Indian Journal of Science and Technology Vol. 4 No. 9 (Sep 2011) ISSN: 0974- 6846

Global optimal solution for active noise control problem

Syed Faiz Ahmed[1], Abdul Rehman Memon[1], Ch. Fahad Azim[2] and Hazry Desa[3]

[1]*Faculty of Engineering Sciences & Technology, Hamdard University, Pakistan*
[2]*School of EEE, Nanyang Technological University, Singapore*
[3]*Engineering division, University Malaysia Perlis, Malaysia*
syed0011@ntu.edu.sg; abdul.rahman@hamdard.edu; fahad.azim@hamdard.edu; hazry@unimap.edu.my

Abstract

This paper presents the global optimal solution for active noise cancellation using Genetic algorithm technique. The conventional active noise control methods such as FXLMS have problem of local minima. The proposed global optimal solution based on Genetic algorithm can handle this problem very well and give batter results. Computer simulation results demonstrate that Genetic algorithm based active noise control system give more optimal results.

Keywords: Active noise control, optimal solution, genetic algorithm.

Introduction

Acoustic noise is composed of a mixture of sound that has no beneficial effect on human beings since it is incomprehensible. In fact, it is a source of irritation that disrupts mental concentration. Generally, it is regarded as a type of environmental pollution that can have adverse effects on human life in various ways.

In recent years, acoustic noise problems are becoming more evident with the increase in the use of industrial equipment such as engines, fans, transformers and compressors. The growth of high-density housing increases the population's exposure to a wider spectrum of noise source. In addition, manufacturers have the tendency to use lighter materials for buildings and transportation that further add to the environmental noise. Hearing loss is probably the most significant and serious health problem caused by excessive noise. Continuous exposure can lead to varying levels of hearing loss ranging from a mild ringing in the ears to total deafness due to the damaged auditory receptors in the ear. Researchers have shown that if a person is subjected to a sound level of over 85 dB for several hours a day, permanent damage will occur. The greater the amount of sound, the longer the exposure and the higher the intensity, the greater will be the possibility of deafness occurring.

Noise can also mask important sounds and disrupt communication between individuals in a variety of settings. This process can cause anything from a slight irritation to a serious safety hazard involving an accident or even a fatality because of the failure to hear the warning sounds of imminent danger. Such warning sounds can include the approach of a rapidly moving motor vehicle, or the sound of malfunctioning machinery.

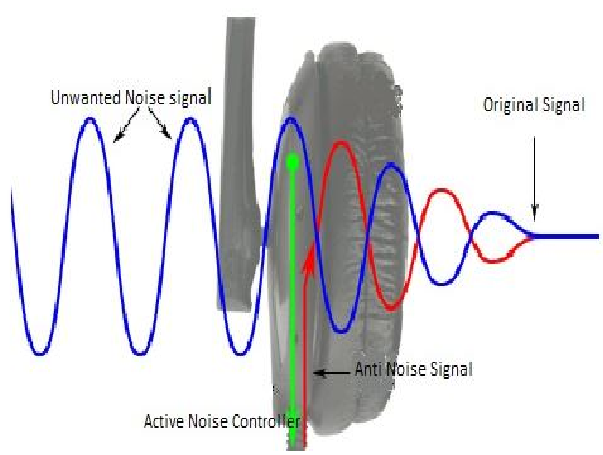
Noise-induced sleep interference is one of the critical components of community annoyance. It can produce short-term adverse effects, such as mood changes and decrements in task performance the next day, with the possibility of more serious effects on health and well being if it continues over long periods.

In an effort to overcome these problems, active noise control has received considerable interest and has shown significant promise. It works on the principle of destructive interference between the sound fields generated by the primary sound source and that due to the secondary anti-sources. Fig.1 shows the primary unwanted noise signal, anti-noise signal, and residual original signal that result when they are superimposed. To achieve the optimal performance of noise cancellation, it is required that the anti-noise signal is of the same amplitude but inverse phase as that of the noise to be canceled.

This paper present a global optimal solution using genetic algorithm based FIR (finite-impulse response) filter to minimize the unwanted noise signal in active noise control system. Genetic algorithm search globally and update the coefficients of FIR filter optimally.

