

# APPLICATION OF VARIATIONS OF THE LMS ADAPTIVE FILTER FOR VOICE COMMUNICATIONS WITH CONTROL SYSTEM

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Original scientific paper

This paper describes a proposed method for optimal adjustment parameters of variations of the LMS adaptive filter in the application of suppression of the additive noise from the speech signal. Selected variation of the LMS adaptive noise canceller is implemented on the TMS320C6713 DSK. This practical realization was used in a voice communication with a control system for controlling of operating – technical functions in buildings.

**Keywords:** variations of the LMS algorithm, adaptive noise canceller, speech signal processing, voice communication, adaptive filter

## Primjena varijacija LMS adaptivnog filtera na govornu komunikaciju sa sustavom upravljanja

Izvorni znanstveni članak

U ovom se radu opisuje predložena metoda za optimalno podešavanje parametara varijacija LMS adaptivnog filtera kod prigušenja aditivne buke iz govornog signala. Izabrana varijacija LMS adaptivnog poništača buke je implementirana na TMS320C6713 DSK. U praksi je ovo primijenjeno na govornu komunikaciju s upravljačkim sustavom za praćenje operativno-tehničkih funkcija u zgradama.

**Ključne riječi:** varijacije LMS algoritma, adaptivni poništač buke, obrada govornog signala, govorna komunikacija, adaptivni filter

### 1

#### Introduction

This paper describes a proposed method for optimal adjustment of parameters of variations of the LMS adaptive filter in the application of suppression of the additive noise in the speech signal. The proposed method is applied for optimal settings of the parameters of the adaptive noise canceller with the Conventional LMS algorithm, with the Signed – Regressor LMS algorithm, with the Sign LMS algorithm and with the Sign-Sign LMS algorithm. Selected variations of the LMS adaptive noise canceller is used in voice communication with the control system.

### 2

#### Description of the adaptive filter with the LMS algorithm and the other variations of the LMS algorithms

The Least Mean – Square (LMS) algorithm was developed by Widrow and Hoff in 1960. This algorithm is a member of the stochastic gradient algorithms [2].

#### 2.1

##### The conventional LMS algorithm

The LMS algorithm is a linear adaptive filtering algorithm, which consists of two basic processes:

- a) a filtering process, which involves
  - computing the output  $y(n)$  of linear filter in response to an input signal  $x(n)$  (1),

$$y(n) = \sum_{i=0}^{M-1} w_i(n) \cdot x(n-1), \quad (1)$$

- generating an estimation error  $e(n)$  by comparing this output  $y(n)$  with the desired response  $d(n)$  (2) (Fig.1),

$$e(n) = d(n) - y(n), \quad (2)$$

- b) an adaptive process (3), which involves the automatic adjustment of the parameters  $w(n+1)$  of the filter in accordance with the estimation error  $e(n)$ .

$$w(n+1) = w(n) + 2\mu e(n)x(n), \quad (3)$$

$w(n)$  is  $M$  tap – weight vector,

$w(n+1)$  is  $M$  tap – weight vector update [1, 2].

#### 2.2

##### The Sign LMS algorithm

This algorithm is obtained from the conventional LMS recursion (3) by replacing  $e(n)$  with its sign. This leads to the following recursion

$$w(n+1) = w(n) + 2\mu \text{sign}(e(n))x(n). \quad (4)$$

Because of the replacement of  $e(n)$  by its sign, implementation of this recursion may be cheaper than conventional LMS recursion [1, 13].

#### 2.3

##### The Signed - Regressor LMS algorithm

The Signed-Regressor algorithm is obtained from the conventional recursion (3) by replacing the tap-input vector  $x(n)$  with the vector  $\text{sign}(x(n))$ , where the sign function is applied to the vector  $x(n)$  on an element-by-element basis. The Signed-Regressor recursion is then [1, 13]

$$w(n+1) = w(n) + 2\mu e(n)\text{sign}(x(n)). \quad (5)$$

#### 2.4

##### The Sign - Sign LMS Algorithm

The Sign-Sign algorithm combines the Sign and Signed-Regressor recursions, resulting in the following recursion [1, 13]

$$\mathbf{w}(n+1) = \mathbf{w}(n) + 2\mu \text{sign}(e(n))\text{sign}(\mathbf{x}(n)). \tag{6}$$

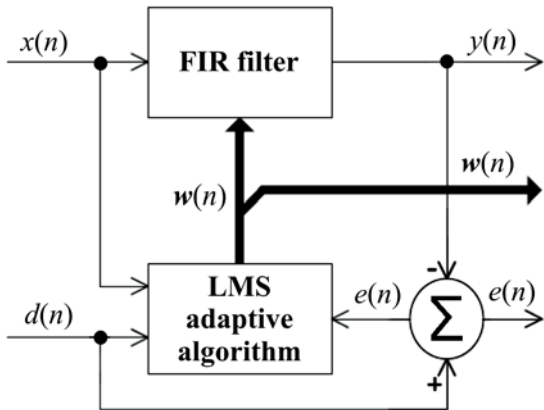


Figure 1 Block diagram of the LMS adaptive filter [3]

### 3 Settings of a step size factor $\mu$

The step size factor  $\mu$  must be selected properly to control the stability and the convergence speed of the adaptive filter with the LMS algorithms [2] and the LMS algorithms variations. Determination of settings of a step size factor  $\mu$  is described in the next text.

