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NEURO-ACTIVE NOISE CONTROL USING A DECOUPLED LINEAR/NONLINEAR SYSTEM APPROACH

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ABSTRACT

This paper presents an investigation into the development of an intelligent neuro-active noise control strategy which accounts for both linear and nonlinear dynamics of the system. Multi-layered perceptron neural networks with a backpropagation learning algorithm and radial basis function neural networks with an orthogonal forward regression algorithm are considered in both the modelling and control contexts. A feedforward active noise control (ANC) structure is considered for optimum cancellation of broadband noise in a three-dimensional propagation medium. An on-line adaptation and training mechanism allowing a neural network architecture to characterise the optimal linear controller and nonlinear system dynamics within the ANC system is developed. The neuro-adaptive ANC algorithm thus developed is implemented within a free-field environment and simulation results verifying its performance in the cancellation of broadband noise are presented and discussed.

Keywords: Active noise control, adaptive control, backpropagation, multi-layered perceptron networks, neural networks, orthogonal forward regression, radial basis function networks.

1. INTRODUCTION

Active noise control (ANC) consists of artificially generating cancelling source(s) to destructively interfere with the unwanted source and thus result in a reduction in the level of the noise (disturbance) at desired location(s). This is realised by detecting and processing the noise by a suitable electronic controller so that when superimposed on the disturbance cancellation occurs (Leitch and Tokhi, 1987). Due to the broadband nature of the noise, it is required that the control mechanism realises suitable frequency-dependent characteristics so that cancellation over a broad range of frequencies is achieved (Leitch and Tokhi, 1987). In practice, the spectral contents of the noise as well as the characteristics of system components are in general subject to variation, giving rise to time-varying phenomena. This implies that the control mechanism is further required to be intelligent enough to track these variations, so that the desired level of performance is achieved and maintained (Leitch and Tokhi, 1987; Tokhi and Leitch, 1991). Such a strategy can be devised through the development of neural network architectures within an adaptive control framework. There has been considerable work on devising various methodologies for active control of noise (Elliott *et al.*, 1987; Leitch and Tokhi, 1987; Snyder and Hansen, 1991; Tokhi and Leitch, 1991). However, little work has been reported on the development of intelligent methods incorporating neural networks for noise cancellation (Tokhi and Wood, 1996).

Considerable research interest in neural networks has been shown during the last decade in various applications. It has been demonstrated that neural networks can successfully be used to model non-linear system dynamics. Previous studies have further shown that neural networks can be used to solve nonlinear control problems (Lapedes and Farber, 1987; Narendra and Parthasarathy, 1990). Neural networks can also be used to approximate any function (Leshno, 1993). In this paper, a control strategy is developed within a decoupled linear/non-linear system framework. It is evidenced in previous studies that in an ANC system the characteristics of the transducers and electronic components used dominantly contribute to the non-linear dynamics of the system. This allows the explicit identification of linear and non-linear components within the ANC structure and development of the corresponding neuro-control strategy. Two alternative methods are proposed and verified in this paper on the basis of this strategy. The paper is presented as follows

Section 2 presents a brief outline of neural networks utilised in this work. Section 3 presents the ANC structure with the controller design relations and the neuro-control strategy. Section 4 presents several simulated exercises verifying the performance of the control strategy in the cancellation of broadband noise in a free-field medium. The paper is finally concluded in Section 5.

2. NEURAL NETWORKS

There are many different classes of artificial neural network models. Among these the multi-layered perceptron (MLP) and radial basis function (RBF) networks are commonly used in the modelling and control of dynamic systems. An MLP network is made up of sets of nodes arranged in layers corresponding to the input layer, the output layer and several hidden layers. The structure of an RBF neural network is similar to that of an MLP network, except that the network consists of only a single hidden layer.

Neural network models attempt to achieve good performance through the process of adapting the weight connections of the neurons through the process of learning. The learning process can be described as an optimisation problem. Theoretical investigations have rigorously proved that multi-layered neural networks can uniformly approximate any continuous function (Hornik *et al.*, 1989). This potential of neural networks is exploited in this work at the development of a neuro-adaptive active control mechanism for broadband cancellation of noise.

In an MLP network the output of each node, except those in the input layer, is computed as a non-linear function of the weighted sum of its inputs. The network commonly uses the backpropagation training algorithm to adapt the connection weights. The backpropagation training algorithm is a gradient search (steepest descent) method which adjusts the weights so that application of a set of inputs produces the desired outputs. An advanced backpropagation algorithm is utilised in this investigation (Tokhi and Wood, 1996). The algorithm uses a better initialisation of the weights and biases which drastically reduce the training time (Nguyen and Widrow, 1990). Moreover, an adaptive learning rate is employed which helps the network avoid local error minima.

