Hindawi Publishing Corporation
EURASIP Journal on Advances in Signal Processing
Volume 2007, Article ID 41679, 7 pages
doi:10.1155/2007/41679

Research Article

Duct Modeling Using the Generalized RBF Neural Network for Active Cancellation of Variable Frequency Narrow Band Noise

Hadi Sadoghi Yazdi,[1] Javad Haddadnia,[1] and Mojtaba Lotfizad[2]

[1] *Engineering Department, Tarbiat Moallem University of Sabzevar, P.O. Box 397, Sabzevar, Iran*
[2] *Department of Electrical Engineering, Tarbiat Modarres University, P.O. Box 14115-143, Tehran, Iran*

Received 27 April 2005; Revised 1 February 2006; Accepted 30 April 2006

Recommended by Shoji Makino

We have shown that duct modeling using the generalized RBF neural network (DM_RBF), which has the capability of modeling the nonlinear behavior, can suppress a variable-frequency narrow band noise of a duct more efficiently than an FX-LMS algorithm. In our method (DM_RBF), at first the duct is identified using a generalized RBF network, after that N stage of time delay of the input signal to the N generalized RBF network is applied, then a linear combiner at their outputs makes an online identification of the nonlinear system. The weights of linear combiner are updated by the normalized LMS algorithm. We have showed that the proposed method is more than three times faster in comparison with the FX-LMS algorithm with 30% lower error. Also the DM_RBF method will converge in changing the input frequency, while it makes the FX-LMS cause divergence.

1. INTRODUCTION

In the recent years, acoustic noise canceling by active methods, due to its numerous applications, has been in the focus of interest of many researches. Contrary to the passive method, it is possible using the active method to suppress or reduce the noise in a small space particularly in low frequencies (below 500 Hz) [1, 2]. Active noise control was introduced for the first time by Paul Lveg in 1936 for suppressing the noise in a duct [3]. In the active control method by producing a sound with the same amplitude but with opposite phase, the noise is removed. For this purpose, the amplitude and phase of a noise must be detected and inverted. The developed system must have the adaptive noise control capability [3]. In usual manner, an FIR filter is used in ANC whose weights are updated by a linear algorithm [4, 5]. Using the linear algorithm of LMS is not possible due to the nonlinear environment of the duct and the appearing of the secondary path transfer function $H(z)$. Hence, the FX-LMS algorithm is presented in which the filtered input noise $x'(n)$ is used as an input to the algorithm [6, 7]. The notable points in ANC are as follows.

(i) The duct length and the distance between the system elements are such that the system becomes causal [8].

(ii) Regarding the speaker response, no decrease will be obtained in frequencies below 200 Hz [2]. Also passive techniques for reducing the noise in frequencies below 500 Hz have not been successful [1, 2]. Therefore, the ANC systems are used in the range of 200 to 500 Hz and above 500 Hz.

The existence of nonlinear effects in ANC complicates the use of the linear algorithm FX-LMS and similar algorithms. Divergence or slow convergence is among these difficulties. For this purpose, identification systems with a nonlinear structure are used where a neural network is among these solutions [9–11]. The radial basis function (RBF) networks are used in processing temporal signals for radar [12], in the predictor filter in position estimation from present and past samples [13], and in adaptive prediction and control [14, 15]. Buffering data, feedback from the output of the system, and state machines are used in modeling temporal signals. In time delay RBF neural networks, also, by buffering data [16], and using the feedback from the output in the recurrent RBF (RRBF) [17], this work is accomplished.

In the present work a new structure with the generalized RBF neural network is presented whereby a linear combination of the outputs of N neural networks causes a time varying nonlinear system being modeled. Samples $x(n)$ to

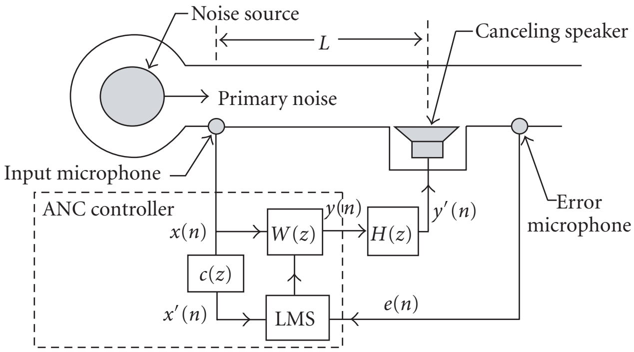


Figure 1: Using the FX-LMS algorithm in a single channel ANC system.

