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Design and Implementation of Dual-Microphone Adaptive-Active Noise Cancellation System for De-Noising Speech Signal

***Abstract**. Active Noise Control (ANC) has become an important field of research in recent decades. Noise Control in industrial environments and conference halls as well as in communication systems has been studied under the title adaptive-active noise cancellation-control (AANCC) and the results of these studies have been used in practical applications. Reducing time dependent noise is one of the ways recommended for speech enhancement. Here we have introduced an artificial neural network called ADALINE as a smart dual microphone active noise control system. This artificial neural network identifies sources of noise and interference during its training phase and adjusts accordingly. In this way the system reduces the input signal noise. Tests and implementations presented here are based on speech in Persian language and cumulative white Gaussian noise and the interference is assumed to be of the cosine type.*

***Streszczenie.** Przedstawiono analizę szumów w otoczeniu przemysłowym i w salach konferencyjnych a następnie przedstawiono metody adaptacyjnych metod redukcji szumów. Szczególną uwagę zwrócono na szum zależny od czasu. Zastosowano metodę podwójnego mikrofonu i wykorzystano sieci neuronowe. Sieć identyfikuje źródło szumu i zakłóceń. Metodę sprawdzono doświadczalnie. (**Projekt i wykorzystanie podwójnego mikrofonu w adaptacyjnej metodzie usuwania szumu z sygnału mowy**).*

Keywords: Signal Enhancement, Noise Reduction, ADALINE Network, Adaptive-Active Filter, LMS Algorithm.
Słowa kluczowe: redukcja szumów, sieć neuronowa ADALINE, filtry adaptacyjne.

Introduction

Adaptive Advances in speech signal transmission and existence of environmental noise and interference has made the subject of speech enhancement a particularly important one. Environment noise and interference increases error and harms precision in applications which involve tasks such as identification of speech, thus reducing functionality [1]. It is possible to optimize the input speech signal through special techniques with the aim of facilitating further reduction in noise and interference. This is usually referred to as pre-processing [2]. Reduction or elimination of noise is one of the most important applications of adaptive active filters. There are many situations in which old filtering techniques for noise reduction are not applicable. Old filtering systems are bulky and have many coefficients of around hundreds and are not very efficient in lower frequencies [3]. Adaptive-active filters, on the other hand, are not dependent on the character of the source of noise or interference once their parameters are adjusted for a dedicated task. These filters generate an equal but opposite signal which acts on the noise signal and reduces or eliminates (cancels) it [1, 3]. Using the optimized Wiener Filter theory is an old and fundamental way for noise reduction. Just as those based on adaptive algorithms such as least mean squares (LMS), this technique can be adapted to dynamic noise environments [2, 4]. Using spectral subtraction has become a common digital method for speech signal noise reduction. Nonlinear spectral subtraction is an effective and popular method for speech enhancement [1, 2]. Using arrays of microphones is another way of reducing noise [3, 5-6]. Here we have discussed the noise reduction effect of an adaptive filter based on the least mean square algorithm, on Persian language speech signal. A noisy Persian speech signal is given to the system as input and the system tries to identify and simulate parameters of the noise source and to generate a similar signal with an opposite sign using the least mean squares algorithm and the steepest descent algorithm. This generated signal is subtracted from the noisy signal and the latter is thus reduced .Functionality of the system is determined by the number of coefficients and the rate of adaptive training of the system undergoes.

ADALINE functionality and LMS algorithm

Considering Fig .1, delayed inputs are multiplied by their respective weights to form the output. The actual output is compared with the desired output and an error signal is thus generated. The error signal is used in tandem with the rate of training of the system so that system coefficients can be improved and the error can be minimized (in fact the actual output signal is being made as close as possible to the desired output signal). Minimizing error is done by updating system weights and getting them as close as possible to an optimal combination .choosing a proper value for adaptive learning rate and choosing a proper number of system coefficients which are in fact the same as taped delay lines are of prime importance here. The latter can be a determining factor for the functionality of the system .If the number of coefficients is too small the noise reduction functionality of the system could be seriously compromised.