For determination, when the LMS algorithm remains stable it is necessary to find the upper bound of  $\mu_{\max}$ , that guarantees the stability of the LMS algorithm (7) [1]

$$\mu_{\max} < \frac{1}{3\text{tr}[\mathbf{R}]}, \tag{7}$$

$\text{tr}[\mathbf{R}]$  – trace of  $\mathbf{R}$ , which means the sum of the diagonal elements of  $\mathbf{R}$ ,  
 $\mathbf{R}$  – Toeplitz autocorrelation matrix calculated from the vector of the input signal  $\mathbf{x}(n)$ , size  $\mathbf{R}$  is  $M \times M$ .

The Toeplitz autocorrelation matrix  $\mathbf{R}$  is calculated by equation (8)[2]

$$\mathbf{R} = E \cdot [\mathbf{x}(n)\mathbf{x}^T(n)]. \tag{8}$$

Convergence behavior of the LMS algorithm is directly linked to the eigenvalue spread of the autocorrelation matrix  $\mathbf{R}$  and the power spectrum of  $\mathbf{x}(n)$ . The convergence of the LMS algorithm is directly related to the flatness in the spectral content of the underlying input process.  $E[\mathbf{v}(n)]$  converges to zero when  $\mu$  remains within the range of formula (9).  $E[\mathbf{v}(n)]$  is expectation of the weight – error vector  $\mathbf{v}(n) = \mathbf{w}(n) - \mathbf{w}_0$ .

$$\mu_{\text{conv}} \leq \frac{1}{\lambda_{\max}}, \tag{9}$$

$\lambda_{\max}$  – maximum eigenvalue of the autocorrelation matrix  $\mathbf{R}$  of the input vector  $\mathbf{x}(n)$ .

The above range does not necessarily guarantee the stability of the LMS algorithm. The convergence of the LMS algorithm requires the convergence of the mean of  $\mathbf{w}(n)$  towards  $\mathbf{w}_0$  and also the convergence of the variance of the elements of  $\mathbf{w}(n)$  to some limited values [1]. Vector  $\mathbf{w}_0$  is calculated by the Wiener-Hopf equation and the superscript

" $_0$ " indicates the optimum Wiener solution for the Wiener filter [2].

Determining of the optimal value of the step size factor  $\mu_{\text{opt}}$  is important in conducting an algorithm LMS. When selecting factor  $\mu_{\text{opt}}$  it becomes a compromise between the two aspects. On the one hand, large values of  $\mu$  can lead quickly to the optimal settings of the LMS algorithm for speech signal processing. On the other hand, high value  $\mu$  may increase an estimate error of the speech signal processing in further steps. A small value  $\mu$ , on the contrary, ensures the stability and the convergence of the LMS algorithm [1]. As a result a small value  $\mu$  slows down the convergence of the LMS algorithm and, consequently, increases the inaccuracies in the filtration of non-stationary signals [3]. The following equation is used for the calculation of the optimal factor  $\mu_{\text{opt}}$  (10), (Tab. 1) [1]

$$\mu_{\text{opt}} = \frac{M}{(1 + M) \cdot \text{tr}[\mathbf{R}]}, \tag{10}$$

$\text{tr}[\mathbf{R}]$  – trace of  $\mathbf{R}$ , which is the mean sum of the diagonal elements of  $\mathbf{R}$ ,  
 $M$  – the misadjustment parameter.

Table 1 Calculation of the step size factors  $\mu_{\text{opt}}$ ,  $\mu_{\max}$ ,  $\mu_{\text{conv}}$  of the LMS adaptive filter for input signal  $\mathbf{x}(n)$  with different SSNR values

