Modeling and Experiment of an Active Noise Control Based on the Radial Basis Function Neural Network

Lifei JIANG
Tangshan Teacher's College, Tangshan city, Hebei province, China, 063000
Email: *jianglifei*1977@163.*com*

Abstract: Now in an active noise control system the adaptive controller is based on the linear theory; however the research shows that the characteristics of practical noises are more nonlinear. In order to trace the timing-varying noise, an active noise control model based on the radial basis function neural network is proposed. Experimental study shows that as a local and whole conjunction neural network the radial basis function neural network can be trained very quickly, and can overcome the shortcomings of local minimum pole in BP networks. Experimental results prove that the model is feasible and effective and the average effect of cancelling noise is up to 10dB in the frequency range from 100–490Hz.

Keywords: model; experiment; active noise control; the radial basis function neural network

1 Introduction

With the people's growing awareness of the environmental protection, vehicle noise has become an important vehicle performance. In China's automobile industry development plan, it has been taken into account as one of the major problems to improve vehicle's ride comfort.

Interior noise comes from engine noise, intaking and exhausting gas noise, and chassis noise. These noises pass into the driver's cab through the air and the structure. Among of them 800 Hz or more higher-frequency noise passes through the air, while the 400 Hz or the lower-frequency noise passes through the structure. Experimental studies have shown that a closed vehicle compartment play a larger role to the external noise, so the noise through the air passing has little effect in the driver's cab. Therefore, the lower-frequency noise is primary in the enclosed driver's cab.

2 The Principle of Active Noise Control[1]

The traditional noise control methods are passive methods, such as changing the device structure, adding sound absorption or sound insulation materials, and which has good effect of noise cancelling on the high frequency noise , but the effect on the low frequency noise is not satisfactory. The method of active noise control has good results with low frequency noise.

Active noise control is based on the theory of elimination and interference or inhibition of two sound wave, by artificially generating a controlling sound source (secondary source), which brings the sound wave equal to the amplitude and opposite to the phase of the original noise source (primary source). When the two sound waves affect each other, the purpose of noise reduction is achieved.

3 The Model of the Adaptive Active Noise Control Based on the Radial Basis Function Neural Network

Now the design of the adaptive controller is more based on linear control theory, but the sound system more manifests the nonlinear features and so the nonlinear controller research is necessary. In the following an adaptive active noise control system based on RBF network is to be given.

3.1 The Structure of the RBF Neural Network

RBF network is a single hidden layer feedforward network based on the knowledge of local regulation and overlap acceptance of bio-regions .The network structure is shown in Figure 1.

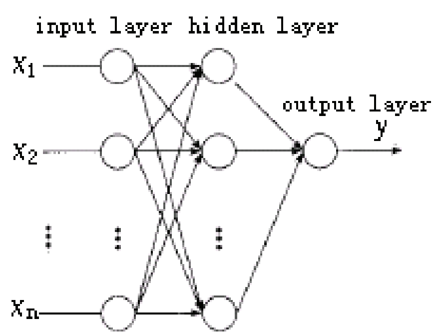

Figure 1. The mode of RBF network

The input layer nodes only pass the input signal to the hidden layer. The hidden layer nodes work as the Gaussian function and the output layer nodes are usually a simple linear function. It is a fully connected network, and it is of simple structure, fast training and can ap-

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proximate any nonlinear function, so it has been widely used.

3.2 The Model of the Active Noise Control Based on the Radial Basis Function Neural Network

Block diagram for the model of the active noise control based on the radial basis function neural network see Figure 2.

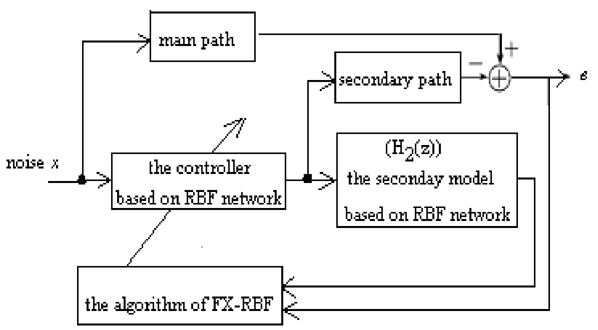

Figure 2. The model of the active noise control based on RBF network

The active noise control (ANC) system consists of the main path and the secondary path. Take the measured signal from noise resource as the main path input and at the same time deliver it to the controller. After the delay the self-adapting controller's output will get superposition with the main path output, and then the error signal e is gained. According to making it approaching zero, self-adapting controller adjust its weights to gain the active noise control.

