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NOISE ANALYSIS AND MODELLING WITH NEURAL NETWORKS AND GENETIC ALGORITHMS

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The aim of the project is to reliably identify the set of constructive features responsible for the highest noise levels in the interior of motor vehicles. A simulation environment based on artificial intelligence techniques such as neural networks and genetic algorithms has been implemented. We used a system identification approach in order to approximate the functional relationship between the target noise series and the sets of constructive parameters corresponding to the cars. The noise levels were measured with a microphone positioned on the driver's chair, and corresponded to a variation of the engine rotation of 600-900 rot/min. The database includes 45 different cars, each described by vectors of 67 constructive features. The available {rotation, noise level} data series were compactly described by means of a reduced set of characteristic features obtained by computing the Discrete Wavelet Transform (DWT) and keeping only the most significant coefficients, which act as the true target series to be modeled. A neural network of RBF type was used to model the relationship between the constructive parameters vectors and the DWT coefficients. The training procedure is based on the Genetic Algorithms (GA) approach. An accurate input-output model was obtained, enabling the interpretation of the found dependencies. This was accomplished through sensitivity analysis, which measures the effect of *including* or *eliminating* each constructive parameter on the perceived noise level.

Keywords: artificial intelligence, noise reduction, sensitivity, wavelets

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 first approach, namely aiming at reliably identifying the subset of constructive features responsible for the highest noise levels in the interior of motor vehicles. The noise levels (expressed in dBA) were measured with a microphone positioned on the driver's chair, and corresponded to a variation of the engine rotation of 6000-9000 rot/min. The database included 45 different cars, each described by vectors of 67 constructive features such as loudspeakers, radar, sun-roof, etc. These vectors have *binary* values: 1's indicates the presence and 0's the absence of specific constructive parameters.
There are several distinct approaches to the problem:

- rule extraction, by using an expert system
- using classification theory methods
- using system identification techniques

We used the third alternative, heavily relying on modern artificial intelligence tools such as neural networks and genetic algorithms. Specifically, we seek to closely approximate the functional relationship between the target noise series and the constructive parameters vectors. After an accurate input-output **model** is obtained**,** it is possible to “decipher” the dependencies through **sensitivity analysis**, which measures the effect of *including* or *eliminating* each constructive parameter on the perceived noise level.

TECHNICAL DETAILS

In order to keep the analysis tractable, the available {rotation, noise level} data series were compactly described by means of a *reduced set* of characteristic features obtained by computing the Discrete Wavelet Transform (DWT) (1)[**]. *Wavelets* represent a special class of functions which can generate bases in functional vector spaces, when certain mathematical requirements are

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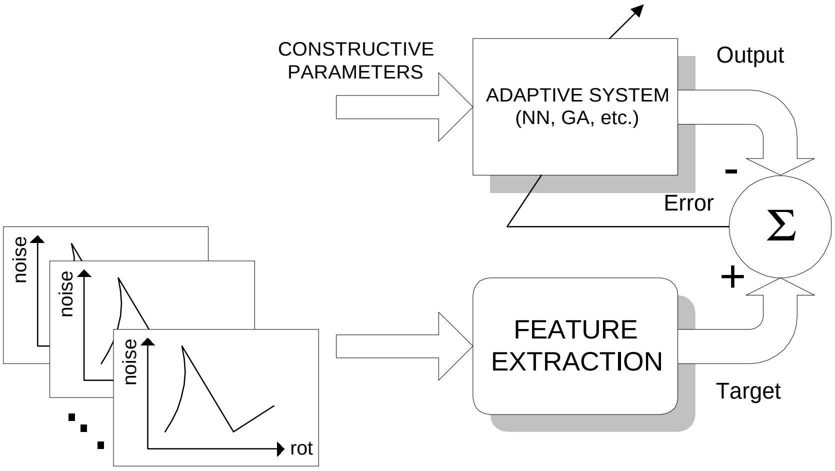


Figure 1 – Block diagram of the approach

fulfilled. In this respect, wavelet analysis is similar to the well-known Fourier analysis, whose basic elements are sines and cosines. Anyway, they differ in a major point: wavelet signals are *both* time and frequency (in fact, scale) localized, as opposed to sines and cosines, which are not time localized. This makes wavelets ideally suited for dealing with signals containing sharp spikes or sudden changes. The main idea behind the wavelet analysis is to implement some kind of *zoom* effect on the data, that is to successively decompose the original sequence in a sum of individual series containing progressively more information. As a result, one may obtain both a coarse (low-frequency) view on the analyzed data and more detailed (high-frequency) components.