SSNR <sub>s</sub> = 6,7 dB	SSNR <sub>w1</sub> = 18,2 dB	SSNR <sub>w2</sub> = 3 dB	SSNR <sub>w3</sub> = -1,8 dB
$\mu_{\max}=3,25 \cdot 10^{-2}$ ( $M=10\%$ )	$\mu_{\max}=3,54 \cdot 10^{-2}$ ( $M=10\%$ )	$\mu_{\max}=2,99 \cdot 10^{-2}$ ( $M=10\%$ )	$\mu_{\max}=2,25 \cdot 10^{-2}$ ( $M=10\%$ )
$\mu_{\text{conv}}=1,21$ ( $M=10\%$ )	$\mu_{\text{conv}}=1,221$ ( $M=10\%$ )	$\mu_{\text{conv}}=1,239$ ( $M=10\%$ )	$\mu_{\text{conv}}=1,168$ ( $M=10\%$ )
$\mu_{\text{opt}}=5,9 \cdot 10^{-3}$ ( $M=10\%$ )	$\mu_{\text{opt}}=6,4 \cdot 10^{-3}$ ( $M=10\%$ )	$\mu_{\text{opt}}=5,4 \cdot 10^{-3}$ ( $M=10\%$ )	$\mu_{\text{opt}}=4,09 \cdot 10^{-3}$ ( $M=10\%$ )
$\mu_{\text{opt}}=1,08 \cdot 10^{-2}$ ( $M=20\%$ )	$\mu_{\text{opt}}=1,18 \cdot 10^{-2}$ ( $M=20\%$ )	$\mu_{\text{opt}}=1 \cdot 10^{-2}$ ( $M=20\%$ )	$\mu_{\text{opt}}=7,5 \cdot 10^{-3}$ ( $M=20\%$ )
$\mu_{\text{opt}}=14,99 \cdot 10^{-3}$ ( $M=30\%$ )	$\mu_{\text{opt}}=1,63 \cdot 10^{-2}$ ( $M=30\%$ )	$\mu_{\text{opt}}=1,38 \cdot 10^{-2}$ ( $M=30\%$ )	$\mu_{\text{opt}}=1,04 \cdot 10^{-2}$ ( $M=30\%$ )

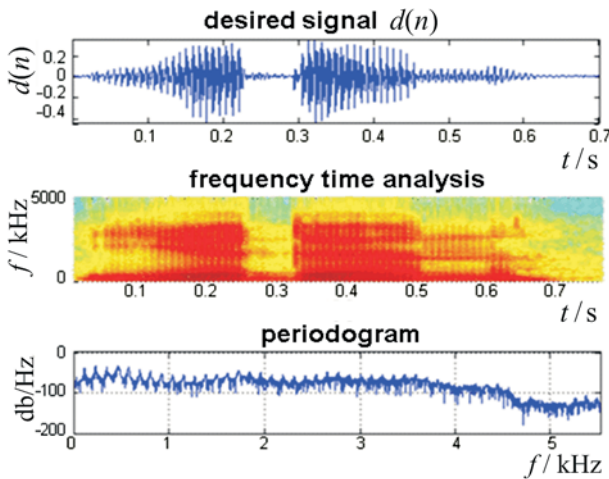
The misadjustment  $M$  parameter is defined as the ratio of the steady – state value of the excess mean-square error (MSE)  $\zeta_{\text{excess}}$  to the minimum mean square (MSE) error  $\zeta_{\text{min}}$ .

$$M = \frac{\zeta_{\text{excess}}}{\zeta_{\text{min}}} = \mu \text{tr}[\mathbf{R}]. \tag{11}$$

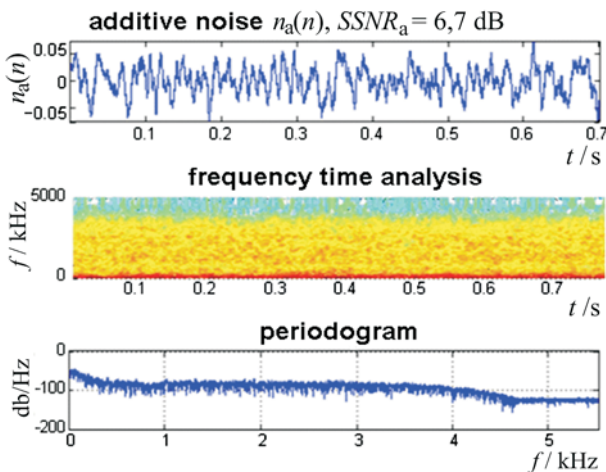
The misadjustment  $M$  is a dimensionless parameter, that provides a measure of how close the LMS algorithm is to optimality in the mean - square – sense. The closer  $M$  is to 0, the more accurate is the adaptive filtering action, which is being performed by the LMS algorithm. The values of the misadjustment  $M$  parameter are usually the 10 %, 20 % and 30 % (Tab. 4), (Tab. 5), (Tab. 6), (Tab. 7), (Tab. 8). The value of  $M = 10 \%$  means that the adaptive system has an MSE only 10 percent greater than  $\zeta_{\text{min}}$  [11].

### 4 Using of the DTW criterion for determination of the adaptive filter length $M$

The dynamic time warping (DTW) criterion is an algorithm for measuring similarity between two sequences which may vary in time or speed. A well known application



**Figure 2** The desired speech signal  $d(n)$  of the Czech isolated word "jeden" (one) to the LMS adaptive filter variations. Waveform, spectrogram (frequency time analysis) and periodogram of the power spectral density estimate.



**Figure 3** The additive noise  $n_a(n)$  (in input signal  $x(n)=d(n)+n_a(n)$ ) to the LMS adaptive filter variations. Waveform, spectrogram (frequency time analysis) and periodogram of the power spectral density estimate.

has been automatic speech recognition, to cope with different speaking speeds [8].

