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OPTIMAL PLACEMENT OF SECONDARY SOURCES FOR ACTIVE NOISE CONTROL USING A GENETIC ALGORITHM

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I. INTRODUCTION

In enclosed spaces, although excellent noise control performance is obtainable by passive means, such as sound absorbing materials, the cost becomes high and the performance is significantly degraded for lower frequency sources. Active noise control (ANC) , on the other hand is most effective when applied in the relatively low frequency range. In active noise control, the pressure field of a primary source is first measured or calculated. The secondary source locations and strengths are then adjusted such that a quadratic cost function is minimised.

In this paper a configuration of secondary sources that maximises the theoretically achievale active noise reduction at a number of control positions greater than the number of error sensors in a general 3D problem is searched. This problem becomes more difficult as the number of secondary sources and the number of discrete candidate positions increases. The number of possible configurations of a fixed number of secondary sources may become very large. Therefor exhaustive search is ruled out and intelligent search techniques have to be employed. A genetic algorithm is used in this work. The method presented in this paper can be applied to general shape sources and spaces.

II. PROBLEM DEFINITION

The overall problem is to find an optimal configuration of secondary sources that maximises the theoretically achievable noise reduction in a predefined region in a general 3D system.In the simulation, additional control sensors are used to obtain a better evaluation of the achieved ANC in the predefined region. The measure of optimality of a given configuration of secondary sources is the achievable noise reduction, which is calculated after having determined the optimal secondary source amplitude and phase settings of a secondary source configuration. For a control system of given complexity, the number of possible secondary source configurations may become very large. The optimisation technique used should therefor be "intelligent". The method must also be able to incorporate some engineering knowledge (in the form of practical constraints). Given the nature of the problem, genetic algorithms seem well suited to tackle such a problem.

III. GENETIC ALGORITHM

The genetic algorithm(GA) is a optimisation technique (Holland 1975) based on an adaptive mechanism of biological systems, i.e. on the process of evolution. In contrast to other search methods, the genetic algorithm is a robust scheme because it simultaneously evaluates many points in the search space (parallelism inherent to the genetic algorithm) and is more likely to converge towards the global solution. The GA can be seen as a randomised search technique which uses a random choice as a tool to guide a highly exploitative search trough a coding of a parameter space. Given a set of points in a search space and a value or cost for each point, the GA selects from that set points with a probability proportional to their value or cost. It then uses genetically inspired operators of cross-over and mutation to generate a new set of points to test. Details of the method can be found in Goldberg, 1989 [2]. In this section is described how the genetic algorithm is formulated to solve the given ANC problem.

Coding. In genetic search, the evolution of a population is studied. The population consist of a number of *individuals* each carrying its genetic information in a *chromosome* In this application the chromosome is divided in sub-chromosomes each representing a secondary source location. For describing the secondary source locations n-bit binary coding is used. Having decided on the coding to be used, an initial random population of individuals (represented by chromosomes) is created.

Reproduction. Each individual corresponds to a secondary source configuration and results in a certain performance . Based on this performance, a *fitness* is awarded to each individual. In this application performance is based on the theoretically achievable amount of noise reduction in the control positions. After evaluation of the individuals, *selection* occurs. Selections picks pairs of individuals from the population. The probability of a string being selected is proportional to its fitness. The basic idea is 'survival of the fittest'. The selection method used in the present application is the roulette-wheel selection. Goldberg [2] describes the value of stretching fitness values to either de-emphasise or accentuate minor differences of the fitness values in a population. Therefor *linear fitness scaling* is used to prevent that during the first generations good individuals take over the population immediately. After many generations, scaling introduces more discrimination between nearly equally fit individuals.

Recombination The pair of strings undergo *recombination*, a process consisting of two operations: *crossover* and *mutation*. Crossover is the sexual operator; it mixes the parents' alleles together. The form of crossover used in this application is *one-point crossover*. It is applied to two parent strings with a certain fixed probability known as the *crossover probability* and works by selecting a point between two bits, breaking the parent strings at that point and exchanging the broken-off sections. In this way two new strings are formed. Mutation then acts on the offspring. With a fixed probability, known as the *mutation probability*, the value of an allele in an offspring changes toits opposite.

Now the offspring have to be reinserted in the population. In this application the population size is kept constant. This means that another individual must die. In this study 3 different ways for reinserting the new individuals created by the offspring in the population are compared.

1.random replacing of old individuals by new ones always keeping the fittest of the population alive (*Rrandom*)
2.replacing old individuals by fitter new ones (*Rfitter*)

3.replacing an old individual in a subset of the population that most resembles the new one (*Rcrowding*)
The process of selection and recombination is repeated until the new population is full. The cycle of producing a new population from an old one by selection and recombination is called a generation. The GA is run until a certain termination condition is met. The optimal secondary source configuration is represented by is the fittest individual from the final population.