An RBF expansion provides a mapping that can be implemented in a two-layered neural network structure. In this manner, the first layer performs a fixed non-linear transformation which maps the input space onto a new space. The output layer implements a linear combiner on this new space. Therefore, the RBF expansion can be viewed as a two-layered neural network which has the important property that it is linear in the unknown parameters. Therefore, the problem of determining the parameter values is reduced to one of a linear least squares optimisation. Since RBF expansions are linearly dependent on the weights, a globally optimum least squares interpolation of non-linear maps can be achieved. An orthogonal forward regression algorithm is utilised in this work to train the network (Tokhi and Wood, 1996).

3. NEURO-ACTIVE NOISE CONTROL

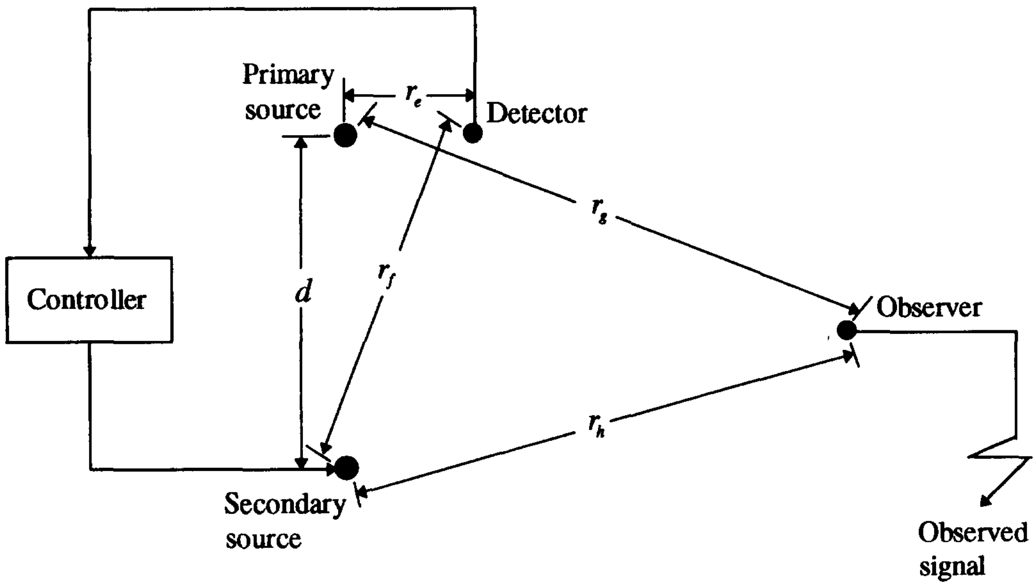
3.1 Control structure

A schematic diagram of the ANC structure is shown in Figure 1(a). An unwanted (primary) point source emits broadband noise into the propagation medium. This is detected by a detector, processed by a controller of suitable transfer characteristics and fed to a cancelling (secondary) point source. The secondary signal thus generated is superimposed on the primary signal so that to achieve cancellation of the noise at and in the vicinity of an observation point. A frequency-domain equivalent block diagram of the ANC structure is shown in Figure 1(b), where E, F, G and H are transfer characteristics of the acoustic paths through the distances r_e, r_f, r_g and r_h respectively. M, C and L are transfer characteristics of the detector, the controller and the secondary source respectively. U_D and U_C are the primary and secondary signals at the source locations whereas Y_{OD} and Y_{OC} are the corresponding signals at the observation point respectively. U_M is the detected signal and Y_O is the observed signal.

