

## ACTIVE NOISE CONTROL IN DUCTS USING GENETIC ALGORITHMS.

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### ABSTRACT

This paper addresses the problem of actively control acoustic noise in ducts through the application of genetic algorithm and genetic programming (termed GENETIC CONTROL). Genetic programming is applied to structure a control strategy and genetic algorithm to adapt the resulting model parameters in real time. For application in real time situations, a gain/delay model was finally coded in the chromosome. The software was designed to run in a parallel DSP TMS320C44 architecture managing processors communication and shared memory with high performance. A mono-processor version was developed to actively reduce acoustic noise in ducts in real time. Two important situations in the presence of acoustic feedback and in its absence through microphone confinement are analyzed in the paper. The most striking result is the convergence of the genetic programming solution structuring a functional control strategy which is exactly the gain/delay model optimized by the GA approach as anticipated by the theory and experiment. We call *Genetic Control* the search of a control model by genetic programming and real time adaptation by genetic algorithm.

**Keywords:** Genetic algorithm; Genetic programming; Active Noise Control; Parallel processing, Self-structuring control

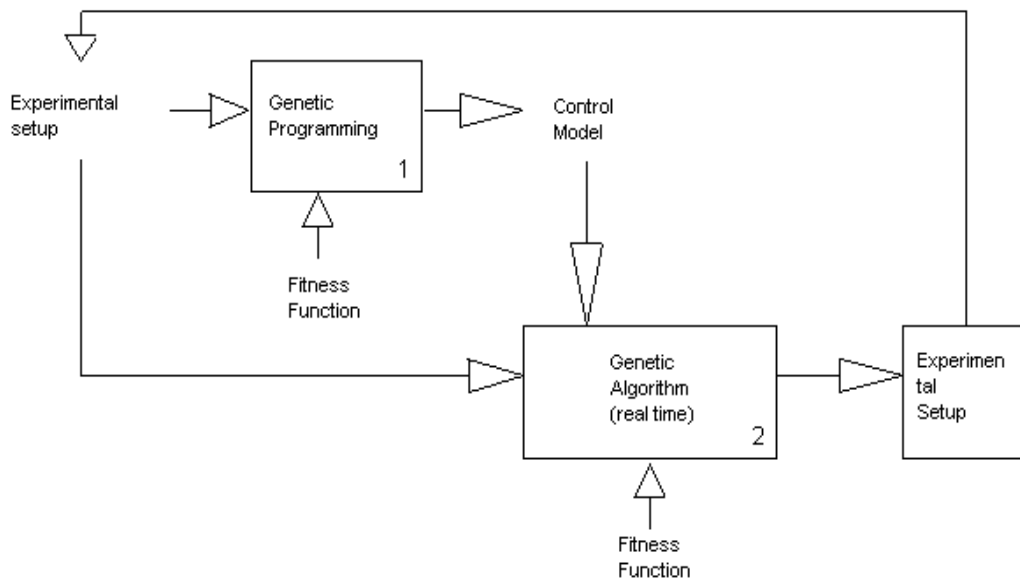
## INTRODUCTION.

The problem of active noise control in ducts is addressed in this work comparing classical adaptive control strategies [1] and genetic programming (GP) that explores artificial intelligence to obtain autonomous self-structured control models (fig. 1-block 1) for implementation and adaptation using genetic algorithm (fig. 1-block 2) in the real time environment of a laboratory setup using Digital Signal Processing -DSP.

The experimental setup of active noise control is a 6 meters long duct of with a speaker in one end producing acoustic noise and a set of speakers located at the midway to generate the canceling sound waves. Two microphones conveniently located along the duct are the sound sensors and inputs to the control algorithms acting to produce the right signal intended to cancel the noise. The closest microphone to the noise source gives the anticipated signal and the downstream microphone acts as the error canceling measurement.

Circular cross section cylindrical ducts were mounted on a wooden supporting platform, without sound box dampers for the speakers. The square cross section duct was built of 2 cm thickness wooden boards having reinforceners every meter apart. The speakers were mounted enclosed in a wooden box covered with Sonex and cellulose isolation in the diagonal, showing a smooth frequency response in the range of operation.

The acquisition system consists of an ADC64 board (Innovative Integration) with a DSP TMS320C32 and the parallel processing system is a PCI44 board (Innovative Integration) with 3 processors TMS320C44.



*Fig. 1 Proposed structure for identification, control and autonomous optimization.*

## SYSTEM IDENTIFICATION.

The identification of the acoustic system was carried out using conventional techniques as frequency sweeping, impact excitation, pulse and random noise inputs. Results were compared with a theoretical model based on the duct acoustical normal modes. The magnitudes were normalized between 0 and 100 with good identification adherence (fig. 2). It shows high modal density and equidistant peaks in frequency, indicating a vibrating-like string superposition model.