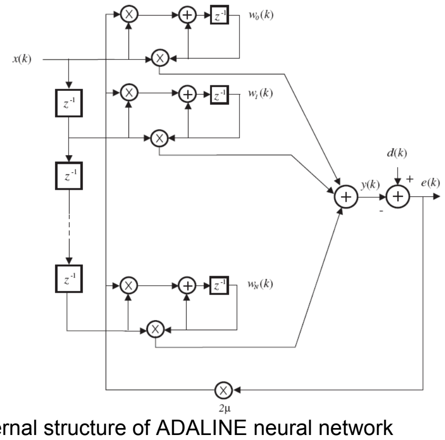

Fig.1. Internal structure of ADALINE neural network

Considering Fig .1, network's output will be:

$$Y = V = \sum w_i . x_i = W . X \tag{1}$$

X is the network's vector of inputs and W is the weights vector.
Based on steepest descent training algorithm:

(2) $$W(m+1) = W(m) - \beta \frac{\partial F}{\partial W(m)}$$

(3) $$F = E^2 = (d-y)^2$$

F is the performance index, d is the desired output and y is the output [1, 3, 7]:

(4) $$W(m+1) = W(m) - \beta \nabla F|_W$$

In equation (4) $\nabla F|_W$ is the performance index gradient vector.

Assuming P-dimension input, the error (E) would be:

(5) $$E = (d-y) = d - \sum_{j=1}^{p} w_j x_j$$

Hence:

(6) $$\frac{\partial E}{\partial W_i} = -X_i$$

Then:

(7) $$\frac{\partial F}{\partial W_i} = -2E.X_i$$

(8) $$W_i(m+1) = W_i(m) + 2\beta.E.X_i(m)$$

Replacing $\eta = 2\beta$ as the learning rate and $\delta = E$ as the error in equation (8):

(9) $$W_i(m+1) = W_i(m) + \eta.\delta X_i(m)$$

After passing through several cycles, the system will adjust weights to an optimal combination for reduction of noise and interference. The adaptation formula of learning weights will be of the form in equation (9) [8, 9].

The leaky LMS algorithm can be implemented by incorporating the coefficient α into the equation. This will improve the stability of the system and accelerate its moving toward an optimal state [10, 11].

(10) $$W_i(m+1) = \alpha W_i(m) + \eta.\delta X_i(m)$$

It is shown in analytical algebra that the maximum value of α which allows for a stable behaviour of the LMS algorithm is:

(11) $$\alpha \le \frac{1}{\lambda_{Max}}$$

Here λ_{Max} is the largest eigen-value of the data correlation matrix:

(12) $$\lambda_{Max} = max(eigenvalue(X^T X))$$

The topology used in this paper is shown in Fig. 2.

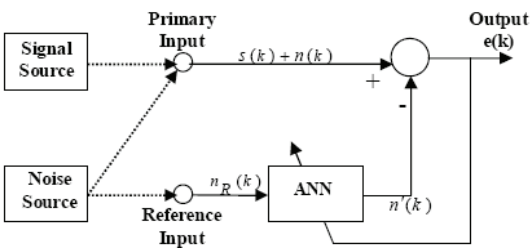

Fig.2. Topology of adaptive-active noise cancellation system

The initial input includes the desired speech signal $s(k)$ and the noise $n(k)$. The reference input, however, includes only the $n_R(k)$ noise. The $n(k)$ noise is not exactly the same as the $n_R(k)$ noise (it has been filtered and attenuated by the noise path). There is also an slight delay due to acoustic propagation. To achieve maximum cancellation, a smart adaptive and active network should be used with the aim of converging the $n_R(k)$ noise to the $n(k)$ noise as much as possible. We have opted for the ADALINE neural network here. Considering the least mean squares (LMS) algorithm [11]:

(13) $$E[e^2(k)] = E[(s(k)+n(k)-n'(k))^2]$$

Assuming $s(k)$, $n(k)$ and $n_R(k)$ to be signals with zero mean and assuming s(k) to be independent of $n(k)$ and $n_R(k)$:

(14) $$E[s(k)(n(k)-n'(k))] = 0$$

and

(15) $$E[e^2(k)] = E[s^2(k)] + E[(n(k)-n'(k))^2]$$

Considering the fact that the reference input signal has no information about the s(k) signal, minimizing the value of $E[e^2(k)]$ will only affect the value of its second term. In other words, minimizing $E[e^2(k)]$ is the same as minimizing the difference between $n(k)$ and $n'(k)$, resulting in reduction or cancellation of the noise signal and leaving the speech signal (the desired signal) as the error $e(k)$ in the output [11, 12].

