SIMULATION OF TIME VARIANT ROOM IMPULSE RESPONSES

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ABSTRACT

For many applications such as acoustic echo compensation, adaptive noise reduction or acoustic feedback control it is of great interest to simulate reproducibly a real, time variant room. One approach to describe the transient behavior of a room is the generation of a physical room model, e.g. [1]. To identify the variation of a room impulse response with time an alternative concept is presented, which uses the *normalized least mean square* (NLMS) algorithm excited by perfect sequences. The proposed general concept is capable to efficiently simulate the fluctuations of the room impulse response. The time variant simulation can be performed without the necessity to store large amounts of data by storing only the reaction of the unknown system instead of all sets of filter coefficients. The practical aspects of the new concept are pointed out for an acoustic echo control application.

1. INTRODUCTION

The simulation of the time variant room impulse response is based on a system identification approach driven by the *normalized least mean square* (NLMS) algorithm [2]. According to Fig. 1 the acoustic echo path from the loudspeaker to the microphone is represented by its time variant room impulse response in terms of vector

$$\underline{g}(i) = (g_0(i),\ g_1(i),\ \ldots,\ g_{N-1}(i))^T \qquad (1)$$

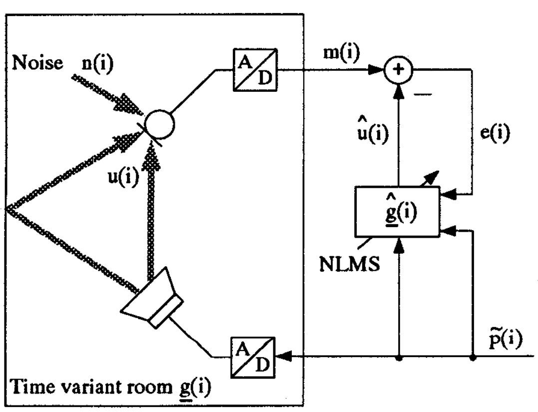

Figure 1: Identification of the room impulse response

of length N, where i denotes the time. In order to identify the unknown impulse response the time variant room is periodically excited by a perfect sequence $\tilde{p}(i)$ of period N. In paragraph 2 it will be shown that for this particular excitation signal the NLMS algorithm

$$\underline{\hat{g}}(i+1) = \underline{\hat{g}}(i) + \alpha\ \frac{e(i)\ \underline{\tilde{p}}(i)}{||\underline{\tilde{p}}(i)||^2} \qquad (2)$$

with: $\alpha = 1$

$$\underline{\hat{g}}(i) = (\hat{g}_0(i), \hat{g}_1(i),\ \ldots, \hat{g}_{N-1}(i))^T$$
$$\underline{\tilde{p}}(i) = (\tilde{p}(i), \tilde{p}(i-1),\ \ldots, \tilde{p}(i-N+1))^T$$
$$||\underline{\tilde{p}}(i)||^2 = \underline{\tilde{p}}^T(i)\ \underline{\tilde{p}}(i)$$

is capable to identify the unknown system within N iterations [3]. Subsequently, paragraph 3 contains the analysis of the tracking properties of the proposed system identification approach. Based on an acoustic echo control application the practical aspects concerning the simulation of time variant room impulse responses are finally discussed.

2. SYSTEM IDENTIFICATION WITH PERFECT SEQUENCES

The geometric interpretation of the NLMS algorithm [4] shows that the convergence properties of the adaptation process depend on the angle of consecutive signal vectors $\underline{\tilde{p}}(i)$, $\underline{\tilde{p}}(i-1)$. Assuming

- a time invariant system $\underline{g}$ during N iterations
- a sufficiently small noise signal $n(i)$ and
- a stepsize of $\alpha = 1$

perfect adaptation, i.e. $\underline{\hat{g}}(i) = \underline{g}$, is achieved, if N consecutive vectors $\underline{\tilde{p}}(i), \underline{\tilde{p}}(i-1), \ldots, \underline{\tilde{p}}(i-N+1)$ are orthogonal in the N dimensional vector space, see [3].

Suppose $\tilde{p}(i)$ is a white noise process then vectors $\underline{\tilde{p}}^*(i), \underline{\tilde{p}}^*(i-1),\ \ldots, \underline{\tilde{p}}^*(i-N+1)$ of infinitive length are orthogonal in the infinitive vector space. So for the projected set of vectors $\underline{\tilde{p}}(i), \underline{\tilde{p}}(i-1), \ldots, \underline{\tilde{p}}(i-N+1)$ the orthogonality in the N dimensional vector space is not guaranteed. Consequently, a white noise process does not really fulfill the requirements of an optimal orthogonal excitation signal.