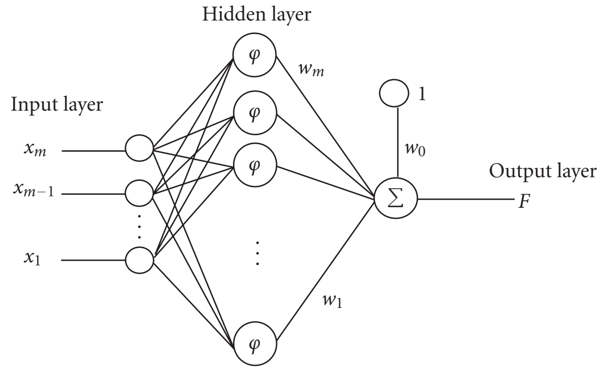


Figure 2: Structure of an RBF network.

$x(n-N+1)$ are fed to N generalized RBF neural networks and then the linear combination of their outputs is used for canceling the acoustic noise inside a duct. For precise simulation of the proposed algorithm and comparison to the conventional FX-LMS method, the transfer function of the primary path (the duct transfer function) and the secondary path must be available, which for this purpose, the information given in [18] which is obtained practically is utilized.

Section 2 of this paper concerns the investigation of the active noise control in a duct and the FX-LMS algorithm. Section 3 contains a short review of the RBF and generalized RBF neural networks. In Section 4, the proposed system and its application in ANC are presented and in Section 5 the conclusions are presented.

2. PRINCIPLE OF ACTIVE NOISE CONTROL IN A DUCT

If we assume the noise propagates in a one-dimensional form, then it is possible to use a single channel ANC for noise cancellation. For simulation and implementation of this system, a narrow duct is used as in Figure 1. According to Figure 1, the primary noise before reaching to the speaker is picked up by the input microphone. The system uses the input signal for generating the noise canceling signal $y(n)$. The generated sound by the speaker gives rise to a reduction in the primary noise. The error microphone measures the remaining signal $e(n)$ which can be minimized using an adaptive filter which is used for identifying the duct's transfer function. Because of using the input and error microphones, we must consider some functions which are known as the secondary path effects. In such a system, usually for canceling the noise, the FX-LMS algorithm, Figure 1, and (1) are considered [1, 19–21]. The vector $x'(n)$ is a filtered copy of the vector $x(n)$.

$$W_{n+1} = W_n - \mu e_n X'_n, \tag{1}$$

where e_n is the residual signal and $W_n = [w_n(1), w_n(2), \ldots, w_n(M)]^T$ is the weight vector of the estimator of length M.

In Figure 1, the $c(z)$ is an estimation of $H(z)$ which can be obtained by some offline techniques [22]. The considerable points in the execution the FX-LMS are the following.

(i) Canceling the broadband noise needs a filter of high order which increases the duct length [22].
(ii) In order to choose the proper stepsize, we need the knowledge of statistical properties of the input data [23, 24].
(iii) To ensure the convergence, the stepsize is chosen small; hence the convergence speed will be low and the performance will be weak.
(iv) For executing the above algorithm, we need to estimate the secondary path.
(v) This algorithm is only applicable to a linear controller and is not either suitable for nonlinear controllers or it is slow. For modeling the nonlinear behavior of this system, neural networks can be employed.

3. THE RBF NEURAL NETWORKS

The RBF networks usually have three layers as shown in Figure 2. The first layer comprises the input nodes, the second layer, which is a hidden layer, includes a nonlinear transformation, and the third layer includes the output layer. The output in terms of the input is given by

$$F_j(x) = \sum_{i=1}^{r} w_{ij}\varphi_i(\|x - c_i\|, \delta_i), \tag{2}$$

where $F_j(x)$ is the response of the jth neuron in the input feature vector x and W_{ij} is the value of the interconnection weight between the ith neuron in the RBF layer and the jth neuron in the output layer. $\|x - c_i\|$ represents the Euclidean distance and φ_i is the stimulation function of the ith neurons in the RBF layer which is also called the kernel. The kernel can be chosen as a simple norm or a Gaussian function or any other suitable function [25]. In practice it is chosen as a Gaussian function which in this case F is a Gaussian mixture function and each neuron in the RBF layer is identified by the two parameters center c_i and width δ_i.