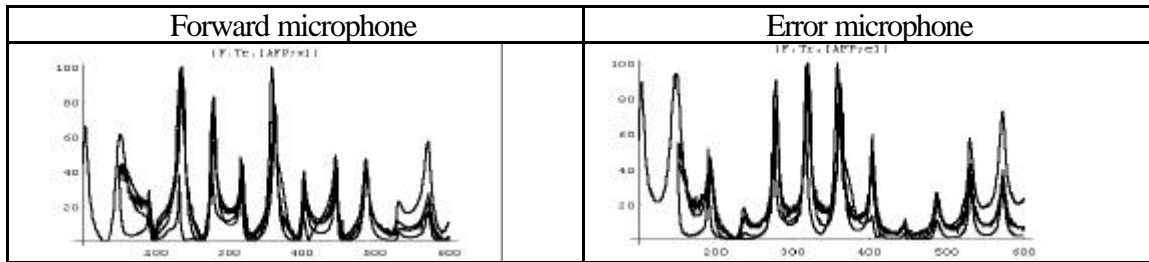


Fig. 2 Transfer function magnitude for the open simple duct.

## ADAPTIVE ACTIVE CONTROL.

Adaptive filters (mainly LMS algorithms) have their coefficients continuously adjusted in time to cope with changes the system is subjected to therefore, maintaining the error signal at acceptably low levels ([2], [3], [4] and [5]), by using the upstream microphone as the anticipated signal (forward control).

During active noise cancellation, the filter parameters are continuously updated to generate the speaker output to cancel the acoustic noise, minimizing the signal of the error microphone, aim to nullify the duct transmission dynamics and eliminating any presence of acoustic feedback residue.

Cancellation efficiency is related to the quality of the system adaptation, and is affected by the rate of the noise frequency change for the digital adaptive control evaluation blocks of 300 machine interruptions have been used for the energy calculation.

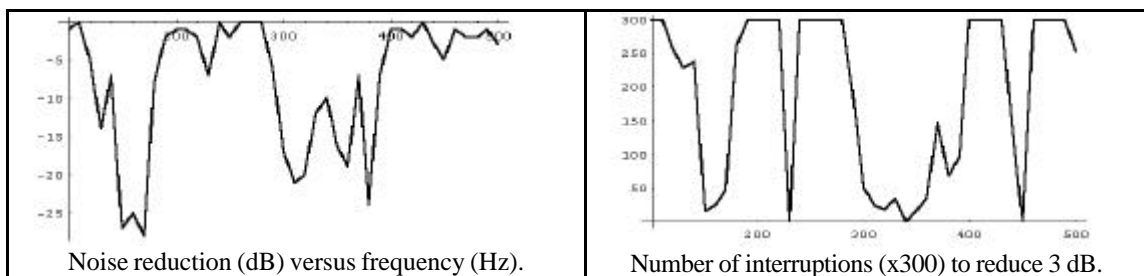
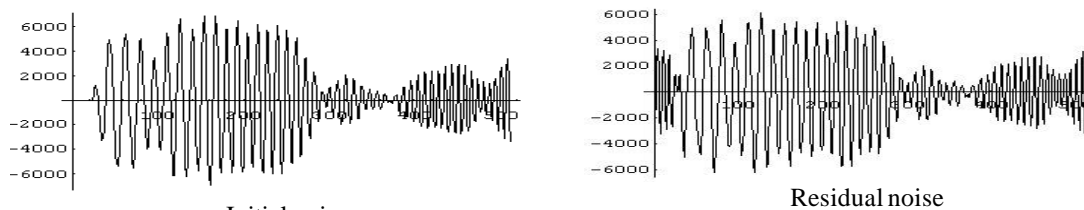


Fig. 3: Adaptive algorithm results for tone noise.

Fig. 3 shows the time necessary (in number of machine interruptions) to achieve a noise reduction of 3 dB where the maximum allowed time for convergence was set to 300.

In these results the LMS convergence parameter  $\mu$  was fixed to  $1.0 \cdot 10^{-13}$ , for all tested frequencies. Some improvement could be achieved in case  $\mu$  is allowed to float since the convergence rate is affected the noise power.

Noises having time variant frequency components showed to be difficult tasks for LMS adaptive control algorithms, presenting either poor convergence or acoustic instability. Experimental results in Fig. 4 show the initial noise and the resulting attenuation using LMS like algorithms for noises with frequency varying at a rate of 200 Hz per second, simulating the acceleration noise generated by a motor vehicle from a zero speed state. It can be observed a low 0.6 dB noise attenuation.



Initial noise  
Residual noise  
*Fig. 4 Time variant frequencies applied to adaptive algorithms.*

### **GENETIC ALGORITHM APPLIED TO ACTIVE NOISE CONTROL.**

Genetic control mimics the evolution and improvement of life through reproduction, when each individual contributes with its own genetic information building a new one with fitness to the environment and more surviving chances. These are the bases of genetic algorithms and programming ([6], [7], [8] and [9]). Specialized Markov Chains underline the theoretical bases of this algorithm change of states and searching procedures.