The following delay-attenuation model is used for modelling the acoustic propagation path of the noise:

(16) $$Y(n)_{Propagated} = (1-A)Y(n-\Delta)_{Source}$$

$Y(n)_{Propagated}$ is the signal propagated on the acoustic path, Y(n) source is the main, un-propagated signal, A is the attenuating factor for the propagation path and Δ is the delay of the propagation path.

Implementation and test

The designed system is implemented and tested in a real environment with noise propagated in the acoustic environment. Fig. 3 shows the acoustic environment used for the test.

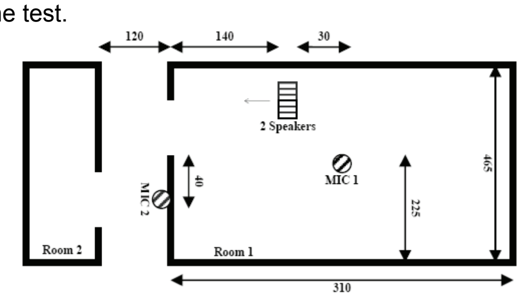

Fig.3. Dimensions of the real environment used for system test (in centimetres)

Results obtained for the sine noise (in different frequencies) are given in following figures and Table 1. (Number of weights=64 , Learning rate=0.0001).

Results obtained in the presence of a 50 Hz sine noise:

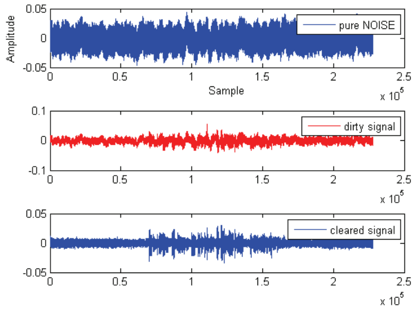

Fig.4. Noise frequency is 50 Hz. Amplitude in terms of sample.

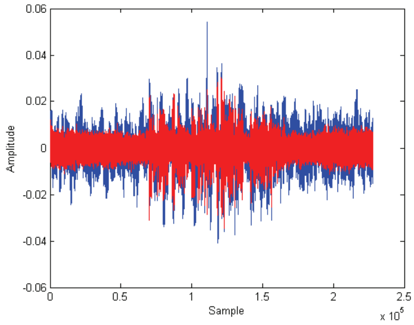

Fig.5. Dirty (blue) and cleaned (red) signals. Amplitude in terms of sample.

Results obtained in the presence of a sine noise with a frequency of 100Hz:

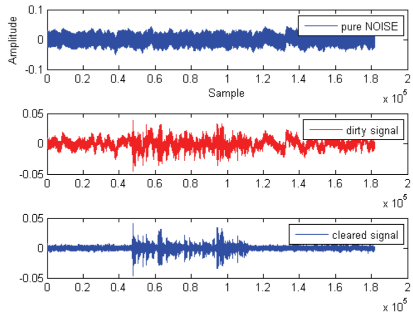

Fig.6. Noise frequency is 100 Hz. Amplitude in terms of sample.

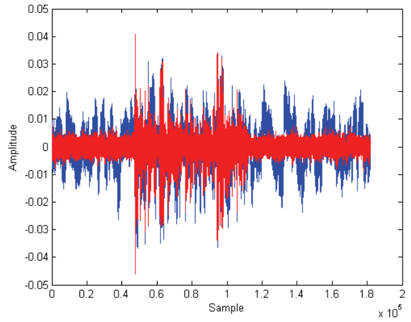

Fig.7. Dirty (blue) and cleaned (red) signals. Amplitude in terms of sample.

Results obtained in the presence of a sine noise with a frequency of 500 Hz:

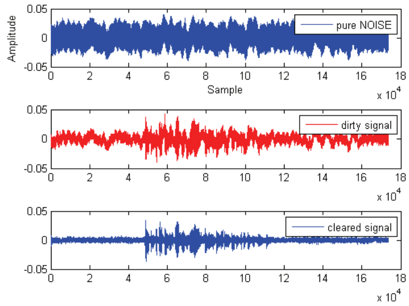

Fig.8. Noise frequency is 500 Hz. Amplitude in terms of sample.