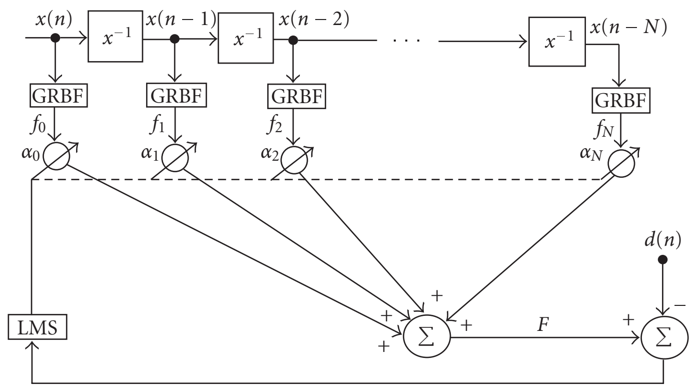


Figure 3: Structure of the proposed method.

3.1. The generalized RBF neural network

In this paper, the generalized neural network is used for modeling the duct. In this type of RBF, the $\varphi_i(x)$ function is computed as [25]

$$\varphi_i(x) = G(\|x - c_i\|) = \exp\left(-\frac{1}{2}(x - c_i)^T \sum{}^{-1}(x - c_i)\right), \tag{3}$$

where $\sum$ is the covariance matrix of the input data and c_i are the centers of the Gaussian functions. The optimum weight vector is obtained as

$$W = (G^T G)^{-1} G^T d, \tag{4}$$

where d is the desired value and G is the Green function which for k inputs x_1 to x_k and Gaussian centers $c = [c_1, \dots, c_m]$, its Green Function is as follows:

$$G = \begin{bmatrix} G(x_1, c_1) & G(x_1, c_2) & \cdots & G(x_1, c_m) \\ G(x_2, c_1) & G(x_2, c_2) & \cdots & G(x_2, c_m) \\ \vdots & \vdots & & \vdots \\ G(x_k, c_1) & G(x_k, c_2) & \cdots & G(x_k, c_m) \end{bmatrix}, \tag{5}$$

where x_k is the kth learning sample.

4. THE PROPOSED ALGORITHM

The time delay neural network presented in this paper includes N stages which are illustrated in Figure 3. At first, the duct is identified by the generalized RBF, GRBF, and then the results are combined by a linear adaptive filter such as LMS. Because of changing space with GRBF, obtaining error will be less than input space or the MSE at Φ-space is smaller than the input space; so we expect LMS has had smaller error without converting space. This subject has been proved in the appendix.

The relation between the output and the input is given in

$$F = \sum_{j=0}^{N} \alpha_j \cdot f_j(x(n-j)),$$
$$F = \sum_{j=0}^{N} \left(\alpha_j \sum_{i=1}^{m} w_i G(\|x(n-j) - c_i\|)\right), \tag{6}$$

where N is the number of the delayed input signal samples and m is the number of the used kernels in the generalized RBF network. w_is are obtained from (4) and α_js are updated with LMS algorithm according to

$$A_{n+1} = A_n - 2\mu \cdot Y_n \cdot e_n, \tag{7}$$

where $A_n = [\alpha_n(1), \alpha_n(2), \dots, \alpha_n(N)]^T$, $Y_n = [f_n(1), f_n(2), \dots, f_n(N)]^T$, and e_n is the system error which is obtained from subtracting the system output, F from the desired value of the signal, d_n at instant n. In noise reduction problem, and d_n is the primary noise which reaches the excitation speaker.

4.1. Applying the proposed algorithm in active noise canceling

The present network is used to active noise cancel as in Figure 4. At instant two points are interested in the proposed system as

(a) deletion of secondary path estimation $c(z)$,
(b) learning the transfer function of GRBF and the linearity of active noise control system using this idea.

