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MODEL IDENTIFICATION FOR ACTIVE NOISE CONTROL IN THE PRESENCE OF PRIMARY NOISE

SUMMARY

A problem of electro-acoustic plant identification for active noise control is discussed. It is assumed that data from identification experiment are contaminated by a primary noise that should be attenuated later. Three examples of such a noise are considered: sine (discrete spectrum), noise generated by a motor (narrowband time-varying spectrum) and broadband noise (pseudorandom). It is shown that thanks to preprocessing the data by disturbance adjusting filtration (DAF) it is possible to improve the results significantly when the data are contaminated by a narrowband primary noise. DAF is the procedure of selective filtration in frequency domain consisting in removing from the spectra all lines for frequencies corresponding to the noise. The results of real-world experiments carried on in a laboratory enclosure show the accuracy of estimated frequency responses obtained in the proposed approach. The procedure is efficient when multisine signals are used to excite the plant.

Keywords*: Active noise control, Process identification, Frequency response, Models*

METODY IDENTYFIKACJI MODELU W UKŁADACH AKTYWNEGO TŁUMIENIA HAŁASU Z ZAKŁÓCENIAMI W POSTACI SZUMU PIERWOTNEGO

W artykule omówiono problem identyfikacji obiektów elektroakustycznych dla celów projektowania układów aktywnego tłumienia hałasu. Przyjęto, że dane pochodzące z eksperymentu identyfikacyjnego są zakłócone przez szum pierwotny, który powinien być później tłumiony. Rozpatrzono trzy przykłady takiego zakłócenia: sinusoida (widmo dyskretne), hałas generowany przez silnik (zmienne w czasie widmo wąskopasmowe) oraz szum szerokopasmowy (pseudolosowy). Pokazano, że stosując wstępne przetwarzanie danych, polegające na odpowiedniej filtracji sygnałów, możliwe jest znaczne poprawienie dokładności wyników w przypadku szumów wąskopasmowych. Filtracja ta realizowana jest w dziedzinie częstotliwości i polega na usunięciu z widma wszystkich linii odpowiadających częstotliwościom zakłócenia. Wyniki doświadczeń przeprowadzonych na obiekcie rzeczywistym (pomieszczenie laboratoryjne) potwierdziły, że dzięki tej metodzie można uzyskać modele o odpowiednio dokładnej charakterystyce amplitudowo-fazowej. Przedstawiona procedura może być stosowana w przypadku, gdy obiekt pobudzany był sygnałem wielosinusoidalnym.

1. INTRODUCTION

Active noise control is concerned with attenuation of unwanted sound (noise) using electro-acoustic devices. Different algorithms for ANC are widely discussed in the literature, *e.g.* [9, 12]. In contemporary ANC implementations, predominantly digital adaptive feedforward systems are used for creating a local zone of quiet. To parameterize such an ANC system, the models of so called secondary and feedback paths are required. It is well known that the performance of ANC is affected by quality of these models as it is a typical feature of a feedforward control. The models of secondary paths are used to filter the reference signal and their accuracy influences noise attenuation because errors in estimation of a magnitude in frequency response reduce speed of convergence in adaptation algorithm while errors in the corresponding phase may result in non-stability of the ANC system [5]. The phase errors for frequencies within the range of operation should not exceed $\pi/2$. The acoustic feedback paths ought to be modelled as accurately as possible to avoid the ANC system destabilization [9].

In the example considered models are required to parameterize an adaptive feedforward ANC system creating a local 3-dimensional zone of quiet in a laboratory enclosure. Since dynamic behaviour of acoustic space in a reverberant enclosure is very complex and ever hard to describe by means of physical relationships, the *only way* to obtain these models is to take advantage of *experimental* process *identification*.

2. PROBLEM STATEMENT

Since the ANC system is implemented using digital signal processing (DSP) techniques, it is assumed that it works with the sampling interval T_s and signals (as well as models) are treated as discrete in time. The enclosure is disturbed by a *primary noise* that should be compensated by acoustic waves generated in control loudspeakers driven by signals computed in a DSP board. These signals are obtained by feedforward adaptive filtering of a signal measured by a *reference* microphone. Parameters of the filters are computed according to signals from *error* microphones. Each path that should be identified is an electro-acoustic plant composed of the following elements: D/A converter, reconstruction filter, amplifier, control loudspeaker, acoustic space between the speaker and the microphone, microphone,

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anti-aliasing filter and A/D converter. Such plants are rather difficult to identification since they differ much from typical industrial processes and can not be modelled by means of low pass filters of low orders.

The system under consideration is designed to attenuate low-frequency noise within the range of about 40–140 Hz. Sampling frequency is set to 500 Hz (T_s = 0.002 s) and both analog filters are the Butterworth 8-th order with cut-off frequency (–3 dB) at 150 Hz (that gives of about 34 dB attenuation at the Nyquist frequency equal to 250 Hz). Controller is based on DS1104 R&D board assembled by dSPACE [11].

