Linear-in-the-parameters nonlinear adaptive filters for loudspeaker modeling in acoustic echo cancellation.*

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In acoustic echo cancellation (AEC), oftentimes the acoustic path from the loudspeaker to the microphone is estimated by means of a linear adaptive filter. However, loudspeakers introduce nonlinear distortions which may strongly degrade the linear adaptive filter performance and, thus, nonlinear adaptive filters have to be considered. In this paper, we focus on the analysis of odd and even nonlinearities in electrodynamic loudspeakers based on periodic random-phase multisine experiments. It is shown that the odd nonlinearities are more predominant than the even nonlinearities. This fact implies that at least a 3rd-order nonlinear loudspeaker model should be used. We, therefore, consider the identification and validation of a loudspeaker model using linear-in-the-parameters nonlinear adaptive filters, in particular, Hammerstein and Legendre polynomial filters of various orders, and a simplified 3rd-order Volterra filter of various lengths. The contribution of this paper is twofold, namely, (1) to propose a method for analyzing and describing the nonlinear response of loudspeaker-enclosure-microphone (LEM) systems, and (2) to compare and analyze several models adopted in linear-in-the-parameters nonlinear adaptive filters that are typically used in nonlinear AEC (NLAEC). In our measurement set-up, the obtained results imply however, that a 3rd-order nonlinear filter does not capture all the nonlinearities, meaning that odd and even nonlinear contributions are produced by higher-order nonlinearities. Legendre polynomial filters show improved performance with increasing order, unlike Hammerstein filters. For the simplified 3rd-order Volterra filter, the performance is remarkably poorer than for the Legendre polynomial filter for the same filter length. The differences between identification and validation appear to be very small for the Legendre polynomial filter, while the simplified 3rd-order Volterra filter presents clear signs of overfitting.

0 Introduction

Acoustic echo cancellation (AEC) is used in many speech communication systems where the existence of echoes degrades the speech intelligibility and listening comfort [1], [2]. Applications range from mobile or hands-free telephony to teleconferencing or voice over IP (VoIP) services, which are often integrated in smartphones, tablets, notebooks, laptops, etc. While mobile devices are becoming smaller, the demand for quality, performance, and special features in audio products is increasing. Moreover, the need for higher sound pressure levels, provided by smaller devices, presents a huge challenge to engineers who have to deal with (usually cheap) loudspeakers working close to saturation.

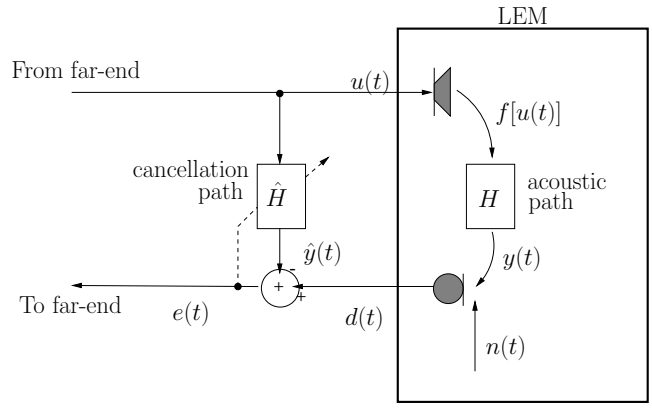


Fig. 1. Typical set-ups for an AEC.

The general set-up for an AEC is depicted in Figure 1. A far-end speech signal $u(t)$ is played back into an enclosure (i.e., the room) through a loudspeaker. In the room, there is a microphone to record a near-end speech signal, which is to be transmitted to the far-end side. An acoustic echo

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path H between the loudspeaker and the microphone exists, so that the microphone (i.e., desired) signal $d(t) = y(t) + n(t)$ contains an undesired echo $y(t)$ plus the background noise $n(t)$. The echo signal $y(t)$ can be considered as the far-end signal $u(t)$ filtered by the loudspeaker-enclosure-microphone (LEM) system's response. An acoustic echo canceler seeks to cancel the echo signal component $y(t)$ in the microphone signal $d(t)$, ideally leading to an *echo-free* error (or residual) signal $e(t)$, which is then transmitted to the far-end side. This is done by subtracting an estimate of the echo signal $\hat{y}(t)$ from the microphone signal, i.e., $e(t) = d(t) - \hat{y}(t) = y(t) - \hat{y}(t) + n(t)$. Thus, the main objective of an echo canceler is to identify a model that represents a best fit to the LEM system.

Typically, a linear finite-impulse-response (FIR) filter is assumed to provide a sufficiently accurate model for the LEM system, leading to a class of linear-adaptive-filter-based AEC systems. This assumption may be valid for some components in the LEM system. In fact, even in nonlinear AEC (NLAEC), the acoustic path and microphone response may be modeled as a linear system. However, loudspeakers, as well as amplifiers, DACs, coders, etc., included in the LEM system introduce nonlinear distortion and must be modeled as a nonlinear system [3]. If the output $f[u(t)]$, in Figure 1, is a highly nonlinear function of $u(t)$, poor performance may be expected from any linear-adaptive-filter-based AEC system [4]. The error signal is contaminated by the nonlinear contribution that is not modeled by the linear adaptive filter making the adaptive filter to converge slowly or even diverge [5]. It is known that the nonlinearity also changes with time [6]-[8]. Therefore, a nonlinear adaptive filter is needed. Several nonlinear adaptive filters, intended to overcome the limitations of linear filters, have been used for NLAEC with more or less success.

linear-in-the-parameters nonlinear adaptive filters, which require nonlinear expansions of the input vector, are appealing from an adaptive filtering perspective since standard linear adaptive filtering techniques can be applied and global optimality can be guaranteed [9]-[11]. The main problem, however, is that many more filter coefficients are needed than in the linear case, resulting in a large computational complexity together with inherently slow convergence [12]-[15]. Volterra [16]-[18] and simplified Volterra [9] filters are commonly used linear-in-the-parameters nonlinear adaptive filters, although typically only very low nonlinear orders are considered due to computational complexity constraints. In [11] a sliding-window leaky kernel affine projection algorithm (SWL-KAPA) has been proposed which belongs to this family and is very efficient in terms of performance and computational complexity. We will, however, not consider SWL-KAPA in this paper because so far it has been studied only for a simulated nonlinear system and controlled scenario, thus avoiding other problems related to real AEC applications.

The answer to 'what model represents a best fit to the LEM system?' is not easily given. Indeed, a nonlinear model may exhibit an excellent performance for one particular system but may be useless for a second one. A number of contributions found in literature appear to select a nonlinear model based on faith more than on a true examination of the LEM system. For instance, 2nd-order Volterra filter are widely used where most of the times only a single reference [13] is used to justify this choice. This nonlinear model assumption may be accurate in some cases, of course, but in other cases without previous study of the system it seems reasonably doubtful. Another problem found in the NLAEC literature is that only the attenuation of the residual echo is considered without taking any prevention for overfitting. This clearly leads to some misinterpretation of the obtained results and a lack of robustness of the adaptive filter.

