REVIEW OF ADAPTIVE NOISE CANCELLATION TECHNIQUES USING FUZZY-NEURAL NETWORKS FOR SPEECH ENHANCEMENT

Pankaj Bactor[1], Er. Anil Garg[2]

1. M-Tech Student, 2. Assistant Professor in MMEC

Electronics and Communication Department

M.M. University, Mullana (Ambala), Haryana, INDIA

Abstract— In this paper, some novel adaptive noise cancellation techniques and algorithms using ANC, ANFIS, DFNN, MDFNN and EDFNN have been discussed. In the proposed algorithms and techniques, the number of radial basis function (RBF) neurons (fuzzy rules) and input–output space clustering is adaptively determined. Furthermore, the structure of the system and the parameters of the corresponding RBF units are trained online automatically and relatively rapid adaptation is attained. By virtue of the self-organizing mapping (SOM) and the recursive least square error (RLSE) estimator

techniques, the proposed algorithms are suitable for real-time applications. Results of simulation studies using different noise sources and noise passage dynamics show that superior performance can be achieved. This paper introduces some popular noise reduction techniques and presents our simulation result of a noise reduction system. It is shown that the system reduces the noise almost completely while keeps the enhanced speech signal very similar to the original speech signal.

Keywords— ANC, DFNN, RBF, RLSE, SOM

I. INTRODUCTION

Speech Enhancement refers respectively to the improvement in the quality or intelligibility of a speech signal [1]. To enhance the speech, many algorithms and noise cancellation techniques are used. Some of them reviewed in this paper are as follows- ALC (adaptive linear combiners), ANC (adaptive noise cancellation), ANFIS (adaptive-network-based fuzzy inference system), DFNN (dynamic fuzzy neural networks), EDFNN (enhanced dynamic fuzzy neural networks), ERR (error reduction ratio), FNN (fuzzy neural networks), LSE (least square error), MDFNN (modified dynamic fuzzy neural networks), RBF (radial basis function), RLSE (recursive least squares error), RMSE (root mean squares error), SOM (self-organizing mapping), SSBNR (spectral subtraction based noise reduction). Methods of adaptive noise cancellation (ANC) were proposed by Widrow and Glover in 1975. The methods were applied successfully in the areas of image processing and communications.

The Artificial Intelligence (AI) has been a predominant technology for intelligent control for many years. By virtue of the learning ability, neural networks can be adapted to constantly changing environments [11]. Fuzzy logic, as a model-free approach, is able to approximate any continuous functions on a compact set to any accuracy. The combination of fuzzy logic and neural networks proves to be a powerful technique in adaptive signal processing. After that, the adaptive neural fuzzy filter (ANFF) algorithm is developed.

The Adaptive Neuro-Fuzzy Inference System (ANFIS), first introduced by Jang. ANFIS is a Neuro-fuzzy system that combines the learning capabilities of neural networks, with the functionality of fuzzy inference systems. The ANFIS is functionally equivalent to fuzzy inference systems [12].

The DFNN algorithm developed by Er and Wu has shown its effectiveness in control engineering and system identification. It is the enhanced algorithm of ANFIS [10]. It is an extended RBF neural network. In this, on-line self-organizing learning is used and then neurons can be recruited or deleted dynamically according to their significance to the system's performance and after that it was demonstrated that fast learning speed can be achieved. In order to exploit the superior structure and computational power of DFNN, two learning algorithms, termed modified-DFNN (MDFNN) learning algorithm and enhanced-DFNN (EDFNN) learning algorithms were proposed.

In MDFNN, the following two modifications are made: - Generation and Allocation of RBF Neurons and Weight Adjustment. EDFNN is the enhanced algorithm of DFNN. In this, the number of radial basis function (RBF) neurons (fuzzy rules) and input–output space clustering is adaptively determined [7].

II. NOISE REDUCTION TECHNIQUES

A. Basic Noise Reduction System

In a noisy environment, the speech signal may be distorted by the background noise, which can be generated by the machine, computer, or even the electronic fans. If a hands free telephone is used in the interview, the intensity of the background noise may be even stronger than the speech signal. The noise will thus distort the speech and make it hardly intelligible [3]. In order to improve the intelligibility, the noise needs to be attenuated to enhance the speech signal. Figure 1 shows the block diagram of a noise reduction system. In this figure, the noisy speech signal $X(n)$ is the combination of the original speech signal $S(n)$ and the noise $N(n)$. The noisy speech signal $X(n)$ passes through a noise reduction system to get a clean speech signal $Y(n)$, which is similar to the original speech signal $S(n)$.

