Seoul 2000 FISITA World Automotive Congress
June 12-15, 2000, Seoul, Korea

F2000H187

ACTIVE NOISE CONTROL WITH ARTIFICIAL NEURAL EXPERTS

R. Suchar [1) *], B. Schalling [2)], I. Ciocoiu [1)], A. Brezulianu [1)]
[1)] nodes GmbH, Warngauer Strasse 31, 81539, München, Germany
[2)] BMW AG, Landshuter Str. 56, 84130 Dingolfing, Germany

The aim of the project is related to active control of in-car noise. Basically, an artificially generated sound is superimposed on the unwanted interior noise in order to cancel it out. The canceling signal is obtained by suitable detection and processing of the interior noise so that the unwanted sound perceived by the human observer is considerably reduced. The core of the system consists of an ensemble of "experts' that are specialized in modeling the in-car noise for predefined engine rotation intervals. These are implemented by artificial neural networks, due to their well-known approximation capabilities. Tracking capabilities of the changes occurring in the environment are provided by adaptive weighting of the experts outputs. This action is driven by a discriminator that is able to distinguish between useful sounds (voice, radio, alarm signals) and unwanted noise. Experimental results show the efficiency of the proposed method, indicating significant noise level reduction in a fairly broad frequency range.

Keywords: noise control, neural networks, artificial intelligence

INTRODUCTION

The problem of noise attenuation in the interior of the cars is not only highly desirable from the comfort viewpoint, but also technically challenging. Two approaches have to be considered: a) noise source identification and removal; b) interior noise attenuation through sound absorbers or active noise control. The present paper reports the results of a project related to the second approach, aiming at active control of in-car noise. Basically, an artificially generated sound is superimposed on the unwanted interior noise in order to cancel it out. The principle of operation is described in Figure 1. The canceling signal (secondary source) is obtained by suitable detection and processing of the interior noise (primary source) so that the noise level perceived by the human observer is considerably reduced.

We have implemented a control procedure with the following advantages:

- the method is effective in a broad range of audio frequencies, especially at low ones, where (passive) sound absorbers are difficult to use due to prohibitively large dimensions;
- it can track time-varying modifications of the primary noise source or system components;
- it preserves useful information such as speech or alarm signals;
- it uses a single detector (microphone)

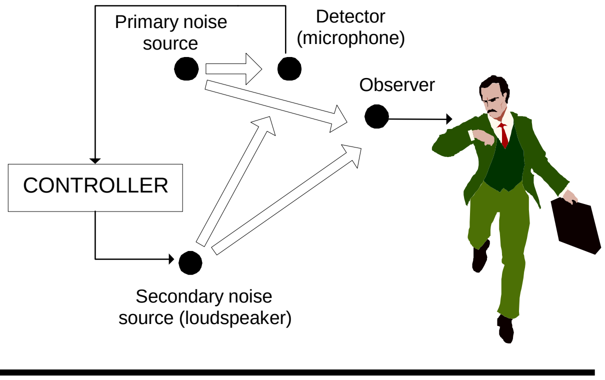

Figure 1 – Block diagram of the approach

* Corresponding author e-mail address: suchar@nodes.de

TECHNICAL DETAILS

Ideally, the secondary noise source should be a **phase-reversed** copy of the primary one. Existing solutions based on neural networks use a single architecture of multilayer perceptron or RBF type (2, 3). Our approach is presented in Figure 2. We may distinguish two separate processing levels:

a) *Off-line learning:* this module is responsible for accurate **prediction** of the primary noise source. It uses an ensemble of "experts' implemented by distinct neural networks which are specialized in modeling the in-car noise for predefined engine rotation intervals. Multilayer perceptron (1)* architectures were used, due to their well-known approximation capabilities. The common input signal x[n] represents an **estimation** of the true primary noise at instant n, whereas each expert output is a prediction of the same signal at the moment n+m. Parameter m depends on the time delay introduced by the DSP circuits implementing the Controller. Two principles have been implemented and tested:
   1. Time-domain approach. input data was provided as a vector of delayed values contained in a sliding window 15 samples long, and one-step ahead prediction was performed.
   2. Spectral Approach. input and target data was obtained after succesively computing the Fourier Transform (FFT) on a sliding window, and 10-step ahead prediction was performed.

b) *On-line learning:* this module offers tracking capabilities of the changes occurring in the system. It performs an adaptive weighting of the experts outputs in order to offer best predictive accuracy, by means of the well-known Least-Mean Square (LMS) algorithm.