Błażej in [1] compared different structures of ANC systems creating a local zone of quiet in a laboratory enclosure and she proposed to implement several feedforward loops, either to increase dimensions of the zone or to create a few such zones.

Here a problem of off-line identification for proper parameterization of the ANC multi-channel system with 3 feedforward loops is considered. Three control loudspeakers, 3 error microphones and a single reference microphone form together 9 secondary paths S_{pq} and 3 feedback paths F_p, (p, q = 1, 2, 3), where p denotes a number of a loudspeaker and q is a number of an error microphone. This can be done by performing 3 consecutive experiments, where every loudspeaker is in turn controlled by a predetermined sequence of excitation and resulting signals from all microphones are collected. Then processing the excitation and observed signals makes it possible to identify the corresponding transfer function separately to each other. This approach is presented in [11]. Another way is to stimulate all 3 loudspeakers at the same time and then think of the signal from a microphone as the output of a MISO (Multi-Input-Single-Output) plant with 3 inputs. This cuts down time needed for experimentation but makes identification more difficult. This approach was considered in [6]. The problem of model structure identification was also discussed there because complexity of the acoustic plant implies that identified models should be of a high order and there are no prerequisites to model structure assumption. To solve this problem a heuristic algorithm for searching a (sub)optimal model structure was proposed. In [8] the problem of experiment design was discussed and it was shown that the best results can be obtained using a specially designed excitation in the form of a vector multi-sine orthogonal signals (VMOS) [2]. Orthogonality means that each element of the vector is composed of sines with the constraint that the same frequency may not appear in more than one VMOS element. Due to the fact that all inputs are orthogonal and every partial output is orthogonal to each other it is possible to decompose the spectrum of the overall MISO response into 3 partial spectrum responses, generated by corresponding components of the VMOS. Hence, removing from the output spectrum lines for all frequencies that are absent in the input spectrum and then performing an inverse FFT enables to estimate the partial output of the particular path in time-domain. This algorithm was proposed in [3] and grants decomposition of the MISO system identification into independent SISO identification tasks.

In [8] it was also shown that only *ARX* or *FIR* structures can be identified because only for these structures model fitting can be solved using the classical *Least Squares* (*LS*) method. For structures like *ARMAX*, *Output Error*, *Box-Jenkins* and others, see *e.g.* [10], minimization of the loss function is a non-linear problem, usually solved by a Newton-Raphson method. This method (known as RPE) involves data filtration with the use of estimates of polynomials calculated whereas the algorithm is carried on. This causes problems with non-stability of models and prevents the convergence of the identification method because of zeros and poles near the unit circle which correspond to peaks and deep valleys in the magnitude of frequency responses of electro-acoustic plants.

In references mentioned above it was assumed that identification can be performed before the ANC system is activated whereas not primary noise is delivered to the enclosure from outside. However, one may also expect that during the normal operation of the ANC system it can be impossible to turn off the source of the noise. Then the data from identification experiment are contaminated by a noise that should be attenuated later. Therefore, the problem of identification in the presence of primary noise will be discussed in subsequence. Here 3 examples of such a noise are considered: sine (spectrum of the noise is discrete), noise generated by a motor (narrowband time-varying spectrum) and broadband noise (pseudorandom) with spectrum from 40 up to 110 Hz.

3. THE RESULTS OF IDENTIFICATION

The experiments were performed with the VMOS excitation for N = 4096 data and the ARX models were identified using the decomposition method, see [8], where the model of the path from the p-th loudspeaker

$$G_p\left(z^{-1}\right)=\frac{z^{-d_p}B_p\left(z^{-1}\right)}{A_p\left(z^{-1}\right)} \tag{1}$$

stands for S_{pq} or F_p (p, q = 1, 2, 3) respectively. z^{-1} denotes the backward shift operator, d_p is a pure time-delay, $A_p(z^{-1})$ and $B_p(z^{-1})$ are polynomials of the operator z^{-1}, with orders dA_p and dB_p respectively:

$$A_p\left(z^{-1}\right)=1+a_{p,1}z^{-1}+a_{p,2}z^{-2}+\ldots+a_{p,dA}z^{-dA} \tag{2}$$

$$B_p\left(z^{-1}\right)=b_{p,0}+b_{p,1}z^{-1}+b_{p,2}z^{-2}+\ldots+b_{dB_p}z^{-dB_p} \tag{3}$$

The structure of $G_p(z^{-1})$ is defined as the set of integers (d_p, dA_p, dB_p) and it should be chosen according to the BIC criterion as it was proposed in [8]. First, the models were identified for the data obtained without primary noise and the corresponding *frequency responses* (FR) were calculated. These are considered as patterns. Then the identification procedure was repeated for data contaminated by noise