B. Spectral Subtraction Based Noise Reduction

Spectral subtraction based noise reduction method (SSBNRM) is the most popular noise reduction method. This method operates in the frequency domain and assumes that the spectrum of the input noisy signal can be expressed as the sum of the speech spectrum and the noise spectrum [3]. Figure 2 shows the block diagram for the spectral subtraction method. The noise spectrum is first estimated and then subtracted from the noisy speech spectrum to get the clean speech spectrum.

C. Adaptive Noise Cancellation

Adaptive noise cancellation method serves to filter out the interference component by identifying a model between a measurable noise source n(k) and the corresponding signal corrupted by interferences represented by y(k). Complying with the main principles of ANC, the following assumptions should hold. The noise signal should be available and independent of the information signal. The information signal must be zero mean [5].

The noisy speech signal is given by y (k) = x (k) + d (k), where x (k) and d (k) represent the clean speech and noise signal, respectively. Adaptive Noise Cancellation is used to remove noise from useful signals. This is a useful technique where a signal is submerged in a noisy environment. The purpose of adaptive noise cancellation is to produce an anti-wave whose magnitude is exactly the same as that of the unwanted noise and whose phase is exactly opposite [4]. The primary input source receives the desired signal x (k) with corrupting noise d (k). The corrupting noise d' (k) is generated by the noise source d (k). The received signal is thus y (k) = x (k) + d (k). A secondary (reference) input source receives a noise d' (k) uncorrelated with the signal source x (k) but correlated with the corrupting noise d (k). This secondary input source provides the reference input to the adaptive noise canceller. Then d (k) is used by an adaptive process to generate an output d' (k) that a replica of d (k) . The output is then subtracted from the primary input y (k) to recover the desired signal x (k). The basic assumptions for the adaptive noise cancellation system include: The x (k) is uncorrelated with d (k) and y (k). The d (k) is correlated with y (k) .The d' (k) are uncorrelated with x (k). it follows ĝ(k) = x (k) + d(k) − d' (k) then the remaining error ĝ(k) is exactly the same as the desired signal x (k) [5].

D. Adaptive Neuro Fuzzy Inference System

ANFIS presents an adaptive noise canceller algorithm based on fuzzy and neural network. The Adaptive Neuro-Fuzzy Inference System, first introduced by Jang, is a universal approximator and as such is able to approximate any real continuous function on a compact set to any degree of accuracy. ANFIS is a neuro-fuzzy system that combines the learning capabilities of neural networks, with the functionality of fuzzy inference systems [12]. The major advantage of the proposed system is its ease of implementation and fast convergence [4].

E. Dynamic Fuzzy Neural Network

The salient characteristics of the algorithm are: 1) hierarchical on-line self-organizing learning is used; 2) neurons can be recruited or deleted dynamically according to their significance to the system's performance; and 3) fast learning speed can be achieved [10].

F. Modified Dynamic Fuzzy Neural Network

As discussed in [10], the DFNN algorithm performs input-space partitioning based on the accommodation boundary and the system error. For applications to the online ANC problem, the system error cannot be evaluated online as the information signal is not measurable. Modifications of the DFNN algorithm are carried out to make it applicable to the ANC problem. Essentially, the following two modifications are made:- Generation and Allocation of RBF Neurons and Weight Adjustment [7].

G. Enhanced Dynamic Fuzzy Neural Network

The EDFNN learning algorithm has the following salient features: 1) online self-organizing mapping (SOM) is introduced for system identification, replacing the original method that was based on accommodation boundary and system error as the latter could hardly be evaluated

online; 2) the recursive least squares error (RLSE) Estimator or Kalman filter method is applied in consequent parameter training, replacing the original least squares error (LSE) method as the former has been proven to be much faster and better in processing online signals in a very noisy environment [7].