The block diagram of the proposed approach is presented in Figure 1.

The ***selected (most significant) DWT coefficients*** act as the true target series to be modeled. Typically, about 25% of the total number of DWT coefficients are sufficient in order to satisfactorily approximate the true rotation-noise level dependence.

The ***adaptive system*** is responsible for modeling the relationship between the vectors of constructive parameters and the selected wavelet coefficients. We used a neural network to implement it, since it is able to "discover" the model based only on the available input-output training pairs, without making any assumptions about the underlying relationship. Best results were obtained with Radial Basis Function (RBF) nets (2), which possess advantages in terms of computational cost and convergence speed over other architectures. The structure of the network is shown in Figure 2.

RBF neural networks have been traditionally used as a multidimensional interpolation technique of general mappings $f: R^m \rightarrow R$ according to:

$$f(\boldsymbol{X}) = w_0 + \sum_{i=1}^{M} w_i \Phi(\|\boldsymbol{X} - \boldsymbol{C}^i\|) \qquad (1)$$

where ϕ is a nonlinear function selected from a set of typical ones, $\| . \|$ denotes the Euclidean norm, w_i are the tap weights and $C^i \in R^m$ are called RBF *centers*.

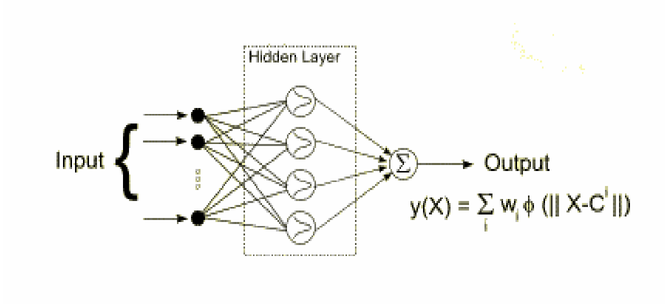


Figure 2 – RBF network architecture

The parameters of the networks were trained with Genetic Algorithms (GA), which have been mainly used as a global optimization tool (3). This concept is based on the natural principle of *survival of the fittest*, which basically states that the survival chances of a species are directly proportional with its capacity to adapt to the environment. Specifically, these algorithms minimize a *fitness function* (*e.g.*, the Mean Square Error between a target information and the actual output of the model used) using special mathematical operators, such as crossover and mutation. A *population* of distinct individuals is repeatedly evaluated, sorted, and processed in order to continually improve its performances in solving specific tasks. Every individual represents a possible solution to the optimization problem, and is typically initialized with random values. Two distinct GA algorithms are implemented (classic and crowding), and two selection procedures (wheel and tournament). The operators act upon the members of the population for a predefined number of *generations* (or until some type of

stopping criterion is met). The best individual from the last generation is declared the final solution of the problem.
A thorough sensitivity analysis was conducted, aiming at indicating the effect of each constructive parameter on the perceived maximum noise level. After the neural networks have been trained each constructive parameter of every car type is altered from 1 to 0 and from 0 to 1, simulating its removal and introduction, respectively. Distinct ($S^{1\to 0}$ and $S^{0\to 1}$) sensitivity matrices are obtained as follows:

1. Noise series for the altered inputs are computed from the outputs of previously trained neural networks.
2. The difference between the original and each altered noise series is computed.
3. The sensitivity coefficients are obtained as the average values of a sliding window of samples from the difference series, centered on the position of the maximum of the original noise series.

