities with memory. Being based on a Taylor expansion, it is adequate for memoryless continuous distortions, while it cannot model accurately discontinuities in the input-output characteristic of the system. Equation (10b) is a Volterra non-recursive model with memory [15-16]. The model has order P, and each submodel (called kernel) of order $i = 0, \dots, P$ has memory L_i, meaning that the output depends on the actual input and its history until L_i past samples. Volterra models are generalization of linear impulse responses and adequate for weakly nonlinear systems without discontinuities, but owing to the nested summations the number of coefficients for a kernel of order i and length L_i is proportional to L_i^i. Finally, equation (10c) is the building block of many neural networks, the tanh perceptron. All these models are nonlinear, and the last two have memory. It is clear that high-order memory models have many free parameters, and quickly become computationally expensive to compute, and even more expensive to identify.

$$y[n] = \sum_{i=0}^{P} \theta_i x^i[n] \tag{10a}$$

$$y[n] = \sum_{i=0}^{P} \sum_{k_1=0}^{L_i} \dots \sum_{k_i=k_{i-1}}^{L_i} \theta_{i,k_1,\dots,k_i} x[n-k_1] \dots x[n-k_i] \tag{10b}$$

$$y[n] = \tanh\left(\theta_{L+1} + \sum_{i=0}^{L} \theta_i x[n-i]\right) \tag{10c}$$

The “curse of dimensionality” of nonlinear models with memory is a huge problem in nonlinear calibration, and techniques to reduce the number of free parameters have been investigated. A priori restrictions which assume that many coefficients are zero are frequent. For instance, from (10b) a very simple model can be obtained assuming that $\theta_{i,k_1,\dots,k_i} \neq 0$ only if $k_1 = k_2 = \dots = k_i$. These restrictions are sometimes theoretically founded, but are often not very accurate. A posteriori simplifications [15-16] may be more effective, and data-driven techniques to obtain simpler models by only using terms which improve accuracy and removing terms which have no impact on accuracy are often more effective. Model selection is a complex topic, and there appears to be no optimal technique for determining the best restricted model (i.e., the most accurate model given a certain number of parameters). Cross-validation, model identification and robustness are complex issues that must be considered when selecting the model.

There is also no general framework for the estimation of nonlinear models, and for this reason many models are linear combinations of nonlinear functions of the input, where the vector parameter θ is a vector of weights. These models are called LIP, linear-in-the-parameters, and can be estimated with linear estimation techniques, for instance least squares algorithms. For background calibration techniques, LIP models are easy to estimate using linear adaptive filters, for instance LMS and RLS. Some models are not LIP, for instance neural network models exploiting single-layer or multi-layer perceptrons, and there are special techniques for their estimation. A LIP model can be written as a linear combination of arbitrary nonlinear functions $f_i(x[n])$, which may have memory:

$$y[n] = \sum_{i=0}^{P} \theta_i f_i(x[n]) \tag{11}$$

Nonlinear effects tend to produce intermodulation and distortion terms over larger bandwidths than the original signal, creating interferers and cross-coupling effects between different frequency bands. A peculiar issue in sampled systems is that the hypothesis that the input signal is a Nyquist signal is not sufficient to ensure that the output of the nonlinear system is also a Nyquist signal. Because of this, distortion terms may alias and fall back in the Nyquist band of the system. For instance, the third harmonic of a 11MHz sinusoid sampled at 40MSps should be at 33MHz, but falls at 7MHz after sampling. Modeling nonlinear systems affected by sampling aliasing may thus be tricky, because distortion terms appear at new frequencies. Nonlinear models and aliasing theory must be combined together to obtain sound models capable of handling these phenomena.

As an example of application of nonlinear calibration, we consider a heterodyne receiver with 2GHz RF input, 30MHz IF output, a signal bandwidth of 10MHz, and sampled at 40MSps. Distortions in the receiver are dominated by the anti-aliasing filter before the ADC, and are affected by aliasing of the third-order (and higher) distortion terms. HD_3 terms around 90MHz fall back in the Nyquist band $[0,20MHz]$ and must be taken into account, because they are visible in the output signal spectrum. What is not modelled cannot be corrected, and the inverse model must be able to estimate the aliased nonlinear terms to remove them.

Fig. 6 shows the output of a 16-QAM waveform with and without nonlinear calibration. The output constellation of a 16-QAM waveform should be of 16 uniformly-spaced points in a 4x4 square, but without calibration and equalization there is strong intersymbol interference (ISI). This cannot be removed by linear equalization alone (Lin EQ), but requires a nonlinear model (called RFeVM) capable of handling nonlinear aliasing to be corrected.