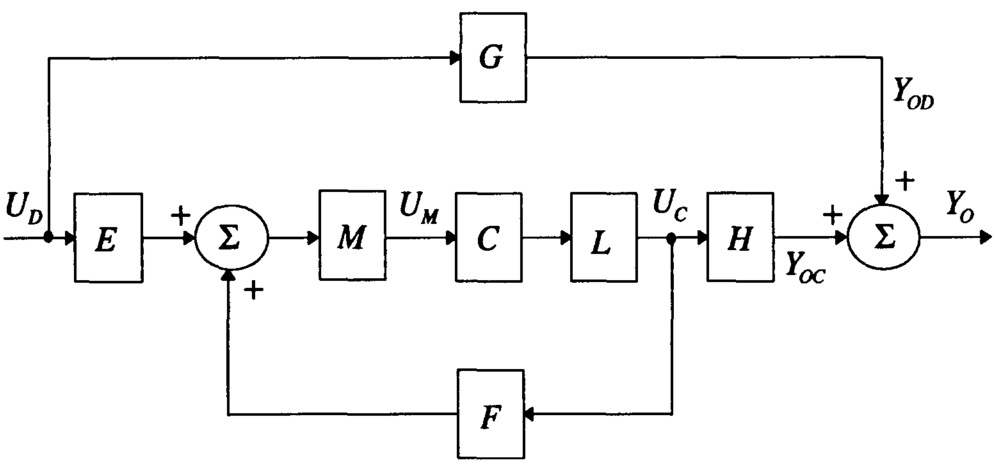
The objective in Figure 1 is to force Y_O to zero. This requires the primary and secondary signals at the observation point to be equal in amplitudes and have a phase difference of 180° relative to each other. Thus, synthesising the controller within the block diagram of Figure 1(b) on the basis of this objective yields

$$C = \frac{G}{ML(FG - EH)} \tag{1}$$

This is the required controller transfer function for optimum cancellation of broadband noise at the observation point.



(a) Schematic diagram.



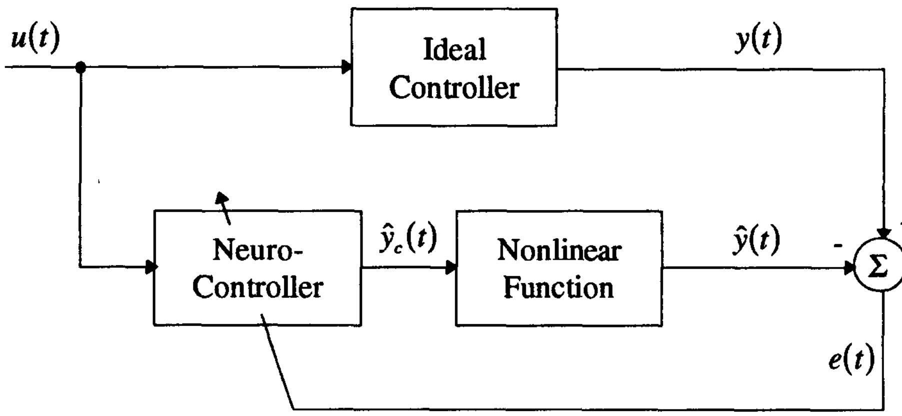
(b) Block diagram.

Figure 1: Active noise control structure.

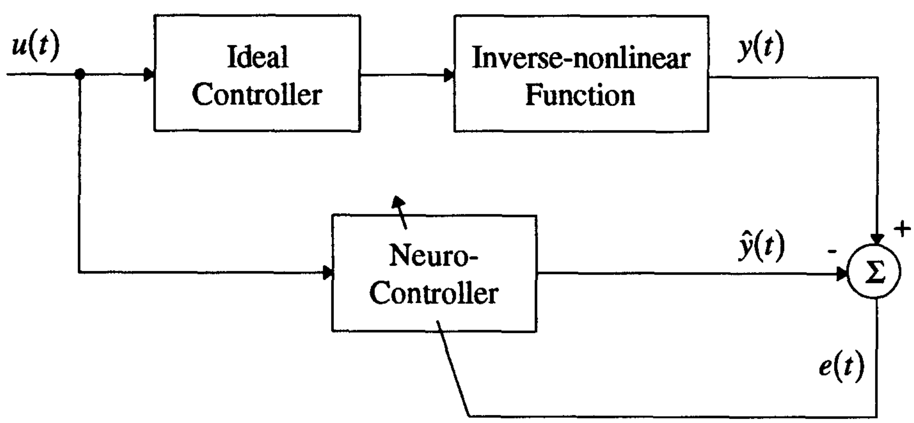
3.2 Training and adaptation

The dominant non-linear dynamics in an ANC system can be thought as those present within the characteristics of transducers and electronic components used. These characteristics in general take the form of an (amplitude) limiting transformation; that is, the input/output transformation is linear up to a certain input signal level and reaches saturation (non-linear behaviour) beyond this level. Note in the ANC structure shown in Figure 1 that the detector, secondary source and associated electronics are all in cascade with one another. This allows the nonlinear dynamics present in these components to be lumped together as a single function, f_n, in cascade with the controller.