Positive sensitivity values indicate that including a specific constructive parameter will increase the maximum noise level, whereas eliminating it will decrease the perceived noise level. Alternatively, negative values indicate that including a parameter will decrease the noise level, while eliminating it will increase the noise level. A global sensitivity coefficient for every constructive parameter is obtained from the matrix $S = S^{1\to 0} - S^{0\to 1}$, as the ratio between the average value and the standard deviation computed across all cars.

EXPERIMENTAL RESULTS

Intensive computer simulations have been performed in order to test the performances of the proposed approach. Figure 3 shows the quality of approximation compared against the true measured noise level values for several distinct car types. We point out the capability of our system to properly reconstruct:

- the noise series over the whole interval of engine rotations
- the maximal noise levels

Groups of low sensitivity constructive parameters were successively eliminated and the networks retrained until a subset of robust significant ones were obtained. Ordered global sensitivity coefficients are shown in Figure 4. These coefficients are defined by the formula $\left|\langle x\rangle / \sigma(x)\right|$, where $\langle x\rangle$ is the average of x, and $\sigma(x)$ is the standard deviation. The least significant ones are those having lowest values. It is remarcable, that semantically not important parameters as car phone, outer skin preservation, etc. have indeed small sensitivity coeficients, whereas other parameters, as sunroof, HI-FI loudspeaker, etc. have essentially larger coefficients. If those parameters, which are known to be meaningless with respect to noise would a prori not participate to the simulation, then the results would become even more reliable.
Synthetic results are indicated in Figure 5.

SIMULATION ENVIRONMENT

The NNA (Neural Noise Analyser) simulation environment provides the following facilities:

- definition of the constructive parameters vectors through user-editable fields and/or file load from disk
- noise level files load, rotation interval selection for subsequent analysis, and plot
- DWT parameters selection and plot of the original and filtered noise series
- selection of the RBF networks parameters (number of centers, parameter value ranges, database splitting among Train/Validation/Test sets)
- definition of the Genetic Algorithms parameters (GA type, genetic operators probabilities, selection method, population dimension)
- extensive options for configuring and performing three types of experiments: Car Simulation, Sensitivity Analysis, and Sliding. True values of constructive parameters of available cars may be altered in order to simulate "virtual" cars with hopefully lower maximum noise levels. Moreover, pairs of real cars may be selected and their constructive parameters vectors gradually changed from one set towards the other, obtaining virtual cars that "slide" between the two. Those having lowest noise levels are of interest, and their constructive features would be carefully inspected.

CONCLUSIONS

The proposed methodology enables clear identification of individual constructive parameters that mostly influence the highest in-car noise levels, eliminating costly, time consuming practical tests. Car manufacturers may choose to eliminate those (combinations of) parameters responsible for generating high noise levels or take supplemental measures in order to diminish their effect. A user-friendly simulation environment permits thorough study of the influence that *groups* of constructive parameters have on the perceived noise levels through sensitivity analysis. According to this procedure, the constructive parameters are ranked according to their relative impact on the noise level expressed in terms of quantitative figures of merit. The environment also offers the possibility of modeling noise levels of *virtual* cars whose parameters result from altering those of real ones.
The proposed approach is not restricted to binary values for the constructive features. In fact, better results may be obtained if such vectors would consist of a combination of binary values (*e.g.*, the engine type: Diesel or spark-ignition) and real (analogic) values (*e.g.*, the thickness of sound absorbing paint).
Within a more general framework, the proposed solution could solve any task requiring the identification of functional dependencies (provided such a relationship exist) between a set of input constructive features and a target information of interest.