3.3 Modeling on the Secondary Path

To realize the self-adapting active noise control, the transfer function $H_2(z)$ of the secondary path is needed. The secondary model based on the radial basis function neural network is shown in Figure 3. *Xo(n)* is the output of the controller , *y(n)* is the real control signal output and z^{-1} is the delay links.

The off-line training method is taken when training the model of $H_2(z)$. For the more detail , please see [3] .

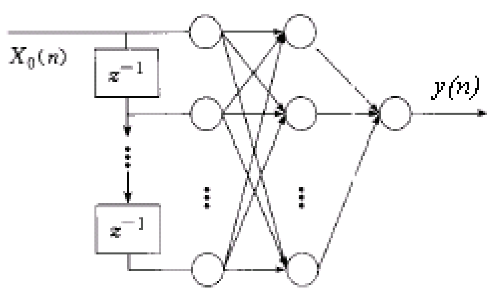

Figure 3. The secondary model based on the radial basis function neural network

3.4 Modeling on the Controller Based on the Radial Basis Function Neural Network

Besides the secondary path, the other model is the controller model, which is the core of the adaptive active noise control. The controller model see figure 4. *x(n)* is the input noise signal, *Xo(n)* is the controller output and z^{-1} is the delay links.

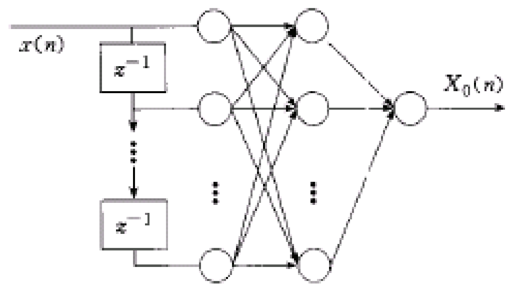

Figure 4. The controller of the active noise control based on RBF network

The control signal will directly decide the effectiveness of the noise cancelling. Because the noise feature is always changing, and the isolated output and input data can't have a real reflection of the object's feature, so we need to train the model on-line and get the variable structure based on RBF neural network.

In the training the variable structure controller based on RBF neural network need amend three parameters: the radial basis function center, width, and the linear output layer weights. Aiming at intuitive adjustment the width of RBF, the width value δ is 0.08326, for more detail information, please see [4]. The vector $X(n)=\{x(n),x(n-1),...,x(n-k+1)\}$ is k rank input signal, the vector C_J (k dimension) ($J=1,2,...,L_1$) is the radial basis function center, The vector $W=\{w_1,w_2,...w_{L1}\}$ is the output layer weighs. The value d_{bar} is the threshold value of the input samples, and the value e_{bar} is the threshold value of the system error. The controller's training algorithm as follows[5] (training the RBF network which include one neuron in the hidden layer, $L_1=1$)

Step 1, calculate the interval between the input vector $X(n)$ and the radial basis function center C_J

$d_{\min}(n)=\min\{\|X(n)-C_J(n-1)\|\}$ ($1\le J\le L_1$), if $d_{\min}(n)<d_{bar}$, take the $d_{\min}(n)$ value's neuron as the winning neuron, then go to step 2. If $d_{\min}(n)=d_{bar}$ and the system error $e\ge e_{bar}$, the trained network should include one new neuron in the hidden layer. Its initialization is:

$L_1=L_1+1$, $C_{L_1}(n)=X(n)$, $w_{L_1}(n)=e(n)$, then go to step 3. If $d_{\min}(n) \geq d_{bar}$ and the system error $e < e_{bar}$, the system error e can be compensated by other neurons in neural network, and it is not necessary to include a new neuron, and directly go to step 3.

