Acoustic Echo Cancellation: Do IIR Models Offer Better Modeling Capabilities than Their FIR Counterparts?

Athanasios P. Liavas and Phillip A. Regalia, *Senior Member, IEEE*

***Abstract*—The adequateness of IIR models for acoustic echo cancellation is a long-standing question, and the answers found in the literature are conflicting. We use results from rational Hankel norm and least-squares approximation, and we recall a test that provides *a priori* performance levels for FIR and IIR models. We apply this test to measured acoustic impulse responses. Upon comparing the performance levels of FIR and IIR models with the same number of free parameters, we do *not* observe any significant gain from the use of IIR models. We attribute this phenomenon to the shape of the energy spectra of the acoustic impulse responses so tested, which possess many strong and sharp peaks. Faithful modeling of these peaks requires many parameters, irrespective of the type of the model.**

***Index Terms*— Acoustic echo cancellation, FIR models, IIR models.**

I. Introduction

LINEAR time-invariant (LTI) infinite impulse response (IIR) models are commonly expected to possess better modeling capabilities than their finite impulse response (FIR) counterparts. The reason for this is that many physical systems can be well described by difference equations involving both the input and the output. These equations lead, in turn, to rational transfer functions corresponding to IIR models.

When we have to cope with unknown systems and/or unknown signal properties, some type of adaptation has to be included in our models. The theory of adaptive FIR filters is well developed (see [1] and [2] among many nice texts) and gives us the ability to predict their behavior under a variety of conditions. There are applications, however, in which achieving an acceptable performance level requires a very high order FIR model, resulting in very high computational complexity. A well-known example is acoustic echo cancellation (AEC), where in order to achieve satisfactory echo compensation, FIR filters with several thousands of taps are often required [3].

In the hopes of reducing computational complexity, adaptive IIR algorithms for AEC have remained of interest. Some early works claim that IIR models cannot offer substantially better performance in the AEC problem than their FIR counterparts. At this point, two comments are in order:

- Conclusions based solely on simulations [4] are not entirely convincing if we cannot guarantee that we have approached the global minimum of the error performance surface for the IIR case.
- The use of an equation error model [5] in the (output error) AEC scheme seems questionable on its principles. This argument becomes stronger in undermodeled cases—including AEC—in which the minimum point of an equation error cost function need not have any particular connection with the minimum point of an output error cost function (e.g., [6, p. 28]).

The first attempt to put the problem under a model reduction framework appears in [7], where the authors use concepts from rational Hankel norm approximation theory in order to examine if IIR models offer better approximation properties than FIR models with the same number of free parameters in the AEC context. Using a measured room acoustic impulse response, they show that IIR models can outperform, for some model orders in Hankel norm approximation terms, their FIR counterparts. This work remains one of the few that has claimed superiority of IIR models in an AEC environment.

Recently, considerable progress has been made in both the theoretical and the algorithmic parts of adaptive IIR filtering. For example, using Hankel norm approximation concepts [8], *a priori* bounds have been developed for the rational least-squares approximation [9], [10], which seems a more natural criterion in adaptive filtering than the Hankel norm criterion. New efficient algorithms have been developed based on the tapped-state lattice structure, overcoming in this way potential instability of the direct-form IIR filters during adaptation [6, chs. 7, 8], [11]. Furthermore, the study of algorithms other than stochastic gradient-based algorithms has rendered it possible to guarantee that, under certain conditions, the stationary points of a family of adaptive IIR algorithms are "close" to the global minimum of the least-squares output error performance surface [12]–[14].

In the sequel, we exploit these results, and we recall *a priori* performance levels for the approximation of acoustic echo paths (AEP's) by IIR and FIR models under an ideal stationary scenario. Strictly speaking, speech signals as encountered in the AEC problem are, in general, nonstationary. In the same vein, AEP's are also nonstationary since they depend on person

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The authors are with the Département Signal et Image, Institut National des Télécommunications, Evry, France (e-mail: liavas@sim.int-evry.fr; regalia@sim.int-evry.fr).