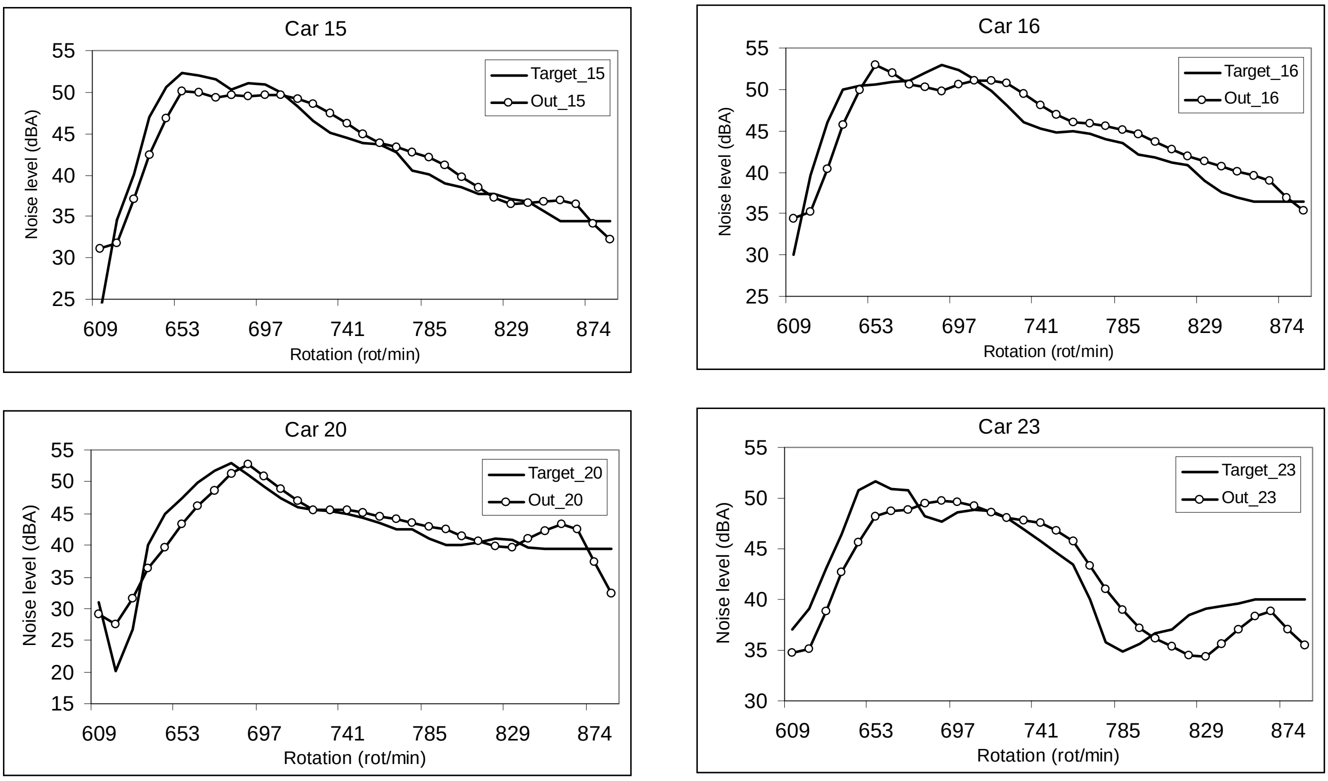
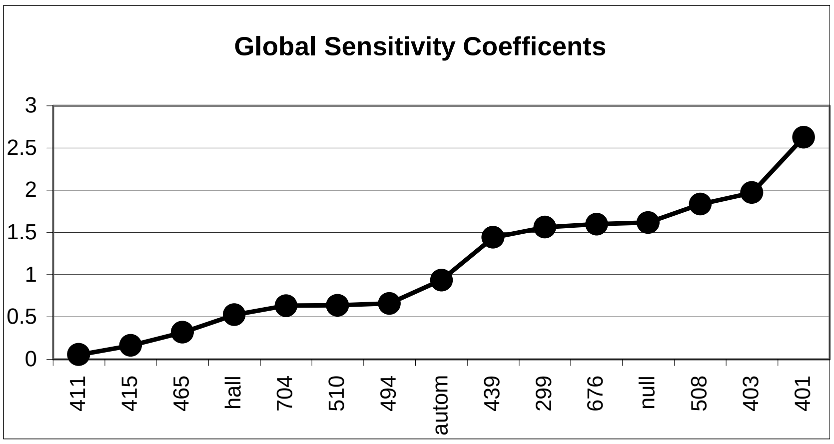


Figure 3 – Experimental results: noise series estimated by RBF networks for 15 selected constructive parameters



401	electrical sunroof
403	sunroof
508	park distance control
null	running idle
676	HI-FI loudspeaker
…	