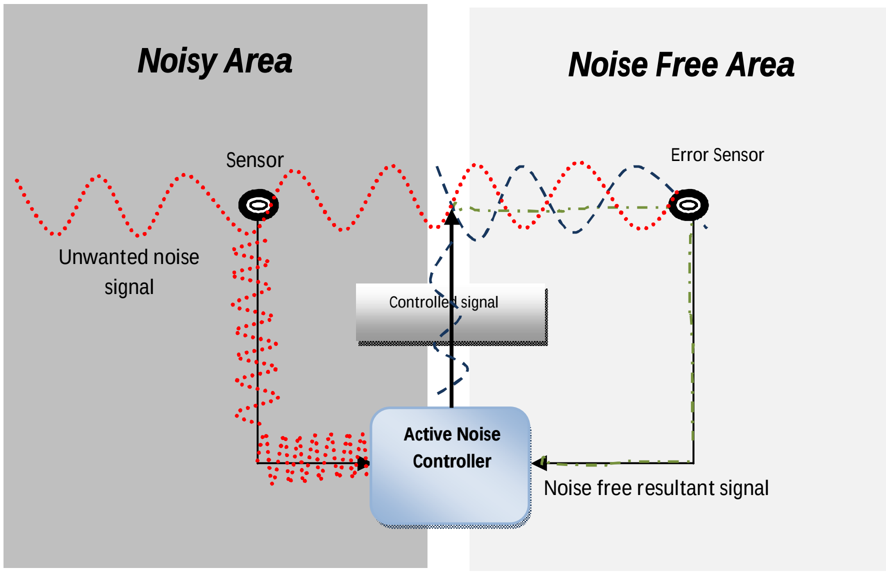
Active noise control (ANC) is an old concept that has received attention for more than 50 years. Traditional approach to acoustic noise control uses passive techniques such as enclosures, barriers, and silencers to attenuate the undesired noise. Besides, the traditional noise control approach often involves the rearrangement of the noise source, the physical structure and

Fig.1.Active noise control system



Indian Journal of Science and Technology Vol. 4 No. 9 (Sep 2011) ISSN: 0974- 6846

Fig.2.Block diagram of active noise control system



surrounding environment. The development of adaptive digital signal processing theory and hardware resolve these problems. Considerable research works had been done in active noise control area and now the ANC systems are commercially implemented in air-conditioning ducts, active headsets, transformer noise, engine noise in certain aircraft cabins and cars (Dehandschutter *et al*., 1995; Smith *et al*., 1996; Crawford & Stewart, 1997). In medical sciences ANC also play very important role, Hirayama and Kida (2008) worked on active noise control system use for reducing noise in MRI machine; this ANC system used optical microphone and piezo-electric loudspeaker for ANC system. Bilinear FXLMS algorithm is proposed by Kuo and Wu (2005) for nonlinear adaptive filters to solve the problems of signal saturation and other nonlinear distortions that occur in ANC systems. A sub-band adaptive filtering (SAF) technique is used by Milani & Panahi (2009) in designing of active noise control (ANC) systems. They reduce the computational complexity of ANC algorithms, particularly, when the acoustic noise is a broadband signal.

Artificial Neural Networks (ANN) had been applied to the ANC due to the limitation of presently employed linear control strategy. Sutton and Elliot (1991) developed a non-linear adaptive harmonic controller by using the ANN. Ma and Sinha (1996) wrote on the development of a neural network based optimal system to control vibration in flexible structures subjected to deterministic and periodic excitation. They used large numbers of actuators on structures to control sound transmission through structures. In an attempt to further simplify the control process. Delemotte and Montassier (1995) suggested using hierarchical bio control in which a small number of signals are sent from an advanced, centralized controller and are then distributed by local simple rules to multiple control actuators.