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Perfect sequences, however, are characterized by their periodic autocorrelation function

$$\tilde{R}_{pp}(i) = \sum_{k=0}^{N-1} \tilde{p}(k)\, \tilde{p}(k+i) = \begin{cases} ||\underline{\tilde{p}}(i)||^2 & \text{for } i \bmod N = 0 \\ 0 & \text{else} \end{cases} \quad (3)$$

which vanishes for all out-of-phase values i, i.e. all N phase shifted perfect sequences $\underline{\tilde{p}}(i)$, $\underline{\tilde{p}}(i-1)$, ..., $\underline{\tilde{p}}(i-N+1)$ are orthogonal in the N dimensional vector space, see for example [5].

For this reason perfect sequences represent an optimal excitation signal for the NLMS algorithm, so that the resulting set of N filter coefficients $\underline{\hat{g}}(i) = (\hat{g}(i), \hat{g}_1(i), ..., \hat{g}_{N-1}(i))^T$ represents exactly the room impulse response of the unknown system. In this case and for $n(i) = 0$ the accuracy of the identification is given by the computational precision.

Figure 2 confirms these results by the comparison of the system distance

$$\frac{D(i)}{\text{dB}} = 10 \log \frac{||\underline{g} - \underline{\hat{g}}(i)||^2}{||\underline{g}||^2} \quad (4)$$

for a white noise and a perfect sequence excitation. Exploiting perfect sequences as stimulus signal for the NLMS algorithm leads to an identification of the unknown system response after an initialization phase of $2N$ iterations. This delay is caused by the N empty filter states of the echo path and by N iterations, which are required to adapt N filter coefficients. In the continuous adaptation process only N iterations are needed to achieve an identification within computational complexity.

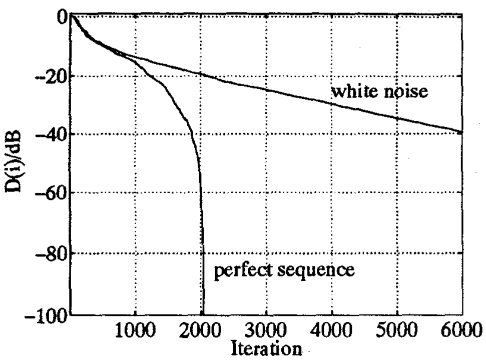

Figure 2: System distance of the NLMS algorithm excited with a white noise process and a perfect sequence ($\underline{g}$ time invariant, $N = 1023$, $\alpha = 1$, $n(i) = 0$)

3. TRACKING PROPERTIES

In [6] the tracking properties of an NLMS-type adaptive filter in the application of modelling an unknown time variant system have been studied, see also [2]. It was concluded that the NLMS driven algorithm with a white noise excitation is not able to track time variant changes. In contrast to these investigations our proposal benefits from the use of the optimal excitation signal, i.e. a perfect sequence. Based on the capability of perfect sequences to identify the unknown system within N iterations, the proposed concept is able to efficiently simulate the fluctuations of the room impulse response.

The most state-of-the-art measuring systems are typically blockwise oriented methods using the *Fast Hadamard Transform* [7], i.e. only every N iterations a completely new set of filter coefficients is obtained. In contrast to this the new approach operates iteratively. In each time instant i a new set of coefficients is available, i.e. $\hat{g}_k(i) \neq \hat{g}_k(i+1)$ for all $0 \leq k < N$.

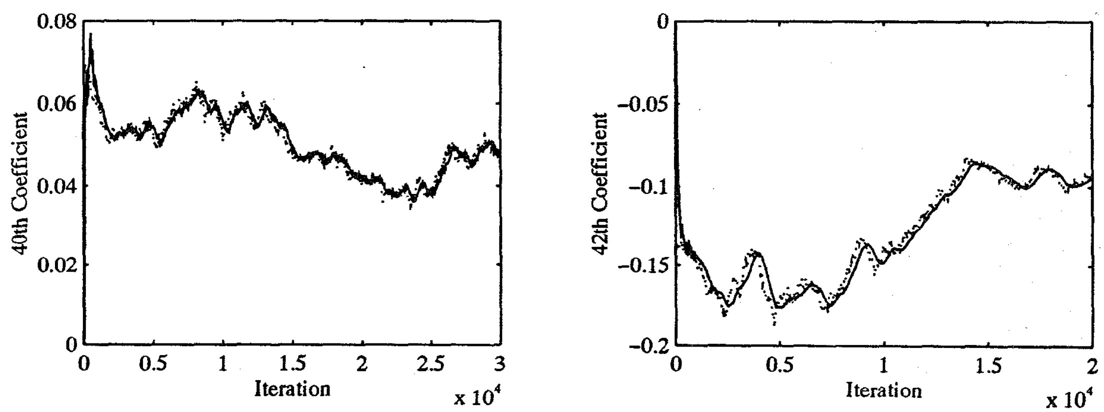

Figure 3: Tracking properties of the identification algorithm exemplary for two different coefficients
.... Time evolution of the synthetically generated coefficient
———— Tracking behavior of the proposed algorithm