In the next subsections duct modeling and noise cancellation are explained.

4.2. Duct system function identification

We begin first by identifying the duct with the GRBF and the proposed system and then compare them. Equation (3) is found by fuzzy k-means clustering. In this problem, 4 centers are used. Therefore, 4 Gaussian functions are obtained. Equation (3) is also rewritten in the form of (8). The

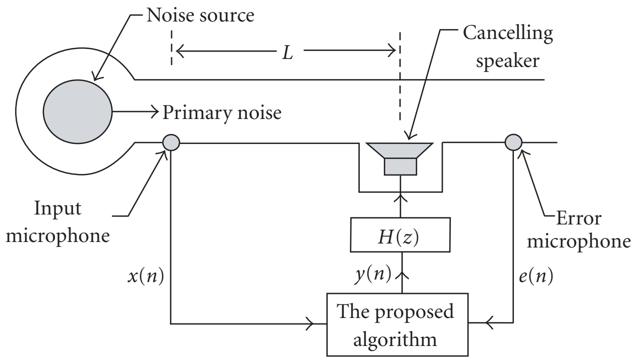


FIGURE 4: A structure for noise canceling in a duct by the proposed method.

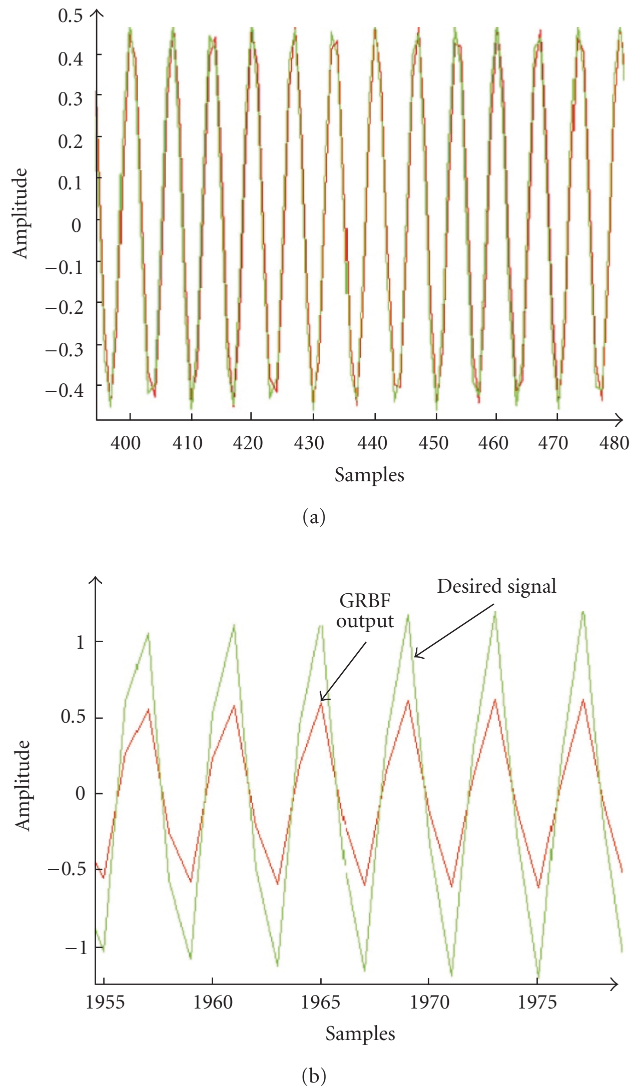


FIGURE 5: Part of the GRBF output and duct output in response to a sinusoidal chirp signal with a variable frequency (a) 300 to 305 Hz, (b) 200 to 500 Hz.