Table 1. Structure identification for different experiments

No.	Description	Structure
1	Without primary noise	(5, 52, 52).
2	Sine 60 Hz (relative frequency $\omega T_s = 0.754$)	(5, 52, 52).
3	Sine 60 Hz with DAF (stop-band 0.74–0.77)	(5, 52, 52).
4	Narrowband time-varying	(4, 71, 71)
5	Narrowband time-varying with DAF (stop-band 0.86–0.92)	(5, 52, 51)
6	Broadband (40–110 Hz, pseudorandom)	(5, 51, 52)

and the new outcomes were compared with patterns. Here the exemplary results for only a one of the identified path are presented as the other are similar. The obtained results of structure identification are presented in Table 1.

The magnitude of FR of the model calculated in the 1st and 2nd experiments are shown in Figure 1. As it was expected, primary noise generated as a sine deteriorates the magnitude at the corresponding relative frequency $\omega T_s = 0.754$. The same happens for the phase of FR.

To improve the results of identification different methods of pre-filtering are proposed, see *e.g.* [10]. Usually the data are filtered in time-domain using a filter being the inverse of AR model of the noise. But in the case considered this method is inefficient due to problems with proper identification of the primary noise whereas dynamic of the plant is so complex. The other reason is that such filtration preclude the possibility of using the decomposition method. Therefore, to improve the identification it is proposed to apply the method called *disturbance adjusted filtering* (DAF) [3]. DAF is the procedure of selective filtration in frequency domain consisting in removing from the spectra all lines for frequencies corresponding to the noise. Then using FFTI it is possible to calculate the values of filtered signals in time-domain. The idea comes from suggestion that if there is a noise disturbing the output spectrum at some particular frequencies, then it is better to remove these frequencies from signals before processing the data, because they do not carry any useful information – even more, they falsify the information. The only problem is to distinguish the frequencies that should be removed from the spectrum of signals. Different modern methods were tested, like Prony's, Pisarenko's, MUSIC and EV, see *e.g.* [4], but the results were not satisfactory. The classical spectral analysis approach is the most reliable solution in this case. The estimated frequency of the noise based on the power spectral density (PSD) of the output signal was within the range of 0.74–0.77 of relative frequencies (due to leakage effect). Hence, all signals were subjected to preprocessing consist in stop-band filtration in frequency domain adequately to estimated frequency of the noise (the 3rd experiment). Comparison of magnitudes of FR obtained for the 1st and the 3rd experiment is shown in Figure 2. It can be clearly seen that proposed approach improves the results significantly. The results for the estimated phase of FR were much better too.

In the next experiment the noise was generated by a motor. It was a narrowband noise and identified relative frequencies varies within the range of 0.86–0.92, adequately to the load. Therefore it is suggested to use the same approach as in the previous case. The results of identification without and with DAF are presented in Figures 3 and 4, respectively and it is possible to draw the similar conclusions as before.