In practice, for time variant systems and $n(i) \neq 0$ the generated set of coefficients does not match exactly the actual impulse response. However, in the presence of noise the use of perfect sequences instead of m-sequences (as in [7]) leads a priori to an identification improved by 3 dB. The negative influence of $n(i)$ can further be reduced by choosing a smaller step size parameter $0 < \alpha < 1$, which results in an averaging procedure.

To visualize the tracking properties of the new identification algorithm a synthetic room model has been developed on the basis of numerous measurements in a strongly time variant room. Fig. 3 outlines the comparison of the curves referring to the time fluctuation of the synthetically generated coefficient and the tracking behavior of the identification algorithm. Though the identification is not able to track exactly the synthetic coefficient in every single time instant, the tendency of the curves do match very well.

4. TIME VARIANT SIMULATION FOR AN ACOUSTIC ECHO CONTROL APPLICATION

As a result of its convergence speed the identification algorithm provides in every iteration step a set of coefficients $\underline{\hat{g}}(i)$, which represents a close approximation of the actual acoustic room impulse response. For this reason consecutive sets of coefficients ($\underline{\hat{g}}(i)$, $\underline{\hat{g}}(i+1)$, ...) can be used to simulate the time varying characteristic of the room. To point out the practical aspects of the time variant simulation an acoustic echo control application (e.g. [8]) is investigated.

For a typically time variant simulation of T=4 seconds duration, at a sampling frequency of $f_a = 8$ kHz and a filter length of $N = 1023$, the total number of coefficients is given by $N \cdot f_a \cdot T = 32.736.000$. The storage needed for a *float* (4 byte) representation amounts to 125 Mbyte – not a practicable amount of storage. To reduce the required storage capacity the different sets of filter coefficients are on-line identified from the room response $m(i)$. During the run time of the simulation the instantaneous room impulse response $\underline{\hat{g}}(i)$ is transferred according to Fig. 4. The on-line identification requires to store only the perfect sequence $\tilde{p}(i)$ and the measured microphone signal $m(i)$. The storage for the recorded microphone signal $m(i)$ and for one period of the perfect sequence amounts to $f_a \cdot T \cdot$ 4 byte = 125 kbyte and $N \cdot 4$ byte = 4 kbyte, respectively. The on-line identification, which generates the coefficients to be transferred, works within the complexity of a NLMS-type adaptation process. So multiply and add operations in an order of $2N$ per sample period are required. The computational complexity for the generation of the echo signal $y(i)$ amounts to N additional operations, due to the evaluation of the inner product between signal vector $\underline{x}(i)$ and echo path $\underline{\hat{g}}(i)$

Besides the reproducibility of computer simulations the *echo return loss enhancement* ERLE-measure $ERLE(i)$ as well as the system distance $D(i)$:

$$ERLE(i) = 10 \log \frac{E\{y^2(i)\}}{E\left\{(y(i) - \hat{y}(i))^2\right\}} \tag{5}$$

$$D(i) = 10 \log \frac{||\underline{\hat{g}}(i) - \underline{c}(i)||^2}{||\underline{\hat{g}}(i)||^2} \tag{6}$$

can be evaluated for time variant conditions in order to enable an objective assessment.

