Proceedings of the Institute of Acoustics

ACTIVE CONTROL OF NOISE USING NEURAL NETWORKS

M O Tokhi and R Wood

Department of Automatic Control and Systems Engineering, The University of Sheffield, UK.

1. INTRODUCTION

Active noise/vibration control 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/vibration (disturbances) at desired location(s). This is realised by detecting and processing the noise/vibration by a suitable electronic controller so that when superimposed on the disturbances cancellation occurs [1]. Due to the broadband nature of these disturbances, it is required that the control mechanism realises suitable frequency-dependent characteristics so that cancellation over a broad range of frequencies is achieved [1]. In practice, the spectral contents of these disturbances 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 [1, 2].

This paper presents an investigation into the development of a neuro-active control mechanism for broadband noise cancellation and vibration suppression. A neural network architecture based on a backpropagation learning algorithm is developed and its performance in characterising dynamic behaviour of systems with non-linearities is investigated and verified. An 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 the neural network architecture to characterise the ideal (optimal) controller within the ANC system is developed. The neuro-adaptive active control algorithm thus developed is implemented within a simulation environment characterising the ANC structure and its performance investigated. Finally, simulated results verifying the performance of the algorithm in the cancellation of broadband noise in comparison to the corresponding optimal controller are presented and discussed.

2. NEURAL NETWORKS

A typical structure of a neural network is shown in Figure 1. This is made up of sets of nodes arranged in layers corresponding to the input layer, the output layer and several hidden layers. 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 non-linear function frequently used in a backpropagation neural network, for instance, is the hyperbolic-tangent sigmoidal function.

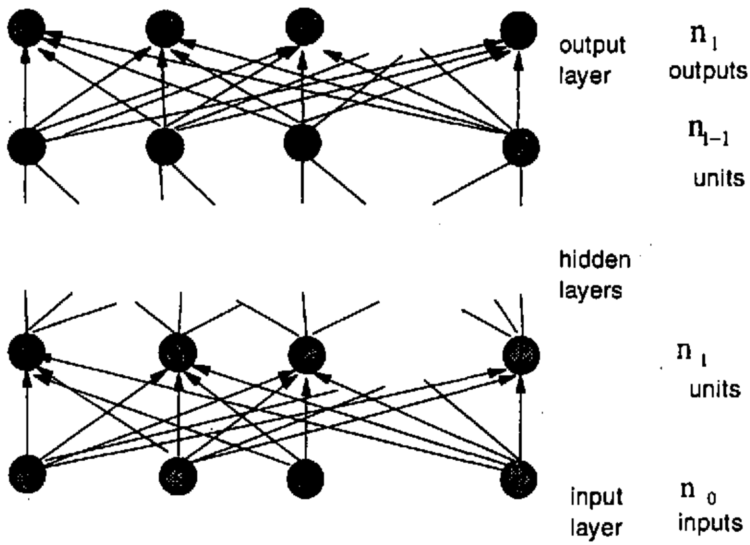


Figure 1: Typical neural network structure.

There are many types of neural networks and training algorithms used. Among them, the backpropagation algorithm is the most commonly applied to control problems. A set of training data inputs is given to the network which propagate through the neuron layers to give an output prediction. The error between this prediction and the required output is used to adjust the gradient information which is back-propagated through the network to change the weights connecting the neurons. 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. It is also dependent on the user selectable parameters to the extent that if an inappropriate combination of the learning rates and momentum constants are chosen the algorithm performs badly. However with the use of better initial conditions and the adaptive learning rate epoch the run time can drastically be reduced.

An advanced backpropagation algorithm is utilised in this investigation. The algorithm uses a better initialisation of the weights and biases [3] which drastically reduce the training time. Moreover, an adaptive learning rate is employed [4] which helps the network avoid local error minima. As a result of using both of these methods together the training time is reduced by a factor of over 60. Weight correction in the new algorithm is the same as for the backpropagation algorithm. The kth correction of the weights is described as

$$\Delta w(k) = -\eta \frac{\partial E}{\partial w}(k-1) + \alpha \Delta w(k-1) \tag{1}$$

where, E is the total error between the required output (training data) and the actual output, expressed as

$$E = \frac{1}{2}\sum_{p}\sum_{i}(t_{pi} - o_{pi})^2 \tag{2}$$

t_{pi} represents the target output for pattern p on node i, o_{pi} represents the actual output at node i, η and α are the learning and momentum constants. The first term in equation (1) indicates that the weights are corrected in proportion to the gradient $\frac{\partial E}{\partial w}$. The second term is added to accelerate the training.