III. SIMULATION STUDIES

MATLAB simulation studies are carried out in this section. The ANFIS is one of the popular paradigms in FNN-based approaches shown in the figure 1.
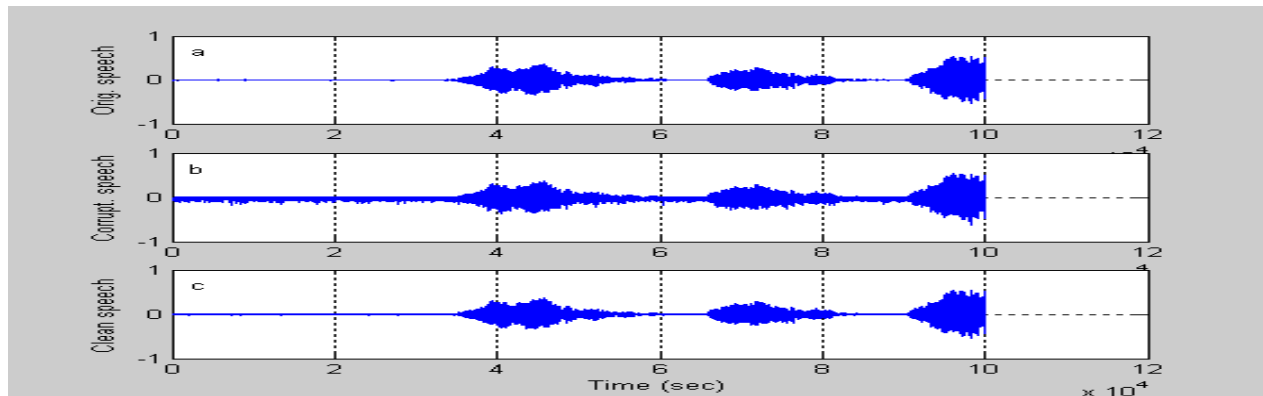

Fig-1 Results of noise cancellation in ANFIS (a) Clean Speech (b) Noisy Speech (4 dB) (c) Speech after noise cancellation

For the ease of comparison, RMSE, which is defined as follows, is selected as the performance index:

$$\text{RMSE} = \sqrt{\frac{\sum_{k=1}^{n}(x(k) - \hat{x}(k))^2}{n}}$$

There were two cases discussed:-

CASE I-

MDFNN Learning Algorithm: This is a relatively simple case, adopted from [5]. For the purpose of comparison, no signal delay or feedback is considered. Fig 2 shows the training results obtained by MDFNN [7].
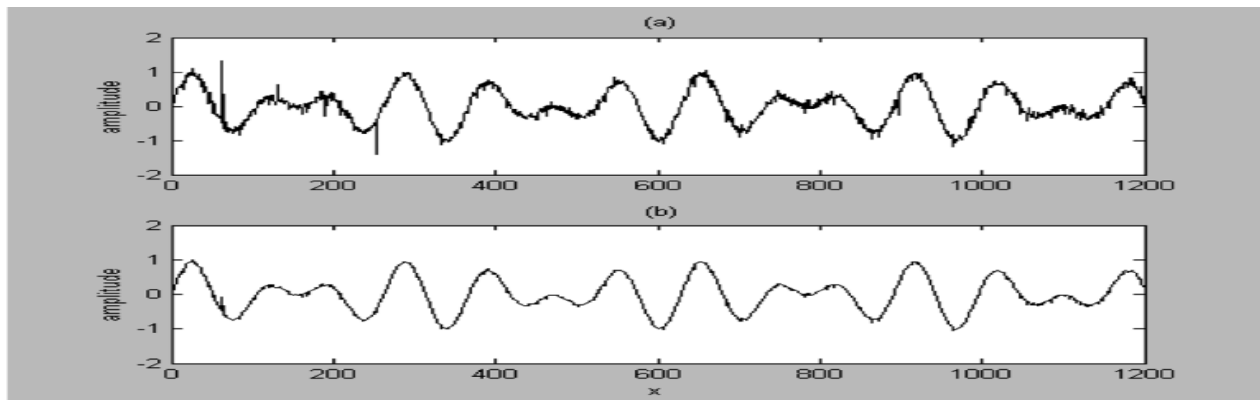

Fig-2 Testing results (a) By ANFIS. (b) By MDFNN

Case II

EDFNN Learning Algorithm: As mentioned above, the EDFNN learning algorithm has employed two techniques.

a) SOM is used to achieve a more sensible and representative input space clustering for better performance.

b) RLSE is used to greatly speed up noise cancellation with promising real-time applications.