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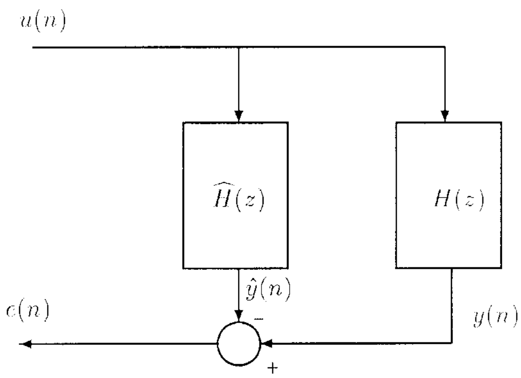

Fig. 1. System approximation/identification problem.

movements, temperature variations, etc. Thus, it would be desirable to treat this problem as one involving nonstationary systems and signals. It is probably true that no such progress can be made until we fully understand simple stationary cases. A complete understanding of the stationary case would possibly serve as a valuable guide toward tackling the more difficult nonstationary case. Thus, our interest in this paper will be restricted to the stationary case.

The performance levels achieved by *equal complexity* IIR and FIR models provide a measure of the approximation capabilities offered by the respective models in the AEC problem. By equal complexity models, we mean models with the same number of free parameters. It is not always true that such models will lead to adaptive algorithms with exactly the same computational complexity. However, we feel that this definition of complexity is the most appropriate for our study because in this way, we measure how effectively the parameters are utilized by the various models.

The rest of the paper is organized as follows. In Section II, we recall some principal results from least-squares approximation theory, which constitute a test for the performance offered by FIR and IIR models in the least-squares approximation/identification problem. In Section III, we apply this test in the AEC context using measured (as opposed to hypothesized) room acoustic impulse responses. For the acoustic impulse responses tested, IIR models do not offer substantially superior modeling capabilities than do their equal complexity FIR counterparts. This phenomenon may be attributed to the shape of the energy spectra of the AEP's so tested; they possess many strong and sharp peaks, whose faithful modeling, as shown in Section IV, requires many parameters, irrespective of the type of the model. Conclusions are drawn in Section V.

II. Least-Squares Approximation Using FIR and IIR Models

In this section, we review the system approximation/identification setup shown in Fig. 1. The unit variance zero mean white noise sequence $u(n)$ drives both $H(z)$ and $\hat{H}(z)$. We assume that $H(z)$ is causal and stable in the l_2 sense, i.e.,

$$H(z) = \sum_{k=0}^{\infty} h_k z^k, \qquad \text{with } \sum_{k=0}^{\infty} h_k^2 < \infty. \tag{1}$$

Note that we use z, instead of z^{-1}, as the unit delay operator, i.e., $z^k u(n) = u(n-k)$. The output of $H(z)$, which is denoted $y(n)$, can be expressed as

$$y(n) = h(n) * u(n) = \sum_{k=0}^{\infty} h_k u(n-k). \tag{2}$$

Our adjustable model $\hat{H}(z)$ is constrained to be causal. It may be either an Mth-order FIR filter

$$\hat{H}(z) = \sum_{k=0}^{M} \hat{h}_k z^k \tag{3}$$

or a Kth-order IIR filter

$$\hat{H}(z) = \frac{B(z)}{A(z)} = \frac{\sum_{k=0}^{K} b_k z^k}{\sum_{k=0}^{K} a_k z^k} = \sum_{k=0}^{\infty} \hat{h}_k z^k. \tag{4}$$

The output of $\hat{H}(z)$, which is denoted $\hat{y}(n)$, in either case, is used as an estimate of $y(n)$.