3. NEURO-ACTIVE NOISE CONTROL

A schematic diagram of the geometrical arrangement of a feedforward ANC structure is shown in Figure 2. An unwanted (primary) point source emits broadband noise into the propagation medium. This is detected by a detector located at a distance r_e relative to the primary source, processed by a controller of suitable transfer characteristics and fed to a cancelling (secondary) point source located at a distance d relative to the primary source and a distance r_f relative to the detector. 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 located at distances r_g and r_h relative to the primary and secondary sources respectively.

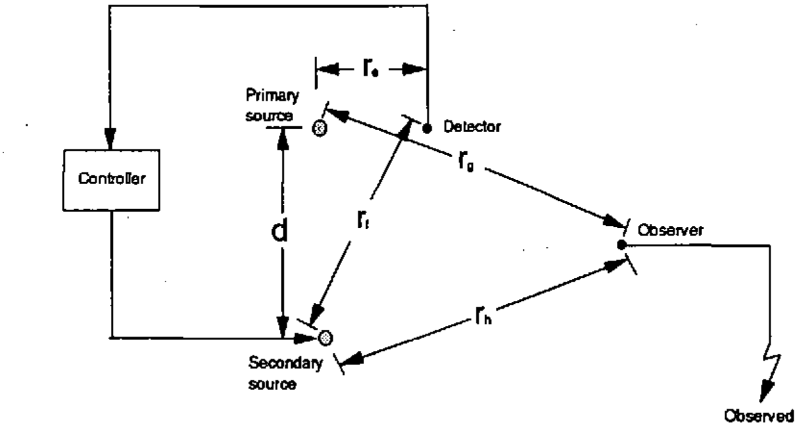
A frequency-domain equivalent block diagram of the ANC structure is shown in Figure 2(b), where E, F, G and H are transfer functions of the acoustic paths through the distances r_e, r_f, r_g and r_h respectively. M, M_o, C and L are transfer characteristics of the detector, the observer, the controller 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 block diagram in Figure 2(b) can be thought of either in the continuous frequency (s) domain or the discrete frequency (z) domain. Therefore, unless specified, the analysis and design developed in this paper apply to both the continuous-time and the discrete-time domains.

The objective in Figure 2 is to force Y_O to zero. This is equivalent to the minimum variance design criterion in a stochastic environment. This requires the primary and secondary signals at the observation point to be equal in amplitudes and have a phase difference of 180^0 relative to each other. Thus, synthesising the controller within the block diagram of Figure 2(b) on the basis of this objective yields

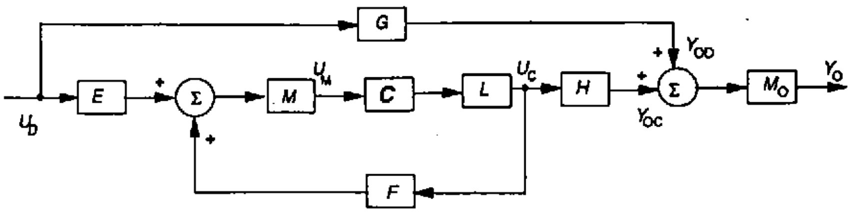
$$C = \frac{G}{ML(FG - EH)} \tag{3}$$

Equation (3) is the required controller transfer function for optimum cancellation of broadband noise at the observation point.

In practice, the characteristics of sources of noise vary due to operating conditions leading to time-varying spectra. Moreover, the characteristics of transducers, sensors and other electronic equipment used are subject to variation due to environmental effects, ageing, etc. To design an ANC system so that the controller characteristics are updated in accordance with these changes in the system such that the required performance is achieved and maintained, a self-tuning control strategy, allowing on-line design and implementation of the controller, can be utilised.



(a) Schematic diagram.



(b) Block diagram.

Figure 2: Active noise control structure.

Consider the system in Figure 2 as a single-input single-output system with the detected signal, U_M, as input and the observed signal, Y_O, as output. Moreover, owing to the state of the secondary source let the system behaviour be characterised by two sub-systems, namely, when the secondary source is *off*, with an equivalent transfer function denoted by Q_0, and when the secondary source is *on*, with an equivalent transfer function denoted by Q_1. Using the block diagram of Figure 2(b), these can be obtained and manipulated to yield an equivalent design relation for the controller in terms of Q_0 and Q_1 as [2]

$$C = \left[1 - \frac{Q_1}{Q_0}\right]^{-1} \tag{4}$$

Equation (4) is the required controller design rule given in terms of transfer characteristics Q_0 and Q_1 which can be measured/estimated on-line. To allow for the non-linearities due to characteristics of system components be accounted for an on-line design and implementation of a neuro-controller can be devised. This can be achieved by *(a)* obtaining the actual frequency responses of Q_0 and Q_1 using on-line measurement of input/output signals, *(b)* using equation (4) to obtain the corresponding frequency-response of the ideal controller and *(c)* training a neural network structure to characterise the ideal controller and implementing the neuro-controller on a digital processor. Moreover, to monitor system performance and update the neuro-controller upon changes in the system a supervisory level control can be utilised. This will result in a neuro-self-tuning ANC mechanism, as shown in Figure 3, where, 'plant' is the system in Figure 2 between the detection point and the observation point.