The figure 3 demonstrates that the REAL-TIME estimated information signal and the estimation error could be achieved identically for the EDFNN algorithm. Here, REAL-TIME means that the output is produced immediately after the current input was processed [7].
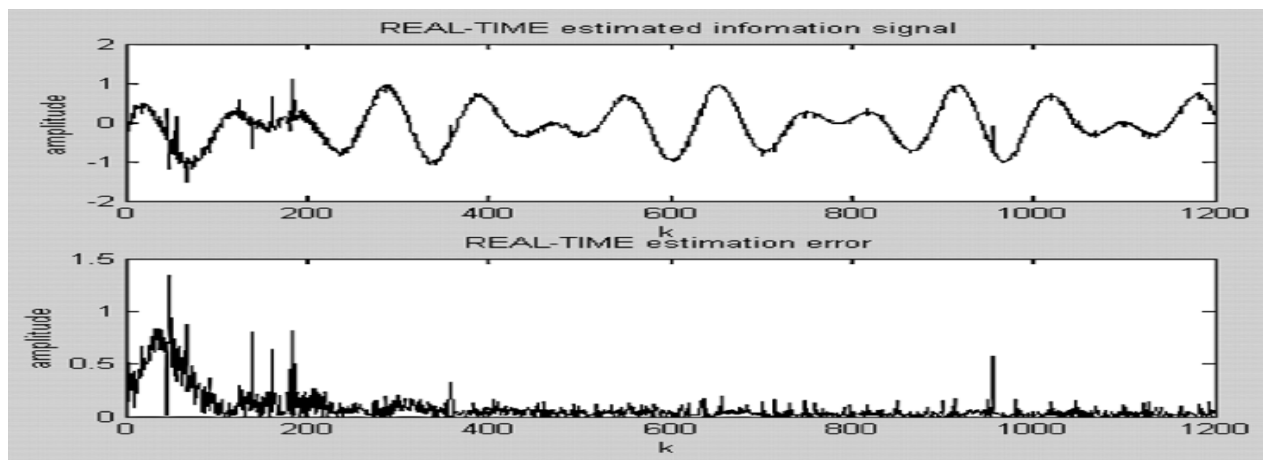

Fig-3 Real Time estimated information signal and estimation error

The figure 4 below shows that when the SOM is applied to input then faster convergence can be achieved.
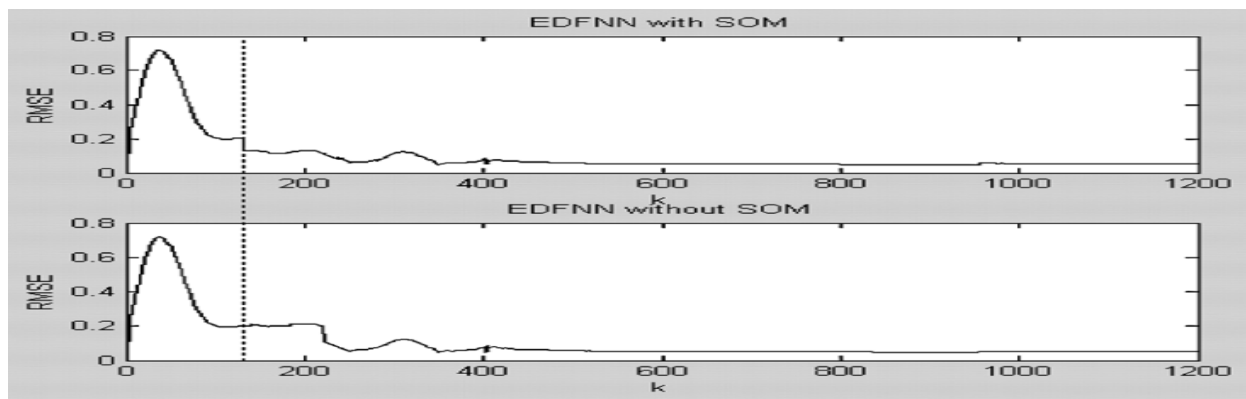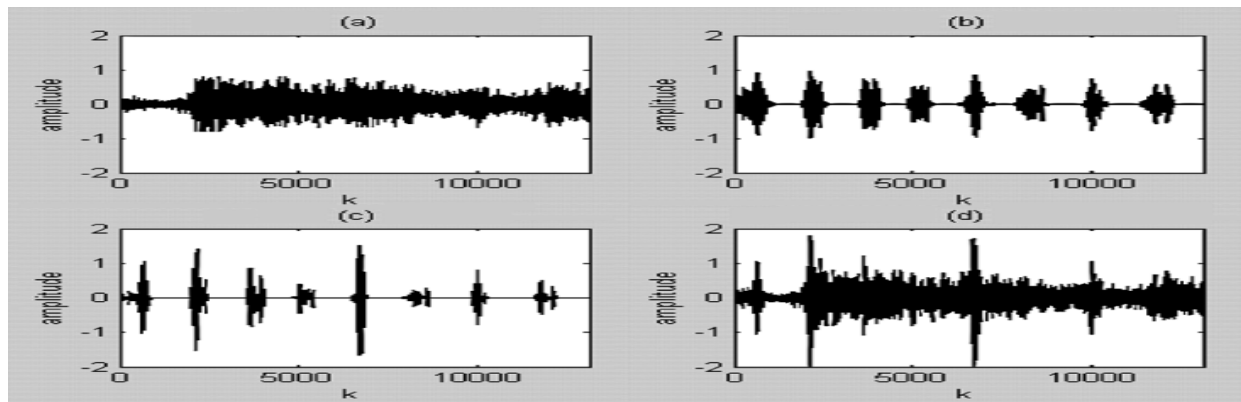
Fig-4 Faster convergence by EDFNN with SOM