Gaussian kernels of the GRBF function are computed using (9), (4.2).

$$\varphi_i(x) = G\left(\|x - c_i\|\right) = \exp\left(-\frac{1}{2\sigma_i}\left(\|x - c_i\|^2\right)\right), \quad (8)$$

$$\sigma_i = \sqrt{\frac{\sum_{m=1}^{k_1}(x_m - c_i)^2}{k_1 - 1}}, \quad (9)$$

$$x_m = \{x_k \mid \mu_{ik} > \mu_{jk},\ j=\{1,2,\ldots,r\} - \{i\},\ k=\{1,\ldots,N\}\}, \quad (10)$$

where μ_{ik} is the degree of membership of the patterns x_k to the ith group and μ_{jk} is the degree of membership to the jth group. In (4.2), the samples whose degrees of membership to the ith group are more than other centers are attributed to that cluster and their standard deviations are considered as the Gaussian kernel standard deviation. The result of executing the generalized RBF on a sinusoidal chirp signal with a variable frequency of 300 to 305 Hz is shown in Figure 5. As shown in Figure 5(a), the output and the desired value in response to the narrow band signal has lower error, but this network is not able to learn the duct output in the broadband spectrum of the input signal of Figure 5(b), while the proposed algorithm gives better results.

Two networks are compared in Figure 6. The error norm of the proposed algorithm compared to the GRBF in duct identification is improved 94%. Hence, in identifying a system, the proposed system can be utilized. Several reasons can be mentioned for superiority of this system relative to the GRBF as follows.

(a) Using a filter bank instead of filter.
(b) Using N buffered samples of data instead of a single stream of data.
(c) General and local consideration of data, that is, buffered data.
(d) Increasing the network capacity by increasing the α coefficient.

4.3. *Active noise cancellation using the proposed algorithm*

After identifying the duct with the GRBF network, we proceed canceling the noise in the duct by the structure presented in Figure 3. The learning curve of the execution result on variable chirp sinusoid of 300–305 Hz for the proposed network in comparison to the FX-LMS algorithm is given in Figure 7.

For this purpose, first the duct is identified by the generalized RBF for excitation frequencies of 200 to 500 Hz, then αs are calculated in the proposed network by the normalized LMS (NLMS) algorithm. Higher convergence speed and lower error for the proposed algorithm in comparison to the FX-LMS algorithm in Figure 7 are observed. On average, the convergence speed has been increased 3 times and the final MSE minimum error is decreased 30%.

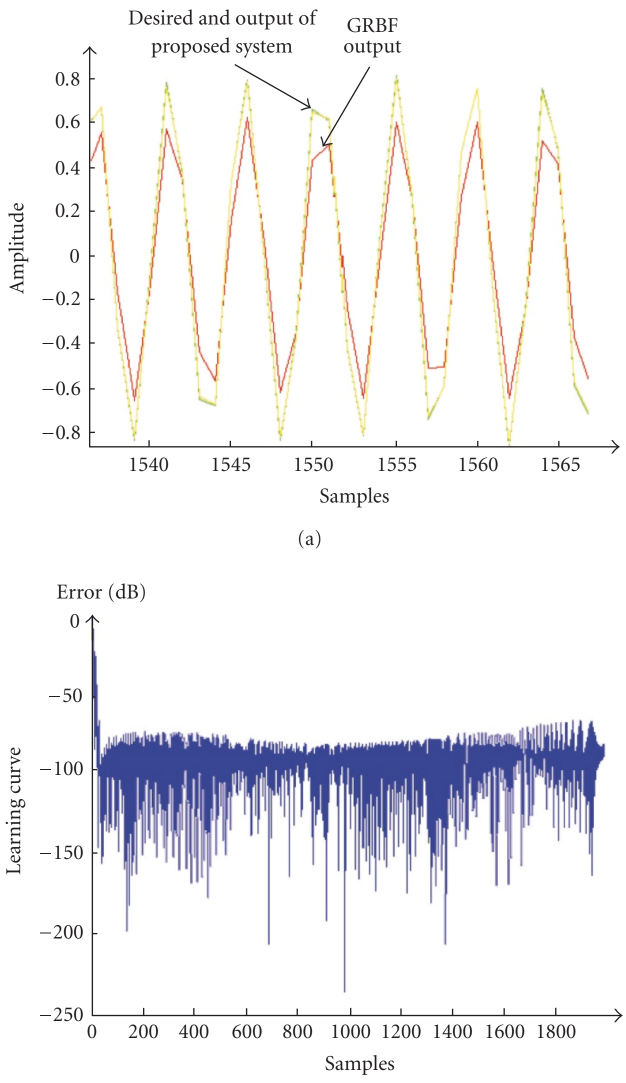


Figure 6: (a) Comparison of the RBF network output and the proposed algorithm in identifying the duct in response to a sinusoidal chirp input of variable frequency 200–500 Hz. (b) The learning curve of the proposed algorithm in duct identification.