To develop an ANC controller based on neural networks, the topology of the network must be selected (input vectors and neuron assignment). The process of selecting the right topology for the network is not exact, as there are no concrete rules regarding this. Generally, the topology is selected in an intuitive manner. The process is similar to the model order is selection in a traditional linear identification process. 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 X to the network consists of both the inputs, u, and outputs, y, of the plant;

$$X(k) = [y(k),\ y(k-1), \ldots,\ y(k-n);\ u(k),\ u(k-1), \ldots,\ u(k-n)]^T \tag{5}$$

During the training process this will help the network learn more easily. For modelling the ideal ANC controller an input vector of the form

$$X(k) = [y(k-1),\ y(k-2),\ y(k-3),\ u(k),\ u(k-1),\ u(k-2)]^T \tag{6}$$

is used in this investigation. Following the process of structure selection, a neural network controller is required to be trained to characterise a particular behaviour. One method is to use a conventional controller for the system to produce the training set. The inputs and their corresponding outputs of the conventional controller become the training pairs for the neural

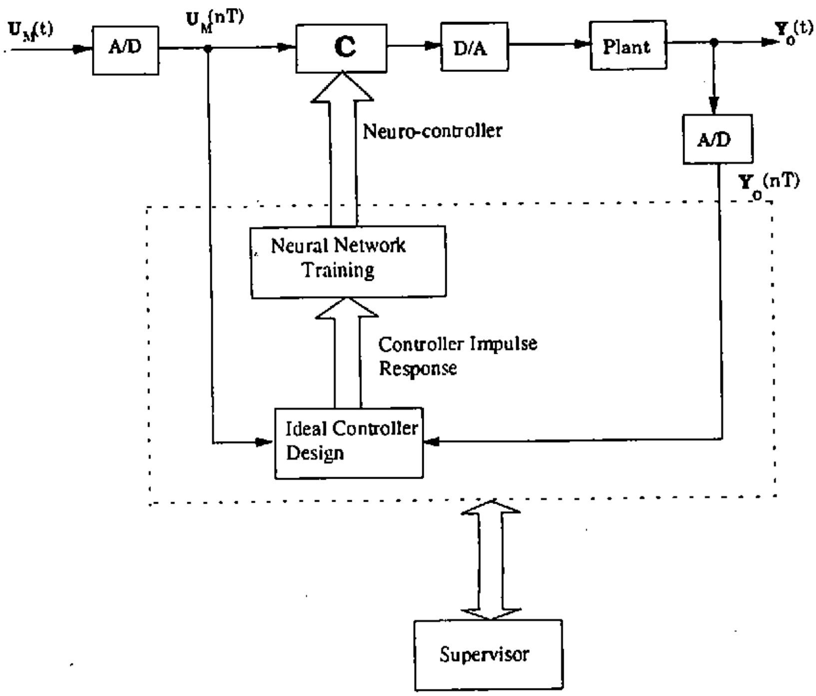


Figure 3: Neuro-self-tuning controller.

network. In this investigation, the training data is obtained from the ideal controller. The ideal controller is, thus, modelled by a neural network controller, using the input/output data pattern. The network is trained using the advanced backpropagation algorithm where the parameters (weights and biases) are updated until the output error becomes sufficiently small or convergence to a suitable minimum error is reached.

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 0-512 Hz PRBS signal was used as the broadband primary noise within the ANC structure in Figure 2. The characteristics of the ideal controller were measured and used to train the neural network according to the procedure outlined in the previous section. Figure 4 shows the output of the neural network (predicting) the output of the ideal controller (target) after the training process. It is noted that the error between the two outputs is reasonably small. To investigate this further, the performance of the ANC system was monitored at the observation point with the ideal controller and with the neuro-controller. Figure 5 shows the performance of the system with the ideal controller, where G_{ppo} and G_{cco} are the autopower spectral densities of the noise before and after cancellation respectively and their difference, $G_{ppo} - G_{cco}$, is the cancelled spectrum. It is noted that an average cancellation of around 20 dB is achieved with the ideal controller. Theoretically, the amount of cancellation achieved with the ideal controller should be infinity. However, due to finite processor wordlength and computational errors the maximum cancellation is limited to this level within the computing platform used. Figure 6 shows the performance of the ANC system with the neuro-controller. It is noted that an average level of around 20 dB cancellation is achieved with the neuro-controller. This is similar to the performance achieved with the ideal controller, demonstrating the significance of the neuro-controller in performing as good as the ideal (optimal) controller in the active control of noise and vibration.