The contribution of this paper is twofold, namely, (1) to propose a method for analyzing and describing the nonlinear response of LEM systems, and (2) to compare and analyze several models adopted in linear-in-the-parameters nonlinear adaptive filters that are typically used in NLAEC.

The outline of the paper is as follows. In Section 1, we present the type of excitation signal used in the considered analysis method, and explain the nonlinear response of a nonlinear system based on this type of signal. In Section 2, the analysis method for classification of nonlinearities is presented and one example is provided based on a simulated Hammerstein system. In Section 3, the structure of the class of linear-in-the-parameters nonlinear adaptive filters is explained and a brief review of the normalized least mean squares (NLMS) algorithm [19] is also provided. The more specific sub-class of nonlinear filters without cross terms is explained in Section 4, where Hammerstein filters and Legendre polynomial filters are elaborated on. Volterra filters and simplified Volterra filters which are a sub-class of nonlinear filters with cross terms are elaborated on in Section 5. In Section 6, the identification and model validation of a simulated 5th-order Hammerstein system using both a Hammerstein filter and a Legendre polynomial filter is performed. In Section 7, the identification and model validation of a real loudspeaker is performed using Hammerstein filters of different orders, Legendre polynomial filter of different orders, and a simplified 3rd-order Volterra of different sizes. Finally, Section 8 concludes the paper.

1 Excitation signal and response of nonlinear systems

A signal $u(t)$ is a *random-phase multisine* [20] excitation when

$$u(t) = \sum_{k=1}^{F} b_k \cos\left(i_k \omega_0 t + \phi_k\right) \tag{1}$$

where $\omega_0 = 2\pi f_0$, and f_0 is the frequency of the first harmonic, i.e., the fundamental frequency. The harmonics are classified as *odd harmonics* and *even harmonics* which refer to odd multiples or even multiples of the fundamental frequency, respectively. F is the number of harmonics, b_k is the deterministic amplitude of the k^{th} harmonic and $i_k \in \mathbb{R}$. If $i_k \in \{k \mid k = 1, 2, ..., F\}$, then all odd and even harmonics are considered. The phases ϕ_k are a realization of independent uniformly distributed random processes on $[0, 2\pi)$

such that $\mathscr{E}\left\{e^{j\phi_k}\right\} = 0$ where $\mathscr{E}\{\cdot\}$ represents the expected value operation. Periodic random-phase multisine signals combine the advantage of broad-band signals and periodicity (i.e., discrete spectrum), while providing total control over the amplitude of each harmonic. In the frequency domain, the signal in (1) is given as

$$U(j\omega) = \sum_{k=-F}^{F} a_k \delta(\omega - i_k\omega_0) e^{j\phi_k} \tag{2}$$

where $a_{-k} = a_k$, $i_{-k} = -i_k$, $\phi_k = -\phi_k$ and $\delta(\cdot)$ represents the Dirac delta function defined as

$$\delta(\omega - i_k\omega_0) \begin{cases} = 0 \ \omega - i_k\omega_0 \neq 0 \\ = 1 \ \omega - i_k\omega_0 = 0. \end{cases} \tag{3}$$

In order to understand the effect of nonlinearities on the output spectrum, let us consider the output signal from a static nonlinearity $y_3(t) = f[u(t)] = u^3(t)$, where $u(t)$ is a random-phase multisine. The operation of the nonlinearity corresponds to a time-domain multiplication of the input samples and, hence, a convolution in the frequency domain, so that

$$Y_3(j\omega) = \sum_{p=-F}^{F} \sum_{m=-F}^{F} \sum_{k=-F}^{F} a_p a_m a_k \delta(\omega - [i_p + i_m + i_k]\omega_0) e^{j[\phi_p + \phi_m + \phi_k]}. \tag{4}$$

In general, the output from a nonlinearity of order n consists on $(2F)^n$ contributions, i.e., of all possible combinations, with permutations, of n input harmonics. It is then clear that a 3rd-order nonlinearity generates harmonics at frequencies that are sums and differences of the frequency of three excited input harmonics. To clarify the effect of static nonlinearities we may consider two types of contributions, namely, *harmonic* contributions and *interharmonic* contributions.

- Harmonic contributions:

These contributions are generated by pairs of equal positive and negative harmonics, and also by one harmonic combined with pairs of equal positive and negative harmonics. For example, for a 2nd-order nonlinearity, a combination such as $(+3\omega_0 - 3\omega_0)$ results in a harmonic contribution at $0\omega_0$ (i.e., the so-called *direct current* (DC) term). For a 3rd-order nonlinearity, combinations such as $(+3\omega_0 + 3\omega_0 - 3\omega_0)$ and $(+3\omega_0 + \omega_0 - \omega_0)$ results in harmonic contributions at $+3\omega_0$. The phase of the harmonic contribution equals the phase of the corresponding input harmonic.

- Interharmonic contributions:

These contributions are generated by combinations of harmonics that follow a different pattern. For example, for a 2nd-order nonlinearity, the harmonic combination $(+3\omega_0 - 2\omega_0)$ results in an interharmonic contribution at ω_0, and, for a 3rd-order nonlinearity, the frequency combination $(+3\omega_0 + \omega_0 + \omega_0)$ generates an interharmonic contribution at $+5\omega_0$. The phases of these contributions vary depending on the phases of the specific input harmonics giving rise to them, i.e., $(+3\omega_0 + 3\omega_0 - \omega_0)$ gives rise to $+5\omega_0$ but with different phase compared to the contribution generated by $(+3\omega_0 + \omega_0 + \omega_0)$.

The specific influence of these two types of contributions will depend on the order of the nonlinearity, namely, *odd-order nonlinearities* and *even-order nonlinearities*. This is explained as follows.

- Odd-order nonlinearities:

The **harmonic contributions** coincide with the excited input harmonics. They always have the same phase as their coinciding excited input harmonic since they are generated by the combination of this input harmonic with pairs of equal positive and negative harmonics, where the phases cancel out. However, it should be noted that, although the phases cancel out, this is not true for the amplitudes which are multiplied together, and hence the resulting amplitudes depend on the specific frequency combinations. Moreover, if the input signal contains only odd harmonics then the **interharmonic contributions** occur only at odd harmonic frequencies.

- Even-order nonlinearities:

The **harmonic contributions** all occur at DC in this case, since they are generated by pairs of equal positive and negative frequencies. If the input signal contains only odd harmonics, then the **interharmonic contributions** occur at even harmonic frequencies.

		Harmonic content	
		Odd	Even
Nonlinearity	Odd	**Odd**	**Even**
	Even	**Even**	**Even**

Table 1: Odd / Even responses

In other words, as it is summarized in Table 1, a combination of *odd* harmonics generates *odd* harmonics only when input to an *odd* nonlinearity (i.e., an *odd* combination of *odd* harmonics generates *odd* harmonics only); however, a combination of *odd* harmonics generates *even* harmonics only when input to an *even* nonlinearity (i.e., an *even* combination of *odd* harmonics generates *even* harmonics only). On the other hand, a combination of *even* harmonics only generates *even* harmonics at the output of both an *even* and *odd* nonlinearity (i.e., there is no *even* combination of *even* harmonics that generates an *odd* harmonic).

