ECHO CANCELLATION I: ALGORITHMS SIMULATION

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Abstract

Echo cancellation system used in mobile communication is analysed. Convergence behaviour and misadjustment of several Least Mean Squares (LMS) algorithms are compared. The misadjustment means errors in filter weight estimation. The resulting echo suppression for discussed algorithms with simulated as well as real speech signals is evaluated. The optional echo cancellation configuration is suggested.

Keywords

echo , echo cancellation, hands free, mobile communication, communication in the car, LMS, adaptive filter

1. Introduction and problem definition

Mobile communication systems, especially hands free telephony suffers from the echo presence. This contribution is devoted to the use of hands free set in a running car. We are evaluating system for mobile phone with one microphone and one loudspeaker. Owing safety rules the microphone must be placed in a dashboard or drivers sun visor in a distance from a driver about 30 – 50 cm. This placement of microphone and loudspeaker creates „hands free“ (HF) mobile phone. Almost the same distance is usually between loudspeaker and the microphone. The couple loudspeaker – microphone creates the acoustic feedback with very high gain. Therefore the possibility of echo or instabilities (whistles) due to the existence of this feedback is very high. The basic idea of the echo suppression is the use of parallel path cancelling the existing acoustic feedback.
The typical echo cancellation system is shown in Fig. 1.

The frequency response of loudspeaker – microphone path is time dependent because of possible driver movements. Therefore as echo canceller an adaptive filter must be used. The aim of this adaptive filter is to estimate the instantaneous frequency response of the loudspeaker – microphone path. If this estimation is precise the far-end speech r(n) coming from the microphone is perfectly cancelled. Now, let us discussed the echo canceller in more details.

For the signal description see the discrete model of echo canceller in Fig. 2. Let us suppose Linear and Time Invariant (LTI) model.

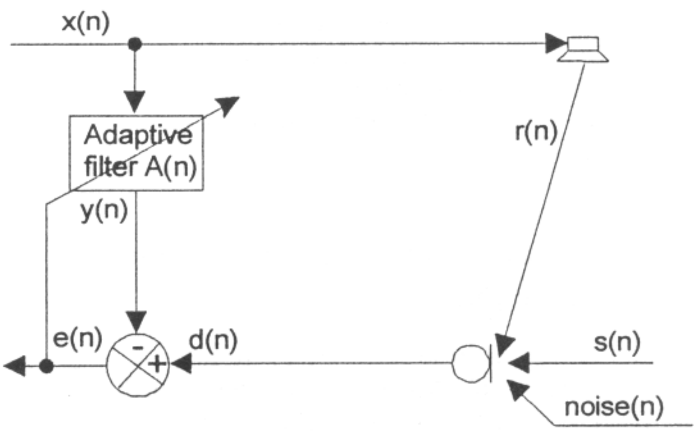

Fig. 2 Discrete model of echo canceller

The microphone output:

$$d(n) = A_{Car}(n) * x(n) + s(n) + noise(n) \tag{1}$$

Where * stands for the convolution, and $A_{Car}(n)$ represents the acoustic impulse response of the car cabin.

The error signal rising from the summer is given by:

$$e(n) = A_{Car}(n) * x(n) + s(n) + noise(n) - A(n) * x(n) \tag{2}$$

Where A(n) is the impulse response of the echo canceller. The echo is caused by the loudspeaker output r(n). If r(n) is perfectly cancelled then e(n) contains the driver's speech only. It is possible only if the impulse response of the echo canceller A(n) equals to the impulse response of the car cabin $A_{Car}(n)$.

The least mean squares criterion $Min\{E[e^2(n)]\}$ is very often used as the cost function for the adaptive algorithm derivation:

$$Min\{e^2(n)\} \quad \Rightarrow \quad e(n) = s(n) + noise(n) \tag{3}$$

When this criterion is used the family of Least Mean Square (LMS) algorithms is presupposed for the implementation.