Its action is driven by a discriminator that is able to distinguish useful sounds (voice, radio, alarm signals) from the primary noise based on the following data:

- the Mean Square Error (MSE) performance:

$$MSE = \sum_{n} \left(x[n] - y[n]\right)^2 \qquad (1)$$

- primary noise level for the current engine rotation value
- spectral pattern for the current engine rotation value: it is defined as a vector of amplitudes of the first 5 harmonics.

Nominal values of the last two quantities are measured in a noise-free environment and stored as a look-up table. Differences between nominal values and those measured on-line are accumulated for a short time interval and compared against predefined thresholds. When simultaneously exceeded, the sound environment is classified as (possibly) useful information and the on-line learning process is inhibited. It is resumed only after all three quantities decrease below the threshold values.

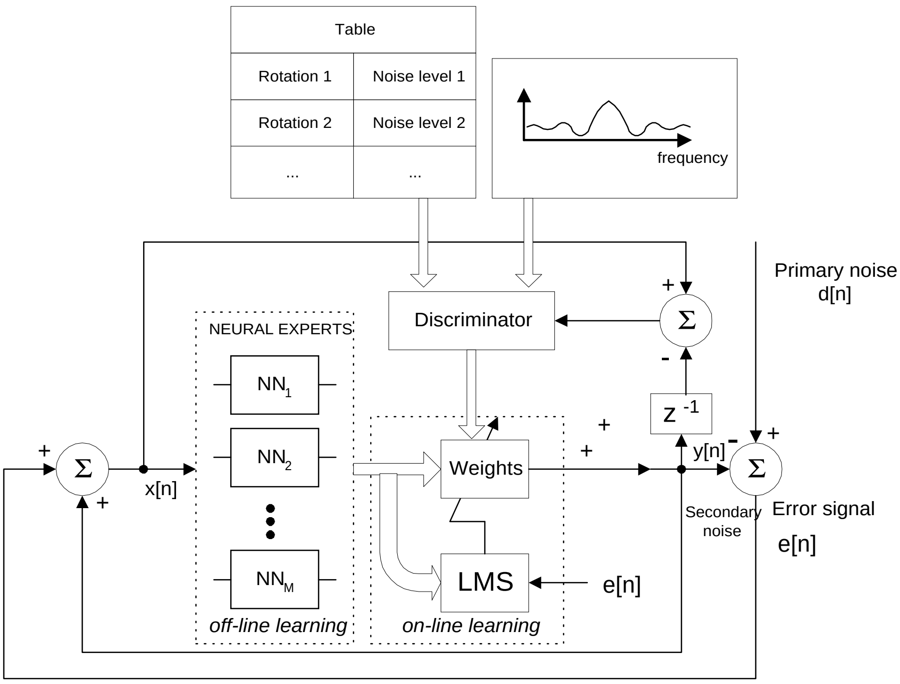

Figure 2 – Block diagram of the active noise control mechanism

Time-domain approach

This approach proved best suited for handling DSP circuits with small delays. Several network topologies (MLP, RBF) have been tested with the same noise data, and the performances were quite similar.

Spectral approach

The spectral approach yielded better results to compensate for larger delays. The available database consisted in noise signals sampled at 8 kHz, and tests were conducted for varying prediction step up to 10 samples.

The frequency domain solution was configured as follows: The time-dependent Fourier coefficients of the noise series have been calculated by applying FFT on a sliding window. Subsequently, distinct networks have been trained to perform for each coefficient a 10-step ahead prediction. By back-transforming the spectral approximations into the time domain, corresponding predictions of the time dependent noise data has been obtained.

EXPERIMENTAL RESULTS

Intensive computer simulations were conducted in order to test the efficiency of the proposed method. They fall into several distinct categories:

a) modeling and canceling the in-car noise perceived by the driver produced only by the car engine
b) modeling and canceling the in-car noise perceived by the driver while speech signals are superimposed on the engine noise
c) modeling and canceling the in-car noise perceived by the driver while alarm signals are superimposed on the engine noise

Time-domain approach: short-term prediction (1 step)

Simulation results are presented in Figures 3, 4, and 5. They show that significant noise level reduction is achieved in a fairly broad range of audio frequencies, especially at low ones where passive sound absorbers are difficult to use.

Spectral approach: long term prediction (10 steps)

Experimental results are indicated in Figures 6 and 7. They should be compared to Figures 8 and 9, where 10 step prediction results using the time domain approach are shown.

CONCLUSIONS

An active noise control mechanism has been proposed and successfully tested. It is based on the use of artificial neural networks, significantly reducing the perceived in-car noise level even in a continuously changing acoustic environment. The system is capable of attenuating the undesired noise level while still preserving important sound information such as speech or alarm signals. Further work will be dedicated to the possibility of improving the discriminator accuracy and the use of multiple loudspeakers for uniform attenuation of noise in every point of the habitacle.