The signals x(k), n(k), d(k) and y(k) are shown in Fig-5 and Fig-6 shows the training results obtained by EDFNN.

Fig-5 (a) Information signal x(k) (b) Noise source signal n(k) (c) Distorted signal d(k) (d) Measured information signal y(k)
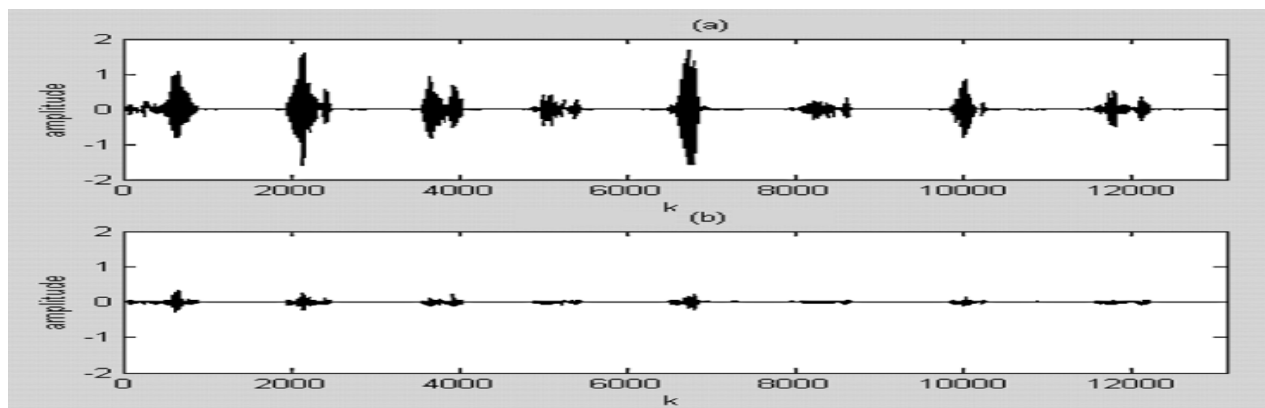

