Eurasia Journal of Science and Technology
Print ISSN: 2663-1024
Online ISSN: 2663-1016
DOI: https://doi.org/10.61784/ejst3171

LINEARIZATION TECHNOLOGY OF HIGH-SPEED MEASUREMENT SYSTEMS

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Abstract: Receiver sensitivity, dynamic range, and adjacent channel interference all degrade when nonlinear distortion is present, which remains a persistent concern in high speed signal acquisition. The distortion is generated as the signal passes through the low noise amplifier, the filters, the mixers and, ultimately, the analog to digital converter (ADC); once these stages are cascaded, their joint nonlinear behaviour becomes hard to characterise, and memory effects make the task harder still. In practice, conventional polynomial models often fail to compensate this kind of distortion to the accuracy a system actually requires. The present study therefore examines a complex valued recurrent neural network (CRNN) to model and then compensate nonlinear errors within a single channel acquisition chain. To capture the input output relationship, the network is fed delayed input samples together with output feedback, and the trained model is subsequently inverted to recover the undistorted signal. Both two tone and quadrature phase shift keying (QPSK) signals are used to run the simulations. For the two tone cases the spectral performance metric gains 3.73 dB and 3.72 dB, while the QPSK case shows a gain of 7.357 dB. Compensation, however, is not uniform: the CRNN suppresses some distortion components more effectively than others.
Keywords: Nonlinear compensation; Complex valued recurrent neural network; High speed signal acquisition; System identification; Analog to digital converter

1 INTRODUCTION

A typical high speed signal receiver is built from a low noise amplifier, a bandpass filter, a mixer and an analog to digital converter (ADC), and nonlinear distortion can arise at any one of these stages, gradually eroding the performance of the whole acquisition chain. Its visible consequences are well known: intermodulation products appear in the spectrum, the spurious free dynamic range shrinks, and neighbouring channels begin to interfere with one another. The situation turns most severe when a weak signal has to be recovered alongside a much stronger one.

Nonlinear system modelling has traditionally relied on polynomial formulations rooted in the Volterra and Wiener frameworks [1-2]. Such descriptions lose accuracy, though, once the nonlinear blocks are cascaded or when the memory effects are strong [3]. As an alternative, neural networks can be trained directly from measured input output data [4-5], adjusting their parameters without the need to describe the full acquisition chain through an explicit polynomial model.

Complex valued recurrent neural networks (CRNNs) can process complex signals and account for temporal dependence. Recurrent connections allow previous outputs to influence the current output. Earlier studies examined complex valued recurrent learning algorithms for nonlinear adaptive filtering [6-7]. Related network structures have also been used for nonlinear system identification [8].

This paper investigates CRNN based compensation for nonlinear distortion in a single channel high speed acquisition system. Delayed input samples and feedback from previous network outputs are used to construct a behavioral model of the acquisition channel. The model parameters are obtained through supervised learning, after which an inverse model is used for nonlinear compensation. The method is examined through simulations involving two-tone signals at different input power levels and a quadrature phase-shift keying (QPSK) signal.

2 MACHINE-LEARNING-BASED LINEARIZATION OF A SINGLE-CHANNEL ADC ACQUISITION SYSTEM

The nonlinear response of an acquisition channel is determined by the combined behavior of its analog components. Because these components operate in sequence, the distortion introduced at one stage may affect the signals entering subsequent stages. A model of the complete channel must therefore account for both nonlinear behavior and signal memory.

A CRNN is used here to describe this input–output relationship. Unlike a feedforward network, the recurrent structure includes information from previous outputs in the calculation at the current time step. Delayed input samples are also supplied to the network to represent the memory associated with the acquisition channel.

A complex-valued recurrent neural network (CRNN) operates directly in the complex domain, with complex-valued inputs, weights, and outputs. Figure 1 illustrates a connected recurrent neural network (CRNN) consisting of N neurons, p delayed external inputs, and N feedback connections. The network comprises an external-input and feedback stage and an output-processing stage. Let yl(k) denote the complex-valued output of the lth neuron. The external inputs consist of p delayed samples of the input sequence s(k). The overall input vector P(k) concatenates the delayed input samples, previous neuron outputs, and the complex bias term $(1 + j)$, as expressed in Eq. (1).

