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NEURAL NETWORK APPROACH FOR ADAPTIVE NOISE CANCELLATION

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Adaptive filters have been used in wide range of signal processing applications because of its simplicity in computation and implementation. Various adaptive algorithms available are associated with high computational complexity when implemented practically. This paper discusses the adaptive noise cancellation problem and how the neural network can be applied for weight convergence. Adaptive filtering provides a nice tradeoff between complexity and convergence speed. The simulation results show that output error decreases with increase in number of iterations if back propagation approach is considered.

Keywords: Neural Network, Adaptive Filter, Backpropagation Technique.

1. Introduction

There are numerous techniques developed for digital filter design, both in frequency domain and in time domain. Most of these methods are analytical techniques. They work well with well-defined filter formats and the availability of accurate design data, such as the input and output of the filter. If the data set used to design filter is noisy, or there is a need for customization in the filter's representation the Neural Network based design technique [1] comes into the picture. The capability of neural networks as universal approximators has been extensively studied for system identification and modeling during the last two decades. Most of the proposed methods are based on two types of Neural Network architectures - back propagation and Hopfield recurrent neural network. However, most of these identification techniques result in NN weight matrices which do not necessarily correspond to the parameters of the original system. A novel NN architecture [1, 2] for design of recursive digital filters from input/output data in the state space form is presented. We use internal hidden neurons to encode the temporal properties of sequential inputs and outputs as the iterative states of the given process. The problem of adaptive noise cancellation has been implemented using NN approach.

2. Adaptive Noise Cancellation

An adaptive filter is a filter that self adjusts its transfer function according to an optimizing algorithm. Because of the complexity of optimizing algorithm most adaptive filters are digital filters that perform digital signal processing and adapt their performance based o the input signal. For some applications adaptive coefficients are required since some parameters of desired processing operation are not known in advance. In such situations adaptive filters [3,4] which uses feedback are used to refine the values of filter coefficients and hence its frequency response. Generally speaking, the adapting process involves the use of a cost function, which is a criterion for optimum performance of the filter (for example, minimizing the noise component of the input), to feed an algorithm, which determines how to modify the filter coefficients to minimize the cost on the next iteration. The error signal or cost function is the difference between the desired and the estimated signal.

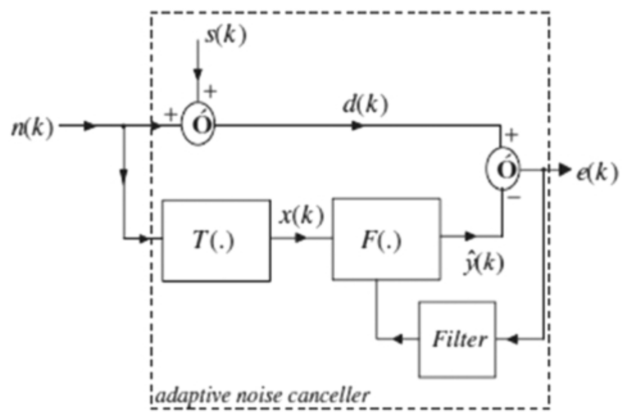

Fig. 1: Problem of Adaptive Noise Cancellation

A typical structure of a noise cancelation system is shown in figure 1 where additive noise, n(k), corrupts the information signal, s(k), resulting in the noise signal, d(k). The noise and information signals are assumed to be uncorrelated. The principle of noise cancelation is based on the assumption that both the noisy signal d(k), and a filtered or distorted measurement of the noise, named reference noise x(k), are available. Noise x(k) is considered to pass through a channel with a transfer function T(.)[5, 6].

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3. Neural Network Approach

Consider an NN consisting of p external input connections, q external output connections and N hidden units. The various neurons can be classified into three categories: input neuron set $u \in Rp$ denoted as I, hidden neuron set $x \in RN$ denoted as H, and output neuron set $y \in Rq$ denoted as O. At discrete time n, let u(n) denote the p x 1 input vector, x(n) denote the N x 1 vector as hidden neuron values, and $S_y(n)$ denote the q x 1 output vector of NN.

$$\underset{j\varepsilon 0}{R_i}(n) = \sum_{i\varepsilon HUI} w_{ji}(n)s_i(n) - d_j(n)$$

$$\underset{j\varepsilon H}{R_i}(n) = \sum_{i\varepsilon HUI} w_{ji}(n)s_i(n)$$

$$\underset{J\varepsilon HUO}{S_j}(n) = \Phi_k(r_j(n))$$

Where, $w_{ji}(n)$ is the weight between two neurons, $\Phi_k(.)$ denotes the activation functions for hidden neurons $\Phi_x(.)$ and output neurons $\Phi_y(.)$, $d_j(n)$ is the desired outputs value at time n. The on-line training objective is to minimize the mean-squared output of the NN at any instant discrete time n,

$$\varepsilon(n) = \tfrac{1}{2}\{\Sigma S^2_y(n)\}$$
$$y\varepsilon o$$

Where $\varepsilon(n)$ is the cost function

3.1 Weight Adjustment

A dynamic approach to minimize the cost function is to make the NN evolve its weight space along a trajectory that descends against the gradient of $\varepsilon(n)$[7,8]. This condition implies that for all $i \in H \cup O$ and $j \in H \cup I$

$$W_{ii}(n+1) = w_{ii}(n) + \Delta w_{ii}(n)$$

$$\Delta w_{ii}(n) = -\eta \;\; f\{\varepsilon(n)\}/f\{w_{ii}(n)\}$$

η is a learning rate which should be selected small enough to make weight change adiabatically and maintain the stability of the model [5]. Under the assumption that the inverse of the filter noise distortion can be estimated, the noise corrupting the signal can be identified and cancelled. In this perspective, the problem of noise cancelation [9] can be transformed to a system identification problem as follows.