Fig 6 (a) Estimated distorted noise (b) Training error

The figure-7 compares the results obtained by ANFIS and EDFNN respectively. Performance comparison of ANFIS and EDFNN in quantitative terms shows that the performance of EDFNN, as measured by RMSE, is significantly better than that of ANFIS.
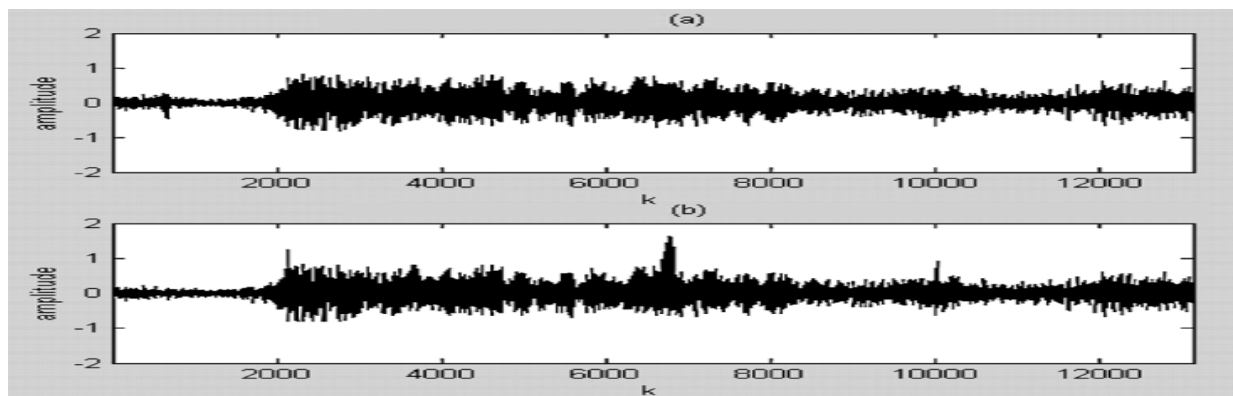
Fig 7(a) Estimated information signal by EDFNN (b) Estimated information signal by ANFIS

IV-CONCLUSION

By virtue of introducing SOM into the training phase, the system construction, that is, the generation of RBF neurons (fuzzy rules) can be adaptively determined without partitioning the input space and selecting initial parameters a priori. The learning speed and parameter adaptation are fast and efficient. By employing the RLSE algorithm in the parameter optimization phase, low computation load and less memory requirements have been achieved. Simulation studies clearly demonstrate the effectiveness and superiority of the proposed MDFNN and EDFNN algorithms.

REFERENCES

[1] P. Loizou, Speech Enhancement: Theory and Practice. New York: Taylor & Francis, 2011.

[2] S. Rajasekaran, G. A. Vijayalakshmi Pai "Neural Networks, Fuzzy Logic and Genetic Algorithms: Synthesis and Applications" PHI publications, 2011.

[3] Zhixin Chen "Simulation of Spectral Subtraction Based Noise Reduction Method" International Journal of Advanced Computer Science and Applications, Vol. 2, No.8, 2011.

[4] Mohammed Hussein Miry, Ali Hussein Miry Hussein Kareem Khleaf "Adaptive Noise Cancellation for speech Employing Fuzzy and Neural Network" 289-296, 2010 1st International Conference on Energy, Power and Control (EPC-IQ), College of Engineering, University of Basrah, Basrah, Iraq, November 30-December 2, 2010.

[5] J. Dheebal and A. Padmal "Intelligent Adaptive Noise Cancellation using Cascaded Correlation Neural Networks" IEEE - ICSCN 2007, MIT Campus, Anna University, Chennai, India. Feb. 22-24, 2007. pp. 178-182.

[6] D. G. Stavrakoudis, and J. B. Theocharis "A Recurrent Fuzzy Neural Network for Adaptive Speech Prediction"2056-2061,1-4244-09918/07/$25.00/©2007, IEEE-ICSCN2007.

[7] Meng Joo Er. et al , "Adaptive Noise Cancellation Using Enhanced Dynamic Fuzzy Neural Networks, IEEE Trans. Fuzzy Systems, Vol. 13, No. 3, June 2005, pp:331-342.

[8] J. Thevaril, H. K. Kwan, "Speech Enhancement using Adaptive Neuro-Fuzzy Filtering", Proc. Of 2005 Int. Sym. on Intelligent Signal Processing and Communication Systems, 13-16 December 2005, pp. 753 – 756.

[9] S. N. Wu and J. S. Wang. "An adaptive recurrent neuro-fuzzy filter for noisy speech enhancement" Proc. of IEEE Int. Joint Conference on Neural Networks, Vol.4, 25-29 July 2004, pp. 3083 – 3088.

[10]   S. Q. Wu and M. J. Er, "Dynamic fuzzy neural networks-A novel approach to function approximation," IEEE Trans. Syst., Man, Cybern. B, Cybern. vol. 30, no.2, pp. 358–364, Apr. 2000.

[11]   Liang Tao and H. K. Kwan "A Neural Network Method for Adaptive Noise Cancellation", 1999 IEEE conf.

[12]   J.-S. R. Jang, "ANFIS: Adaptive-network-based fuzzy inference system," IEEE Trans. Syst., Man, Cybern., vol. 23, no. 3, pp. 665–685, May/Jun. 1993.