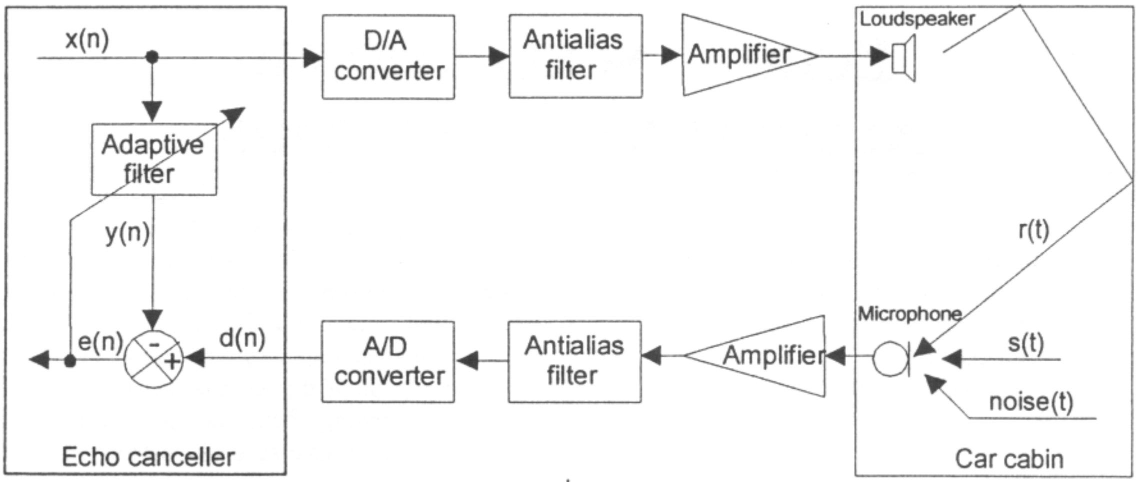

Fig. 1 Echo cancellation system

Legend:

x(n) … speech of far-end speaker
r(t) … far-end speaker output
noise(t) … environmental car noise
s(t) … driver's speech
d(n) … digitised microphone signal
e(n) … error signal

2. Adaptive filter and algorithms description

As the adaptive filter the Finite Impulse Response (FIR) transversal filter is used. The filter length must be equal or greater than the impulse response of the car cabin. The typical length of the measured impulse response was between 180 – 250 milliseconds (150-200 samples) [6] depending on the cabin type and the number of person in the cabin. Its simplicity and stability influenced this filter choice.

Brief overview of potential algorithms for an echo cancellation is published in [7].

Several LMS algorithms updating the FIR impulse response were studied:

- Widrow – Hoff LMS algorithm [1]
- block LMS (BLMS) in time domain
- block LMS in frequency domain using periodic convolution (FLMSPC) [2]
- block LMS in frequency domain using linear convolution (FLMS) [3]
- normalised LMS in frequency domain (FNLMS) [4]
- multidelay normalised LMS in frequency domain (MDF) [5]

Individual algorithms vary by construction of input signal block, by the type of convolution used (linear or periodic), by the equation for the estimate of gradient and also by the computing complexity of whole algorithm.

Each of these algorithms can be described by two equations. First equation is common to all algorithms and represents the filtration equation:

$$e(n) = d(n) - y(n) = d(n) - \vec{b}(n) * \vec{x}(n) \tag{4}$$

where $\vec{b}(n)$ are filter coefficients forming its impulse response, $\vec{x}(n) = [x(n), x(n-1) \dots x(n - N_b + 1)]$ represents the vector of input signal, N_b is filter length.

Second equation explains the coefficients update and will be presented for each case separately.

I. The **LMS** algorithm can be specified by the equation for the coefficients update:

$$\vec{b}(n+1) = \vec{b}(n) + 2\mu e(n)\vec{x}(n) \tag{5}$$

Where $0<\mu<1/P_x$ is the convergence factor. P_x stands for the power of signal x(n).

II. The **BLMS** is very similar to the LMS algorithm but instead of the vector $\vec{x}(n)$ the matrix of the input samples $\underline{x}(n)$ is used (only indexes of vector $\vec{x}(n)$ are implemented in the matrix structure shown below):

$\underline{x}(n.L_{Block}) \approx$

$$\approx \begin{pmatrix} nL_{Block}+1 & nL_{Block}+2 & \cdots & (n+1)L_{Block} \\ nL_{Block} & nL_{Block}+1 & & (n+1)L_{Block}-1 \\ \vdots & & & \vdots \\ nL_{Block}-N_b+2 & nL_{Block}-N_b+3 & \dots & (n+1)L_{Block}-N_b+1 \end{pmatrix}$$

Where L_{Block} is the length of one data block forming one row of matrix $\underline{x}(n)$. Index n now represents the block index. The coefficients update:

$$\vec{b}(n+1) = \vec{b}(n) + (2.\mu / L_{Block})\,.\,\vec{e}(n).\underline{x}(n)^T \tag{6}$$

The convergence rate of the BLMS is the same as the convergence rate of the LMS for $L_{Block}=1$, in other cases it is smaller.

III. The **FLMSPC** and **FLMS** algorithm are both based on the use of FFT algorithm for performing the convolution $\vec{b}(n) * x(n)$ in the frequency domain. More detailed description can be found in [2], [3].