Our objective is to determine the filters $\hat{H}(z)$ that minimize the mean square estimation error

$$\begin{aligned} E[e^2(n)] &= E[(y(n) - \hat{y}(n))^2] \\ &= \frac{1}{2\pi} \int_{-\pi}^{\pi} S_u(e^{j\omega}) |H(e^{j\omega}) - \hat{H}(e^{j\omega})|^2 \, d\omega \end{aligned} \tag{5}$$

where $S_u(e^{j\omega})$ is the power spectral density of the input $u(n)$. Since our input is unit variance zero mean white noise, this minimization problem reduces to

$$\begin{aligned} &\min_{\hat{H}(z)} \|H(z) - \hat{H}(z)\|_2^2 \\ &= \min_{\hat{H}(z)} \frac{1}{2\pi} \int_{-\pi}^{\pi} |H(e^{j\omega}) - \hat{H}(e^{j\omega})|^2 \, d\omega \\ &= \min_{\hat{H}(z)} \sum_{k=0}^{\infty} (h_k - \hat{h}_k)^2 \end{aligned} \tag{6}$$

where $\|\cdot\|_2$ denotes the $\mathcal{L}_2$ norm.

In the sequel, we assume that the degree M or K (FIR or IIR, respectively) is insufficient to allow the $\mathcal{L}_2$ norm of the estimation error to reach zero. In the next three subsections, we review known results that express how small the $\mathcal{L}_2$ norm of the estimation error can become versus the model order in terms of the impulse response $\{h_k\}$. These bounds will form the basis for the comparison of the modeling capabilities of FIR and IIR models in the AEC context.

A. Mth-Order FIR Case

When $\hat{H}(z)$ is an Mth-order FIR model, our minimization problem becomes

$$\begin{aligned} &\min_{\hat{h}_0, \cdots, \hat{h}_M} \left\| H(z) - \sum_{k=0}^{M} \hat{h}_k z^k \right\|_2^2 \\ &= \min_{\hat{h}_0, \cdots, \hat{h}_M} \left(\sum_{k=0}^{M} (h_k - \hat{h}_k)^2 + \sum_{k=M+1}^{\infty} h_k^2 \right). \end{aligned} \tag{7}$$

It is clear that the coefficients of the optimum Mth-order FIR filter match the first $M+1$ coefficients of $H(z)$, giving

$$\min_{\hat{h}_0, \cdots, \hat{h}_M} \left\| H(z) - \sum_{k=0}^{M} \hat{h}_k z^k \right\|_2^2 = \sum_{k=M+1}^{\infty} h_k^2. \tag{8}$$

Thus, given the impulse response h_k, $k = 0, 1, \cdots$, we can compute *a priori* the performance achieved by the optimum FIR models as a function of the model order M.

B. Kth-Order IIR Case

When $\hat{H}(z)$ is a Kth-order IIR model, the minimization problem (6) becomes

$$\min_{\deg \hat{H}(z) \le K} \|H(z) - \hat{H}(z)\|_2^2. \tag{9}$$

In this case, we cannot derive, in general, exact expressions for the minimum $\mathcal{L}_2$ error versus the model order in terms of the impulse response. We can, however, obtain, given h_k, $k = 0, 1, \cdots$, *a priori* upper and lower bounds for the minimum $\mathcal{L}_2$ norm of the estimation error as a function of the model order K. These bounds depend on the Hankel singular values of $H(z)$, and we find it useful to introduce some notation at this point.

Given a stable and causal $H(z)$ as in (1), its Hankel form is defined as the doubly infinite Hankel matrix

$$\Gamma_H = \begin{bmatrix} h_1 & h_2 & h_3 & \cdots \\ h_2 & h_3 & h_4 & \cdots \\ h_3 & h_4 & h_5 & \cdots \\ \vdots & \vdots & \vdots & \ddots \end{bmatrix}. \tag{10}$$

The Hankel singular values of $H(z)$ are the singular values of Γ_H, $\sigma_i(\Gamma_H)$, and they are usually given in descending order. The Hankel norm of $H(z)$ is defined as

$$\|H(z)\|_{\mathcal{H}} = \|\Gamma_H\| = \sigma_1(\Gamma_H) \tag{11}$$

where $\|\Gamma_H\|$ denotes the induced 2-norm of the operator Γ_H. Kronecker's theorem states that the rank of Γ_H is equal to the McMillan degree of $H(z)$. The rational Hankel norm approximation problem is fully resolved by the celebrated theorem of Adamjan *et al.* [8], which states the following.