To achieve cancellation of the noise at the observation point, the controller in an ANC system is principally required to compensate for the characteristics of the system components in the secondary path so as to result in 180° phase difference of the secondary signal relative to the primary signal at the observation point. This compensation for the detector, secondary source and their associated electronics, as noted in the design relation in equation (1), appear inversely. This implies that, for optimum cancellation to be achieved at the observation point, the controller is, additionally required to compensate for the non-linear function f_n. Thus, to develop a neuro-adaptive ANC strategy, two alternative schemes namely direct function learning (DFL) and inverse function learning (IFL) are proposed. These are schematically outlined in Figure 2, where 'ideal controller' represents the characteristics in equation (1) corresponding to linear dynamic characteristics of the system. In this process, the linear and nonlinear dynamics of the system can be estimated/measured by exciting the system with small signal and large signal levels accordingly.



(a) Direct function learning.



(b) Inverse function learning.

Figure 2: Neuro-ANC learning schemes incorporating nonlinear dynamics.

It follows from Figure 2(a) that realisation of the DFL requires a characterisation of the nonlinear function f_n. This can, in practice, be achieved by driving the detector (microphone) and secondary source (loudspeaker) in cascade as a unit, with an acoustic separation between them, by a signal of large enough amplitude to drive the unit into its non-linear dynamic range, and training a neural network to characterise the unit. This will result in a neural network emulator characterising the nonlinear function f_n. Note in this process that, the characteristics of the acoustic path between the loudspeaker and the microphone will not dominantly affect the characteristic behaviour of the non-linear dynamics of the unit. In this manner, the direct nonlinear function emulator (DNFE) can be used to represent the nonlinear function f_n in Figure 2(a) and thus train the neuro-controller accordingly. The neuro-controller thus obtained can be used within the ANC system in Figure 1 for broadband cancellation of noise at the observation point.

It follows from Figure 2(b) that realisation of the IFL scheme requires a suitable characterisation of the inverse nonlinear function f_n^{-1}. This can be achieved in a similar manner as above by training a neural network to the inverse of f_n. This will result in an inverse nonlinear function emulator (INFE). The neural network INFE thus obtained can be used within the IFL scheme of Figure 2(b), replacing the inverse non-linear function block, to train the required neuro-controller. The neuro-controller thus obtained can be used within the ANC system in Figure 1 for broadband cancellation of noise at the observation point.

In selecting the topology of the neural networks, it is assumed that the output of the plant is a non-linear function of the present and past outputs and inputs of the plant. This means that the input vector to the network consists of both the inputs and outputs of the plant.

4. IMPLEMENTATION AND RESULTS

To verify the neuro-ANC algorithm a simulation environment characterising a free-field medium was created using experimentally measured data. A tansigmoid function was incorporated within the simulation environment to represent the nonlinear dynamics, f_n, of the system. The characteristics of the ideal controller were measured and used within the schemes in Figure 2 to train the neuro-controller accordingly. A $0-500$ Hz PRBS signal, of sufficient amplitude exciting the full range of f_n, was used as the broadband primary noise within the ANC structure in Figure 1.

The DFL scheme was realised with MLP networks. The IFL scheme, on the other hand, was realised with MLP as well as RBF networks. The neuro-controllers thus obtained were implemented within the ANC system and their performances were measured at the observation point. Figure 3 shows the performance of the system with the MLP neuro-controller trained according to the DFL scheme. Figure 4 shows the performance of the system with the MLP and RBF neuro-controllers trained according to the IFL scheme. It is noted that in each case an average level of above 35 dB cancellation is consistently achieved over the broad frequency range of the noise with the neuro-ANC system.

5. CONCLUSION

A neuro-active control mechanism for broadband cancellation of noise has been presented and verified through simulation exercises. The active control system developed has incorporated on-line modelling of the ideal controller and training of the neuro-controller using a decoupled linear/nonlinear system strategy. Two alternative methods, namely, the direct function learning and inverse function learning schemes have been proposed. Both MLP and RBF networks have been utilised in realising the neuro-controller. The neuro-control strategies thus developed have been verified within an ANC structure in a free-field environment. It has been shown that significant levels of performance is achieved in the cancellation of broadband noise with the neuro-controller thus developed.