Active noise control system

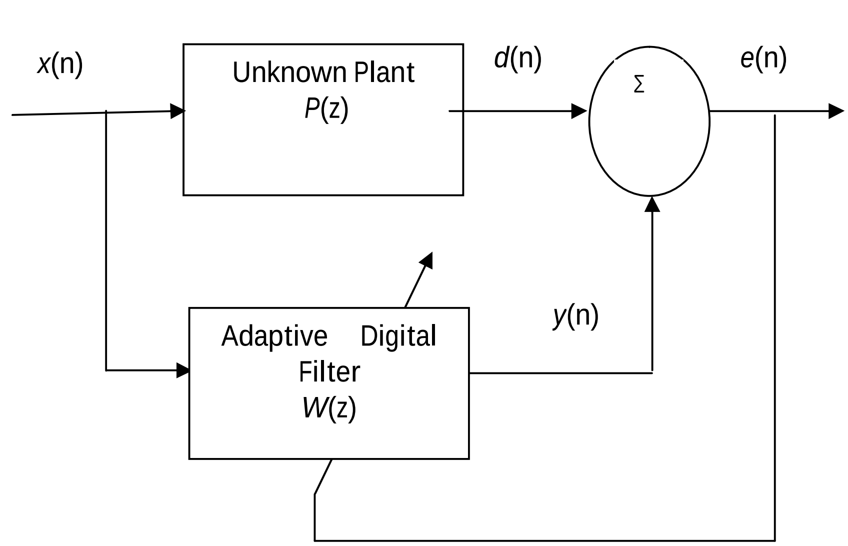
The basic block diagram of Active Noise Control system is shown in Fig.2. The unwanted noise signal is detected by sensor and fed in to the active noise controller. The controller generates control signal whose amplitude is same but inverse in phase from unwanted noise signal. The ANC controller manipulates the control signal according to the input signal and the feedback signal coming from the error sensor. The efficiency of unwanted noise cancellation depends upon the effectiveness of the ANC controller algorithm.

Active noise control system can also be realized in an adaptive control system classification structure, shown in Fig. 3; where adaptive filter $w(z)$ is used to predict an unknown plant $p(z)$.

When adaptive filter converged, then $w(z) = p(z)$ and error signal will become zero and the output of the adaptive filter $y(n)$ will become equal to $d(n)$ which is unwanted signal and resultant error signal will be