Theorem: Let Γ_H be a given Hankel form, and let $\Gamma_{\hat{H}}$ be a candidate Hankel approximant. Then

$$\min_{\operatorname{rank} \Gamma_{\hat{H}} \le K} \|\Gamma_H - \Gamma_{\hat{H}}\| = \sigma_{K+1}(\Gamma_H). \tag{12}$$

Furthermore, there is a unique Hankel form of rank not exceeding K that attains this bound.

A connection between the rational Hankel norm and $\mathcal{L}_2$ norm approximations is provided through the $\mathcal{L}_2$ norm/Hankel norm inequality [15], [6, p. 154]

$$\left(\sum_{k=1}^{\infty} (h_k - \hat{h}_k)^2 \right)^{1/2} \le \sigma_1(\Gamma_H - \Gamma_{\hat{H}}). \tag{13}$$

From (12) and (13), we obtain

$$\min_{\operatorname{rank} \Gamma_{\hat{H}} \le K} \left(\sum_{k=1}^{\infty} (h_k - \hat{h}_k)^2 \right)^{1/2} \le \sigma_{K+1}(\Gamma_H). \tag{14}$$

Furthermore, since at each minimum point of $\|H(z) - \hat{H}(z)\|_2$ it happens that $h_0 = \hat{h}_0$ [6, p. 129], then

$$\min_{\deg \hat{H}(z) \le K} \|H(z) - \hat{H}(z)\|_2 \le \sigma_{K+1}(\Gamma_H). \tag{15}$$

It can also be shown [10] that

$$\min_{\deg \hat{H}(z) \le K} \|H(z) - \hat{H}(z)\|_2 \ge \left(\sum_{i=K+1}^{\infty} \sigma_i^2(D\Gamma_H D) \right)^{1/2} \tag{16}$$

where $D = \operatorname{diag}(d_0, d_1, \cdots)$, with

$$d_k = d_{k-1} \sqrt{\frac{2k-1}{2k}}, \qquad d_0 = 1. \tag{17}$$

Thus, given h_k, $k = 0, 1, \cdots$, we can derive *a priori* upper and lower bounds [via (15) and (16), respectively] for the performance offered by the IIR models as a function of the model order K. At this point, we must note that in general, both bounds are *loose*, and we do not know *a priori* which bound is closer to the minimum $\mathcal{L}_2$ error norm achieved by the IIR models.

C. ARMA(p, q) Case, $p > q$

In [7], it was claimed that the shape of the acoustic impulse response suggests the use of models with unequal numbers of poles and zeros, i.e., the use of ARMA(p, q) models with longer numerator than denominator ($p > q$). It turns out that upper and lower $\mathcal{L}_2$ error bounds for the ARMA(p, q) case can be derived by slightly rearranging the previous case [6, p. 141]. More specifically, we need only remove the first $(p-q)$ samples $h_0, h_1, \cdots, h_{p-q-1}$, thereby obtaining

$$T(z) = \sum_{k=0}^{\infty} h_{p-q+k} z^k. \tag{18}$$

Then, we perform a qth-order rational least squares approximation to $T(z)$. Bounds for this approximation still obey (15) and (16) with $K = q$ (the denominator order).

III. IIR versus FIR Models for Acoustic Echo Cancellation

Formulas (8), (15), and (16) can be used to derive *a priori* approximation levels for FIR and IIR models in any approximation/identification problem, which can be described by Fig. 1. In this section, we use these formulas to compare the modeling capabilities of IIR versus FIR models for AEC. We apply them here to measured (not hypothesized) room acoustic impulse responses. The dimensions of the room are $7.36 \times 3.65 \times 2.77$ m^3, the floor is covered by carpets, and two sides have windows.

In Fig. 2(a), we plot the magnitude of the measured impulse response of the AEP on a decibel scale (sampling frequency 8 kHz). In Fig. 2(b), we plot the magnitude of its energy spectrum in the frequency range 100–1000 Hz (the frequency interval is constrained simply for visualization purposes).