2 Analysis method for classification of nonlinearities

In this section, a method is reviewed that has been developed in [20] in the context of characterizing operational amplifiers, and which will be the basis for our analysis. This method has been applied on different loudspeakers in [3] to detect (i.e., know if there is any nonlinear distortion), quantify (i.e., know the level of nonlinear distortions) and qualify (i.e., know the type of nonlinear distortions) nonlinear distortions. This method is suitable for nonlinear (dynamic) systems that can be approximated arbitrarily well (in a least-squares sense) by a Volterra series. The method allows for a description of nonlinearities such as saturation (i.e., amplifiers, loudspeakers) and discontinuities (i.e., relays, quantizers), but excludes chaotic systems and systems producing subharmonics [20].

An *odd multisine* is a signal as in (1), where only harmonics $i_k \in \{(2k-1) \mid k = 1,2,...,F\}$ (i.e. odd harmonics) are excited. In the analysis that follows, a particular type of odd multisine will be used as excitation signal, which is referred to as an *odd-random multisine*. An odd-random multisine is an odd multisine where in every set of K consecutive odd harmonics one randomly-chosen odd harmonic is not excited. The complete set of non-excited odd harmonics is called the *harmonic grid*. The non-excited odd harmonics together with the even harmonics are called the *detection lines*.

As the input detection lines have zero magnitude, the presence of signal energy at the corresponding output detection lines is due to the nonlinear distortion of the system plus, probably, some measurement noise. The average output spectrum is calculated at all frequencies (excited and non-excited harmonics) [21], based on

$$\hat{Y}(j\omega_k) = \frac{1}{P}\sum_{p=1}^{P} Y^{[p]}(j\omega_k) \quad k = 1,...,F \tag{5}$$

where $\omega_k = i_k\omega_0$, and $Y^{[p]}(j\omega_k)$ is the DFT spectrum of one period p of the output signal. It follows the measurement scheme illustrated in Figure 2 where P periods are considered to average down the measurement noise.

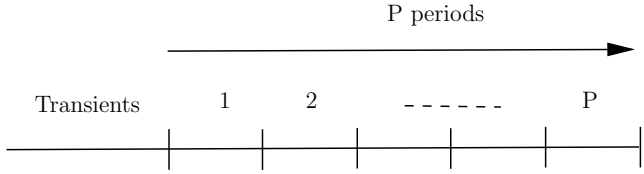


Fig. 2. Measurement scheme where P periods of the signal spectrum are taken and applied to (5).

To classify the type of nonlinearities, odd-random multisine signals are used. The information about the nonlinear contribution (excluding the harmonic contribution generated by an odd-order nonlinearity) is obtained via the detection lines in the output DFT spectrum. The system is said to have an odd or even nonlinearity if the odd or even detection lines, respectively, in the output spectrum contain significant energy. As an example, we consider the Hammerstein system illustrated in Figure 3, where a 5th-order power-series nonlinearity, i.e., $f[u(t)] = u(t) + \alpha u^2(t) + \beta u^3(t) + \gamma u^4(t) + \delta u^5(t)$ is used. The linear filter is a 16-coefficient finite impulse response (FIR) low-pass filter (LPF) with cut-off frequency $1/4$ of the sampling frequency. Figure 4 shows the simulated Hammerstein system input and output signals. The input signal is an odd-random multisine, the harmonic grid parameter $K = 6$, and the analysis method is based on (5). Figure 4(a) shows the spectrum of the input odd-random multisine after conversion to a 16-bit pulse code modulation (PCM) representation. The round-off noise appears as a low-level (-60 dB) odd and even harmonics contribution. Figure 4(b) shows the spectrum of the Hammerstein system output signal. The spectrum of the nonlinear contribution of $f[u(t)]$ is clearly shown, where α, β, γ, and δ are chosen such that the nonlinear contributions are scaled to -20 dB compared to the linear contribution.

3 Linear-in-the-parameters nonlinear adaptive filters

In this section, so-called linear-in-the-parameters nonlinear filters are reviewed, which are characterized by a linear dependence of the filter output on the filter coefficients. These filters are particulary suited to AEC, where adaptive filters are typically used to adapt to changes in the acoustic echo path, now including also the nonlinearities. Linear-in-the-parameters nonlinear adaptive filters then have derisable characteristics, namely, that they are inherently stable, and that they can converge to a globally minimum solution (in contrast to other types of nonlinear filters whose cost function may exhibit many local minima) avoiding the undesired possibility of getting stuck in a local minimum during adaptation.

In the general case, a linear-in-the-parameters nonlinear filter is described by the input-output relationship

$$y_F(t) = \mathbf{h}_F^T \mathbf{u}_F(t) \tag{6}$$

where $\mathbf{h}_F$ is a vector containing L filter coefficients and $\mathbf{u}_F(t)$ is the corresponding vector whose L elements are nonlinear combinations and/or expansions of the input samples in $\mathbf{u}(t) = [u(t), u(t-1), \cdots, u(t-N+1)]^T$. In fact, (6) can be interpreted as an FIR filter with L coefficients in which $\mathbf{u}_F(t)$ is used instead of the usual $\mathbf{u}(t)$. If $\mathbf{u}_F(t)$ is chosen equal to $\mathbf{u}(t)$, the filter is truly a linear FIR filter with $L = N$ coefficients. In the nonlinear case, we may define $\mathbf{u}_F(t)$ and $\mathbf{h}_F$ as a set of sub-vectors $\mathbf{u}_r(t)$ and $\mathbf{h}_r$, with $r = 1,\ldots,M$. Thus, we may define the input

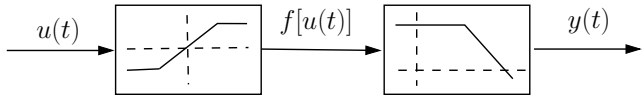


Fig. 3. Hammerstein system: Static nonlinearity followed by a linear filter.