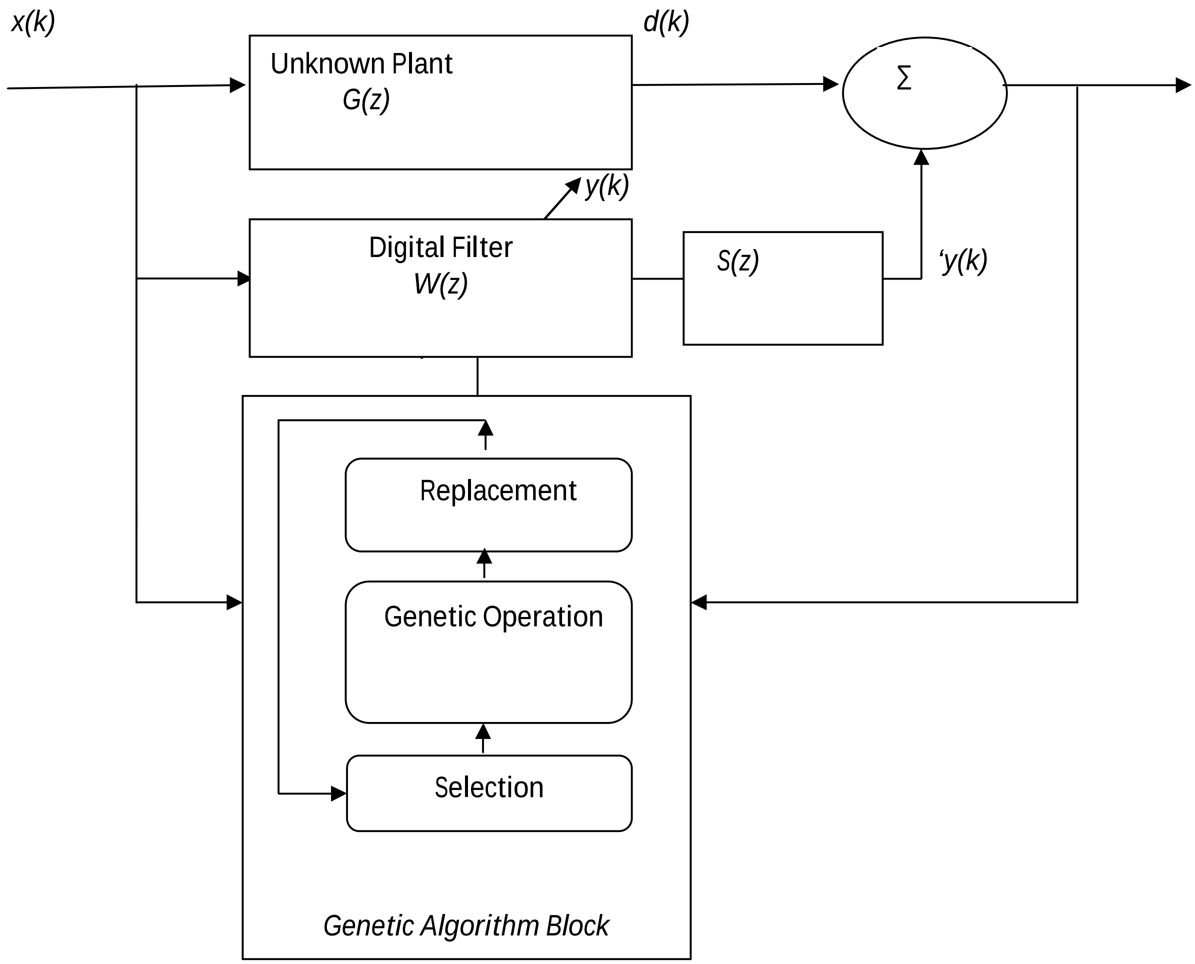
$$e(n) = d(n) - y(n) = 0 \qquad (1)$$

Fig.3. ANC control system in adaptive filter configuration



Indian Journal of Science and Technology Vol. 4 No. 9 (Sep 2011) ISSN: 0974- 6846

Fig.4. Genetic algorithm based ANC system



Well-known Least Mean Square (LMS) algorithm as adaptive filter algorithm has been widely studied and applied to noise cancellation (Clarkson & White, 1989). Beside LMS, the FXLMS algorithm is also very famous algorithm for the ANC system. It is in essence a method searching local optimum with a gradient following technique. These conventional approaches are easy to converge to a local optimal solution if the initial condition is not appropriate. To solve the problem of local minima, genetic algorithm can be use as an alternative and more efficient methodology in the ANC.

Proposed global optimal solution

The application of GA in the ANC is demonstrated in Fig.4, which shows the block diagram of the Genetic Algorithm based Active Noise Control system. The adaptive filter used here is a Finite Impulse Response (FIR) filter with order of *L-1*. FIR filter incorporates only zeros. Hence, it is always stable and can provide a linear phase response.

In this diagram *x(k)* is the unwanted noise sensed by the primary sensor, *d(k)* is the acoustic signal at the error sensor, *y(k)* is the anti-phase signal that is generated by the adaptive filter, *y'(k)* is the signal filtered through the secondary path, *e(k)* is the residual noise signal after cancellation. *S (z)* denotes the acoustic path from the secondary source to the error microphone, *G(z)* denotes acoustic path from the primary noise source to the error sensor and *W(z)* is FIR filter whose coefficients are updated by using GA algorithm.

Since the unwanted noise date vector signal is:

$$x(k) = [x(k), x(k-1), x(k-2) ...., x(k-L+1)]^T \qquad (2)$$

And adaptive filter weight vector is:

$$w(k) = [w_j(0,k), w_j(1,k), w_j\ (2,k) ...., w_j(L-1,k)] \qquad (3)$$

with $j = 1 \ \ 2 \ \ . \ \ . \ \ p$

Where "p" is the groups of population for Genetic algorithm.