Figure 4 – Ordered values of sensitivity coefficients for 15 constructive parameters

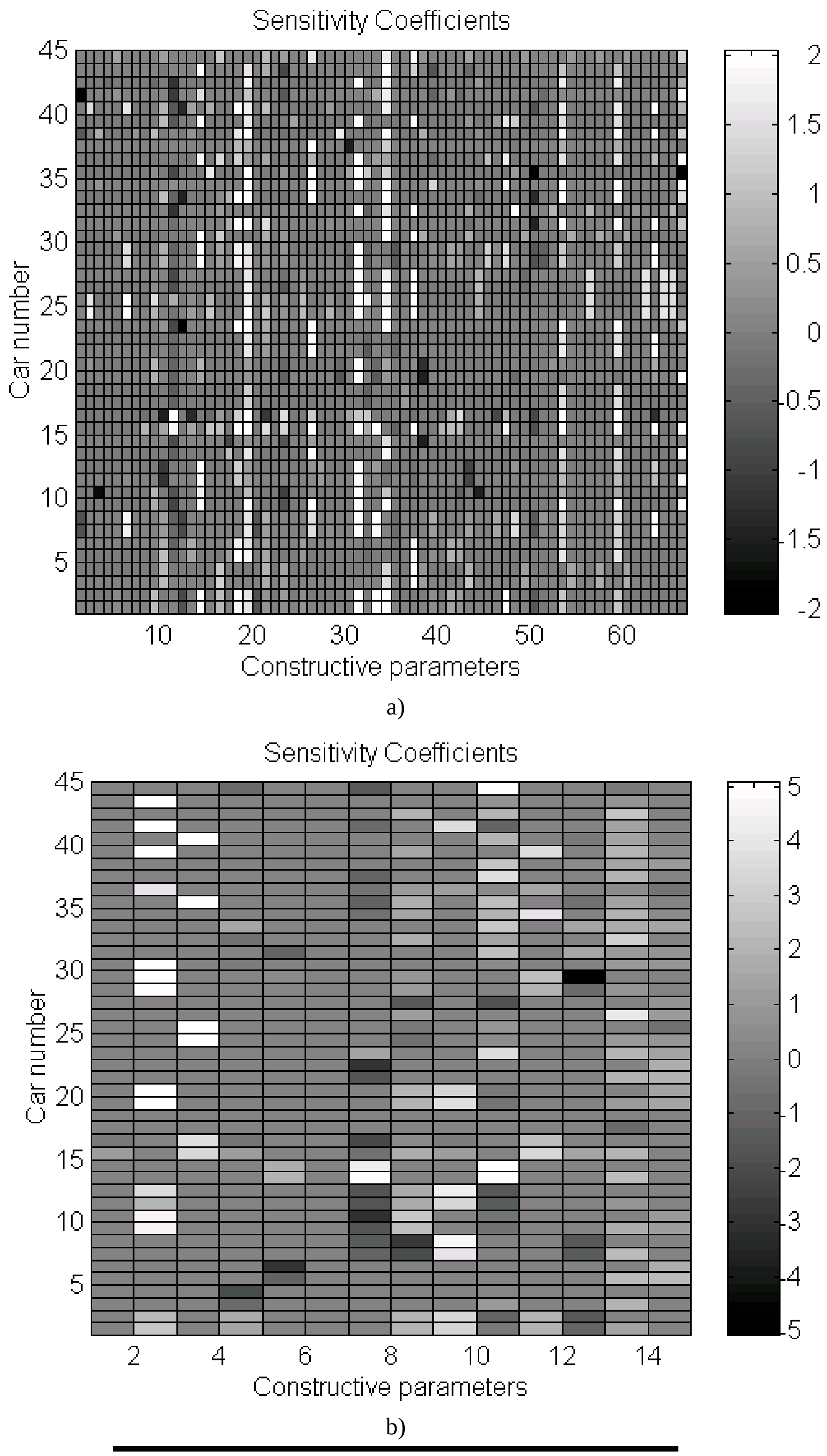


Figure 5 – Sensitivity results for: a) original 67; b) 15 selected constructive parameters

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