These two algorithms are only effective versions of the BLMS saving operational costs. Moreover the greater convergence rate can be achieved as the consequence of splitting the input signal into many frequency bands.

IV. Normalised algorithms **FNLMS** and **MDF** use the normalised convergence factor :

$$\vec{\mu}(k+1) = \vec{\mu}(k) / \overrightarrow{P\hat{S}D_x}(k) \tag{7}$$

Where independent variable k represents frequency domain and $\overrightarrow{P\hat{S}D_x}$ stands for the estimate of power spectral density of the input signal yielding the signal power or each frequency band. The result of this normalisation is the convergence rate independence on the input signal power. The better convergence behaviour and smaller misadjustment can be expected. The first simulations and comparison some of these algorithms are published in [6].

3. Criteria used for comparison of algorithms

If we know the acoustic properties of the car cabin (given by $A_{Car}(n)$) and final weights of vector b(n) we can use the criteria of Mean Square Error (MSE):

$$MSE = \frac{1}{N_b} \sum_{i=1}^{N_b} (A_{Car\,i} - b_i)^2 \quad [-] \tag{8}$$

The precision of the algorithm in the case of concrete signals we describe by the factor called Echo Return Loss Enhancement (ERLE). The ERLE factor is defined as a ratio of powers of the error signal e(n) and the desired signal d(n). Powers are calculated from segments of 128 samples without overlapping:

$$ERLE = 10 \log \frac{E\left(\vec{e}^{\,2}(n)\right)}{E\left(\vec{d}^{\,2}(n)\right)} \quad [dB] \tag{9}$$

For the evaluation of the convergence rate the convergence time t_{Conv} [s] is used. t_{Conv} is defined as a time need for reaching 90% of final value of ERLE after algorithm convergence ($ERLE_{Min}$).

4. Simulations and results

The initial convergence behaviour of each studied algorithm is compared in this section. The convergence time t_{Conv} [s] is evaluated by means of the smoothed ERLE (second curve in next figures 3-6). The order of analysed filters is 256, the speech signal with 66.400 samples is used for testing, sampling rate is 8 kHz. The mean value $ERLE_{Mean}$ and the minimal value $ERLE_{Min}$ representing the precision are evaluated.

The influence of block length on the BLMS convergence can be seen in Fig. 3 and Tab. 1.

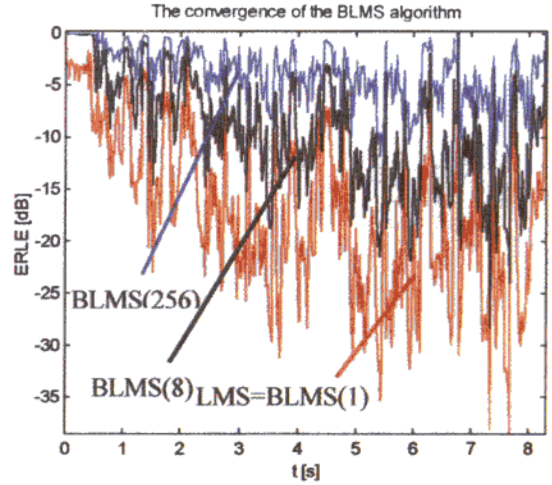

Fig. 3 Influence of block length (L_{Block} shown into brackets)

block length L_{Block} [-]	256	32	8	2	1
$ERLE_{Mean}$ [dB], μ=1.10^{-1}	-3,7	-9,3	-16, 5	-25,8	
$ERLE_{Mean}$ [dB] , μ=2.10^{-2}	-1,2	-4,6	-8,4	-15,2	-19,1

Tab. 1 The convergence properties of BLMS

The greater block length causes the higher (worse) ERLE.

The comparison of time constants and ERLE of all algorithms are summarised in Tab. 2. Figures 4 – 6 illustrate convergence behaviour.