Then signal y(k) that is generated by the adaptive filter in vector form will be:

Indian Journal of Science and Technology Vol. 4 No. 9 (Sep 2011) ISSN: 0974- 6846

$$\begin{bmatrix} y_1(k) \\ y_2(k) \\ \cdot \\ \cdot \\ \cdot \\ \cdot \\ \cdot \\ y_p(k) \end{bmatrix} = \begin{bmatrix} w_1(0,k) & w_1(1,k) & \cdots & w_1(L-1,k) \\ w_2(0,k) & w_2(1,k) & \cdots & w_2(L-1,k) \\ \cdot & \cdot & \cdots & \cdot \\ \cdot & \cdot & \cdots & \cdot \\ \cdot & \cdot & \cdots & \cdot \\ \cdot & \cdot & \cdots & \cdot \\ \cdot & \cdot & \cdots & \cdot \\ w_p(0,k) & w_p(1,k) & \cdots & w_p(L-1,k) \end{bmatrix} \begin{bmatrix} x(k) \\ x(k-1) \\ \cdot \\ \cdot \\ \cdot \\ \cdot \\ \cdot \\ x(k-L+1) \end{bmatrix} \quad (4)$$

And the signal y'(k) that is filtered through the secondary path

$$\begin{bmatrix} y_1'(k) \\ y_2'(k) \\ \cdot \\ \cdot \\ \cdot \\ \cdot \\ \cdot \\ y_p'(k) \end{bmatrix} = \begin{bmatrix} y_1(k) & y_1(K-1) & \cdots & y_1(k-L+1) \\ y_2(k) & y_2(k-1) & \cdots & y_2(k-L+1) \\ \cdot & \cdot & \cdots & \cdot \\ \cdot & \cdot & \cdots & \cdot \\ \cdot & \cdot & \cdots & \cdot \\ \cdot & \cdot & \cdots & \cdot \\ \cdot & \cdot & \cdots & \cdot \\ y_p(k) & w_p(k-1) & \cdots & y_p(k-L+1) \end{bmatrix} \begin{bmatrix} s_1 \\ s_2 \\ \cdot \\ \cdot \\ \cdot \\ \cdot \\ \cdot \\ s_{L-1} \end{bmatrix} \quad (5)$$

Therefore the residual noise signal e(k) after cancellation of unwanted noise can be calculated by equation:

$$e_j(k) = d(k) - y_j'(k) \quad (6)$$

Genetic algorithm in active noise control system

Genetic Algorithm consists of three operations: *Selection, Genetic Operation, and Replacement.* The population is basically a group of chromosomes from which candidates can be selected for the solution of a problem. Initially, a population is generated randomly. The fitness values of the all chromosomes are evaluated by calculating the objective function (Omar Ali Beg & Vali uddin, 2009).

a) Fitness evaluation

To evaluate the goodness of chromosomes, an objective function is needed to calculate the fitness value. The results of this evaluation will provide an indication on the fitness level of the individual chromosome.

A 'windowed mean-square-error' function is proposed here for the fitness evaluation.

$$C_i(e) = \left[\frac{1}{z} \sum_{n=n_0}^{n_0+z-1} e^2(k) \right] \quad (7)$$

Where:

C_i *(e)* = fitness value of *i th* chromosome in the population

e *(k)* = calculated error signal at *k* time

i $=1,2,3,.....p$

z = window size.

b) Selecting Parenting Population

The reproduction operator determines how the parents are selected to generate the offspring. This operator is a process in which chromosomes are copied according to their objective function values (Rahman, 2001).

A chromosome with the lowest value has the greatest probability of mating. The cost weighting technique can be use for the selection.

Cost weighting

In cost weighting method, the probability is calculated according to the cost of the chromosomes.

$$pb_i = \left| \frac{\sum_{i=1}^{n} C_i - C_j}{\sum_{i=1}^{n} C_i} \right| \quad (8)$$

Where:

C_i = Fitness value of *i th* chromosome

C_j = Fitness value of *jth* chromosome with lowest cost weight.

pb_i = Probability of *jth* chromosome being selected as a parent.

This approach weights the top chromosome more when there is a large cost difference between the best and worst chromosomes.

c) Crossover operator

Crossover is the core operator of the GA. It creates a group of children from the parents by exchanging genes among them. A new offspring contains mixed information from both the parents.

Gene exchange

For the binary coding, the crossover is based on bit exchange. It selects one or more points in the chromosome randomly. The genes among these points are swapped between the two parents.