In Fig. 3, we plot the performance levels offered by the models as a function of the number of the model parameters. The thick lines plot the upper and lower mean square

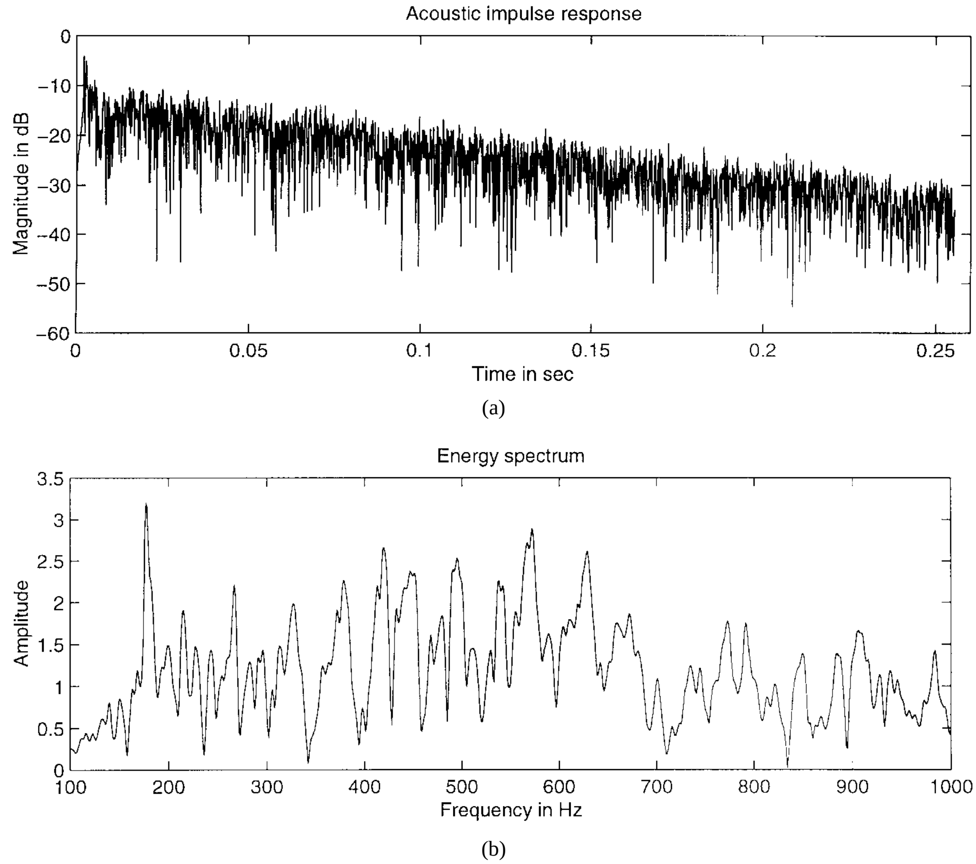

Fig. 2. (a) Magnitude of acoustic impulse response in decibel scale. (b) Energy spectrum of acoustic impulse response (frequency interval 100–1000 Hz).

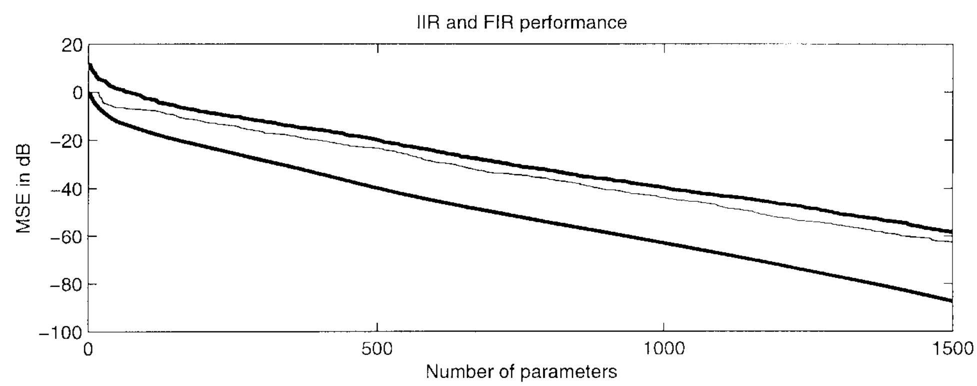

Fig. 3. Performance levels for IIR and FIR models. Thick lines: Upper and lower mean square error bounds for IIR models. Thin line: Minimum mean square error for FIR models.