The correct determination of the adaptive filter length  $M$  is very important. When the length  $M$  of the adaptive filter is low, the speech signal processing is inaccurate as a result of the adaptive filter's small number of parameters. A high value of the adaptive filter length  $M$  leads to inaccurate speech signal processing by the influence of the estimator variance increase. The proposed method in this work used the DTW criterion for determining the value of the filter length  $M$  of the LMS adaptive filter.

The DTW criterion is used to compare the two sequences of vectors: reference vector  $\mathbf{P}=[p(1), \dots, p(P)]$  of length  $P$  and test vector  $\mathbf{O}=[o(1), \dots, o(T)]$  of length  $T$  [5]. The value of the LMS adaptive filter length  $M$  is determined by setting values of the length  $M$  in intervals  $\{0 \text{ to } 150\}$  and calculating of the minimum distance (similarity) between the reference vector  $\mathbf{R}=[r(1), \dots, r(R)]$  of the length  $R$  (the desired signal  $d(n)$  (Fig. 2)) and the test sequence  $\mathbf{O}=[o(1), \dots, o(T)]$  of the length  $T$  (the error signal  $e(n)$  (Fig. 6), (Fig. 10), (Fig. 11)). Words are almost never represented by the sequence of the same length  $R \neq T$  [7]. The distance between the sequences  $\mathbf{O}$  and  $\mathbf{R}$  is given as minimum distance over the settings of all possible paths (all possible lengths) [5, 7, 8]. When the value of distance  $d$  was  $d < 0.2$ , the isolated word **was recognised**. This value  $d < 0.2$  was

determined from experiments with isolated word recognition (Tab. 3) [10] for comparison of the distances  $d$  between isolated words.

Minimum distance computation

$$D(\mathbf{O}, \mathbf{R}) = \min_{\{C\}} D_c(\mathbf{O}, \mathbf{R}), \tag{12}$$

is simple, when normalization factor  $N_c$  is not a function of the path and it is possible to write  $N_c=N$  for

$$\forall_c D(\mathbf{O}, \mathbf{R}) = \frac{1}{N} \min_{\{C\}} \sum_{k=1}^{K_c} d[o(t_c(k)), r(r_c(k))] W_c(k). \tag{13}$$

## 5

### The segmental signal to noise ratio calculation

In the speech signal processing in a real environment must be expected in the speech signal interference. The standard benchmark for measuring of the level of noise in the signal is the signal to noise ratio criterion -  $SNR$  (Signal-to-Noise Ratio). In analyzing of the speech signal it is expected that the speech signal is disturbed by two basic types of interference. These types of interference are described as additive noise or convolution distortion. The additive noise (Tab. 2) is added to the speech signal either as background noise environment where the speech is sensed as the noise or the speech signal transmission path. The additive noise is added to speech signal processing and the speech coding operations in the digital signal processors with fixed-point.

**Table 2** The Segmental Signal to Noise ratio values calculated for the speech signal of Czech word "jeden" (Fig. 2) to additive noise  $n_a(n)$  (Fig. 3) and to additive white noise  $n_w(n)$ .

Type of noise	Values of Segmental SNR
additive noise $n_a(n)$	$SSNR_a=6,7$ dB
additive white noise 1 $n_{w1}(n)$	$SSNR_{w1}=18,2$ dB
additive white noise 2 $n_{w2}(n)$	$SSNR_{w2}=3$ dB
additive white noise 3 $n_{w3}(n)$	$SSNR_{w3}=-1,8$ dB

For implementation of experiments are used the additive noises with a calculated Segmental  $SNR$  (Signal to Noise Ratio) –  $SSNR$  (Tab. 2) for speech signal processing [9]

$$SSNR = \frac{1}{K} \sum_{i=0}^{L-1} SNR_i VAD_i, \tag{14}$$

$L$  – is the number of segments of speech signal,  
 $K$  – the number of segments in speech activity,  
 $VAD_i$  – is information about speech activity  $SNR_i$ .

## 6

### Using the proposed method with the DTW criterion for the LMS adaptive noise cancelling from the speech signal

#### 6.1

##### MATLAB simulation

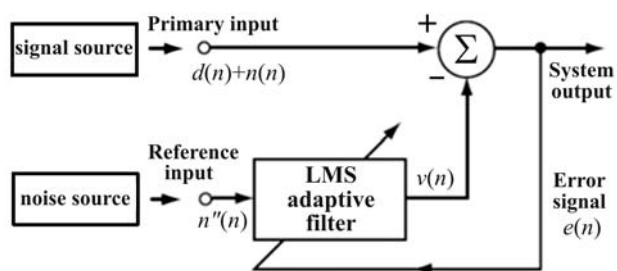
The proposed method with the DTW criterion was used in two channel structures of variations of the LMS adaptive noise canceller (Fig. 4).