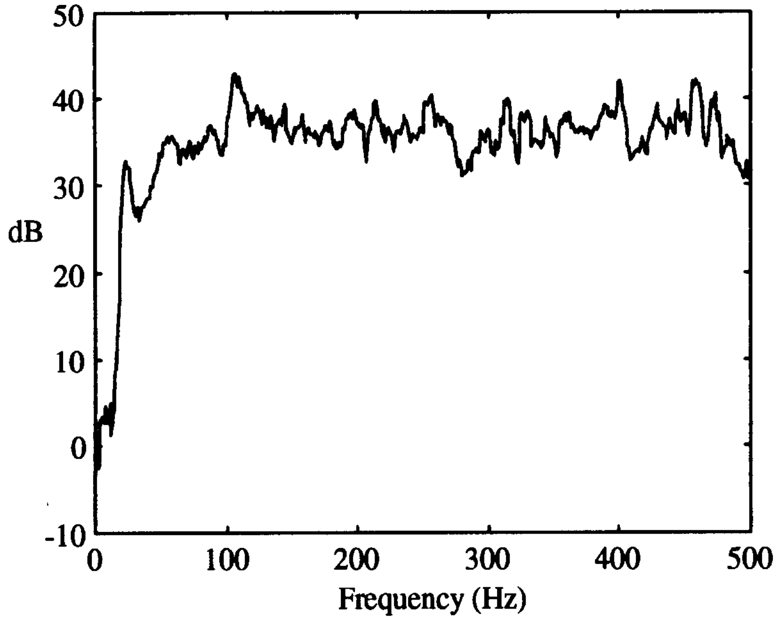


Figure 3: Cancelled spectrum with the MLP neuro-controller (DFL scheme).

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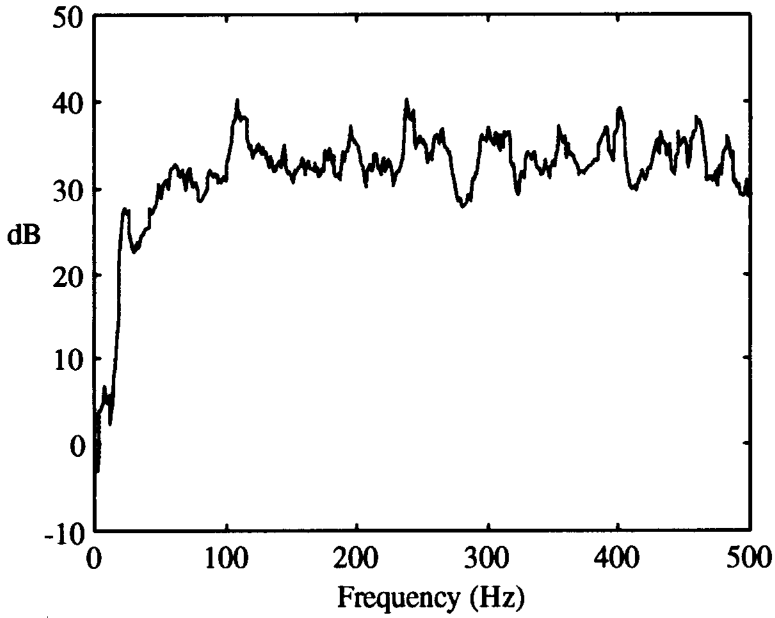
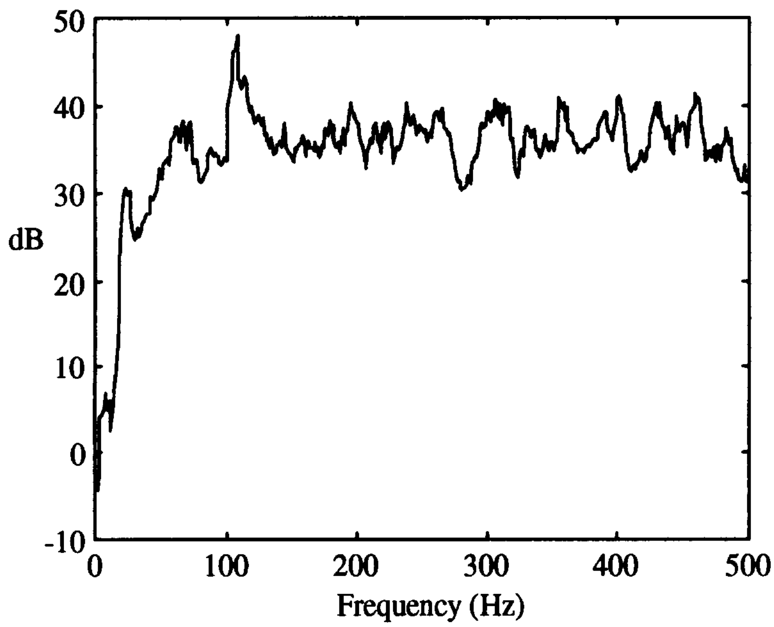


(a) With MLP neuro-controller.



(b) With RBF neuro-controller.

Figure 4: Cancelled spectrum using IFL scheme.

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