Each 'individual' of the generation represents a feasible solution to the problem, coding distinct algorithms/parameters that should be evaluated by a fitness function, in this application chosen to be proportional to the inverse of the acoustic energy (noise + acting signal), which can be seen topologically as a hyper surface having several local minima, due to partial sound destructive interference, and a global minimum leading to total noise cancellation.

The best individuals are continuously being selected, and crossover and mutation take place. Following few generations, the population converges to the solution that better reduces the acoustic noise.

Three different approaches have been studied using genetic algorithms (GA). In the *Simple Genetic Algorithm* (SGA) each individual of a generation is coded with specific attributes of the canceling sound: frequency, phase and amplitude, and the fitness function as the average sound energy measured at the downstream microphone (error microphone). A 180 Hz pure tone acoustic experiment illustrated the results (fig.5), using two different convergence techniques (with and w/o) elitism reinsertion in subsequent generations.

The evolution of each attribute in the chromosome and the evaluated fitness is shown (fig.6) as function of individuals' distribution for each generation. A high concentration of individuals around a value leads to peaks, indicating the convergence of the algorithm.

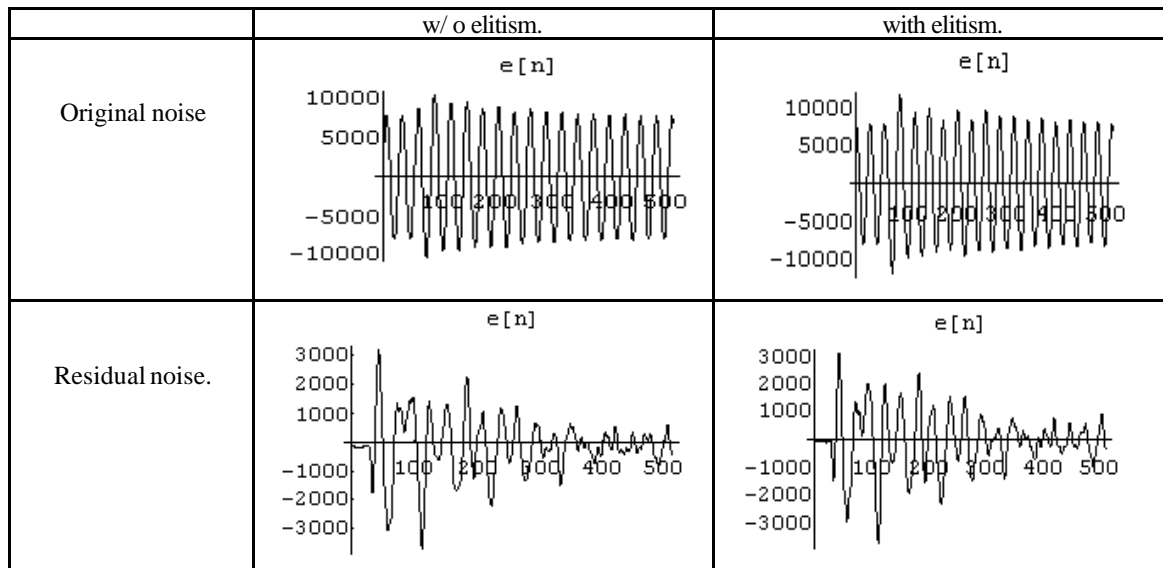


Fig. 5 Noise cancellation with open-end duct in the error microphone.