To achieve better chromosomes, the gene values from both the parents are combined into new parameter values in the children using following equation.

$$C_{new1} = (0.5-\beta).p_1 + (0.5+\beta).p_2 \quad (9)$$

$$C_{new2} = (0.5+\beta).p_1 + (0.5-\beta).p_2 \quad (10)$$

Indian Journal of Science and Technology Vol. 4 No. 9 (Sep 2011) ISSN: 0974- 6846

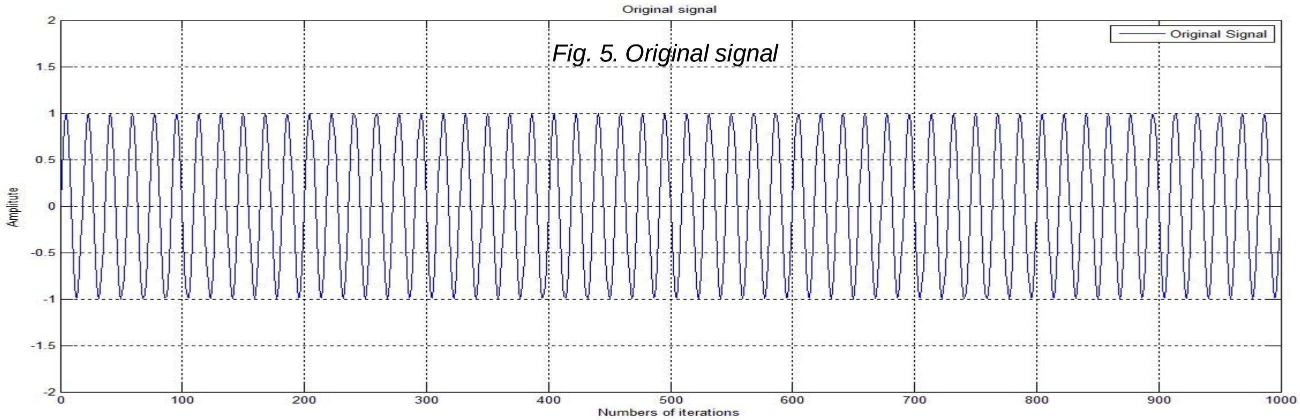


Fig. 5. Original signal

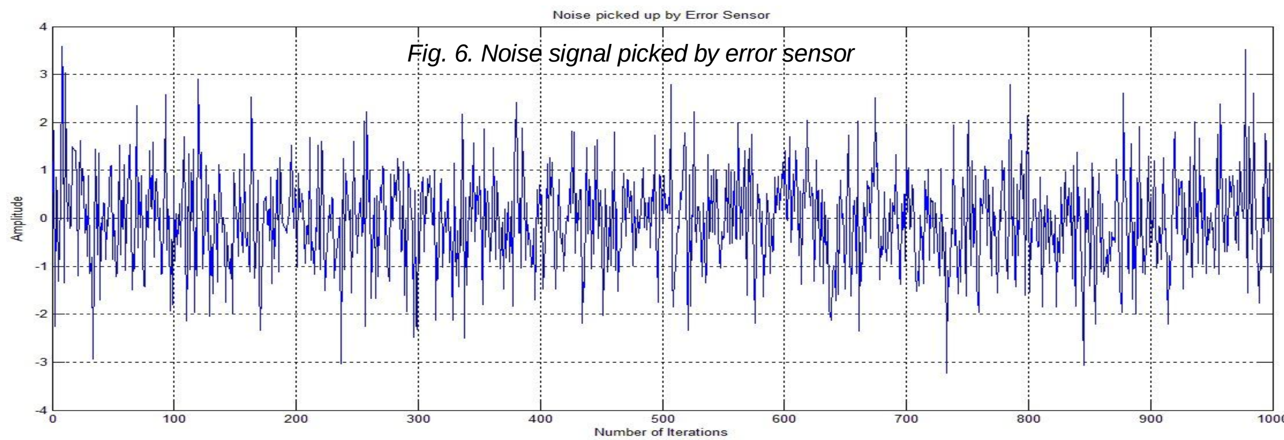


Fig. 6. Noise signal picked by error sensor

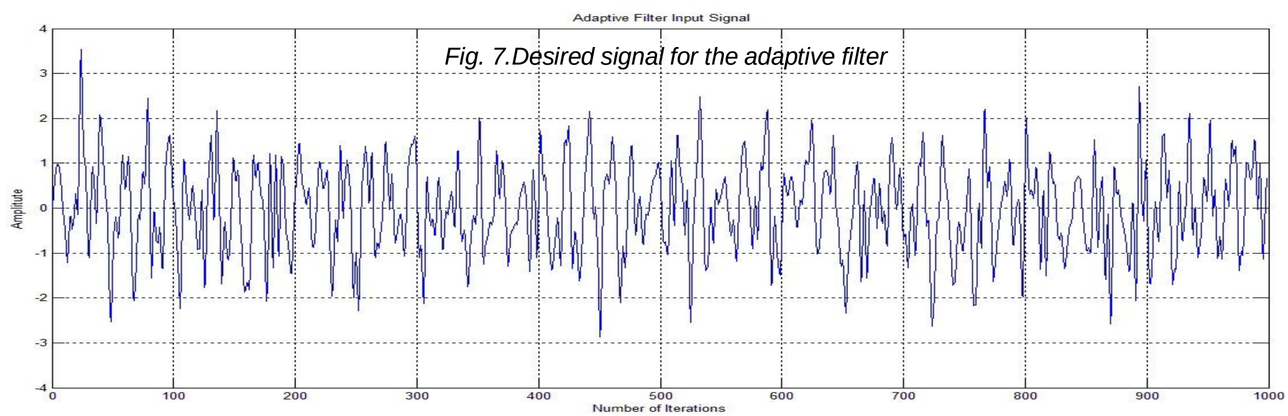


Fig. 7.Desired signal for the adaptive filter

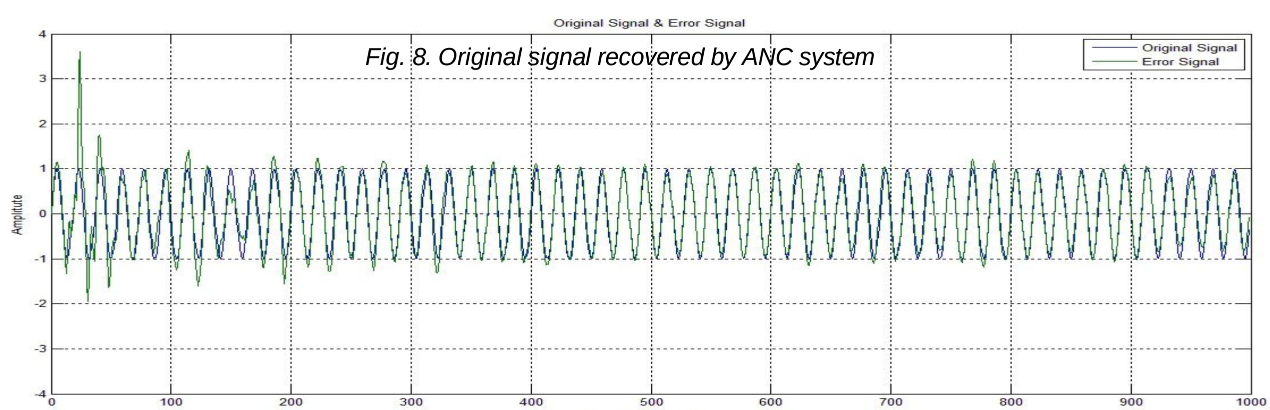


Fig. 8. Original signal recovered by ANC system

Indian Journal of Science and Technology Vol. 4 No. 9 (Sep 2011) ISSN: 0974- 6846

Where: p_1 & p_2 = Values of two parent genes;

C_{new1} & C_{new2} =Values of two child genes;

β =Random value between [-0.6, 0.6].

d) Mutation operator

Even though the reproduction and crossover come up with many new chromosomes, they do not introduce any new information into the population at a gene level (Erguo Li, 2004). *Mutation* operator solves this problem by randomly disturbing the genetic information.

e) Replacement of population

The replacement is the last stage of any breeding cycle. It determines how new chromosomes will be put into the population, and how chromosomes are to be eliminated. Through one GA cycle, two parents are drawn from a population. They breed two children. But not all of them can return to the population, two have to be discarded. Two of the weakest individuals in the population are replaced by the two children, so long as the children are fitter.

f) Termination criterion

After *Reproduction, Crossover, Mutation, and Replacement,* the new generation of the offspring forms a new population with part of the previous generation. This new generation will undergo further round of the GA operation until a predefined *Termination Criterion* is met. This criterion can be a given minimum acoustic energy $e^2(k)$. The GA will stop searching when the minimum fitness value in the population drops below the convergence value. It can bring the search to a speedy conclusion while ensure to reduce noise to a low level.

