NONLINEAR ECHO CANCELLATION USING DECOUPLED A-B NET STRUCTURE

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ABSTRACT

This paper proposes a general nonlinear digital filter structure for echo cancellation applications. Although echo cancelers employing linear digital filter structures are more widely used, there are many applications where nonlinear filters must be used. In this paper, we propose using the DABNet (Decoupled A-B Net) filter, which is composed of a decoupled linear dynamic system followed by a nonlinear static map, for echo cancellation. The linear dynamic system is initially spanned by a set of discrete Laguerre systems, and then cascaded with a single hidden layer Perceptron. A model reduction technique can be performed not only to identify the main time constants, but also to reduce the dimensionality of the Perceptron input. The DABNet structure is able to approximate any nonlinear, causal, discrete time invariant, multiple-input single-output system with fading memory. Comparisons between echo cancelers implemented with the DABnet and nonlinear FIR filters are presented.

1. INTRODUCTION

This work is focused on modeling issues related to nonlinear echo cancellation. Although linear filtering is more widely used, there are many areas where nonlinear filters have found application [9], [2]. In the area of digital communications, nonlinear phenomena are present in different situations: in QAM data transmission systems (microwave radio [11], and voice modems [7]); in satellite channel equalization [3]; in high-density recording channels [5]; in intermodulation distortion Echo cancellation is a common technique applied in telephone lines and in digital subscriber lines (DSL) because of the requirements of full duplex transmission. The inherent two-wire transmission facility is turned into an equivalent four-wire connection using a hybrid at each end, where data can then be transmitted in both directions. However, the attenuation of the hybrid between its 2-4 wire inputs can be as low as 10dB. The nonlinearities in A/D–D/A data converters, and the saturation nonlinearities in the hybrid limit the performance of the linear echo canceler to about 60 dB with 1% differential nonlinearity [10], [1]. These arguments justify the need for efficient nonlinear models.

There is no general framework for describing arbitrary nonlinear discrete systems yet, unlike the case of linear systems that are completely characterized by the system's unit-impulse response. Consequently, the research in this area is restricted to certain nonlinear filter models, namely: cascade-parallel filters [8], nonlinear FIR filters [12], and Volterra (polynomial) filters [4].The Volterra filters are the most widely used. However, those models have some drawbacks for practical implementation. Korenberg [8] has proposed a method for identifying models composed of finite sums of parallel cascades, each comprising a linear dynamic and nonlinear static. The nonlinear FIR (NFIR) structure is composed by a tapped delay time of the inputs followed by a Multilayered Perceptron [12]. This scheme is difficult to implement when the system memory is large due to the high dimension of the involved input-output mapping. For example, if the system memory is 40, the tapped delay line would take 40 past inputs. A Volterra model with 10 Laguerre systems and 2^{nd} order nonlinearities would have 2^{10} coefficients what turning it practically unusable [4].

In this paper, we use nonlinear models consisting of a linear dynamic part followed by a nonlinear static map using input-output data. The linear dynamic system is initially spanned by a set of discrete Laguerre systems, and then cascaded with a single hidden layer Perceptron as depicted in Figure 2. In previous work [13], it was shown that a nonlinear combination of discrete Laguerre systems is able to approximate any single-input nonlinear discrete system having fading memory. The fading memory concept [10] is an important part of the characterization. After the initial span of the linear layer by Laguerre systems, a model reduction technique [14] is performed on the hidden nodes of the neural network as part of the identification process. The balancing is performed in such a way that the linear state-space representation is de-coupled by blocks. By doing so, it is possible not only to identify the main time constants, but also to reduce the dimensionality of the Perceptron input space. In addition, the non-controllable/non-observable modes are removed from the model. The final DABNet model (De-coupled A-B matrices Neural Network) consists of a sparse linear state-space system whose states, de-coupled by blocks, are mapped by a neural network. This de-coupled representation provides insight into the final model, because in a practical identification scheme, the individual state-space matrices can themselves be represented as loosely coupled first- and second-order sections.

This paper is organized as follows. In section 2 we present the model structure. In section 3, we apply the proposed model structure in the equalization of a nonlinear channel and we compare the results with a NFIR filters. Finally, we present our conclusions and the future work arising from this study.

2. NONLINEAR MODEL REPRESENTATION

DABNet models, depicted in Figure 2, are multi-input single-output systems but for clarity we will write the equations for single input single output (SISO) systems. The use of the Laguerre systems is very appealing due to their highly structured shape. As a consequence, computing the derivatives of a certain function of the output with respect to a sequence of inputs is simple. The output of a DABNet model for a SISO case with n Laguerre systems (with a basis pole a) and with H hidden neurons is expressed as:

$$y(k) = \boldsymbol{c}^T \boldsymbol{\eta}(k) \tag{1}$$

The vector $\boldsymbol{c}$ is made of output weights:

$$\boldsymbol{c} = [c_0, c_1, ..., c_H]^T \in R^{H+1} \tag{2}$$

where $\boldsymbol{\eta}(k)$ is the vector of outputs of the hidden layer

$$\boldsymbol{\eta}(k) = [1, \eta_1(k), ..., \eta_H(k)]^T, \qquad i:1,...,H \tag{3}$$