error bounds for IIR models, whereas the thin line plots the minimum mean square error achieved by the respective FIR models. We observe that for this impulse response, for parameter numbers up to 1500, the FIR performance lies between the upper and lower IIR bounds. That is, for parameter numbers up to 1500, the FIR and IIR models provide comparable echo reduction. We may remark here that in an adaptive filtering context, neither the FIR nor the IIR models will reach identically their respective global minima due to inevitable misadjustment effects. Given the large number of parameters—extending well into the hundreds here—misadjustment effects may render the two solutions virtually indistinguishable in terms of their actual performance measures.

In Table I, we present bounds for various ARMA(p, q) models and the minimum mean square error achieved by FIR models with the same number of parameters. Again, we observe comparable performance levels using FIR and IIR approximants.

We performed the aforementioned tests using ten measured typical room acoustic impulse responses. No significant differences in performance levels were observed between FIR and IIR approximants.

Thus, even if we overlook problems commonly appearing in the study of adaptive IIR filters, such as potential existence of local minima and potential instability during the adaptation and slow convergence speed—some of which have been solved in

TABLE I
BOUNDS FOR VARIOUS ARMA(p, q) MODELS

	ARMA $E[\epsilon^2(n)]$	ARMA $E[\epsilon^2(n)]$	FIR $E[\epsilon^2(n)]$
(p, q)	upper bound	lower bound	min
(310, 10)	-8.6532	-23.6271	-19.9502
(350, 50)	-18.1654	-32.9206	-23.0518
(400,100)	-23.9676	-41.3913	-26.8974
(510, 10)	-12.3106	-28.6896	-27.9778
(600,100)	-29.1848	-46.1556	-38.5145
(600,200)	-34.0131	-53.7087	-41.7014
(710, 10)	-22.3008	-38.4258	-38.9031
(800,100)	-38.2060	-54.2866	-46.8171

certain cases—we may anticipate that adaptive IIR algorithms will not offer echo reduction levels substantially superior to their FIR counterparts. Refer to [16] for further examples, which are in general agreement with the results presented here.

IV. ADEQUATENESS OF IIR MODELS FOR ACOUSTIC ECHO CANCELLATION

In the previous section, we observed that IIR and FIR offer comparable echo reduction for the AEC problem. Our objective in this section is to isolate those characteristics of AEP's, which seem to be the main causes for this phenomenon.

With reference to the impulse response plotted in Fig. 2(a), we observe a decreasing exponential envelope, which has been the impetus in many works for using IIR models to capture AEP's.

With respect to the magnitude of the energy spectrum of this impulse response, in Fig. 2(b), the most striking observation is the existence of many strong sharp spectral peaks (for a related discussion, see [17]). As a result, for this particular energy spectrum, there exist $L \approx 1000$ extrema points in the frequency range 0–4000 Hz. This means that in order to model this energy spectrum faithfully, we need no fewer than L parameters. In the sequel, we justify this claim.

Consider first the FIR case. In order to compute the maximum number of extrema of $|\hat{H}(e^{j\omega})|^2 = \hat{H}(e^{j\omega})\hat{H}(e^{-j\omega})$, on the interval $[0, \pi]$, with

$$\hat{H}(z) = \sum_{k=0}^{M} \hat{h}_k z^k \tag{19}$$

we first write

$$|\hat{H}(e^{j\omega})|^2 = \sum_{k=0}^{M} \alpha_k \cos(\omega k) \tag{20}$$

for some α_k, $k = 0, \cdots, M$. Then, we follow the same steps as in [18, p. 128], and we conclude that the maximum number of extrema of $|\hat{H}(e^{j\omega})|^2$ on the interval $[0, \pi]$ is $M + 1$.