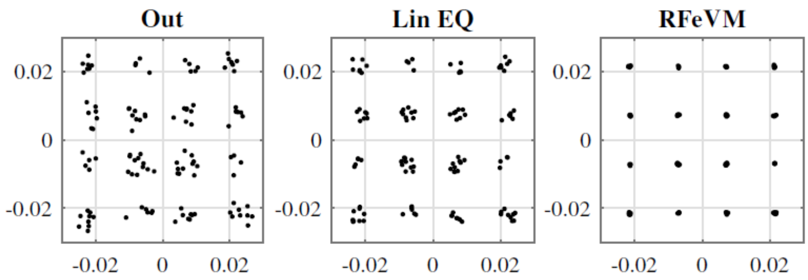

Fig. 6. Nonlinear calibration of 16-QAM receiver.

6. Benefits of nonlinear calibration

Nonlinear calibration is a complex endeavor. The modeling, estimation and correction steps of digital calibration techniques become more complex, the analytical and computational resources increase and model identification becomes harder. There is no single unifying theory and no model which is valid in every case, and the number of free parameters in the model easily becomes excessive. However, nonlinear calibration has potentially enormous benefits in electronic systems.

More linear transmitters are less affected by spectral regrowth, which cause interference to nearby channels, called Adjacent Channel Interference (ACI), and reduce the capacity of tightly spaced frequency channels in communications systems.

More linear receivers are less affected by interferences, for instance intermodulation products disturbing nearby frequency channels, and thus they can be made more robust to clutter (in radar systems), jammers (in radars and communication systems), and powerful interferers in nearby channels.

More linear transmitters and receivers are less affected by nonlinear intersymbol interference (ISI), obtaining cleaner eye diagrams and potentially allowing the use of more complex modulation schemes.

More linear systems in general can operate with larger signals and have larger gains, thus reducing the effect of noise and reaching higher levels of SNR, increasing communication capacity. For instance, in Fig. 7 a calibrated system has lower distortions (as depicted by the lower third-order harmonic line) and can be operated with a larger input power. Though noise cannot be calibrated away, unlike deterministic errors, its system effect can be reduced by maximizing SNR (at the expense of THD) and then improving THD by means of nonlinear calibration.

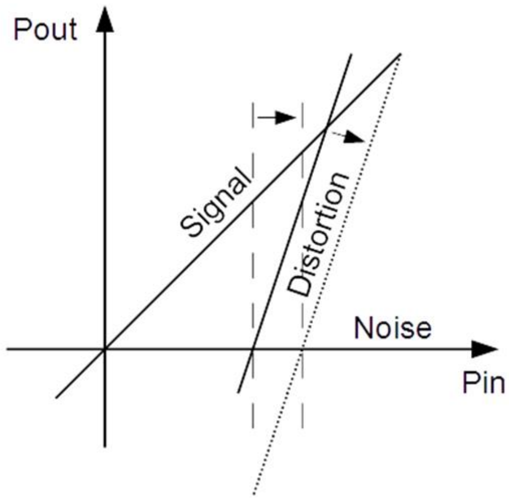

Fig. 7. Signal, noise and distortions before (solid distortion line) and after (dotted distortion line) nonlinear digital calibration. Allowing higher input power, it is possible to improve both the SNR and the THD.

7. Conclusions

Digital calibration is the use of the rapidly increasing processing power of digital systems to reduce the effect of impairments in analog, mixed-signal and radio-frequency systems. Because the trend in increasing system complexity and digital processing power and power efficiency is inherent in the evolution of electronic technology, the applicability of digital calibration techniques increase with time.

A coherent and systematic approach to digital calibration allows the determination of abstract concepts of interest in a variety of applications. The three steps of modeling, estimation and correction can be used to describe apparently dissimilar problems like linear equalization of the channel’s frequency response and nonlinear compensation of distortions in power amplifiers. Modeling requires a variety of theoretical approaches, tailored on the specific application: Volterra series, neural networks, multirate signal processing, adaptive filters and statistical estimation concepts are used to model the effects of analog impairments and to identify the underlying models. Model identification is a statistical and measurement problem, requiring the use of statistical tools, test signals and measurement instrumentation. Digital correction – and in background techniques also parameter estimation – is a problem of digital design. A large number of different skills, from analog and digital design to statistical, measurement and signal processing theory, must be combined together.

Calibration at system level allows improving system performance by removing the effects of linear and nonlinear impairments. The end result is a system which is half analog (or radio-frequency) and half digital, where gain, timing or nonlinear errors are digitally compensated in a way that should be as transparent as possible to the final user.

Abstracting beyond the single electronic system, it is also possible to interpret many problems in terms of digital calibration: for instance, a space-borne direction-of-arrival (DOA) estimation system for geolocalization of radiofrequency emitters on the Earth’s surface must compensate for the position and orientation (attitude) errors of the satellite. Estimating and correcting the effects of these errors can be interpreted as a problem of digital calibration.

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