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$$p(k) = [s(k-1), ..., s(k-p), 1+j, y_1(k-1), ..., y_N(k-1)]^T = p_n^r(k) + jp_n^i(k) \quad (1)$$

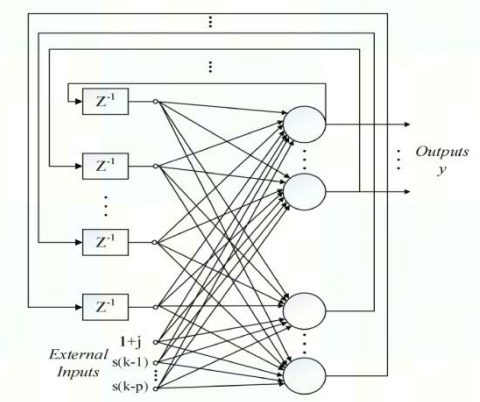


Figure 1 Schematic Structure of the CRNN

For the lth neuron, the weights form a $(p + N + 1) \times 1$-dimensional vector, as shown in Eq. (2). The complex-valued weight matrix of the network is given in Eq. (3).

$$w_l^T = [w_{l,1}, ..., w_{l,p+N+1}], l = 1, ..., N \quad (2)$$

$$w = [w_1, ..., w_N] \quad (3)$$

The output of each neuron is defined as follows:

$$y_l(k) = \Phi(\text{net}_l(k)), l = 1, ..., N \quad (4)$$

Here, Φ denotes the complex-valued nonlinear activation function, and $\text{net}_l(k)$ denotes its input at time k, calculated as the weighted sum of all inputs to the neuron, as shown in Eq. (5).

$$net_l(k) = \sum_{n=1}^{p+N=1} w_{l,n}(k) P_N(k) \quad (5)$$

For convenience, yl(k) can be expressed in terms of its real and imaginary components as follows:

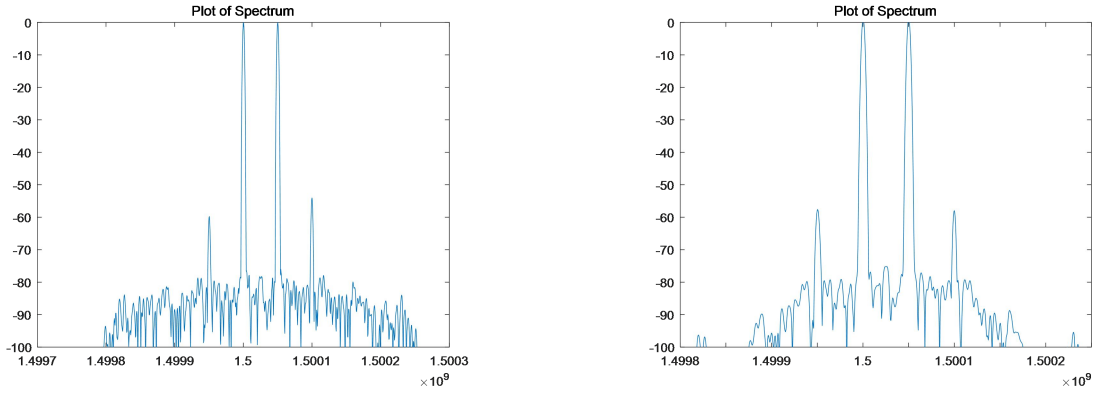
$$y_l(k) = \Phi^r(net_l(k)) + j\Phi^i(net_l(k)) = u_l(k) + jv_l(k) \quad (6)$$

The CRNN captures both the memory depth of the input signal and the feedback memory of previous outputs, making it suitable as a behavioral model of the acquisition channel.

The model is trained using supervised learning. Delayed input samples and feedback signals from preceding time steps are supplied to the network, while the measured output of the acquisition channel serves as the reference signal associated with the first output neuron. An error function is constructed from the difference between the predicted and reference outputs, and the network parameters are updated by the training algorithm. The identified nonlinear model is then inverted to obtain a compensation model. Applying the resulting model parameters to the nonlinear compensation system enables suppression of nonlinear errors.

3 SIMULATION-BASED VALIDATION

A two-tone signal with an input power of 0 dBm, a center frequency of 1.5 GHz, and a tone spacing of 50 kHz is applied. Figures 2(a) and 2(b) show the output spectra before and after compensation, respectively. The corresponding measurements are presented in Table 1.



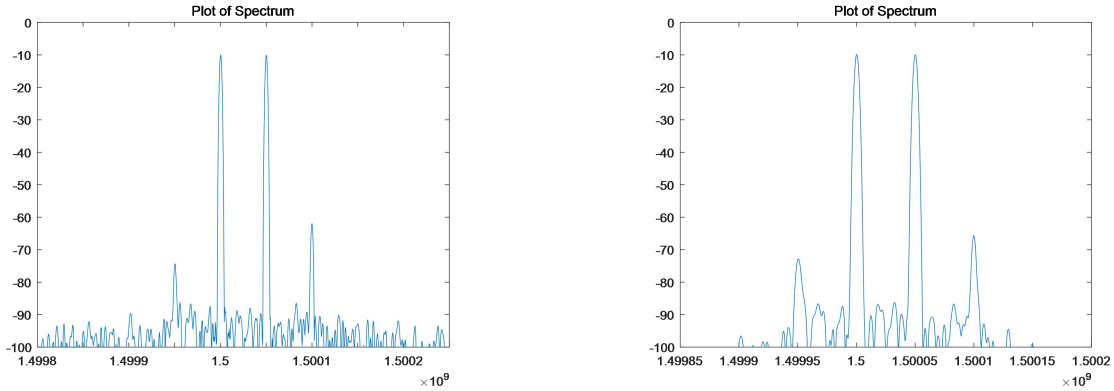
(a) Before compensation (b) After compensation