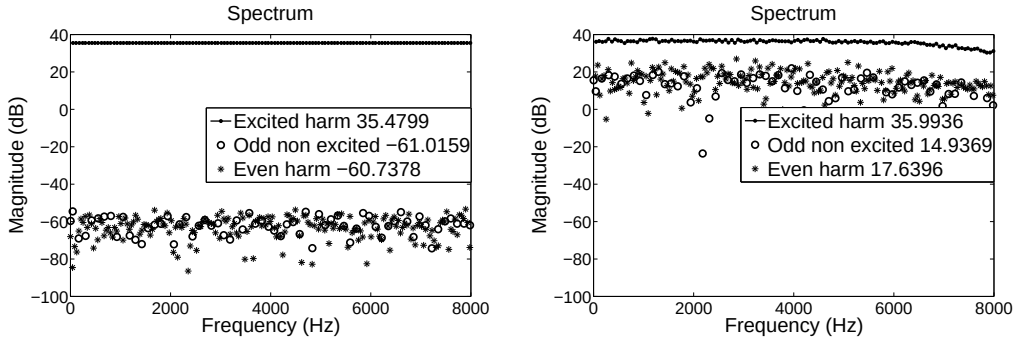


Fig. 4. Hammerstein system analysis using odd-random multisine. Spectrum estimated using (5). (a) Input spectrum (16-bit precision PCM represenation). (b) Output spectrum.

vector as

$$\mathbf{u}_F(t) = \left[\mathbf{u}_1^T(t)\ \mathbf{u}_2^T(t)\ \cdots\ \mathbf{u}_M^T(t)\right]^T, \tag{7}$$

and then the output is given as

$$y_F(t) = \mathbf{h}_1^T\mathbf{u}_1(t) + \mathbf{h}_2^T\mathbf{u}_2(t) + \cdots + \mathbf{h}_M^T\mathbf{u}_M(t) \tag{8}$$

where the vector $\mathbf{h}_F$ has been divided in sub-vectors of matching lentghs.

The next sections present a collection of linear-in-the-parameters nonlinear filters that have been successfully applied in NLAEC [9]-[13]. A complete review of linear-in-the-parameters nonlinear filters with and without cross terms can be found in [22].

3.1 Adaptive algorithm

Adaptive filter algorithms developed for the identification and tracking of linear FIR systems can also be applied to the nonlinear filter structure of (6). The popular NLMS algorithm [19], for instance, can be adopted, of which the update equations are given as

The Normalized Least Mean Squares (NLMS)

1. Initialize for $t < 0$, $d(t) = 0$, $\hat{\mathbf{h}}_F(t) = \mathbf{0}$, $e(t) = 0$ and $\mathbf{u}_F(t) = \mathbf{0}$.
2. Then for $t \geq 0$:

$$e(t) = d(t) - \hat{\mathbf{h}}_F^T(t)\mathbf{u}_F(t) \tag{9}$$

$$\hat{\mathbf{h}}_F(t+1) = \hat{\mathbf{h}}_F(t) + \mu\frac{\mathbf{u}_F(t)e(t)}{\mathbf{u}_F^T(t)\mathbf{u}_F(t) + \varepsilon} \tag{10}$$

where ε is a small positive constant to avoid overflow.

4 Nonlinear filters *without* cross terms

This section introduces linear-in-the-parameters nonlinear filters involving only instantaneous nonlinear expansions of the input samples. This sub-class of filters includes Hammerstein filters [23] as well as filters involving nonlinear expansions based on orthogonal polynomials [22], [23].

4.1 Hammerstein filters

A Hammerstein filter is formed by a static nonlinearity followed by a linear filter $h(n)$. Since the nonlinearity is usually expressed as a polynomial function and the linear filter has a finite impulse response of N samples, it is considered as a simple example of a truncated Volterra filter. Thus, for the Hammerstein filter, the input-output relation is given as

$$y_F(t) = \sum_{n=0}^{N-1} h(n) \sum_{m=1}^{M} g_m u^m(t-n) \tag{11}$$

including a linear term, and higher-order polynomial terms up to order M. This model, which is linear-in-the-parameters $h(n)g_m$, has been studied and used for many applications including NLAEC [12], [22]. The vector $\mathbf{u}_F(t)$ is a collection of instantaneous nonlinear expansions, using powers, of the input samples, as shown in the following expression

$$\begin{aligned}\mathbf{u}_F(t) = [&u(t),\ u(t-1),\ \cdots, u(t-N+1)\\ &u^2(t), u^2(t-1),\ \cdots, u^2(t-N+1)\\ &\vdots\\ &u^M(t), u^M(t-1), \cdots, u^M(t-N+1)].\end{aligned} \tag{12}$$

It is worth noting that Hammerstein filters have been called "power filters" in [12]. As observed, the terms in (12) are not mutually orthogonal. In [12] a Gram-Schmidt orthogonalization of the input data matrix has been proposed for improved convergence. However the computational load of the orthogonalization is very high even when considering a low-order filter.

4.2 Filters based on orthogonal polynomials

Filters using nonlinear expansions within the family of orthogonal polynomials have been mentioned in [24]. While Hammerstein filters are based on a power-series expansion of the input signal, a better approximation can be

achieved with signal-independent polynomials such as orthogonal polynomials in the interval $[-1,1]$, as for example Legendre, Chebyshev, and Hermite polynomials.

In Legendre polynomial filters, the sub-vectors are formed with

$$L_1[u(t)] = u(t) \tag{13}$$

$$L_2[u(t)] = u^2(t) \tag{14}$$

$$L_{m+1}[u(t)] = \frac{1}{m+1}\left[L_m[u(t)](2m+1)u(t) - mL_{m-1}[u(t)]\right] \quad m = 3,...,M \tag{15}$$

Thus, a Legendre polynomial filter is described by the following input-output relationship

$$y_F(t) = \sum_{n=0}^{N-1} h(n) \sum_{m=1}^{M} g_m L_m[u(t-n)] \tag{16}$$

including a linear term, and higher-order polynomial terms up to order M. This model is again linear-in-the-parameters $h(n)g_m$. The vector $\mathbf{u}_F(t)$ is a collection of instantaneous nonlinear expansions, using Legendre polynomials, as shown in the following expression

$$\begin{aligned}\mathbf{u}_F(t) = &\big[L_1[u(t)],\ L_1[u(t-1)],\ \cdots, L_1[u(t-N+1)] \\ &L_2[u(t)],\ L_2[u(t-1)],\ \cdots, L_2[u(t-N+1)] \\ &\vdots \quad \vdots \\ &L_M[u(t)],\ L_M[u(t-1)],\ \cdots, L_M[u(t-N+1)]\big]\end{aligned} \tag{17}$$

The number of filter parameters in the Hammerstein filters as well as in the Legendre filters is $L_{\mathrm{H}} = L_{\mathrm{L}} = MN$.

5 Nonlinear filters *with* cross terms

The class of filters described by (6) includes also more general nonlinear filters involving cross terms, i.e., products of input samples with different time shifts, such as truncated Volterra filters [23] and simplified Volterra filters [9].