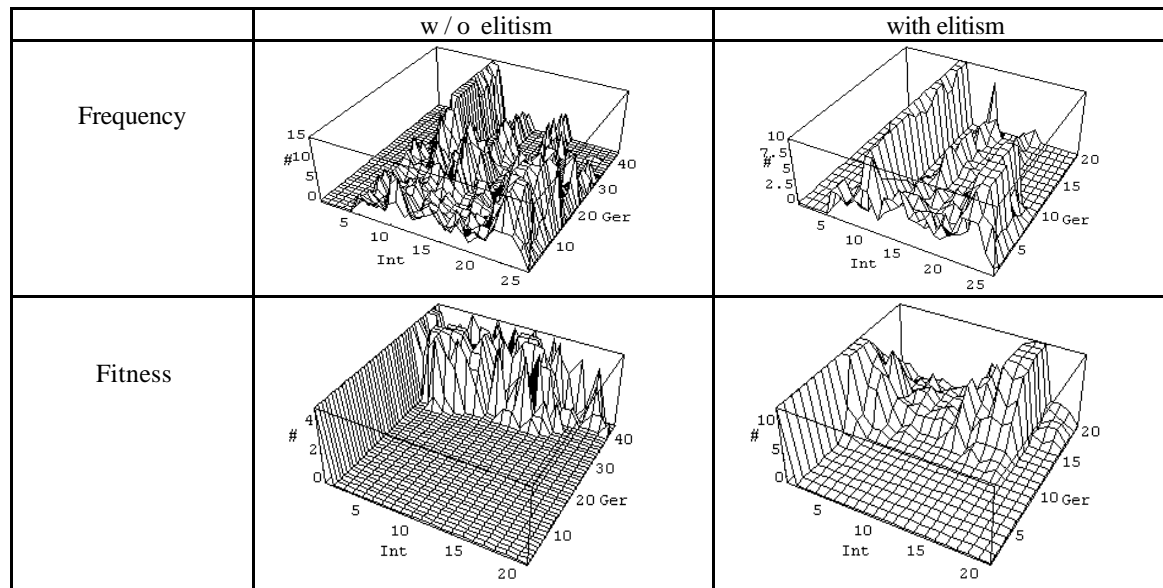


Fig. 6 GA evolution in open-end duct.

The *Successive Approach Genetic Algorithm* (SAGA) is a modification of SGA, where a first level procedure (fig. 8) searches for most probable candidate frequencies (in frequency domain) and a second level (fig. 9) improves them between fixed limits (in time domain). The 180 Hz pure tone is shown in fig. 7. The explicit time dependence is a bottleneck of this approach, due to needs for synchronization, periodicity and exhaustive sampling of each individual.

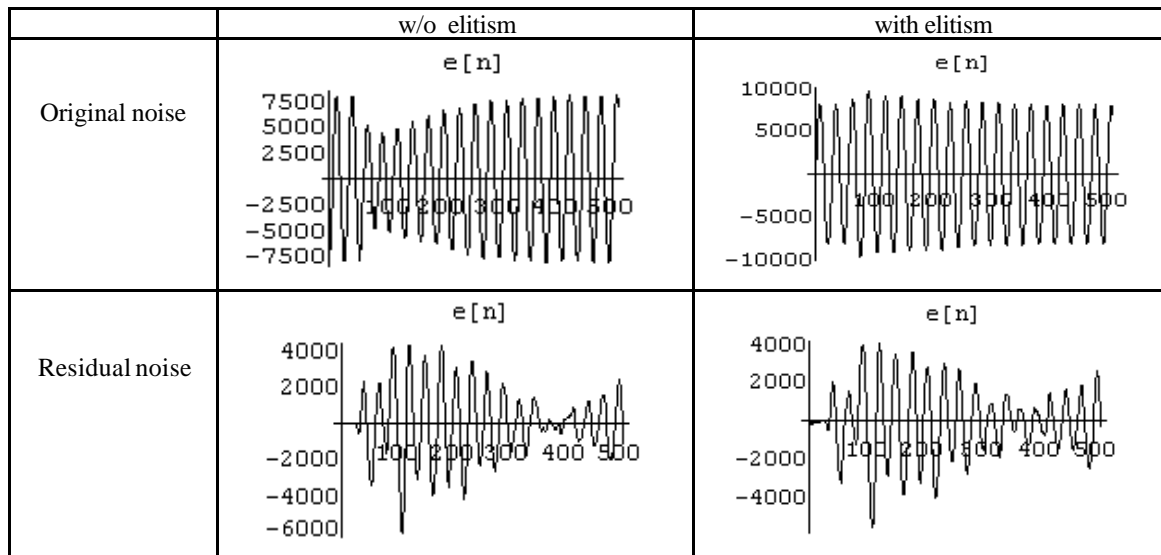


Fig. 7 Noise cancellation with open-end duct in the error microphone.