For any of the H hidden neurons, there exists a nonlinear sigmoidal mapping σ

$$\eta_i(k) = \sigma(\xi i(k)), \qquad i:1,...,H \tag{4}$$

applied to the pre-synaptic signals $\xi i(k)$. These signals are connected to the outputs of Laguerre systems through the weights of the input layer $\boldsymbol{w}_i$

$$\xi i(k) = w_{i0} + \boldsymbol{w}_i^T \boldsymbol{z}(k), \qquad i:1,...,H \tag{5}$$

The model is completed with the following description of the linear dynamic part, composed of a set of linear Laguerre systems whose states $\boldsymbol{x}(k) = (k) = [x_1(k), ..., x_n(k)]^T$, for the generating pole a, are given by:

$$\begin{aligned} x_1(k+1) &= a x_1(k) - \left(1-a^2\right)^{-1/2} u(k) \\ &\vdots \\ x_n(k+1) &= a x_n(k) + z_{n-1}(k) \end{aligned} \tag{6}$$

and their outputs:

$$\begin{aligned} z_1(k) &= \left(a^2-1\right) x_1(k) \\ &\vdots \\ z_n(k+1) &= \left(a^2-1\right) x_{j+1}(k) + a z_j(k) \end{aligned} \tag{7}$$

Let us now define a vector $\boldsymbol{\theta}$ containing all of the parameters: the output weights $\boldsymbol{c}$ and the input weights $\boldsymbol{w}_i$:

$$\theta = [c_0, c_1, ..., c_H, w_{10}, ..., w_{1n}, ..., w_{H0}, ..., w_{Hn}] \tag{8}$$

Using θ, the output of the system can be expressed as

$$y(k) = f(u(k), \boldsymbol{\theta}, k) \tag{9}$$

Given a certain system, we assume that the model and the system are realizations of the same structure but characterized by a different vector $\tilde{\boldsymbol{\theta}}$:

$$\tilde{y}(k) = f\left(u(k), \tilde{\boldsymbol{\theta}}, k\right) + \varepsilon(k) \tag{10}$$

where $\varepsilon(k)$ is noise, with variance σ_m^2. Then we have the following theorem.

Theorem: Let N be any time invariant operator with fading memory in a subset $\boldsymbol{K}$ of the input domain. Then, given any $\varepsilon > o$, there is a set of Laguerre operators and a single hidden layer Perceptron such that for all $\boldsymbol{u} \in \boldsymbol{K}$

$$\left\| N\boldsymbol{u} - \widetilde{N}\boldsymbol{u} \right\| \leq \varepsilon, \tag{11}$$

where $\widetilde{N}u = \tilde{y}(k)$, $Nu = y(k)$ are given by (10) and (9) respectively (for a proof see [13]).

DABNet models are simple to evaluate since they require very little dynamic information [13], are easy to implement because of they have highly structured form, and have simple derivatives formulation. The DABNet structure is used in the next section in a nonlinear echo cancellation application, in order to illustrate its modeling capabilities.

3. A NONLINEAR ECHO-CANCELLATION APPLICATION

This example presents a nonlinear echo cancellation in the near-end of a telephone system sketched in Figure 3, by using DABNet and NFIR filters. The near-end digital signal $r[k]$ is analog converted by the D/A converter to g_1 and shaped by the linear low-pass transmit filter H_1 to produce the signal $\widetilde{r}(t)$. The hybrid circuit separates $\widetilde{r}(t)$ from the received far-end signal $s(t)$, placing $\widetilde{r}(t)$ on the transmission line, while routing $s(t)$ through the linear filter H_2 and the S/H (sample and hold) device. Because of the "leakage" in the hybrid circuit (denoted by g_2), the near-end output $\widetilde{d}(t)$ contains contributions from both $s(t)$, and an attenuated echo term originating from $\widetilde{r}(t)$. The task of the echo canceler Σ is to estimate the echo component $d[k]$ and cancel it in the analog domain. Even though it is possible to perform the cancellation in the digital domain, the nonlinearity of the A/D converter at the signal $d[k]$ would create a nonlinear function of the sum of two signals, resulting into an intermodulation term that could not be canceled. This problem might arise if the attenuation g_2 through the hybrid path is as low as 10 dB, and the transmission-line attenuation of the far-end signal $s(t)$ is as high as 40 dB. The nonlinearities in data the converters (g_1, g_4), and in the hybrid circuit (g_2, g_3) limit the performance of the linear echo canceler to about 60 dB with 1% differential nonlinearity [10], [1].