Using similar arguments, we can prove that the maximum number of extrema points of $|\hat{H}(e^{j\omega})|^2$, where $\hat{H}(z)$ is the Kth-order IIR model given by (4), is $2K - 1$, and the corresponding number for the ARMA(p, q) model is $p+q-1$.

This means that to faithfully model an energy spectrum whose magnitude exhibits M extrema points on the interval $[0, \pi]$, we require no fewer than M parameters for the FIR case and $M + 2$ for the IIR and ARMA cases.

The shape of the magnitude of the energy spectrum of the AEP exhibiting many strong and sharp peaks implies that in order to provide faithful AEP approximations, we must use models possessing many spectral peaks. From the previous discussion, it is clear that existence of many peaks implies many parameters in order to obtain a sufficient number of extrema, irrespective of the type of the model. Thus, if we accept that the existence of many strong and sharp spectral peaks is a generic property of AEP's (as is evidenced by many studies, e.g., [7] and [17]), then we deduce that in order to provide good AEP approximations, we must use an FIR, an IIR, or an ARMA model with a very large number of parameters. As concerns the FIR models, this fact is well known and can be deduced by a simple inspection of the impulse response of an AEP. However, we feel that the part concerning the IIR models is somewhat surprising (although perhaps anticipated in view of some earlier studies [7], [19]) and gives a plausible explanation to the phenomenon related to the performance of adaptive IIR algorithms for AEC.

V. CONCLUSIONS

Our main purpose is to answer the question "*Do IIR models exhibit modeling capabilities that are to their FIR counterparts in the AEC problem*?" Using theoretical results from least squares approximation theory, we recalled a test that can be used to derive *a priori* performance levels for these models as a function of the number of the model parameters. Applying this test to a number of measured typical room acoustic impulse responses, we did not observe any substantial improvement by the use of IIR models. This observation is of great practical importance and requires a satisfying explanation. The main cause of this phenomenon lies, in our opinion, in the shape of the energy spectra of the AEP's so tested. Their striking characteristic is the existence of many strong sharp spectral peaks. We showed that faithful modeling of many peaks requires many parameters, irrespective of the type of model. It seems that IIR models do not outperform their equal complexity FIR counterparts in modeling such cases.

We may also remark that no study has shown, to our knowledge, that acoustic echo paths may be considered to be finite-order systems. This may be attributed to distributed parameter effects of acoustic wave propagation or possibly other modeling considerations. In short, both polynomial and rational transfer functions are "inadequate" for this application to comparable degrees.

Whether similar conclusions may apply to other application areas involving "infinite-order" systems is not immediately clear. For this reason, we have been careful to focus on a particular artifact common to most acoustic echo paths: an impressive number of sharp spectral peaks. At the very least, the acoustic echo cancellation problem serves as a cogent reminder that modeling hypotheses, which assume a finite number of linear lumped energy storage elements, which lead, in turn, to finite order difference or differential equations, are often inadequate for dealing with physical systems of practical engineering interest.