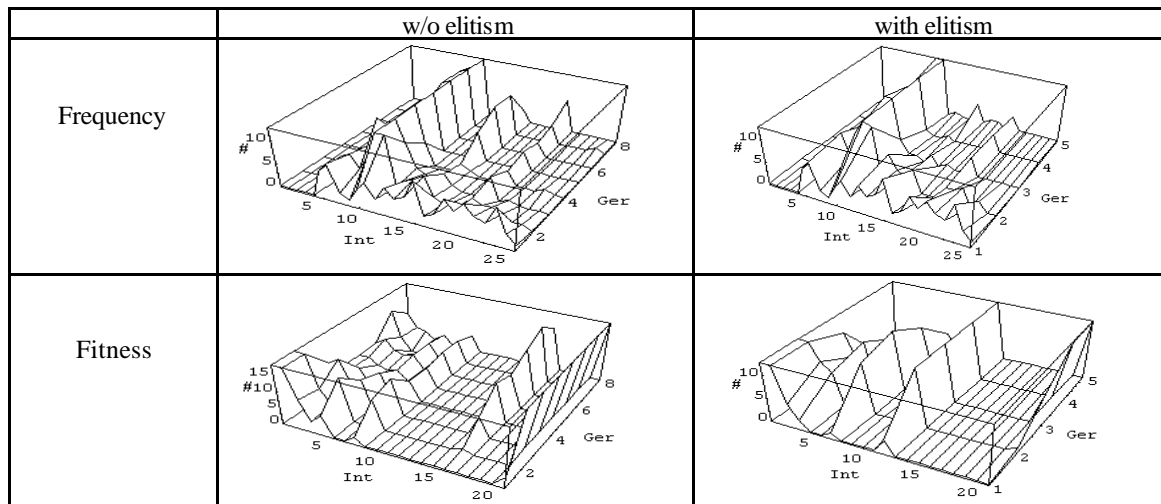


Fig. 8 SAGA evolution in open-end duct – Level 0.

An alternative operator based model coding the canceling sound have been considered using GA. For a pure tone plane traveling wave the best result turns out to be a gain-delay model with parameters chosen to essentially generate a  $180^\circ$  out of phase sound wave. The results obtained for a 180 Hz pure tone noise is shown in fig. 10. The evolution of the solutions (fig. 11) can be evaluated by the distribution of the individuals in subsequent generations showing the convergence to the noise cancellation condition.

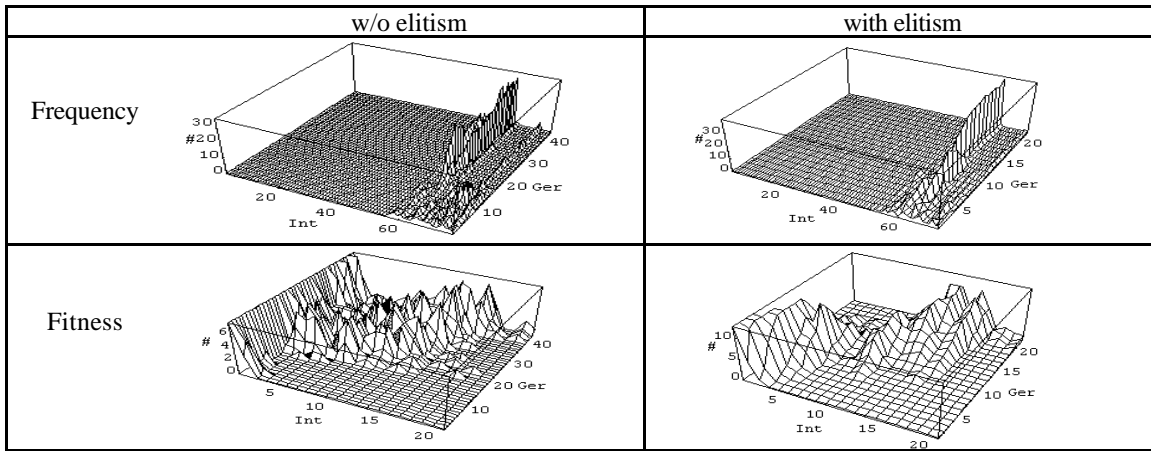


Fig. 9 SAGA evolution in open-end duct – Level 1.

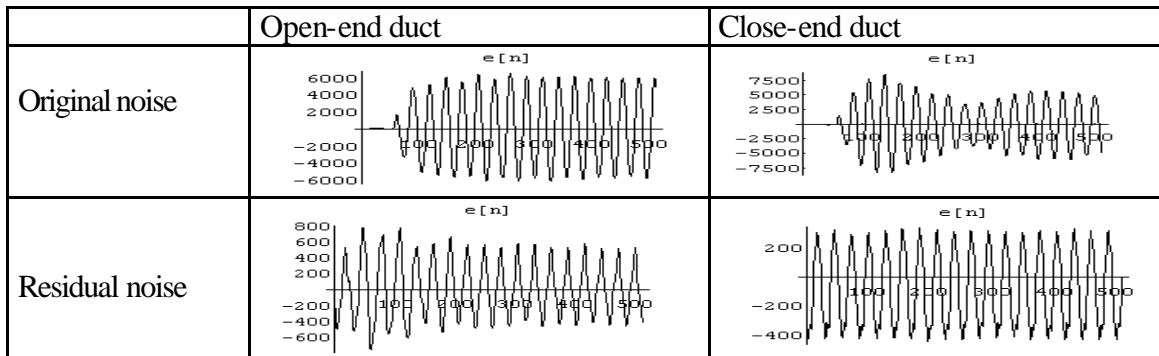


Fig. 10 Noise cancellation in the error microphone.