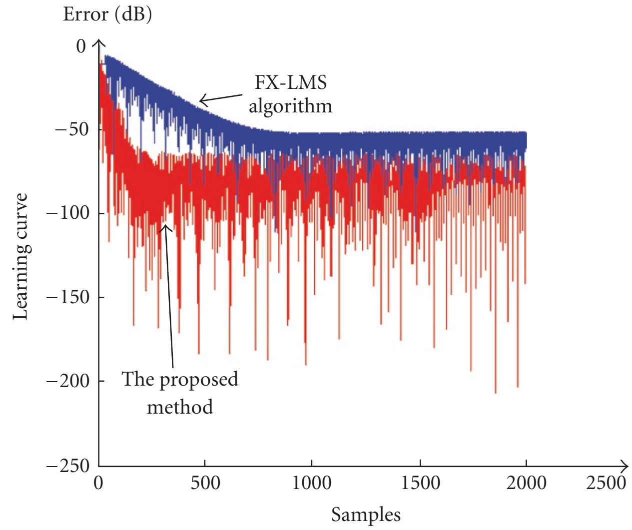


Figure 7: The learning curve to sinusoidal chirp with variable frequency of 300 to 305 Hz for the proposed system and the FX-LMS algorithm.

5. CONCLUSIONS

The process of canceling the acoustic noise in a duct has a nonlinear nature. Therefore, linear adaptive filters such as LMS are not able to actively cancel the noise. Due to the good tracking capability of the LMS filter in a noisy environment, the FX-LMS has been presented as a basic method in ANC which models some what the nonlinear nature of the duct. In this paper, by modeling the duct using the generalized RBF neural network, it is possible to suppress the narrow band variable frequency noise in the duct in a better way than the FX-LMS method. The proposed method in comparison to the FX-LMS algorithm is more than three times faster and has 30% less error. Also, the change in the input frequency causes the divergence, which the proposed method converges as well.

In the proposed method, first the duct is identified by the GRBF neural network and using a linear adaptive combiner at their outputs, online identification of the nonlinear system becomes possible. The weights of the linear combiner are updated using the normalized LMS algorithm.

APPENDIX

Theorem A.1. *Assume that* $\mathrm{MSE}_i = E\{e^2\}$ *is the mean-square error in the input space, then the* MSE *at* Φ*-space will be smaller than the input space.*

Proof. the mapping is according to

$$Y = \Phi(X), \tag{A.1}$$

where $\Phi(X) = [\varphi(x, c_1), \varphi(x, c_2), \ldots, \varphi(x, c_K)]$ and we can assume that $\varphi(x, c_i) = \exp(-(x - c_i)^2/2\sigma^2)$. In simple form we can write $\varphi(x, c_i) = \exp(-x^2)$. By substituting $e(k) = x_m(k) - x(k)$ in $\varphi(x, c_i)$, $x_m(k)$ is the actual state of the signal, then we have

$$\begin{aligned}\varphi(x(k), c_i) &\\ &= \exp\left(-x(k)^2\right) = \exp\left(-\left(x_m(k) + e(k)\right)^2\right)\\ &= \exp\left(-x_m(k)^2\right)\exp\left(-e_m(k)^2\right)\exp\left(-2e_m(k)x_m(k)\right).\end{aligned} \tag{A.2}$$

Assuming $e_m(k)$ is small enough, we can betake $\exp(-e_m(k)^2)$ term. Also we know that $\exp(-x_m(k)^2)$ is the desired output in each dimension at the Φ-space. For simplification, we substitute $y = \varphi(x(k), c_i)$, thus we have

$$y = y_m \exp\left(-2e_m(k)x_m(k)\right), \tag{A.3}$$

where $y_m = e(-x_m(k)^2)$. The Taylor series expansion of term $\exp(-2e_m(k)x_m(k))$ is

$$\exp\left(-2e_m(k)x_m(k)\right) \cong 1 - 2e_m(k)x_m(k),$$
$$y = y_m - 2e_m x_m y_m = y_m - 2e_m x_m e^{-x_m^2} = y_m - \alpha e_m. \tag{A.4}$$