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REFERENCES

[1] S. Haykin, *Adaptive Filter Theory.* Englewood Cliffs, NJ: Prentice-Hall, 1996.
[2] N. Kalouptsidis and S. Theodoridis, *Adaptive System Identification and Signal Processing Algorithms.* Englewood Cliffs, NJ: Prentice-Hall, 1993.
[3] E. Hänsler, "The hands-free telephone problem—An annotated bibliography," *Signal Process.,* vol. 27, no. 3, pp. 259–271, June 1992.
[4] O. Muron and J. Sikorav, "Modeling of reverberators and audioconference rooms," in *Proc. ICASSP,* Tokyo, Japan, 1986, pp. 921–924.
[5] G. Long, D. Shwed, and D. Falconer, "Study of a pole-zero adaptive echo canceller," *IEEE Trans. Circuits Syst.,* vol. CAS-34, pp. 765–769, July 1987.
[6] P. A. Regalia, *Adaptive IIR Filtering in Signal Processing and Control.* New York: Marcel Dekker, 1995.
[7] M. Mboup and M. Bonnet, "On the adequateness of IIR adaptive filtering for acoustic echo cancellation," in *Proc. EUSIPCO,* Brussels, Belgium, 1992, pp. 111–114.
[8] V. M. Adamjan, D. Z. Arov, and M. G. Krein, "Analytic properties of Schmidt pairs for a Hankel operator and the generalized Schur–Takagi problem," *Math. USSR Sbornik,* vol. 15, pp. 31–73, 1971.
[9] K. Glover, "All optimal Hankel-norm approximations to linear multivariable systems and their L^{∞}-error bounds," *Int. J. Contr.,* vol. 39, pp. 1115–1193, 1984.
[10] K. Glover, J. Lam, and J. R. Partington, "Rational approximation of a class of infinite dimensional systems: The $\mathcal{L}_2$ case," in *Progress in Approximation Theory.* New York: Academic, 1991, pp. 405–440.
[11] K. X. Miao, H. Fan, and D. Doroslovački, "Cascade normalized lattice adaptive IIR filters," *IEEE Trans. Signal Processing,* vol. 42, pp. 729–742, Apr. 1994.
[12] P. A. Regalia and M. Mboup, "Undermodeled adaptive filtering: An *a priori* error bound for the Steiglitz–McBride method," *IEEE Trans. Circuits Syst. II,* vol. 43, pp. 105–116, Feb. 1996.
[13] P. A. Regalia, M. Mboup, and M. Ashari, "On the existence of stationary points for the Steiglitz–McBride algorithm," *IEEE Trans. Automat. Contr.,* vol. 42, pp. 1592–1596, Nov. 1997.
[14] H. Fan and D. Doroslovački, "On 'global convergence' of Steiglitz–McBride adaptive algorithm," *IEEE Trans. Circuits Syst. II,* vol. 40, pp. 73–87, Feb. 1993.
[15] Y. Genin and S. Y. Kung, "A two-variable approach to the model reduction problem with Hankel norm criterion," *IEEE Trans. Circuits Syst.,* vol. CAS-28, pp. 912–924, Sept. 1981.
[16] M. Ashari Astani, "Rational approximation and adaptive filtering. Application in acoustic echo cancellation," Ph.D. dissertation, Univ. Paris-Sud, Paris, France, Nov. 1996.
[17] M. R. Schroeder, "Improvement of acoustic-feedback stability by frequency shifting," *J. Acoust. Soc. Amer.,* vol. 36, pp. 1718–1724, Sept. 1964.
[18] L. Rabiner and B. Gold, *Theory and Application of Digital Signal Processing.* Englewood Cliffs, NJ: Prentice-Hall, 1975.
[19] A. V. Zitzewitz, "Considerations on acoustic echo cancellation based on real time experiments," in *Proc. EUSIPCO,* Barcelona, Spain, 1990, pp. 1987–1990.

Athanasios P. Liavas was born in Pyrgos, Greece, in 1966. He received the diploma and the Ph.D. degrees in computer engineering from the University of Patras, Patras, Greece, in 1989 and 1993, respectively.

He is currently a Research Fellow with the Département Signal et Image, Institut National des Télécommunications, Evry, France, under the framework of the Training and Mobility of Researchers (TMR) program of the European Commission. His research interests include adaptive signal processing algorithms, blind system identification, and biomedical signal processing.

Dr. Liavas is a member of the Technical Chamber of Greece.

Phillip A. Regalia (SM'96) was born in Walnut Creek, CA, in 1962. He received the B.Sc. (highest honors), M.Sc., and Ph.D. degrees in electrical and computer engineering from the University of California, Santa Barbara, in 1985, 1987, and 1988, respectively. He also received the Habilitation à Diriger des Recherches from the University of Paris, Orsay, in 1994.

He is presently a Professor with the Institut National des Télécommunications, Evry, France, where his research interests focus on adaptive signal processing.

Dr. Regalia serves as an Associate Editor for the IEEE TRANSACTIONS ON SIGNAL PROCESSING and as an Editor for the *International Journal of Adaptive Control and Signal Processing*.