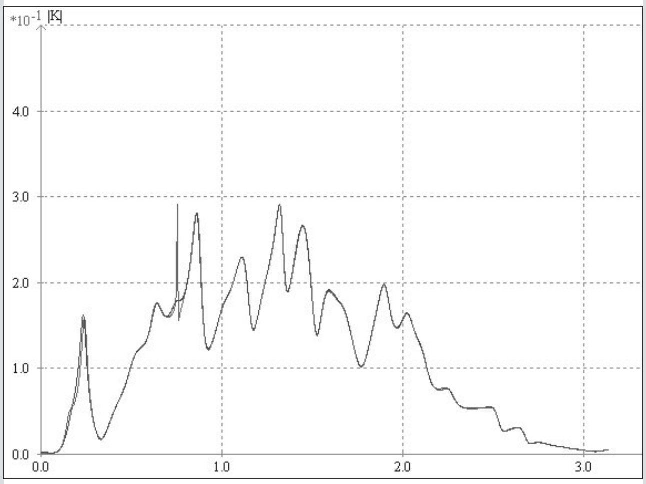

Fig. 1. Comparison of magnitudes of FR obtained in the 1st and 2nd experiment

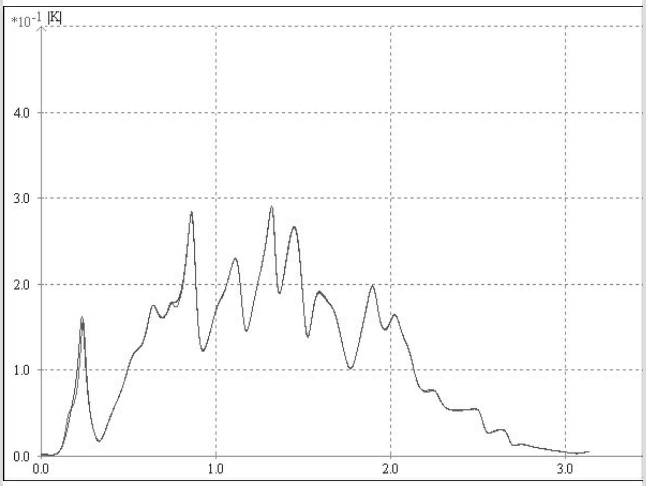

Fig. 2. Comparison of magnitudes of FR obtained in the 1st and 3rd experiment

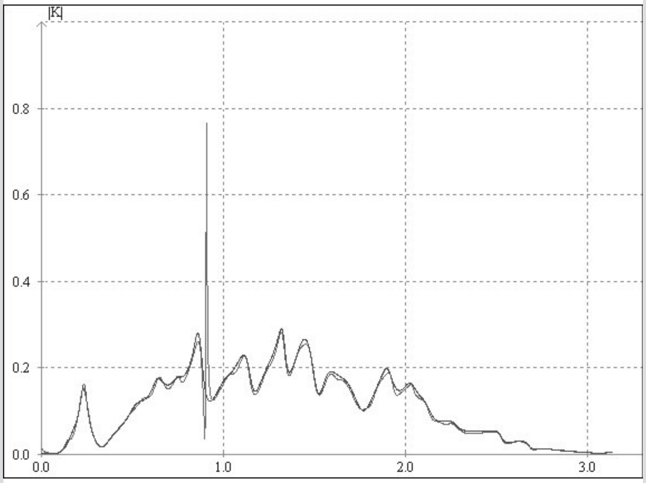

Fig. 3. Comparison of magnitudes of FR obtained in the 1st and 4th experiment

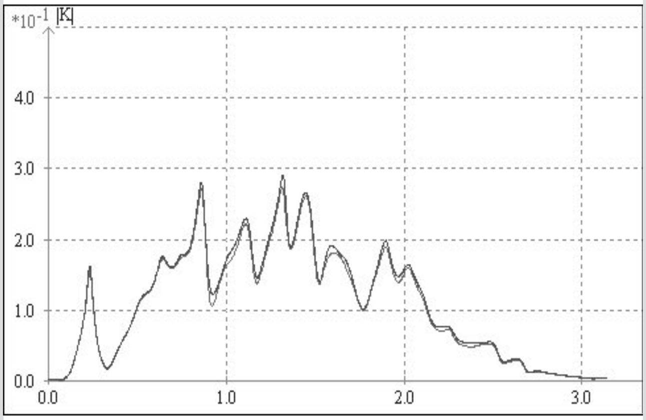

Fig. 4. Comparison of magnitudes of FR obtained in the 1st and 5th experiment

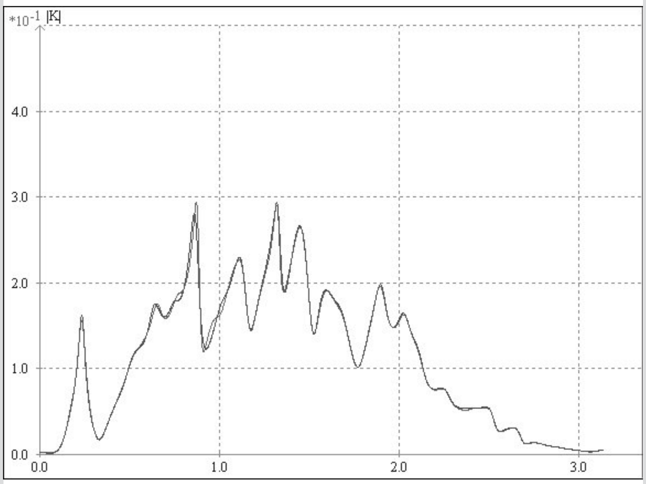

Fig. 5. Comparison of magnitudes of FR obtained in the 1st and 6th experiment

In the last experiment (Fig. 5) pseudorandom signal was generated as primary noise within the range 40–110 Hz at noise-to-signal ratio (NSR) little less than 2. In this case the band of the noise is too wide to use pre-filtering. But the results obtained by direct data processing are acceptable. It can be suggested to lengthen the data sample to improve the identification results but the experiments carried on don't show such improvement.

All the presented results were obtained using an intelligent software package *MULTI-EDIP* [7].

4. CONCLUSIONS

The off-line identification procedure for the MISO electroacoustic plant is discussed. Assuming ARX models and using VMOS signals to excite the plant it is possible to obtain the data in a one-shot experiment that enables identification of all secondary and feedback paths. Thanks to DAF preprocessing it is possible to improve the results significantly when the data are contaminated by a narrowband primary noise. The results of real-world experiments show the accuracy of estimated frequency responses obtained in the proposed approach.

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