Figure 2 Output Spectra of the Two-Tone Signal at 0 dBm Input Power and 50 kHz Tone Spacing, Before and After Compensation

Table 1 Measurements Before and After Compensation (0 dBm Two-Tone Input)

	Input Power (dBm)	Lower IMD (dBm)	Upper IMD (dBm)	Δ (dB)
Before Compensation	0	-59.77	-54.06	54.06
After Compensation	0	-57.79	-57.96	57.79

A two-tone signal with an input power of −10 dBm, a center frequency of 1.5 GHz, and a tone spacing of 50 kHz is applied. Figures 3(a) and 3(b) show the output spectra before and after compensation. The measurements are summarized in Table 2.



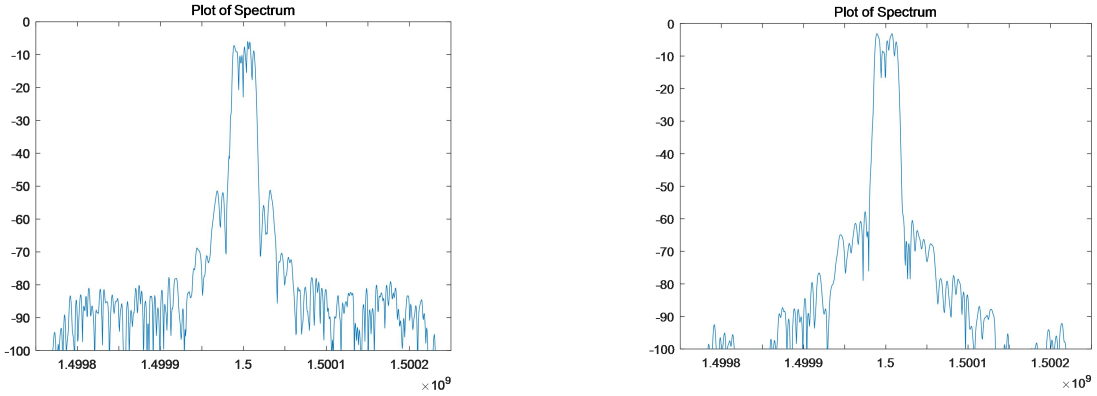
(a) Before compensation (b) After compensation

Figure 3 Output Spectra of the Two-Tone Signal at −10 dBm Input Power and 50 kHz Tone Spacing, Before and After Compensation

Table 2 Measurements Before and After Compensation (−10 dBm Two-Tone Input)

	Input Power (dBm)	Lower IMD (dBm)	Upper IMD (dBm)	Δ (dB)
Before Compensation	-10	-74.35	-61.91	51.91
After Compensation	-10	-72.8	-65.63	55.63

A quadrature phase-shift keying (QPSK) signal centered at 1.5 GHz is used to evaluate the compensation scheme. The output spectra before and after compensation are shown in Figures 4(a) and 4(b), with the corresponding measurements listed in Table 3.



(a) Before compensation (b) After compensation

Figure 4 Output Spectra of the QPSK Signal Before and After Compensation

Table 3 Measurements Before and After Compensation (QPSK Input)

	Input Power (dBm)	Lower IMD (dBm)	Upper IMD (dBm)	Δ (dB)
Before Compensation	-4.982	-51.42	-51.29	46.308
After Compensation	-4.145	-57.81	-60.53	53.665

4 CONCLUSION

A CRNN-based method was examined for nonlinear compensation in a single-channel high-speed signal acquisition system. The network uses delayed input samples and recurrent output feedback to model the channel response, and an inverse model is applied for compensation.

Simulation tests were carried out using two-tone signals at 0 and −10 dBm and a QPSK signal centered at 1.5 GHz. The reported spectral metric improved by 3.73 and 3.72 dB in the two-tone tests, respectively. A larger improvement of 7.357 dB was obtained for the QPSK signal.

The results also show differences between individual distortion components. In both two-tone tests, the upper intermodulation component decreased after compensation, while the lower component increased. The method therefore improves the reported overall metric under the tested conditions, but does not suppress every distortion component. Further work should examine a broader range of input signals, operating conditions, and hardware measurements to assess its performance in practical acquisition systems.

COMPETING INTERESTS

The authors have no relevant financial or non-financial interests to disclose.

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