5.1 Volterra filters

Volterra filters are described by input-output relationships that result from two truncations of the discrete Volterra series [23], namely, a memory truncation $(N-1)$ of the Volterra kernel orders, and a nonlinearity order truncation (M) to limit the number of Volterra kernels. The Volterra kernels can be assumed to be symmetric and, thus, the Volterra filter input/output relationship can be cast in the compact triangular form as

$$\begin{aligned}y(t) = &\sum_{n_1=0}^{N-1} h_1(n_1)u(t-n_1) \\ &+ \sum_{n_1=0}^{N-1}\sum_{n_2=n_1}^{N-1} h_2(n_1,n_2)u(t-n_1)u(t-n_2) + \cdots \\ &+ \sum_{n_1=0}^{N-1}\cdots\sum_{n_M=n_{M-1}}^{N-1} h_M(n_1...n_M)u(t-n_1)...u(t-n_M)\end{aligned} \tag{18}$$

The model in (18) includes an FIR filter $h_1(n_1)$ and higher-order kernels $h_m(n_1,\cdots,n_m)$ with $m = 2,\ldots,M$. For instance, a 3rd-order Volterra filter, which includes a 2nd-order and a 3rd-order kernel, involves the following nonlinear expansions

$$\begin{aligned}\mathbf{u}_2(t) = &[u^2(t), u(t)u(t-1), ..., u^2(t-1), \\ &u(t-1)u(t-2), ..., u^2(t-N+1)]^T\end{aligned}$$

with dimension $N(N+1)/2$ and

$$\begin{aligned}\mathbf{u}_3(t) = &[u^3(t), u(t)u(t)u(t-1), ..., u(t)u(t-1)u(t-2), \\ &..., u^3(t-N+1)]^T\end{aligned}$$

with dimension $N(N+1)(N+2)/6$. Thus, the total number of filter coefficients is $L_{\mathrm{V}} = N + N(N+1)/2 + N(N+1)(N+2)/6$.

5.2 Simplified 3rd-order Volterra kernel

Based on the simplified 2nd-order Volterra kernel presented in [9], we propose a simplified 3rd-order Volterra kernel. In [9], a simplification is made where only a reduced number of terms is considered depending on the desired complexity. By analyzing the 2nd-order Volterra kernel obtained from a loudspeaker, it has been observed that the coefficients with the most significant amplitude correspond to small values of $N_d = n_2 - n_1$. For this reason, a good approximation of a 2nd-order Volterra filter may be achieved when coefficients corresponding to large values of $n_2 - n_1$ are not selected, i.e.,

$$V_{2K}(t) = \sum_{n_1=n_2=0}^{N-1} h_2(n_1,n_2)u(t-n_1)u(t-n_2) \tag{19}$$

$$+ \sum_{n_1=0}^{N-2}\sum_{n_2=n_1+1}^{\min(n_1+N_d,N-1)} h_2(n_1,n_2)u(t-n_1)u(t-n_2). \tag{20}$$

In the 3rd-order case, there is no evidence a similar approximation is justified. However, with the idea of reducing computation, we propose the following simplification for the 3rd-order Volterra kernel,

$$V_{3K}(t) = \sum_{n_1=n_2=n_3=0}^{N-1} h_3(n_1,n_2,n_3)u(t-n_1)u(t-n_2)u(t-n_3) \tag{21}$$

$$+ \sum_{n_1=0}^{N-2}\sum_{n_2=n_1+1}^{\min(n_1+N_d,N-1)}\sum_{n_3=n_2+1}^{\min(n_2+N_d,N-1)} h_3(n_1,n_2,n_3)u(t-n_1)u(t-n_2)u(t-n_3) \tag{22}$$

The vector $\mathbf{u}_2(t)$ is then a collection of 2nd-order combinations of input samples with different time shifts, i.e.,

$$\begin{aligned}\mathbf{u}_2(t) = &[u^2(t), u^2(t-1), ..., u^2(t-N+1) \\ &u(t)u(t-1), ..., u(t-N)u(t-N+1) \\ &\cdots \\ &u(t)u(t-N+1)]^T\end{aligned} \tag{23}$$

with dimension $N(N+1)/2$. Similary, the vector $\mathbf{u}_3(t)$ is a collection of 3rd-order combinations of input samples with different time shifts, i.e.,

$$\begin{aligned}\mathbf{u}_3(t) = [&u^3(t), u^3(t-1), ..., u^3(t-N+1)\\ &u(t)u(t-1)u(t-2), ..., u(t-N-1)u(t-N)u(t-N+1)\\ &\dots\\ &u(t)u(t-N)u(t-N+1)]^T\end{aligned}$$

with dimension $N(N_d+1)(N_d+2)/6$. Thus, the total number of filter coefficients is $L_{\mathrm{SV}} = L + N(N_d+1)/2 + N(N_d+1)(N_d+2)/6$.

6 Simulated Hammerstein system identification

In this section, the identification of a simulated Hammerstein system is performed using NLMS and two different nonlinear filters, a 5th-order Hammerstein filter, and a 5th-order Legendre polynomial filter. The (static) nonlinearity and the linear filter are those of Figure 4 (5th-order power-series nonlinearity, 16-taps FIR LPF). By adjusting α, β, γ, and δ, the level of the nonlinear -odd and even- contributions are scaled to be -20 dB below the linear contribution.

The input signal is an odd-random multisine, the fundamental frequency is 2 Hz, the first frequency with non-zero amplitude is $f_{\min} = 40$ Hz, the maximum excited frequency $f_{\max} = 8$ kHz, the sampling frequency is 32 kHz and the harmonic grid parameter is $K = 6$. From the total number of periods, i.e., $P = 40$, we use the first 35 periods for identification and the last 5 periods for validation. In identification, the analysis method is applied to the residual signal after the adaptive filters have sufficiently converged. In validation, we fix the filter parameters obtained previously in the identification and analyze the residual signal. A very useful feature of the analysis method is that one can easily calculate the power of the different contributions independently. The values we show correspond to the averaged power of the excited odd, non-excited odd and even harmonics independently.

Figure 5 shows that the Legendre polynomial filter achieves significantly better performance than the Hammerstein filter. Interestingly, the Legendre polynomial filter achieves -59 dB in the non-excited odd harmonics and -57 dB in the even harmonics. These values are nearly the same as the level of the nonlinear distortion due to 16-bit format, see Figure 4(b). These two facts, shed some light on the benefits of using orthogonal polynomial expansions (e.g., Legendre) if higher orders are considered. It is known that non-orthogonal polynomials (e.g., power series) are not well behaved when using higher orders. Indeed, even when the underlying nonlinear and linear systems are exactly known, the (high order) Hammerstein filter does not provide a good approximation.