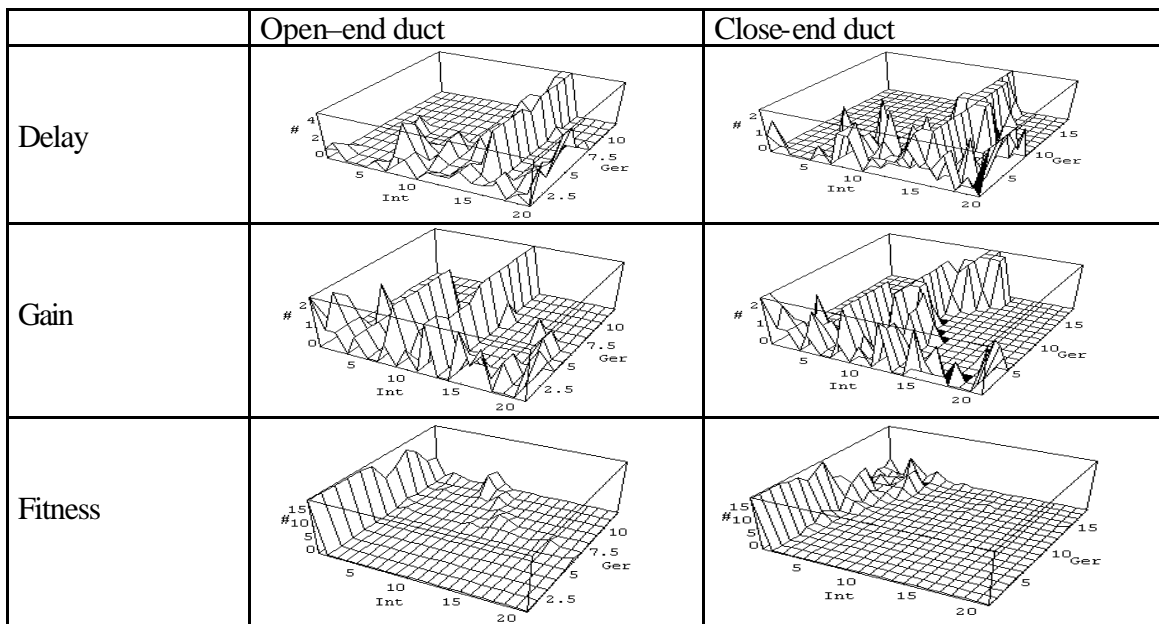


Fig. 11 GA evolution with gain-delay structure.

Genetic algorithm attenuation results (dB) for pure tone acoustic noise is presented in the fig. 12, on the 100 Hz and 500 Hz range. Compared with the LMS adaptive control approach the results show attenuation to be less sensitivity to noise frequency (fig. 3).

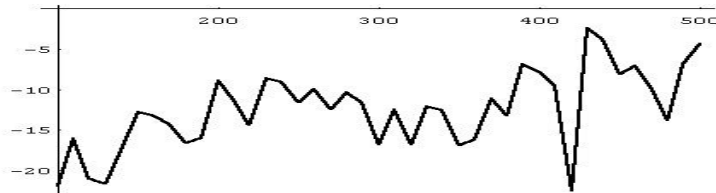


Fig. 12: GA results with gain-delay model.

### THE ACOUSTIC FEEDBACK.

The microphone positioned closer to the noise source senses both noise and acting signals, which can lead to system instability if the measured signal is not carefully handled. By confining the upstream microphone inside specially constructed sound damper boxes a considerable sound attenuation improvement is achievable as can be seen in fig 13, for experiments carried out with the rectangular cross section duct for a 180Hz pure tone noise.

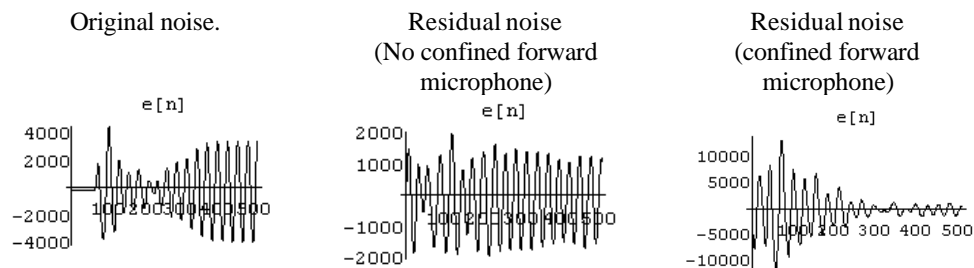


Fig. 13 GA results with forward microphone configurations.

### THE PARALLEL GENETIC ALGORITHM.

The implementation using three TMS320C44 DSPs explores the parallel feature of genetic algorithms with minimum system computation overhead if the parent's generation is mapped into the shared memory and children's generation in local memory, with collision semaphores settings (Table 1 and fig. 14). It can be verified that the use of the processors ended up been quite efficient.

The increase of computing speed obtained by parallel computers with n identical processors working in the same problem has a maximum performance of n times faster than of a single sequential processor and a minimum expressed by  $n \log n$  due to memory access conflicts or communication delays and inefficient algorithms (Minsky conjectures).

Table 1: parallel genetic algorithms performance.