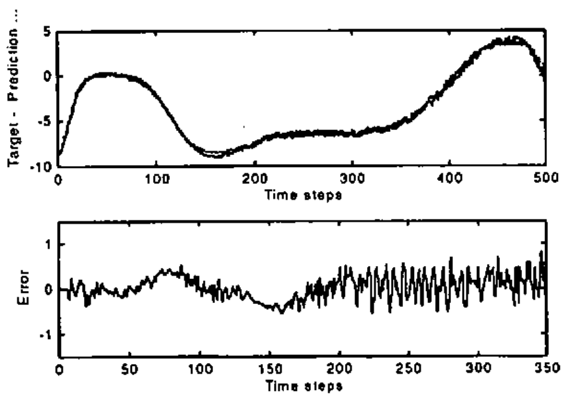
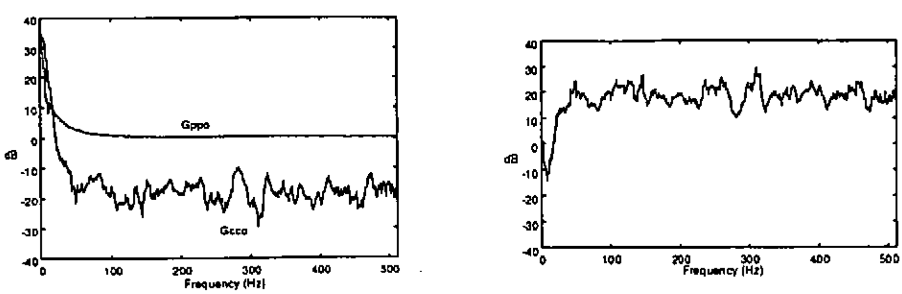


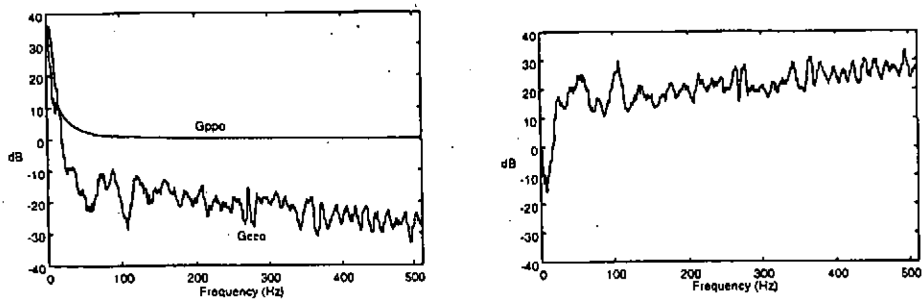
Figure 4: Output of the ideal controller as predicted by the neuro-controller.



(a) Spectra before and after cancellation.

(b) Cancelled spectrum.

Figure 5: Performance of the ANC system with the ideal controller.



(a) Spectra before and after cancellation. (b) Cancelled spectrum.

Figure 6: Performance of the ANC system with the neuro-controller.

5. CONCLUSION

A neuro-adaptive active control mechanism for broadband noise cancellation and vibration suppression has been presented, discussed and verified through simulation experiments. The active control system developed incorporates on-line modelling of the ideal (optimal) controller using a backpropagation neural network learning algorithm and a self-tuning control strategy allowing for updating the neuro-controller under time-varying conditions in the system. The neuro-control strategy thus developed has been verified within an ANC structure in comparison to the optimal controller. It has been shown that a performance as good as the optimal controller is achieved with the neuro-controller.

6. REFERENCES

[1] R R Leitch & M O Tokhi, 'Active noise control systems', IEE Proceedings-A, **134**, pp. 525-546 (1987)

[2] M O Tokhi & R R Leitch, 'Design and implementation of self-tuning active noise control system', IEE Proceedings-D, **138**, pp. 421-430 (1991)

[3] D Nguyen & B Widrow, 'Improving the learning speed of 2-layer neural networks by choosing initial values of the adaptive weights', Proceedings of the International Joint Conference on Neural Networks, **3**, pp. 21-26 (1990)

[4] T P Vogel et.al, 'Accelerating the convergence of the backpropagation method', Biological Cybernetics, **59**, pp. 257-263 (1988)