Step2, amend the winning neuron $C_{win}(n) = C_{win}(n-1) + \alpha(n)[X(n) - C_{win}(n-1)]$, ($\alpha(n)$ is a decreasing function, and the initialized value approaches to one, then trends to zero).

Step 3, calculate the output of the controller, $X_0(n) = W(n)X_1(n)$, then it drive the secondary speaker. At the same time amend the linear output weight W.

$$W(n) = W(n-1) + \beta H_2(n) X_1(n) e$$

($X_1(n)$ is the controller's output vector of the hidden layer, $0 \leq \beta \leq 1$), then go to step 1 until satisfy the control request.

4 The Experiment on the System[2]

Using the high speed digital signal processor ADSP-2111, combined with the variable structure controller based on the radial basis function neural network, an experiment on cancelling noise is carried out. The noise sensor is laid on the front of the primary sound source and the distance is 0.05 meters .And the error sensor is laid on the front of the secondary sound source and the distance is 0.5 meters. The block shows in Figure 5 and the effect of noise cancelling see the Table 1.

5 Conclusions

Using the high speed digital signal processor ADSP-2111, combined with the variable structure controller based on the radial basis function neural network, an experiment on cancelling noise is carried out. During the experiment it is found that the position of the noise source and sensor can take affection to the effect of noise canceling. The narrower of the noise frequency band, the better effect we get. According to the result, the effect we get less than 400Hz, the max amount can be 20dB and it reaches our goal. But when the frequency is higher than 450Hz, because the signal is changing very fast and the algorithm slow iteration, the result is not good. So, to satisfy the real-time control request, a deeper research of algorithm on rapidity and robustness is needed.

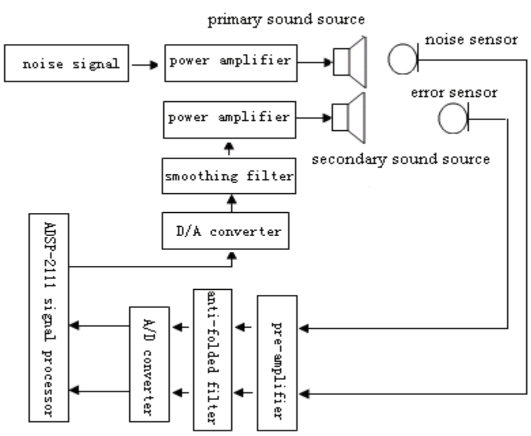

Figure 5. The block of the experiment

Table 1. The effect of noise cancelling

frequency (Hz)	before noise cancelling (dB)	after noise cancelling (dB)	noise reduction (dB)
100	76.099	72.339	3.76
110	78.380	73.639	4.74
120	76.589	69.960	6.63
130	82.250	77.269	4.98
140	82.599	78.809	3.79
150	78.220	69.900	7.32
160	80.599	67.589	12.97
170	80.620	64.639	15.98
180	85.419	80.669	4.75
190	86.000	66.260	19.74
200	80.199	64.870	15.25
210	83.724	61.751	21.97
220	83.356	61.185	22.17
230	77.699	60.665	17.03
240	79.195	61.815	17.38
250	83.644	71.543	12.10
260	82.019	62.800	19.22
270	82.080	62.291	19.79
280	84.490	73.125	11.37
290	83.224	67.105	16.12
300	84.132	72.588	11.54
310	84.985	69.866	15.12
320	82.866	67.355	15.51
330	83.765	66.359	17.41
340	83.188	68.526	14.66
350	83.168	70.125	13.14
360	84.285	72.558	11.73
370	82.375	70.058	12.32
380	78.995	67.840	11.16
390	79.995	70.006	9.99
400	80.775	73.965	6.81
410	78.678	69.358	9.32
420	78.005	71.032	6.97
430	79.386	74.245	5.14
440	76.895	74.004	2.89
450	77.458	75.324	2.13
460	77.332	72.995	4.34
470	74.005	72.995	1.01
480	77.095	74.886	2.21
490	76.876	74.985	1.89

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