	Mono processor	1 parallel processor.	2 parallel processor.	3 parallel processor.
180 individuals	317 ms	347 ms	168 ms	109 ms
Performance	100 %	109 %	52 %	34 %
	91 %	100 %	48%	31 %

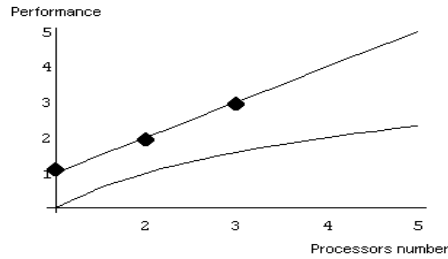


Fig. 14: Multi processing performance bounds and GA implementation.

## SELF-STRUCTURING THE CONTROL MODEL BY GENETIC PROGRAMMING.

The previously considered control schemes use GA in real time to fit the best parameters to a beforehand defined control structure. The approach followed hereafter uses genetic programming to obtaining a self-structured control model exploring artificial intelligence combined with GA to fit the best parameters in sequence.

In this application the GP uses the following function and terminal bases to build the control model in real time: multiplication, sum, random numbers, the past 30 microphones input and speakers output data for time independent structure and sin, cosine, multiplication, add, subtraction, random numbers for time dependent models.

Different (GA) approaches have been considered to adapt the control model in real time. Table 2 shows the final control model to cancel pure tone noise, with size population per generation of 5000 individuals. The achieved control structures are highly consistent with theoretical and experimental results for pure tone noises as can be see in Table 2

Table 2: The genetic control results to active noise cancellation: GP obtains the control model and GA adapts the parameters controller in the experimental setup.

	Base	Control Model
1.GP	+, -, *, Sin, Cos, Exp, t, random number	$y(t)=3311*\cos(716.9 t + 791.9 + \exp(t)+t- t)=3311*\sin(2 p 115.14 t +1.36)$
2.SAGA (experimental)		$y(t)=4570 \sin(2 p 115.14 t + 2.44)$

a) Genetic Control results for time dependent model

	Base	Control Model
1.GP	*, +, -, random number, past 30 noise acquisitions	$y[n]= 0.54 R[n-12]$
2GA (experimental)		$y[n]=0.47 R[n-13]$

b) Genetic Control results for time independent model with previous noise knowledge.

	Options	Base	Control Model
1.GP	Extended Base	*, +, -, x[n], y[n], e[n], random number.	$y[n]=y[n-17]+e[n-4]$
	Reduced Base	*, +, -, x[n], random number.	$y[n]=0.40 x[n-18]$
2.GA (experimental)	With acoustic feedback.		$y[n]=0.48 x[n-21]$
	With out acoustic feedback		$y[n]=0.50 x[n-18]$

c) Genetic Control with confined microphone.

	Option	Base	Control Model
1.GP	Extended Base	*, +, -, x[n], y[n], e[n], random number.	$y[n]=y[n-17]+e[n-4] + 0.06$
	Reduced Base	*, +, -, x[n], random number.	$y[n]=0.20 x[n-20]$
2.GA (experimental)	With acoustic feedback.		$y[n]=0.36 x[n-21]$
	With out acoustic feedback		$y[n]=0.36 x[n-20]$

d) Genetic Control with microphone on the duct mid-length.

## CONCLUSION.

The mathematical model and the experiments agreed quite well and supplied subsidies for understanding the physics of the active noise cancellation in ducts, that can be synthesized as plane traveling waves along the duct modulated by an infinite number of standing waves having high density spectrum modes. The particularity of canceling sound with sound waves, introduces the acoustic feedback drawback in the control problem.

The transfer function obtained by several experimental techniques such as the pulse response, random noise, impact and sweeping in frequency showed high adherence among them and confirmed the theoretical expected resonant frequencies of the acoustic system, and allowed the selection of the most relevant configurations for the study of the effect of the acoustic feedback (6" circular cross section cylindrical duct with junction and 10" sides square cross section cylindrical duct).

SGA has been formulated to be operated in real time, allowing the parametric optimization of pre-defined control structures both based on operators and time wave shape, showing convergence and dealing properly with instabilities caused by acoustic feedback.

SAGA has faster convergence rates than SGA by limiting the search space to the neighborhood of the frequency value obtained in the first level. This strategy has potential for application in systems with large number of attributes.

The gain-delay GA code representation of the canceling wave performed well besides the instability of the acoustic system, obtaining a good noise reduction.

In comparison with the adaptive approach (FBFXLMS) GA had a stable uniform performance in experimental frequency range, although GA has not been conceived a priori to explicitly handle the acoustic feedback in the way the adaptive algorithm has (the use of a LMS filter for compensating the system transmission is a crucial advantage).