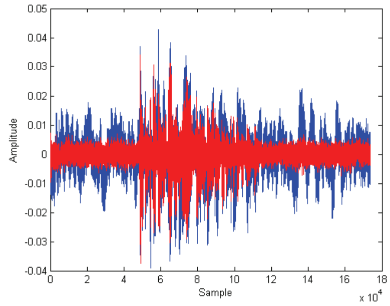

Fig.9. Dirty (blue) signal and cleaned (red) signals. Amplitude in terms of sample.

Results obtained in the presence of a sine noise with a frequency of 1000 Hz:

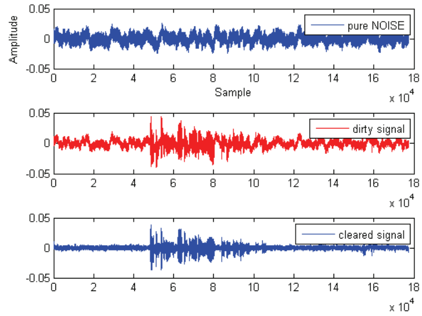

Fig.10. Noise frequency is 1000 Hz. Amplitude in terms of sample.

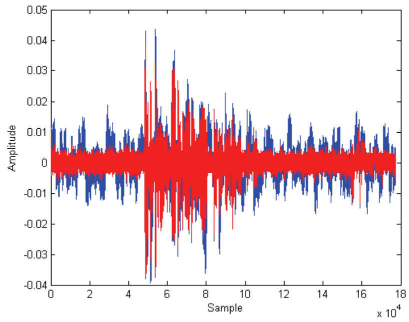

Fig.11. Dirty (blue) and cleaned (red) signals. Amplitude in terms of sample.

Results obtained in the presence of a sine noise with a varying frequency of first 15 Hz, then 100 Hz and finally 710 Hz):

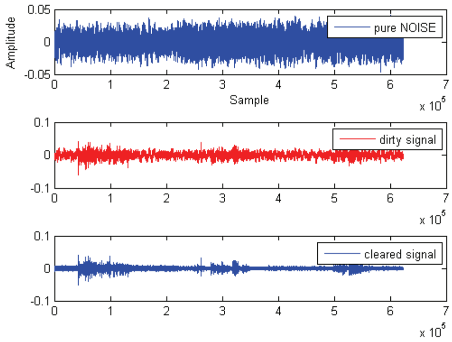

Fig.12. Varying noise. Amplitude in terms of sample.

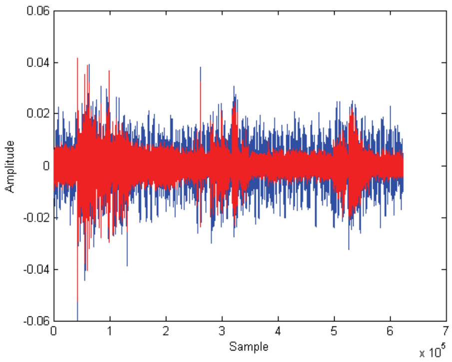

Fig.13. Dirty (blue) and cleaned (red) signals. Amplitude in terms of sample.

Table 1. SNR improvements

Sine Noise Frequency (Hz)	SNR Improvement (dB)
50	43.54
100	43.91
500	44.92
1000	45.69
15, 100, 710	44.46

Considering the above figures and SNR improvements in Table 1 and also by hearing the output of the system, we can conclude that the implemented system has good functionality. The above tests were carried out in a real noise environment by using the sound card of a P4 computer.

Conclusion and recommendation

An adaptive-active noise cancellation-control system based on two microphones was proposed. This System can drastically reduce noise, whether in conference halls or cockpits or for applications such as commercial headsets. The system was tested in real noise environments and its functionality for real-time noise reduction in commercial or military applications was confirmed. This system can be implemented using a PC (for conference halls and etc.), DSP or FPGA Processors for stand-alone purposes. Simple and relatively low calculations are among advantages of this system. Because the system is adaptive, it has the ability to converge and estimate the new acoustic path in a short time when microphones positions or propagation path are changed; (adaptive learning).

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