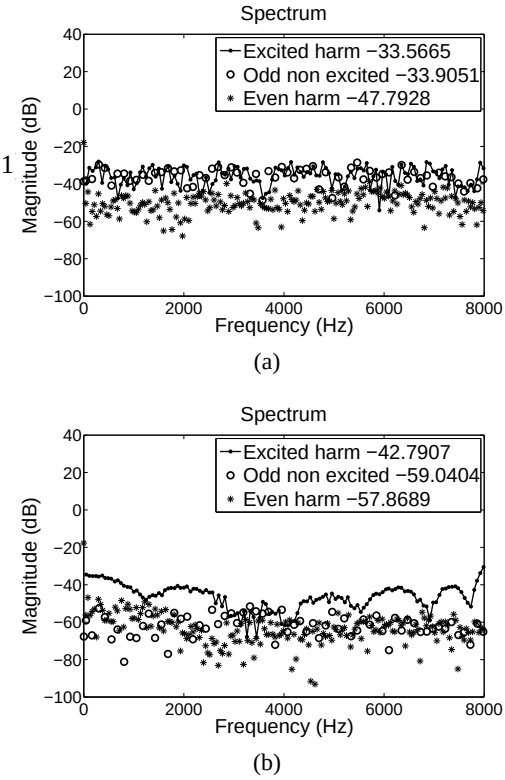


Fig. 5. Results of simulated **Hammerstein system** identification using NLMS adaptation and where the nonlinearity is a 5th-order power-series expansion. (a) Validation of the 5th-order **Hammerstein filter**. (b) Validation of the 5th-order **Legendre polynomial filter**

7 Loudspeaker identification

Measurements are conducted in a room that is acoustically conditioned and prepared to have low reverberation times and listening comfort but that is not anechoic. Hence, it is expected that some (linear) dynamics are added to the measured frequency response. The microphone is a condenser microphone, AKG CK97-C with an AKG SE300-B pre-amplifier, connected to a PC running Cool Edit pro 2.0 through a RME Multiface II sound card. The distance between loudspeaker and microphone is 15 cm and 1.25 m from the floor. It is expected that none of these elements will cause any significant harmonic distortion. The loudspeaker is a Boss MA-12 active monitor, which is measured using the same input signal as in the previous section, shown in Figure 4(a).

Figure 6(a) shows the spectrum of the output signal of the loudspeaker at low input level where the non-excited odd and even harmonics levels are -24 and -22 dB respectively. Figure 6(b) shows the output spectrum of the loudspeaker at high input level ($+10$ dB) where the even harmonics lay at -9 dB and the non-excited odd harmonics are at much higher level $+8$ dB. The loudspeaker clearly presents an odd-order nonlinearity that is more predominant than the even-order nonlinearity, which means that at least a 3rd-order nonlinear model must be considered for identification.

Figure 6(c) shows the estimated impulse response using a linear least-squares (LS) estimate based on the low level signal. Similarly, Figure 6(d) shows the estimated impulse response based on the high level signal. The estimated impulse response is clearly less noisy in the low level case, as

Simp. Volt.			
	Size	$N_d = N/32$	$N_d = N/16$
Excited	Id.	5.6	5.5
	Val.	6.4	5.8
Odd	Id.	4	4.3
	Val.	2.6	2.7
Even	Id.	-14.9	-16
	Val.	-4.3	-2.9

Table 2: Loudspeaker identification using a simplified 3rd-order Volterra filter. The values correspond to the averaged power of the excited odd, non-excited odd and even harmonics independently.

the nonlinear distortion is around 47 dB lower compared to the high level case, as shown in Figures 6(a) and 6(b). From the estimated impulse response we define the length of the linear filter, i.e., 360 coefficients.

We now proceed with the identification of the loudspeaker and validation of the model when using a Hammerstein filter and a Legendre polynomial filter, with nonlinear orders 3 ,7, 15, 31, 47, 55, and 67. We also identify and validate the model when using a simplified 3rd-order Volterra filter with $N_d = N/32$ and $N_d = N/16$ in both the 2nd and 3rd-order Volterra kernel. The reason for this choice is to keep the size of the filter reasonably small and comparable with the length of the other filters without cross terms. The value of the different averaged power spectra is shown in Table II, III, IV, and V, where Id. stands for "in identification" and Val. for "in validation". In Figures 7 and 8, the spectrum obtained with the 3rd-order and 67th-order Hammerstein and Legendre polynomial filter is shown, and in Figure 9, the spectrum obtained with the simplified 3rd-order Volterra using $N_d = N/32$ and $N_d = N/16$ is shown.

In the 3rd-order case, the Hammerstein, Legendre, and simplified Volterra (both with $N_d = N/32$ and $N_d = N/16$) filter obtain similar values in identification and validation of the excited odd harmonics (around 5.5 Id. and 6.5 Val. respectively) and non-excited odd harmonics (around 4 Id. and 2.6 Val. respectively). For the even harmonics, the simplified Volterra filter achieves 2 dB performance improvement compared to the Hammerstein and Legendre polynomial filter, but this is only in the identification step. In the validation step, the Hammerstein and Legendre polynomial filter achieve a much better performance, -8.8 and -9.5 dB respectively, w.r.t. the simplified Volterra filter using $N_d = N/32$ and $N_d = N/16$, which only achieves -4.3 and -2.9 dB respectively. Moreover, in the simplified 3rd-order Volterra filter case, the performance improvement between the $N_d = N/32$ and $N_d = N/16$ is nearly negligible.

The Legendre polynomial filter achieves a better performance than the Hammerstein filter during identification and validation. Interestingly, the Hammerstein filter performance does not improve with increasing order. Indeed, beyond 7th order there is no improvement whatsoever in identification or validation. On the other hand, the Legendre polynomial filter performance improves with increasing order in identification and, most importantly, in validation. For instance, using order 7, in the validation step the Legendre polynomial filter achieves Excited= 4.1, Odd= -3.1, and Even= -9.5 dB, whereas using order 67, in the validation step the Legendre polynomial filter achieves Excited= -1.9, Odd= -4.3, and Even= -13.2 dB. The 7th-order Legendre polynomial filter achieves a remarkable performance improvement over the simplified Volterra filter, which in the validation step, achieves Excited= 5.8, Odd= 2.7, and Even= -2.9 dB only.

The differences between identification and validation, comparing the simplified 3rd-order Volterra filter with $N_d = N/16$ and the 67th-order Legendre polynomial filter, appear to be similar for the excited odd harmonics (0.3 and 0.2 dB respectively) and non-excited odd harmonics (1.6 and 0.9 dB respectively). However, for the even harmonics, the difference between identification and validation is remarkably high for the simplified 3rd-order Volterra filter with $N_d = N/16$ (13.1 dB) compared to the 31st-order Legendre filter case (3.4 dB). This is a clear sign of overfitting.

A general trend for the Hammerstein and Legendre filters is that the differences between identification and validation decrease with increasing order. This implies that the identified model is a better model for the actual system. However, for the simplified 3rd-order Volterra filter, the differences between identification and validation tend to increase with increasing N_d. In particular, for the even harmonics, these differences are quite high (10.6 and 13.1 dB respectively). The reason is that in the 3rd-order simplified Volterra filter, the order of the filter is constant, i.e., 3, but the length of the filter is increasing. The risk of overfitting in this case is clear, since keeping the order but increasing the filter length makes identification and validation differ considerably.