A primary input contains the desired signal  $d(n)$  (Fig. 2)

**Table 3** Using the DTW criterion for recognition of the isolated Czech words (numbers one - ten, one - ten) from a single speaker

jeden-jeden (one-one)	jeden-dva (one-two)	jeden-tři (one-three)	jeden-čtyři (one-four)	jeden-pět (one-five)	jeden-šest (one-six)	jeden-sedm (one-seven)	jeden-osm (one-eight)	jeden-devět (one-nine)	jeden-deset (one-ten)
$d=0$	$d=0,713$	$d=1,218$	$d=1,415$	$d=0,552$	$d=1,917$	$d=1,46$	$d=1,071$	$d=0,553$	$d=1,268$
dva-jeden (two-one)	dva-dva (two-two)	dva-tři (two-three)	dva-čtyři (two-four)	dva-pět (two-five)	dva-šest (two-six)	dva-sedm (two-seven)	dva-osm (two-eight)	dva-devět (two-nine)	dva-deset (two-ten)
$d=0,713$	$d=0$	$d=0,406$	$d=0,568$	$d=0,373$	$d=1,165$	$d=0,791$	$d=0,39$	$d=0,37$	$d=0,592$

and the additive noise  $n(n)$ . A noise reference input is assumed to be available containing  $n''(n)$ , which is correlated with the original corrupting noise  $n(n)$ . As shown in Fig. 4, the LMS adaptive filter receives the reference noise, filters it, and subtracts the result from the primary input.



**Figure 4** Block diagram of the LMS adaptive noise canceller [6, 11]

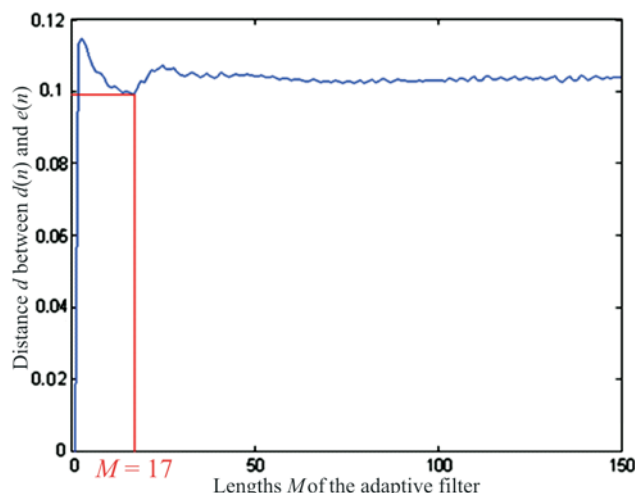
From the point of view of the adaptive filter, the primary input  $(d(n)+n(n))$  acts as its desired response and the system output acts as its error. The noise canceller output  $e(n)$  (Fig. 6) is obtained by subtracting the filtered reference noise  $n(n)$  from the primary input. Adaptive noise canceling generally performs better than the classical approach since the noise is subtracted out rather than filtered out [11].

The proposed DTW method was used for optimal settings values of the filter length  $M$  and a step size factor  $\mu$  of the adaptive filter with the LMS algorithm in the application of the suppression of additive noise from the speech signal. Optimal values of the filter length  $M$  of the LMS adaptive noise canceller and distance  $d$  between desired speech signal  $d(n)$  (Fig. 2) and error signal  $e(n)$  (Fig. 6) from the LMS adaptive noise canceller are calculated in Tab. 5.

The proposed method for optimal adjustment of a step size factor  $\mu_{opt}$  and the filter length  $M$  of the LMS adaptive filter in an application for the suppression of additive noise from the speech signal was applied in the next steps [10, 12]:

1. Calculation of a step size factor  $\mu_{opt}$  optimal value (10) from the input signal  $x(n)$  to variations of the LMS adaptive noise canceller ( $\mathcal{M}=10\%$ ,  $\mathcal{M}=20\%$ ,  $\mathcal{M}=30\%$ ), ( $SSNR_a=6,7$  dB,  $SSNR_{w1}=18,2$  dB,  $SSNR_{w2}=3$  dB,  $SSNR_{w3}=-1,8$  dB), (Tab. 1).
2. As the reference vector  $P$  is used the desired signal  $d(n)$  (Fig. 2).
3. As a test vector  $O$  was chosen the error signal  $e(n)$ .
4. Further were calculated the distance  $d$  (12), (13) between the signals  $d(n)$  and  $e(n)$  for settings of the filter lengths  $M$  of variations of the LMS adaptive noise canceller in interval  $\{1$  to  $150\}$  (Fig. 5).
5. As the optimal value of the LMS adaptive noise canceller length  $M$  was chosen for example value  $M=17$  for minimum distance  $d=9,9 \times 10^{-2}$  (Fig. 5), (Tab. 5) between two compared signals  $d(n)$  (Fig. 2) and  $e(n)$  (Fig. 6) ( $SSNR_a=6,7$  dB,  $\mu_1=5,9 \times 10^{-3}$ ).
6. The same procedure was used for the calculation of optimal filter length  $M$  of other variations of the LMS

adaptive noise canceller (the Signed LMS algorithm, the Signed-Regressor LMS algorithm and the Signed-Signed LMS algorithm) (Tab. 6, Tab. 7 and Tab. 8).