IV. EXAMPLE

Introduction. As a example of the described optimisation method the theoretical achievable reduction of the emission through two openings in a 3D enclosure (see fig.1) is optimised by changing secondary source positions as a function of the number of secondary sources and error sensors used in the active noise control. The primary source is a general sound source emitting sound of a single frequency. 22 control locations are chosen in front of the openings in order to obtain a good characterisation of the sound emitted through the openings. Figure 1 also shows the 90 possible secondary source locations. Prior to the optimisation the acoustical field was completely characterised by calculating the primary source contribution and the transfer functions from all possible secondary source locations to all control positions using FDTD-simulations. The use of reciprocity enhances calculation speed considerably. Details of the FDTD-simulations and examples can be found in Botteldooren,1993[1].

GA parameter choice. Prior to the optimisation several tests were done to find the optimal set of GA-parameters: population size, mutation probability, replacement rule and scaling factor. The overall goal is to find the combination of parameters that makes the population converge with a high probability to the optimum result, using the least possible number of objective function evaluations (the CPU-time is determined by the number of function evaluations). Optimum parameter choice depends on the complexity of the problem at hand. The complexity of our ANC problem increases with the number of secondary sources used in the ANC system. So for each number of secondary the GA-parameters are studied in detail. As performance criterion we used the amount of dB-reduction after 250000 fitness evaluations. Due to the stochastic character of the GA, the average of the results of 10 runs are compared. The optimal sets of GA-parameters for different numbers of secondary are given in table 1.

Results. First the contribution of the primary source at the 22 control positions is calculated. From these control positions 14 positions receiving the largest signal from the primary source are chosen as error sensor locations. With this error sensor configuration the theoretically achievable noise reduction for each number of secondary sources is obtained by optimising secondary source positions. Next, from the 14-error sensor set the error sensor receiving the smallest signal is omitted and again the theoretically achievable noise reduction as a function of the number of secondary sources was calculated. These calculations are repeated for smaller numbe of error sensors and the results are given in table 2. To each result corresponds a certain secondary source configuration. A certain amount of noise reduction can be achieved in different ways. This lets the designer the possibility to choose the most cost-efficient and the most practical configuration. The benefit of using more secondary sources is more pronounced when using more error sensors.

V. CONCLUSIONS

The GA-FDTD combination is a promising optimisation technique in the field of active noise control. It can result in more cost-efficient noise control systems and has the advantage of finding more than one configuration with near optimal noise reduction. Future developments will include the optimisation of the configuration of secondary sources in a ANC-system for sources emitting sound in a limited frequency range or equivalently emmitting a tone of changing wavelength.

References

[1] Botteldooren D. (1993) "Acoustical finite-difference time-domain simulation in a quasi-Cartesian grid", J. Acoust. Soc. Am, 95(5), pp. 2313-2319

[2] Goldberg, D.E. (1989) "Genetic Algorithms in Search, Optimisation & Machine Learning", Addison-Wesley, 1989.

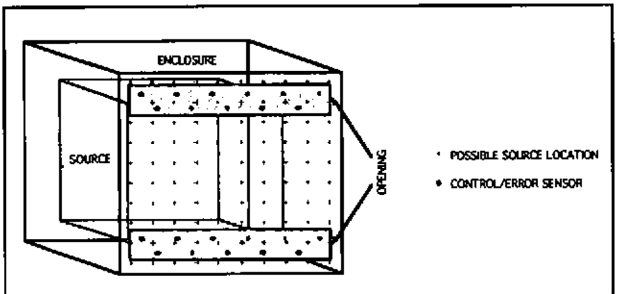

Figure 1: Shematic representation of the situation used in the example

parameter	number of secondary sources												
	2	3	4	5	6	7	8	9	10	11	12	13	14
population size	1000	1000	500	500	500	250	250	250	250	250	250	250	250
mutation probability	0.01	0.01	0.01	0.01	0.01	0.007	0.006	0.005	0.005	0.005	0.004	0.004	0.004
replacement rule	Rr	Rr	Rr	Rr	Rr	Rr	Rr	Rr	Rr	Rr	Rr	Rr	Rr
scaling factor	1.7	1.7	1.7	1.7	1.5	1.5	1.5	1.5	1.2	1.2	1.2	1.2	1.2

Table 1: Optimal GA-parameter sets

# error sensors	2	3	4	5	6	7	8	9	10	11	12	13	14
2	2												
3	3	5											
4	4	5	6										
5	5	6	7	8									
6	5	6	7	8	8								
7	5	6	8	8	9	8							
8	5	6	8	9	9	9	9						
9	5	7	8	9	10	10	11	9					
10	6	7	8	9	10	11	12	11	12				
11	6	7	9	10	10	12	12	13	14	15			
12	6	7	9	10	11	12	13	13	14	16	16		
13	6	7	9	10	11	12	13	14	16	18	18	19	
14	6	7	9	10	11	13	14	15	19	19	20	20	20
	# secondary sources												

Table 2: Theoretically achievable noise reduction (dB) for different ANC-systems.