8 Conclusions

In this paper, we have presented a method to analyze the nonlinear response, in terms of odd and even nonlinearities, of an electrodynamic loudspeaker by means of periodic random-phase multisine experiments. Moreover, we have considered the identification of a loudspeaker model by means of linear-in-the-parameters nonlinear adaptive filters. First of all, we have seen that the nonlinear odd contribution is much more predominant than the nonlinear even contribution. This mean that *at least* a 3rd-order nonlinear filter must be considered. By analyzing the residual signal after the adaptive filter has converged, we have shown, however, that a 3rd-order nonlinear filter is not sufficient to capture all the nonlinearities. This means that the odd and even nonlinear contributions are produced by higher-order nonlinearities. Second, we have compared nonlinear filters without cross-terms (i.e., Hammerstein and Legendre polynomial filters) and with cross-terms (i.e., simplified 3rd-order Volterra filters). Increasing the filter order beyond order 7 does not improve performance of Hammerstein filters. This may lead to misinterpreation of the

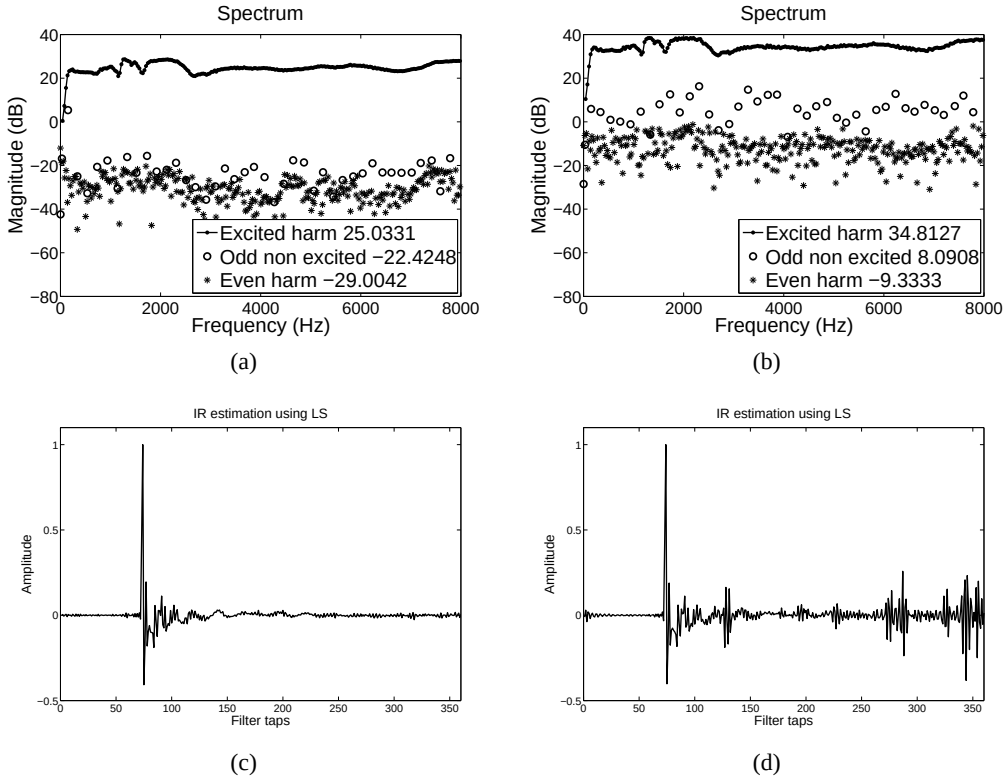


Fig. 6. Loudspeaker measurements. (a)-(b) Output spectrum measured using two input levels with 10 dB difference. (c)-(d) Normalized impulse response estimates with least-squares using two input levels with 10 dB difference.

results, concluding that this is a characteristic of the system and not of the nonlinear filter. Simplified Volterra filters, even when using low-order filters, present signs of overfitting with increasing length. Moreover, for the simplified 3rd-order Volterra filter, the performance is remarkably poorer than for the Legendre polynomial filter with the same filter length. On the other hand, Legendre polynomial filters have shown improved performance with increasing order. For the Legendre polynomial filter, the differences between identification and validation appear to be very small, which tend to decrease with increasing order. We have shown that in our set-up, a high-order nonlinear filter is much more important than the memory of a Volterra filter. Moreover, we have shown how easily a Volterra filter can give misleading results due to overfitting. This means that, although the attenuation of the error signal in AEC may be large, this does not necessarily mean that the identified model is a valid one.

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Hammerstein								
	Order	3	7	15	31	47	55	67
Excited	Id.	5.3	3.8	3.8	3.8	3.8	3.8	3.8
	Val.	6.9	5.7	5.7	5.7	5.7	5.7	5.7
Odd	Id.	3.8	1.2	1.1	1.1	1.1	1.1	1.1
	Val.	2.6	-0.7	-0.8	-0.8	-0.8	-0.8	-0.8
Even	Id.	-12.7	-13.5	-13.7	-13.7	-13.7	-13.7	-13.7
	Val.	-8.8	-10.2	-10.4	-10.4	-10.4	-10.4	-10.4

Table 3: Loudspeaker identification using Hammerstein filter. The values correspond to the averaged power of the excited odd, non-excited odd and even harmonics independently.

Legendre								
	Order	3	7	15	31	47	55	67
Excited	Id.	5.3	2.9	2.3	1.1	0	-0.6	-1.7
	Val.	6.9	4.1	3	1.4	0.1	-0.7	-1.9
Odd	Id.	3.8	-0.2	-1	-1.4	-1.9	-2.3	-3.2
	Val.	2.6	-3.1	-3.4	-3.1	-3.3	-3.5	-4.3
Even	Id.	-12.5	-14	-14.6	-15.5	-16.2	-16.5	-16.6
	Val.	-9.5	-9.5	-9.6	-11.5	-12.3	-12.7	-13.2

Table 4: Loudspeaker identification using Legendre polynomial filter. The values correspond to the averaged power of the excited odd, non-excited odd and even harmonics independently.