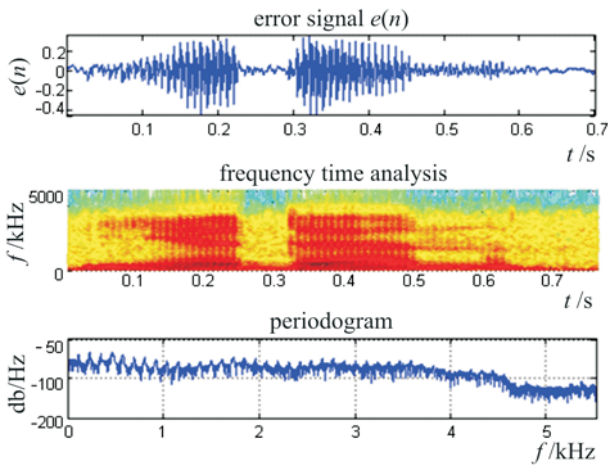
**Figure 5** Calculation of the filter length  $M=17$  of the LMS adaptive noise canceller, (first iteration cycle), ( $SSNR_a=6,7$  dB and  $\mu_1=5,9 \times 10^{-3}$ ) and distance  $d=9,9 \times 10^{-2}$  between  $e(n)$  (Fig. 6) and  $d(n)$  (Fig. 2) ( $SSNR_a=6,7$  dB,  $\mu_1=5,9 \times 10^{-3}$ , (Tab. 5)).

The output signal  $e(n)$  from the LMS adaptive noise canceller (first iteration cycle) **was recognized** ( $d < 0,2$ ) only for the next conditions:  $SSNR_a=6,7$  dB ( $\mu_1=5,9 \times 10^{-3}$ ,  $M=17$ ,  $\mathcal{M}=10\%$ ), ( $\mu_2=1,08 \times 10^{-2}$ ,  $M=10$ ,  $\mathcal{M}=20\%$ ), ( $\mu_3=14,996 \times 10^{-3}$ ,  $M=7$ ,  $\mathcal{M}=30\%$ ), (Tab. 5). When the additive white noise values in the speech signal were higher ( $SSNR_w$ ), the speech signal was not recognized.

The output signal  $e(n)$  from the LMS Sign adaptive noise canceller (first iteration cycle) **was recognized** ( $d < 0,2$ ) only for the next conditions:  $SSNR_a=6,7$  dB ( $\mu_1=5,9 \times 10^{-3}$ ,  $M=8$ ,  $\mathcal{M}=10\%$ ), ( $\mu_2=1,08 \times 10^{-2}$ ,  $M=10$ ,  $\mathcal{M}=30\%$ ), (Tab. 6). When the additive white noise values  $SSNR_w$  in the speech signal were higher, the speech signal was not recognized.

The output signal  $e(n)$  from the LMS Sign-Sign adaptive noise canceller (first iteration cycle) **was recognized** ( $d < 0,2$ ) for next conditions:  $SSNR_a=6,7$  dB ( $\mu_1=5,9 \times 10^{-3}$ ,  $M=2$ ,  $\mathcal{M}=10\%$ ), ( $\mu_2=1,08 \times 10^{-2}$ ,  $M=2$ ,  $\mathcal{M}=20\%$ ) and for  $SSNR_{w1}=18,2$  dB ( $\mu_1=6,4 \times 10^{-3}$ ,  $M=2$ ,  $\mathcal{M}=10\%$ ), ( $\mu_2=1,18 \times 10^{-2}$ ,  $M=2$ ,  $\mathcal{M}=20\%$ ), ( $\mu_3=1,63 \times 10^{-2}$ ,  $M=2$ ,  $\mathcal{M}=30\%$ ) (Tab. 7), but the filter lengths  $M$  of the LMS Sign-Sign adaptive noise canceller was very low ( $M=2$ ).

The output signal  $e(n)$  from the LMS Sign-Regressor adaptive noise canceller (first iteration cycle) **was recognized** ( $d < 0,2$ ) only in one case for next conditions:  $SSNR_a=6,7$  dB ( $\mu_1=5,9 \times 10^{-3}$ ,  $M=12$ ,  $\mathcal{M}=10\%$ ), (Tab. 8).



**Figure 6** The error signal  $e(n)$  from the LMS adaptive noise canceller (first iteration cycle), ( $M = 17, \mu = 5,9 \times 10^{-3}, SSNR_a = 6,7$  dB,  $d = 9,9 \times 10^{-2}$  word **was recognized**, (Tab. 5)), (simulated in MATLAB) [10].