The term $\alpha = 2x_m e^{-x_m^2}$ is always smaller than one, or $e_\Phi = \alpha e_m$, thus we have

$$\begin{aligned} \mathrm{MSE}_\Phi &= E\{e_\Phi^2\} = \alpha^2 E\{e^2\}, \\ \mathrm{MSE}_\Phi &= \alpha^2\,\mathrm{MSE}_i . \end{aligned} \tag{A.5}$$

The above equation shows that $\mathrm{MSE}_\Phi < \mathrm{MSE}_i$ or "MSE *in* Φ*-space is smaller than* MSE *in the input space.*" □

REFERENCES

[1] S. M. Kuo and D. R. Morgan, "Active noise control: a tutorial review," *Proceedings of the IEEE*, vol. 87, no. 6, pp. 943–973, 1999.

[2] L. J. Eriksson, M. C. Allie, and R. A. Greiner, "The selection and application of an IIR adaptive filter for use in active sound attenuation," *IEEE Transactions on Acoustics, Speech, and Signal Processing*, vol. 35, no. 4, pp. 433–437, 1987.

[3] L. J. Eriksson and M. C. Allie, "System considerations for adaptive modelling applied to active noise control," in *Proceedings of IEEE International Symposium on Circuits and Systems (ISCAS '88)*, vol. 3, pp. 2387–2390, Espoo, Finland, June 1988.

[4] M. Bouchard and Y. Feng, "Inverse structure for active noise control and combined active noise control/sound reproduction systems," *IEEE Transactions on Speech and Audio Processing*, vol. 9, no. 2, pp. 141–151, 2001.

[5] S. J. Elliott and P. A. Nelson, "Active noise control," *IEEE Signal Processing Magazine*, vol. 10, no. 4, pp. 12–35, 1993.

[6] D. R. Morgan, "An analysis of multiple correlation cancellation loops with a filter in the auxiliary path," *IEEE Transactions on Acoustics, Speech, and Signal Processing*, vol. 28, no. 4, pp. 454–467, 1980.

[7] J. C. Burgess, "Active adaptive sound control in a duct: a computer simulation," *Journal of the Acoustical Society of America*, vol. 70, no. 3, pp. 715–726, 1981.

[8] B. Rafaely, J. Carrilho, and P. Gardonio, "Novel active noise-reducing headset using earshell vibration control," *Journal of the Acoustical Society of America*, vol. 112, no. 4, pp. 1471–1481, 2002.

[9] M. Bouchard, B. Paillard, and C. T. Le Dinh, "Improved training of neural networks for the nonlinear active control of sound and vibration," *IEEE Transactions on Neural Networks*, vol. 10, no. 2, pp. 391–401, 1999.

[10] L. S. H. Ngia and J. H. Sjoberg, "Efficient training of neural nets for nonlinear adaptive filtering using a recursive Levenberg-Marquardt algorithm," *IEEE Transactions on Signal Processing*, vol. 48, no. 7, pp. 1915–1927, 2000.

[11] S. D. Snyder and N. Tanaka, "Active control of vibration using a neural network," *IEEE Transactions on Neural Networks*, vol. 6, no. 4, pp. 819–828, 1995.

[12] T. Wong, T. Lo, H. Leung, J. Litva, and E. Bosse, "Low-angle radar tracking using radial basis function neural network," *IEE Proceedings F: Radar and Signal Processing*, vol. 140, no. 5, pp. 323–328, 1993.

[13] N. E. Longinov, "Predicting pilot look-angle with a radial basis function network," *IEEE Transaction on Systems, Man, and Cybernetics*, vol. 24, no. 10, pp. 1511–1518, 1994.

[14] S. Clen, "Nonlinear time series modelling and prediction using Gaussian RBF networks with enhanced clustering and RLS learning," *Electronics Letters*, vol. 31, no. 2, pp. 117–118, 1995.