Simulation and results

At the beginning of the simulation, GA parameters are initialized as population size is 30 chromosomes, crossover rate is 0.75, mutation rate is 0.1 and the order of the filter is 32. The chromosome values are given randomly and are evaluated according to an objective function. Then a parenting population is selected. The whole GA cycle will consist of Crossover, Mutation, Fitness re-evaluation, and Replacement. The best chromosome will be chosen to generate the anti-noise signal. In simulation results Fig.5 shows the original signal, the signal picked by the error sensor is shown in Fig.6. The desired signal for the adaptive filter which is the combination of original signal and filtered noise signal (Fig.7) and the recovered original signal is illustrated in Fig.8. From these results, it has been observed that the error between the two signals reduces gradually. It is noticed that the noise can be reduced significantly in first 50 iterations and after around 100 iterations the noise signal is almost vanished and original signal is recovered.

Conclusion

We have proposed and implement the global optimal solution for active noise cancellation problem by using genetic algorithms. From the simulated results we can concluded that genetic algorithm is feasible solution for active noise control system problem, it search globally and find optimal solution. This technique is simple, effective and can generate batter results with high stability.

References

1. Delemotte Ch. Carme V and Montassier A (1995) ANR (active noise reduction) in turbo-prop aircraft. *Active 95*. 607-618.
2. Clarkson PM and White PR (1989) Simplified analysis of the LMS adaptive filter using a transfer function approximation. IEEE Trans. ASSP, 35 (7), 987-992.
3. Crawford DH and Stewart RW (1997) Adaptive IK. filtered-V algorithms for active noie control, *J. Acoust. Soc. Am*. 101(4) 2071-2080.
4. Dehandschutter W et al, (1995) Active structural acoustic control of structure borne road noise: theory, simulations, and experiments. *Active 95*. 735-746.
5. Erguo Li (2004) A genetic neural fuzzy system and its application in quality prediction in the injection process. *Chem. Engg. Commun*. 191(3) 335-355.
6. Hirayama R, Kida M Kajikawa (2008) An active noise control system for MR noise: A study on an available ANC system in magnetic field. Intl. Conf. on Signal Processing, Beijing, ICSP (9). 2693 - 2696.
7. Kuo SM and Hsien-Tsai Wu (2005) Nonlinear adaptive bilinear filters for active noise control systems. IEEE Transactions on Circuits and Systems I. Regular Papers. 52, 617-624.
8. Ma RP and Sinha A (1996) A neural network based active vibration absorber with state feedback control. Letters to Editor. *J. Sound & Vibration*. 190(1), 121-128.
9. Milani AA and Panahi IMS Loizou (2009) A new delayless subband adaptive filtering algorithm for active noise control systems, audio, speech, and language processing. *IEEE Transact*. 17, 1038-1045.
10. Omar Ali Beg and Vali uddin (2009) Implementation of genetic algorithms for parameter estimation of LTI systems. 2nd IEEE Intl. Conf. Computer Control and Communication. Karachi, IEEE- IC-4 (2). 71-76.
11. Rahman MA (2001) A flexible way to generate PWM-SHE switching patterns using genetic algorithm. Sixteenth Annual IEEE Applied Power Electronics Conference and Exposition (Cat No 01CH37181) APEC-01. 1133.
12. Smith SP et al (1996) Active control of low-frequency broadband jet engine exhaust noise, *Noise Control Eng. J*. 44(1), 45-52.
13. Sutton TJ, Elliot SJ and Moore I (1991) Use of nonlinear controllers in the active attenuation of road noise inside cars. Proc. Recent Advances in Active Control of Sound and Vibration. Technomic Publ. Inc., Pennsylvania. pp: 932.