The control strategy to combine GA and GP [10] has shown high potential for self-structuring control models in real time applications specially for autonomous systems by exploring artificial intelligence and the parallel processing capabilities as shown in this paper. The combined methodology is termed GENETIC CONTROL (GC) for real time applications.

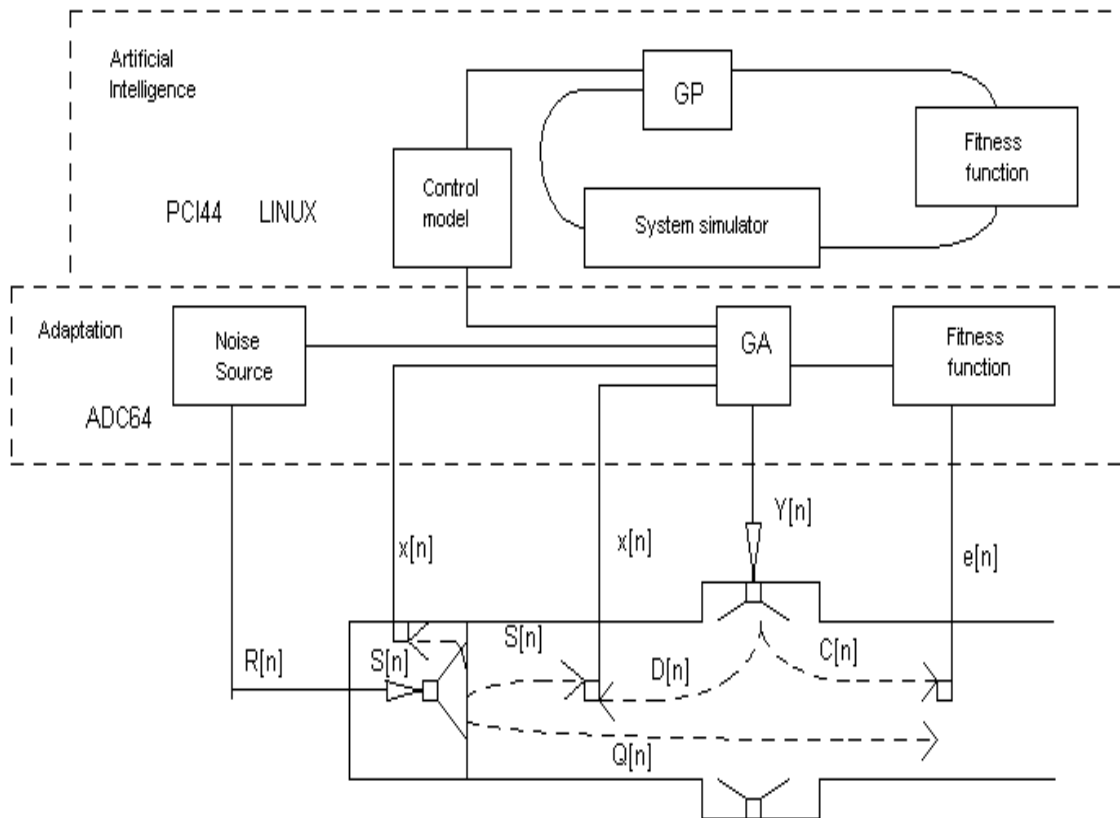


Fig. 15. Genetic control (GC) heuristic.

To further explore these features of GC it will be applied to several classes of problems like industrial control systems such as fermentation, transportation systems and information technology problems (classification, clustering, evaluation, decision taking and multi agent systems).

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## BIBLIOGRAPHY

1. Nelson, P.A.; Elliott, S.L.; “*Active Control of Sound*” - Academic Press (1994)
2. Chassaing,R.; “*Digital signal processing with C and TMS320C30*” John Willey & Sons,Inc 1992.
3. Haykin, S.; “*Introduction to adaptative filters*” New York MacMillan 1984
4. Kuo,S.M.; Morgan,D.R.; “*Active noise control systems:algorithms and DSP implementations*”John Willey & Sons, Inc 1996. Kuo,S.M.; Panahi,I; “*Design of active noise control systems with the TMS320 family*” Texas Instruments 1996.
5. Widrow, B.; Stearns, S.D. ; “*Adaptive signal processing*” - Englewood-Clifs Prentice-Hall 1985.
6. Holland,J.H.; “*Adaptation in natural and artificial systems*” Univ. Michigan, Ann Arbor, 1975.
7. Goldberg,D.E.; “*Genetic Algorithms in Search, Optimization, and Machine Learning*” Addison-Whesley 1989.
8. Koza,J.R.; “*Genetic programming: On the programming of computers by means of natural selection*” MIT press 1992.
9. Koza,J.R.; “*Genetic programming II:Automatic discovery of reusable programs*” MIT press 1994.
10. Werner,J.C.; “*Active noise control in ducts using genetic algorithm*” PhD. Thesis- São Paulo University- São Paulo-Brazil-1999.