[15] E. S. Chng, S. Chen, and B. Mulgrew, "Gradient radial basis function networks for nonlinear and nonstationary time series prediction," *IEEE Transactions on Neural Networks*, vol. 7, no. 1, pp. 190–194, 1996.

[16] M. R. Berthold, "A time delay radial basis function network for phoneme recognition," in *Proceedings of IEEE International Conference on Neural Networks*, vol. 7, pp. 4470–4472, 4472a, Orlando, Fla, USA, June-July 1994.

[17] Z. Ryad, R. Daniel, and Z. Noureddine, "The RRBF. Dynamic representation of time in radial basis function network," in *Proceedings of 8th IEEE International Conference on Emerging Technologies and Factory Automation (ETFA '01)*, vol. 2, pp. 737–740, Antibes-Juan les Pins, France, October 2001.

[18] B. Sayyarrodsari, J. P. How, B. Hassibi, and A. Carrier, "An estimation-based approach to the design of adaptive IIR filters," in *Proceedings of the American Control Conference*, vol. 5, pp. 3148–3152, Philadelphia, Pa, USA, June 1998.

[19] P. Lveg, "Process of silencing sound oscillations," US Patent no. 2043416, June, 1936.

[20] E. Bjarnason, "Analysis of the filtered-X LMS algorithm," *IEEE Transactions on Speech and Audio Processing*, vol. 3, no. 6, pp. 504–514, 1995.

[21] M. Rupp, "Saving complexity of modified filtered-X-LMS and delayed update LMS algorithms," *IEEE Transactions on Circuits and Systems II: Analog and Digital Signal Processing*, vol. 44, no. 1, pp. 57–60, 1997.

[22] S. M. Kuo, I. Panahi, K. M. Chung, T. Horner, M. Nadeski, and J. Chyan, "Design of active noise control systems with the TMS320 family," Tech. Rep. SPRA042, Texas Instruments, Dallas, Tex, USA, 1996.

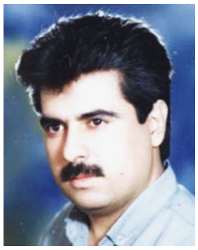
[23] S. K. Phooi, M. Zhihong, and H. R. Wu, "Nonlinear active noise control using Lyapunov theory and RBF network," in *Proceedings of the IEEE Workshop on Neural Networks for Signal Processing*, vol. 2, pp. 916–925, Sydney, NSW, Australia, December 2000.

[24] D. A. Cartes, L. R. Ray, and R. D. Collier, "Lyapunov turning of the leaky LMS algorithm for single-source, single-point noise cancellation," *Mechanical System and Signal Processing*, vol. 17, no. 5, pp. 925–944, 2003.

[25] S. Haykin, *Neural Networks: A Comprehensive Foundation*, MacMillan College, New York, NY, USA, 1994.

Hadi Sadoghi Yazdi was born in Sabzevar, Iran, in 1971. He received the B.S. degree in electrical engineering from Ferdosi Mashad University of Iran in 1994, and then he received to the M.S. and Ph.D. degrees in electrical engineering from Tarbiat Modarres University of Iran, Tehran, in 1996 and 2005, respectively. He works in Engineering Department as Assistant Professor at Tarbiat Moallem University of Sabzevar. His research interests include adaptive filtering, image and video processing. He has more than 70 journal and conference publications in subjects of interest areas.

Javad Haddadnia works as an Assistant Professor at Tarbiat Moallem University of Sabzevar. He received the M.S. and Ph.D. degrees in electrical engineering from Amir Kabir University of Iran, Tehran, in 1999 and 2002, respectively. His research interests include image processing.



Mojtaba Lotfizad was born in Tehran, Iran, in 1955. He received the B.S. degree in electrical engineering from Amir Kabir University of Iran in 1980 and the M.S. and Ph.D. degrees from the University of Wales, UK, in 1985 and 1988, respectively. He joined the engineering faculty of Tarbiat Modarres University of Iran. He has also been a Consultant to several industrial and government organizations. His current research interests are signal processing, adaptive filtering, and speech processing and specialized processors.