Algorithm:	$ERLE_{Mean}$ [dB]	$ERLE_{Min}$ [dB]	t_{Conv} [s]
LMS	-15,00	-22.91	5.469
BLMS(8)	-16,30	-24,41	5,453
FLMSPC	-2,39	-4,26	5,993
FLMS	-2,62	-6,79	6,025
FNLMS	-36,37	-43,84	3,974
MDF	-44,51	-51,36	2,159

Tab. 2 Properties of algorithms

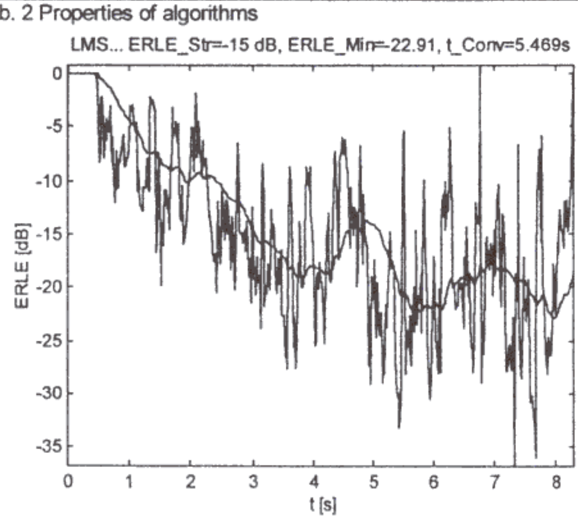

Fig. 4 Time evolution of ERLE for LMS algorithm

The convergence properties of the BLMS algorithm are shown in Fig. 3. Behaviour of BLMS with length 8 (L_{Block}=8) is very similar to the LMS. The $ERLE_{Min}$ improvement is 6,5 % for the same convergence time.

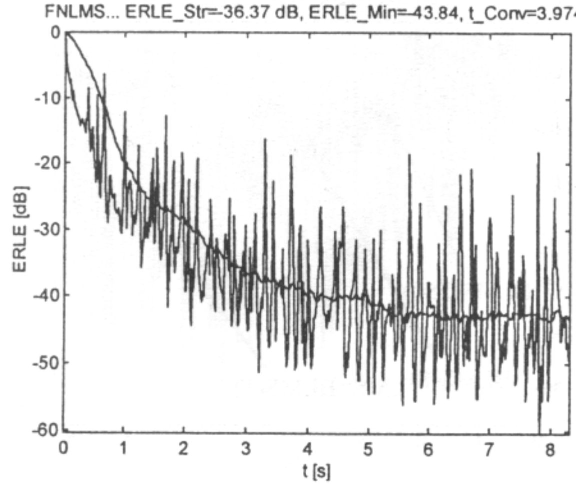

Fig. 5 Time evolution of ERLE for FNLMS algorithm

Using the linear convolution in FLMS instead of the cyclic convolution in FLMSCY improves ERLE factor about 60 %. On the other hand, this step increases the computing complexity (double size of FFT).

The best betterment of ERLE suppression capability is reached by normalising the convergence factor μ. This means 550 % improvement of FNLMS ERLE owing to FLMS algorithm. Also convergence time was successfully decreased about 34%.

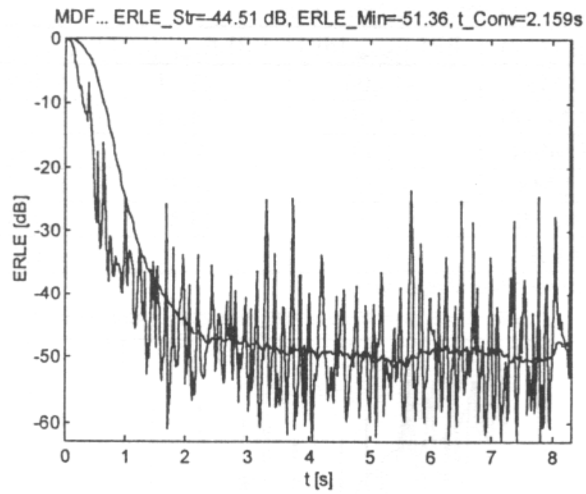

Fig. 6 Time evolution of ERLE for MDF algorithm

The comparison reveals that the best solution (the greatest convergence rate and ERLE) is gained by using the MDF algorithm. The considerable shortening of convergence time on 54 % comparing to the previous value of NLMS algorithm is reached. Also ERLE improved about 17 % owing to NLMS can be seen.

5. Discussion

Convergence rate is the best for MDF (splitted into 4 blocks) and FNLMS algorithm. The slower is the LMS – time domain version. The slowest is FLMS because of the use of the constant convergence factor and the block length 265 samples (sampling rate 8 kHz).

Resulting ERLE is the greatest for the MDF and FNLMS algorithms.

From the point of view of computation complexity the using of frequency domain adaptive filter is necessary. It implies using some sort of normalised algorithm, where the normalisation process contributes greatly to the precision of the algorithm. The best performance is reached by MDF algorithm, which can be therefore regarded as the best one for echo cancellation.

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Pavel SOVKA – see contribution in vol.8, No.4, Dec 1999