**6.2 Implementation of the LMS adaptive noise canceller on the TMS320C6713 DSK**

The proposed method with DTW criterion for determining the filter length  $M$  of the adaptive filter with the LMS algorithm was used in an application to suppress additive noise  $n(n)$  from the speech signal  $x(n)$ . It was implemented with a two channel structure of the LMS adaptive noise canceller on the TMS320C6713 DSP (Digital Signal Processor), Starter Kit (DSK) (Fig. 7) [10] and it was programmed in the C programming language through the CCS studio version 3.1 [13].

The input signal  $x(n)$  is composed of the desired signal  $d(n)$  and the additive noise  $n(n)$ . The segmental signal to noise ratio of the input signal  $x(n)$  was  $SSNR_a = 6,7$  dB.

Application of the proposed method with the DTW criterion with implementation of the LMS adaptive noise

**Table 4** Calculation of distance  $d$ , the filter length  $M$  and step size factor  $\mu$  of the LMS adaptive noise canceller (first iteration cycle), ( $\mathcal{M} = 10\%$ ,  $\mathcal{M} = 20\%$ ,  $\mathcal{M} = 30\%$ ,  $SSNR_a = 6,7$  dB), (calculated in MATLAB).

$\mathcal{M}$	$\mathcal{M} = 10\%$	$\mathcal{M} = 20\%$	$\mathcal{M} = 30\%$
$\mu$	$\mu_1 = 0,103$	$\mu_2 = 0,188$	$\mu_3 = 0,26$
$M$	$M = 21$	$M = 40$	$M = 99$
$d$	$d = 0,184$	$d = 0,265$	$d = 0,307$

canceller on the TMS320C6713 DSK was carried out in several steps:

1. step – calculation of optimal value of a step size factor  $\mu$  from the input signal  $x(n)$  to the TMS320C6713 DSK (calculated in MATLAB).

2. step – calculation of the filter length  $M$  values of the LMS adaptive noise canceller (Tab. 4), (calculated in MATLAB).

3. step – empirically was found, that the factor  $\mu$  for the LMS adaptive noise canceller, implemented on the TMS320C6713 DSK allows settings only in the range  $\mu = 10^{-8}$  to  $\mu = 10^{-12}$ . The filter length  $M$  of the LMS adaptive noise canceller can be set only in the range  $M = 16$  to  $M = 52$ . This indicates the possibility of only partial use of the proposed method in practical implementation of the LMS adaptive noise canceller on the TMS320C6713 DSK.

4. step – settings of the filter length  $M = 21$ , settings values of the step size factor  $\mu = 10^{-8}, \mu = 10^{-10}, \mu = 10^{-12}$  (Tab. 9) and implementation of the LMS adaptive noise canceller on the TMS320C6713 DSK. The input signal is  $x(n) = d(n) + n(n)$ , where  $d(n)$  (Fig. 2) is isolated Czech word "jeden" (one) and  $n(n)$  is additive noise with  $SSNR_a = 6,7$  dB.

5. step – calculation of distance  $d$  between  $e(n)$  (for example (Fig. 10 and Fig. 11) and  $d(n)$  (Fig. 2) for settings of the filter length  $M = 21$  and step size factor  $\mu$  ( $SSNR_a = 6,7$  dB) (Tab. 9). The optimal settings values of a step size factor  $\mu$  and the filter length  $M$  were  $M = 21$  and  $\mu = 10^{-8}$  for the LMS adaptive noise canceller, implemented on the TMS320C6713 DSK.

**Table 5** Calculation of the length  $M$  of the adaptive filter and distance  $d$  between the desired speech signal  $d(n)$  to the **LMS Adaptive Noise Canceller** and the error signal  $e(n)$  from the LMS adaptive noise canceller (first iteration), calculated by way of the draft method with the DTW criterion (simulated in MATLAB).

	$SSNR_a = 6,7$ dB	$SSNR_{w1} = 18,2$ dB	$SSNR_{w2} = 3$ dB	$SSNR_{w3} = -1,8$ dB
$\mathcal{M} = 10\%$	$\mu_1 = 5,9 \times 10^{-3}; M = 17$ $d = 9,9 \times 10^{-2}$	$\mu_1 = 6,4 \times 10^{-3}; M = 43$ $d = 5,421 \times 10^{-1}$	$\mu_1 = 5,4 \times 10^{-3}; M = 149$ $d = 9,142 \times 10^{-1}$	$\mu_1 = 4,09 \times 10^{-3}; M = 74$ $d = 1,473$
$\mathcal{M} = 20\%$	$\mu_2 = 1,08 \times 10^{-2}; M = 10$ $d = 9,8 \times 10^{-2}$	$\mu_2 = 1,18 \times 10^{-2}; M = 99$ $d = 5,409 \times 10^{-1}$	$\mu_2 = 1 \times 10^{-2}; M = 103$ $d = 1,127$	$\mu_2 = 7,5 \times 10^{-3}; M = 74$ $d = 1,42$
$\mathcal{M} = 30\%$	$\mu_3 = 14,996 \times 10^{-3}; M = 7$ $d = 9,87 \times 10^{-2}$	$\mu_3 = 1,63 \times 10^{-2}; M = 99$ $d = 5,405 \times 10^{-1}$	$\mu_3 = 1,38 \times 10^{-2}; M = 103$ $d = 1,111$	$\mu_3 = 1,04 \times 10^{-2}; M = 74$ $d = 1,374$