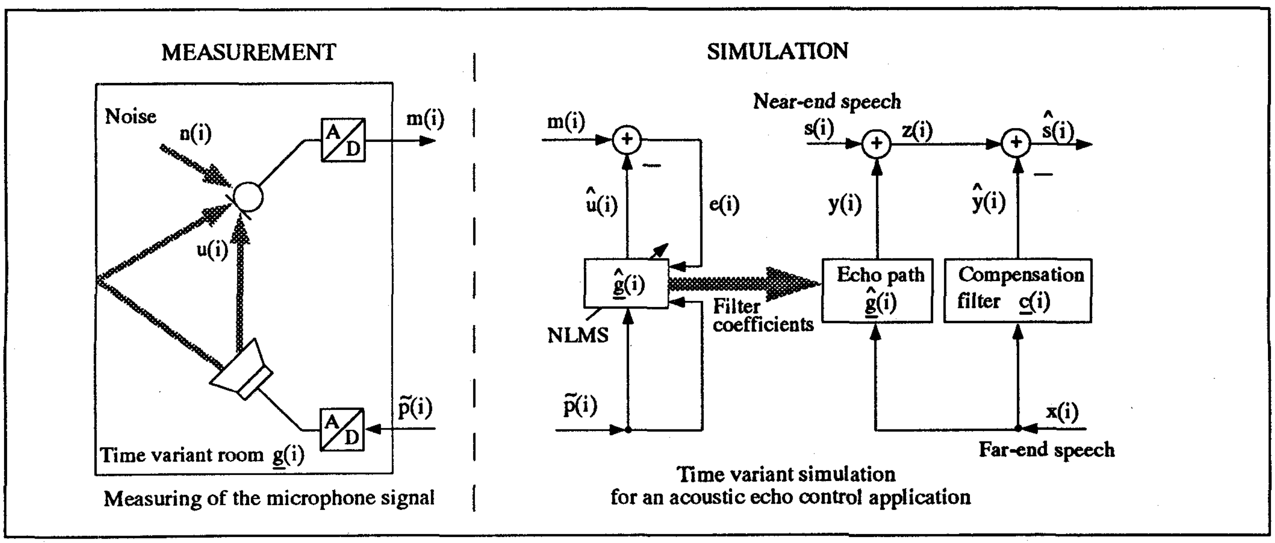

Figure 4: Identification and simulation of a real, time variant room for an acoustic echo control application

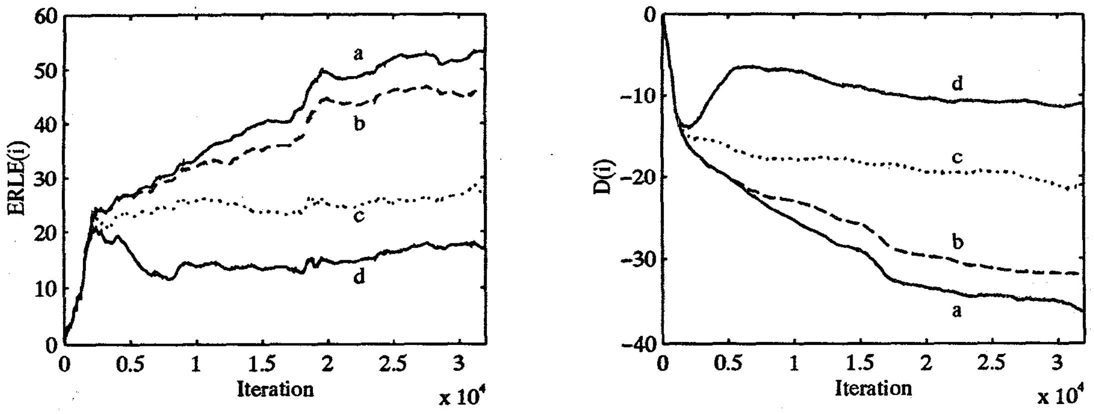

Figure 5: Comparison of the objective quality measures for different extents of time variance:
a ——— no person in the measured room
b – – – – inactive person in the room
c .... moving person in the room
d ——— strongly moving person in the room
Identification: $N = 2801$, $n(i) \neq 0$, $\alpha = 1$
Simulation: $N = 553$, $s(i) = 0$, $\alpha(i)$ adaptive

Fig. 5 shows the ERLE-measure and the system distance for different extents of time variance. These simulations clearly indicate the degradation of the echo cancellers performance under time variant conditions.

5. CONCLUSIONS

In this contribution a new identification approach has been introduced, which is based on an NLMS driven algorithm excited by perfect sequences. Due to the special orthogonal properties of perfect sequences the NLMS algorithm is capable to identify an unknown impulse response within N iterations. For this reason the new identification algorithm provides an efficient tool to track the time evolution of an acoustic room impulse response, which can be used for the simulation of time variant room impulse responses.

By storing the reaction of the unknown system instead of all sets of filter coefficients the time variant simulation can be performed without the necessity to store large amounts of data. The on-line identification of the impulse response can be performed within the complexity of an NLMS type adaptation algorithm.

Due to its generality the proposed concept can be employed in many applications such as acoustic echo compensation, adaptive noise reduction or acoustic feedback control. Besides the reproducibility of simulation results it is now possible – for instance in an acoustic echo control application – to evaluate objective measures such as *echo return loss enhancement* $ERLE(i)$ and system distance $D(i)$ for an objective assessment.

Furthermore it is of interest, that the NLMS algorithm already exists in many of these applications, so that the required implementation effort is low.

6. REFERENCES

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