Let F(.) denote the transfer function of the system. It is derived from figure 2

$$\hat{y}(k) = F(x(k)) = n(k) = \hat{T}^{-1}(x(k))$$

$$e(k) = d(k) - \hat{y}(k)$$

$$e(k) = s(k) + n(k) - \hat{y}(k)$$

$$e^2(k) = [s(k) + n(k) - \hat{y}(k)]^2$$

$$e^2(k) = s^2(k) + (n(k) - \hat{y}(k))^2 + 2s(k)\,(n(k) - \hat{y}(k))$$

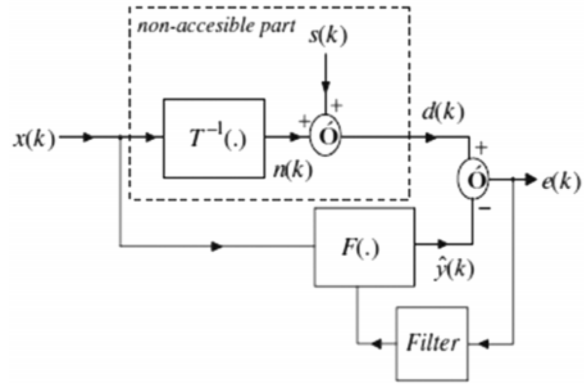

Fig.2: Adaptive Noise Cancellation as System Identification Problem

Let x(k), d(k) be considered as the desired input and output, respectively, of the system F(.). The error e(k) will correspond to the information signal, which can be regarded as noise, additive to the output of the system y^(k).

4. Results and Discussion

The pole zero plot of adapted IIR filter has been plotted in figure 3 using MATLAB. The largest pole radius obtained from plot is 0.926530. The mean squared output error has been obtained at each iteration in figure 4. The X-axis shows the number of iterations and the Y-axis shows the value of the error at that iteration. It is clear from graph that the error decreases as the number of iterations increases. The Figure 5shows the variation of the coefficient values at each iteration and it is observed coefficients converge in about 25000 iterations. The settling time of the filter depends on the pole radii, which is close to one for this example.

5. Conclusion

In this paper a novel neural network approach has been presented for adaptive noise cancellation problem. The simulated results show the pole zero plot of adapted filter. The variation in output error and filter coefficients with increase in iterations has been studied. In future neurofuzzy technique can be applied and variation in output error can be viewed using MATLAB.

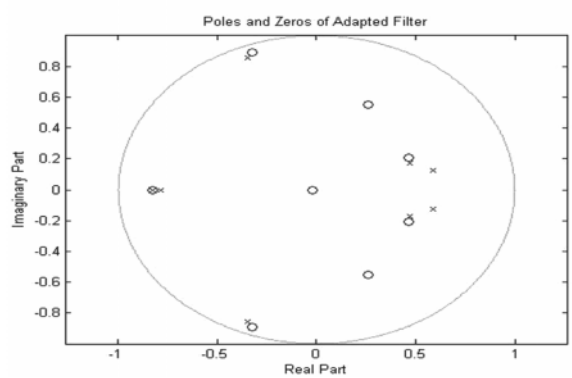

Fig.3: Pole Zero Plot of Adapted Filter

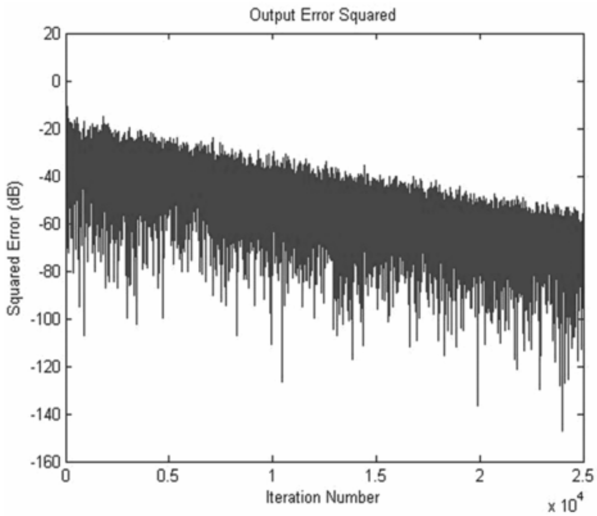

Fig. 4: Squared Error Plot

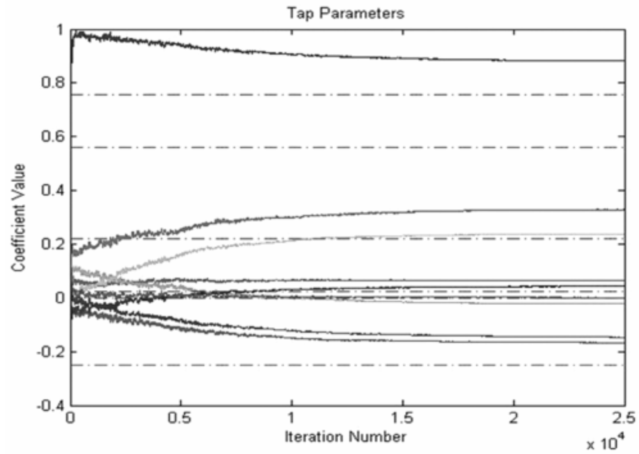

Fig.5: Tap Parameters Variation

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