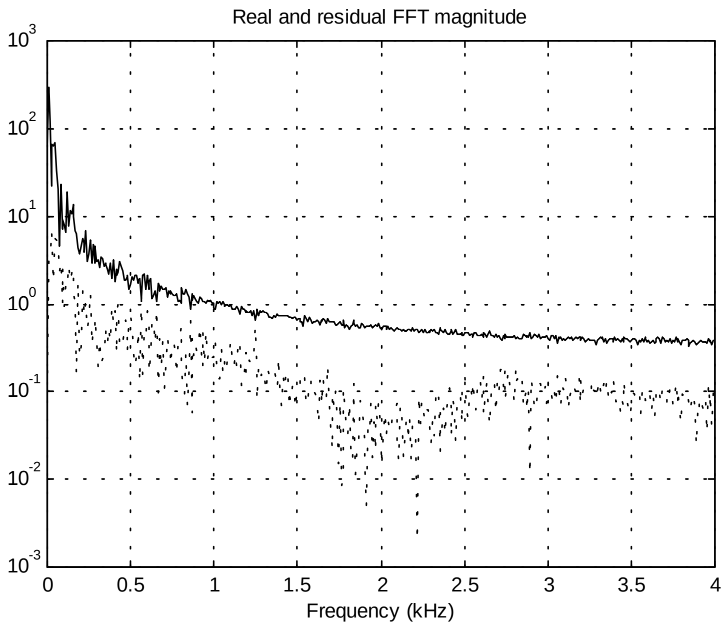

Figure 3 – Time domain approach, 1-step prediction horizon
Power spectrum of primary and residual noise series

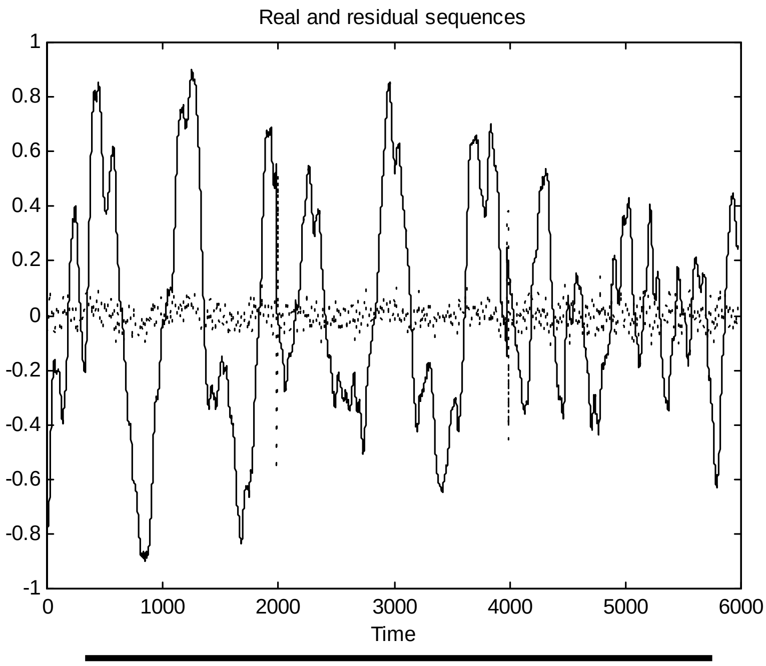

Figure 4 – Time domain approach, 1-step prediction horizon
Real and residual noise series