Neglecting the effect of the far-end signal, the task of a nonlinear echo canceler would be to implement the system $g_4^{-1} \circ H_2(s) \circ g_2 \circ H_1(s) \circ g_1$. In the absence of hysteresis, it is clear that such a system has fading memory on any set of input sequences, and therefore, a DABNet model can be used to approximate Σ. In this example, the D/A converter transfer function g_1 and the hybrid transfer function g_2 were modeled as $g_1(u) = u^3$ and $g_2(u) = 2\tan^{-1}(5u) + .25u$ respectively. The transmit and receive filters H_1, and H_2 were modeled as linear systems with unit impulse response $h_1(q^{-1}) = .5276q^{-1}(1 + .4724q^{-1})^{-1}$ and $h_2(q^{-1}) = .1045q^{-1}(1 + .4724q^{-1})^{-1}$. Two situations were tested without attempting to optimize the models. a) A DABNet model with 4 Laguerre systems and a 6 neurons Perceptron, and a NFIR structure with 4 tap delayed inputs followed by a 6 neurons Perceptron. The results are shown on Figure 1. b) A DABNet model with 6 Laguerre systems and a 15 neurons Perceptron, and a NFIR structure with 6 tap delayed inputs followed by 15 neurons Perceptron. The results are shown on Figure 4. It is easy to see that in both cases the Perceptrons have the same number of inputs, and that the DABNet models outperformed the NFIR structures.

4. CONCLUSIONS

We have presented a general nonlinear digital filter structure for echo cancellation applications. We compared the DABNet with a nonlinear FIR structure. The results had shown that the nonlinear DABnet structure outperforms the nonlinear FIR filter in echo cancellation problems.

5. REFERENCES

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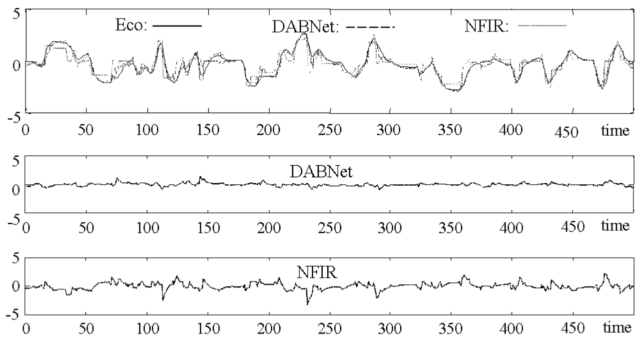

Fig. 1. 4 Tap/Laguerre Systems and 6 Neurons.

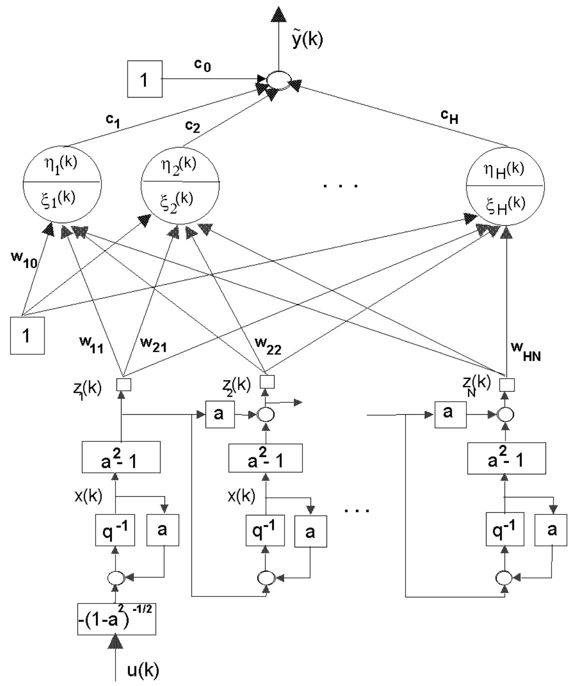

Fig. 2. DABNet Structure.

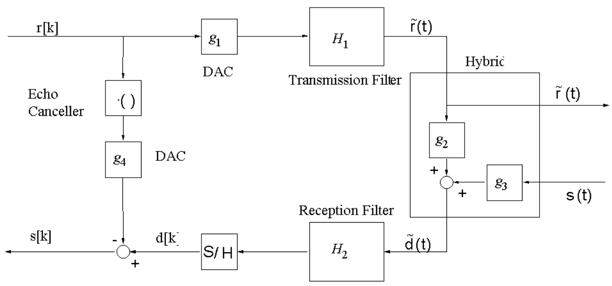

Fig. 3. Echo cancelling.

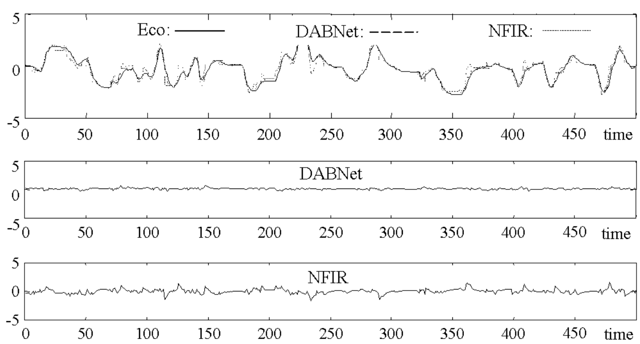

Fig. 4. 6 Tap/Laguerre Systems and 15 Neurons.