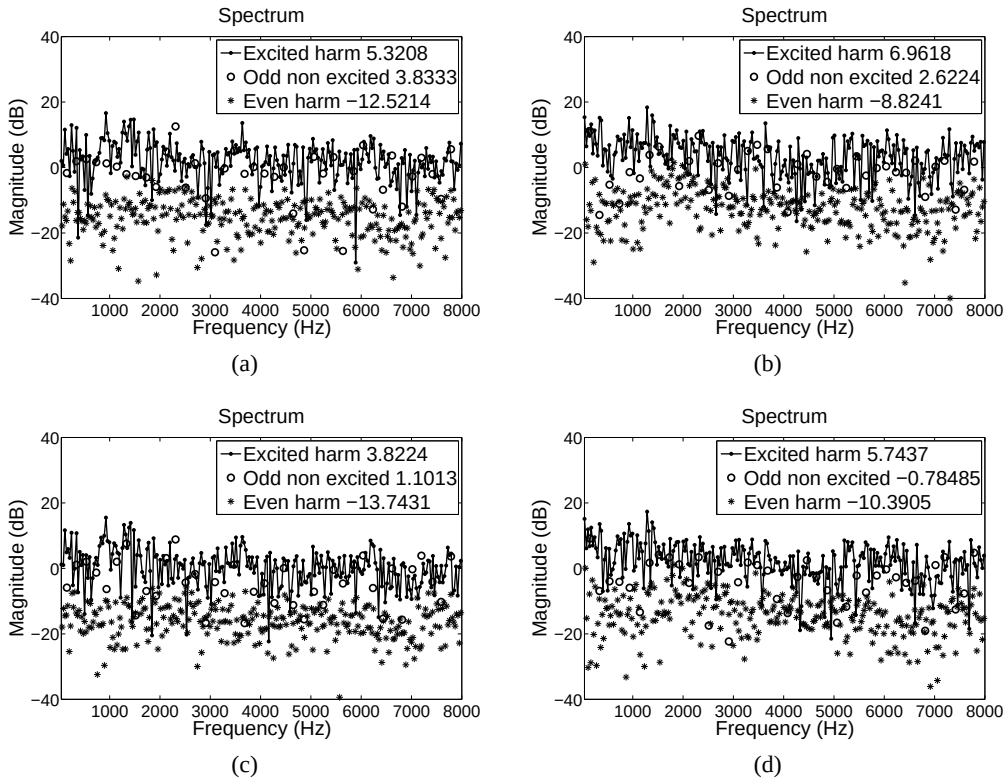


Fig. 7. **Loudspeaker** identification and validation using a **Hammerstein filter** and NLMS. (a) Identification and (b) Validation using a 3rd-order filter. (c) Identification and (d) Validation using 67th-order filter.

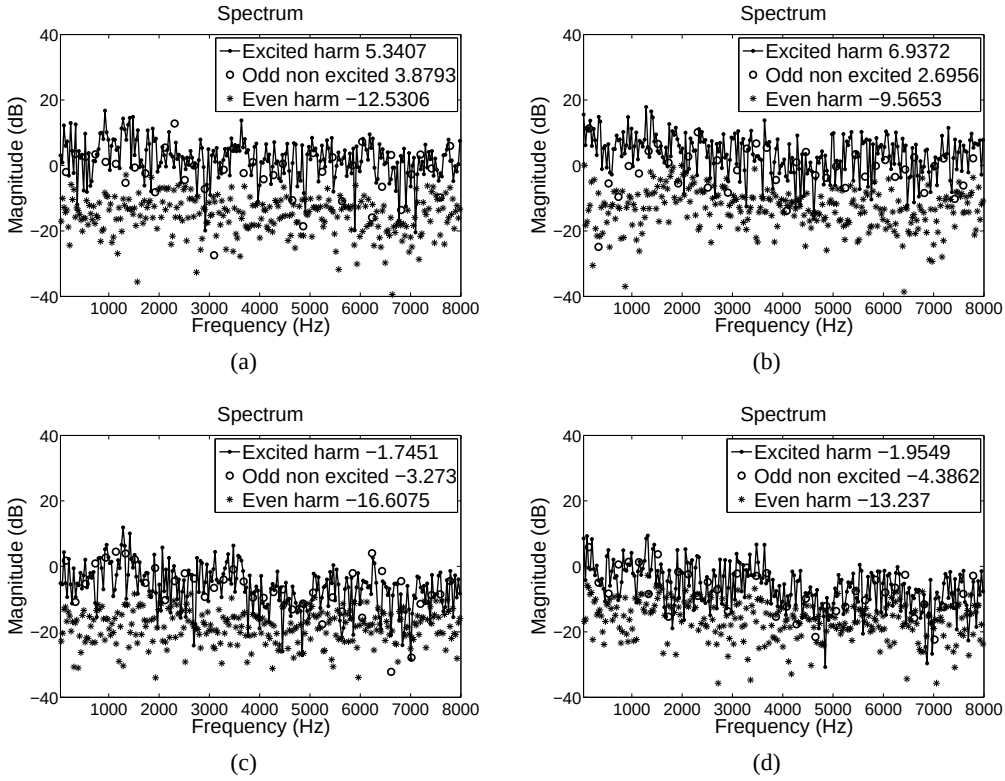


Fig. 8. **Loudspeaker** identification and validation using a **Legendre polynomial filter** and NLMS. (a) Identification and (b) Validation using a 3rd-order filter. (c) Identification and (d) Validation using 67th-order filter.

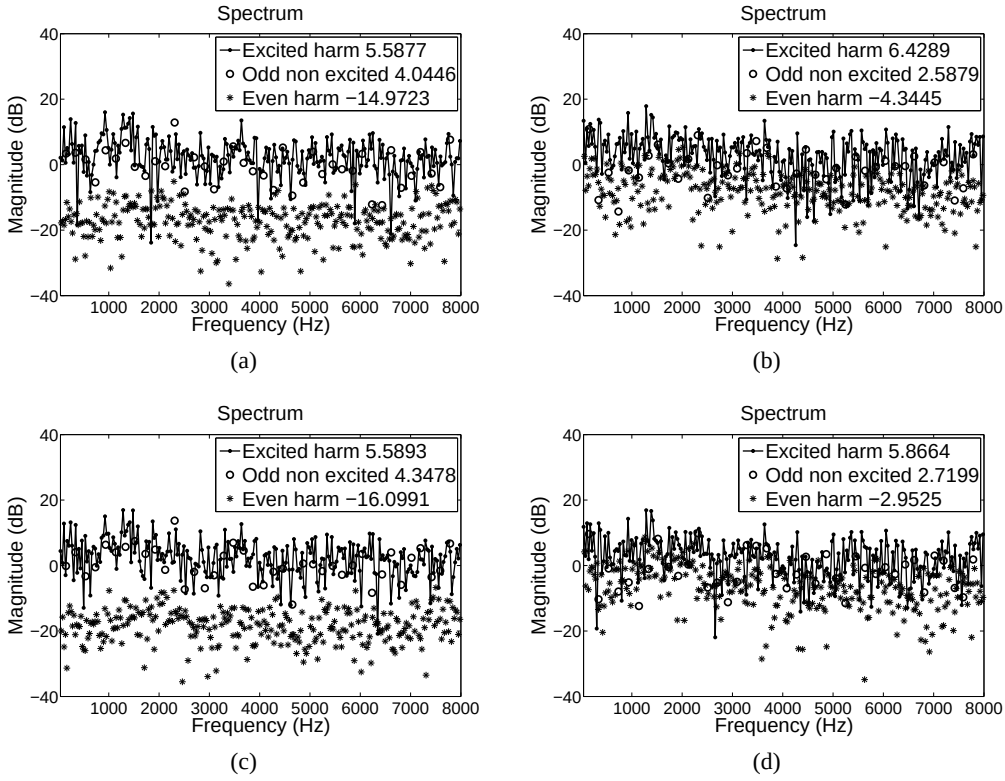


Fig. 9. **Loudspeaker** identification and validation with a **simplified** 3**rd-order Volterra filter** and NLMS. (a) Identification and (b) Validation using $N_d = N/32$. (c) Identification and (d) Validation using $N_d = N/16$.

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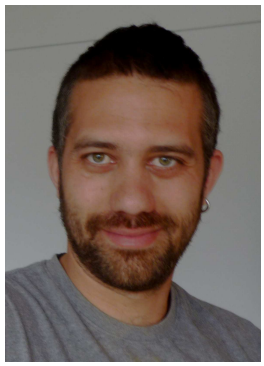
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