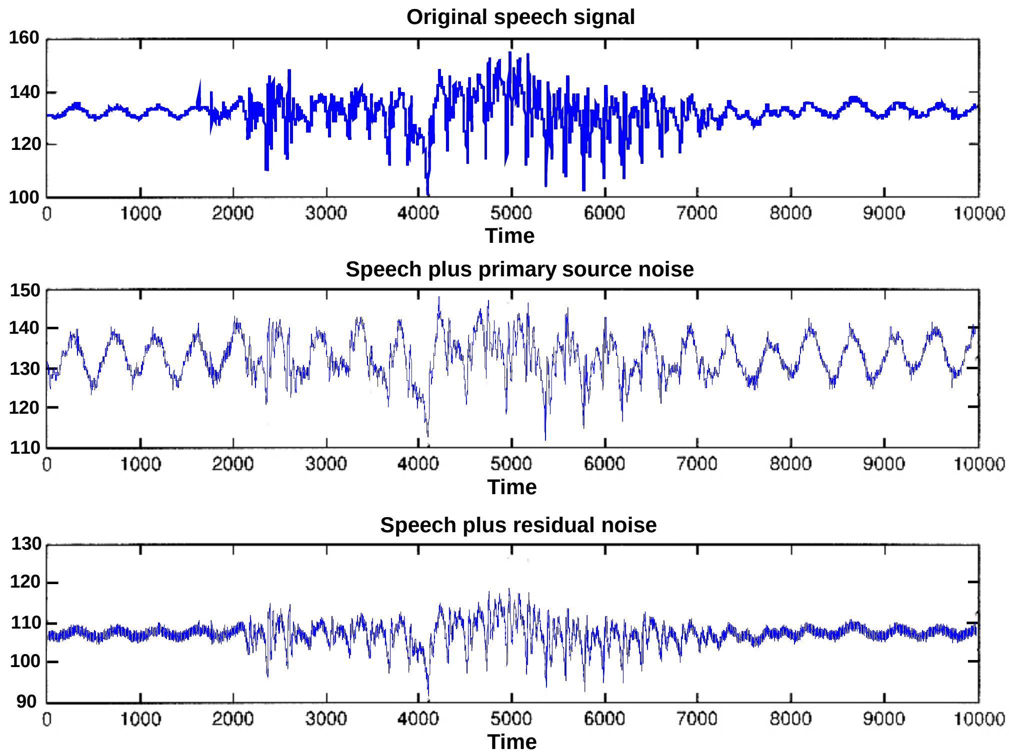

Figure 5 – Test waveforms using speech signals: residual noise represents the difference between the primary noise level and the canceling one synthesized by the controller

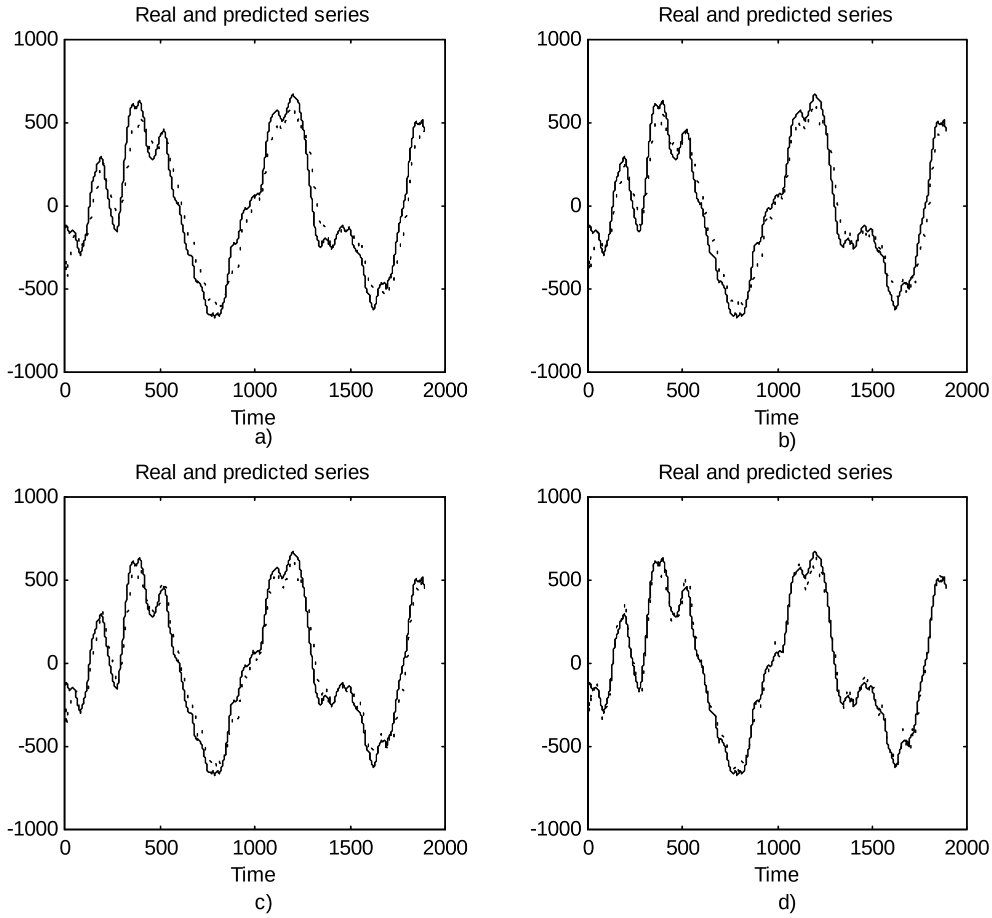

Figure 6 – Spectral domain approach, 10-step prediction horizon: Real and predicted time series
Approximation results using: a) first 12 harmonics; b) first 16 harmonics;
c) first 20 harmonics; d) all 64 FFT coefficients

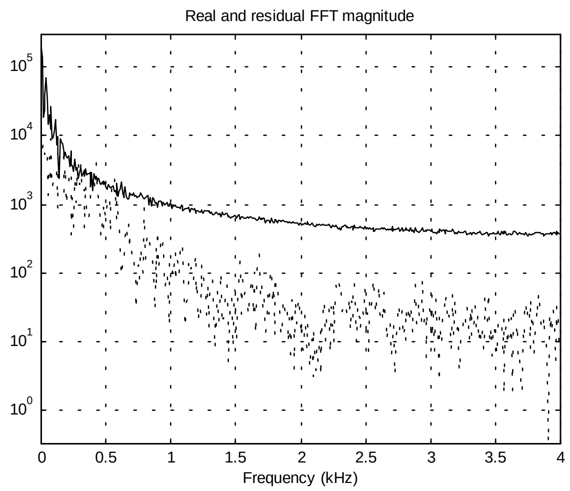

Figure 7 – Spectral domain approach, 10-step prediction horizon
Power spectrum of primary and residual noise series

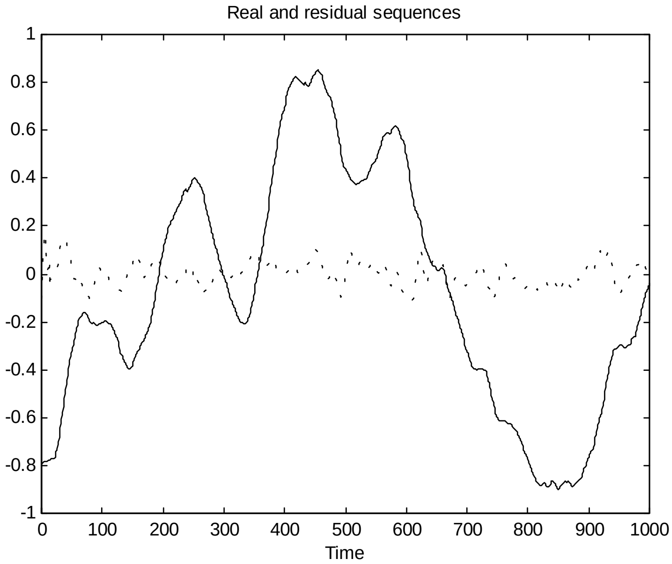

Figure 8 – Time domain approach, 10-step prediction horizon
Real and residual noise series

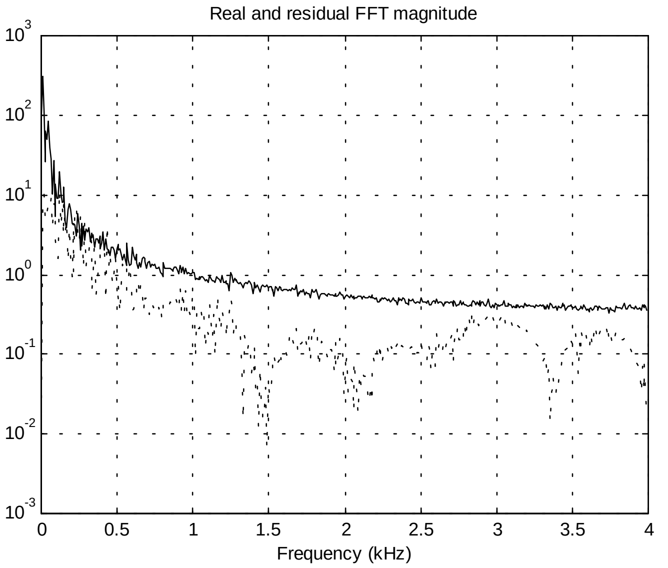

Figure 9 – Time domain approach, 10-step prediction horizon
Power spectrum of primary and residual noise series

REFERENCES

[1] Haykin, S. 1996. *Neural Networks – A Comprehensive Foundation*. IEEE Press

[2] Tokhi, M.O., and Wood, R. 1997. Active Noise Control Using Multi-Layered Perceptron Neural Networks. *J. of Low Frequency Noise, Vibration and Active Control* 16: 109-144

[3] Tokhi, M.O., and Wood, R. 1997. Active Noise Control Using Radial Basis Function Networks. *Control Eng. Practice* 9: 1311-1322