**Table 6** Calculation of the length  $M$  of the adaptive filter and distance  $d$  between the desired speech signal  $d(n)$  to the **LMS Sign Adaptive Noise Canceller** and the error signal  $e(n)$  from the LMS Sign adaptive noise canceller (first iteration), calculated by way of the draft method with the DTW criterion (simulated in MATLAB).

	$SSNR_a = 6,7$ dB	$SSNR_{w1} = 18,2$ dB	$SSNR_{w2} = 3,1$ dB	$SSNR_{w3} = -1,8$ dB
$\mathcal{M} = 10\%$	$\mu_1 = 5,9 \times 10^{-3}; M = 8$ $d = 0,103$	$\mu_1 = 6,4 \times 10^{-3}; M = 2$ $d = 0,53$	$\mu_1 = 5,4 \times 10^{-3}; M = 2$ $d = 0,7411$	$\mu_1 = 4,09 \times 10^{-3}; M = 2$ $d = 0,5568$
$\mathcal{M} = 20\%$	$\mu_2 = 1,08 \times 10^{-2}; M = 10$ $d = 0,109$	$\mu_2 = 1,18 \times 10^{-2}; M = 2$ $d = 0,5189$	$\mu_2 = 1 \times 10^{-2}; M = 2$ $d = 0,4053$	$\mu_2 = 7,5 \times 10^{-3}; M = 2$ $d = 0,5580$
$\mathcal{M} = 30\%$	$\mu_3 = 14,996 \times 10^{-3}; M = 10$ $d = 0,113$	$\mu_3 = 1,63 \times 10^{-2}; M = 2$ $d = 0,51$	$\mu_3 = 1,38 \times 10^{-2}; M = 2$ $d = 0,3238$	$\mu_3 = 1,04 \times 10^{-2}; M = 117$ $d = 0,4526$

The speech error signal  $e(n)$  (Fig. 10) from the LMS adaptive noise canceller (implemented on the TMS320C6713 DSK) **was recognized** as ( $d < 0,2$ ) (first

iteration cycle of the LMS adaptive noise canceller) for settings of parameters ( $SSNR_a = 6,7$  dB),  $\mu = 1 \times 10^{-8}, M = 21$ ).

**Table 7** Calculation of the length  $M$  of the adaptive filter and distance  $d$  between the desired speech signal  $d(n)$  to the **LMS Sign-Sign Adaptive Noise Canceller** and the error signal  $e(n)$  from the LMS Sign-Sign adaptive noise canceller (first iteration), calculated by way of the draft method with the DTW criterion (simulated in MATLAB).

	$SSNR_a=6,7$ dB	$SSNR_{w1}=18,2$ dB	$SSNR_{w2}=3,1$ dB	$SSNR_{w3}=-1,8$ dB
$M=10$ %	$\mu_1=5,9 \times 10^{-3}$ ; $M=2$ $d=0,136$	$\mu_1=6,4 \times 10^{-3}$ ; $M=2$ $d=0,118$	$\mu_1=5,4 \times 10^{-3}$ ; $M=2$ $d=0,229$	$\mu_1=4,09 \times 10^{-3}$ ; $M=2$ $d=0,276$
$M=20$ %	$\mu_2=1,08 \times 10^{-2}$ ; $M=2$ $d=0,179$	$\mu_2=1,18 \times 10^{-2}$ ; $M=2$ $d=0,148$	$\mu_2=1 \times 10^{-2}$ ; $M=2$ $d=0,305$	$\mu_2=7,5 \times 10^{-3}$ ; $M=2$ $d=0,384$
$M=30$ %	$\mu_3=14,996 \times 10^{-3}$ ; $M=2$ $d=0,215$	$\mu_3=1,63 \times 10^{-2}$ ; $M=2$ $d=0,194$	$\mu_3=1,38 \times 10^{-2}$ ; $M=2$ $d=0,355$	$\mu_3=1,04 \times 10^{-2}$ ; $M=2$ $d=0,414$

**Table 8** Calculation of the length  $M$  of the adaptive filter and distance  $d$  between the desired speech signal  $d(n)$  to the **LMS Sign-Regressor Adaptive Noise Canceller** and the error signal  $e(n)$  from the LMS Sign-Regressor adaptive noise canceller (first iteration), calculated by way of the draft method with the DTW criterion (simulated in MATLAB).

	$SSNR_a=6,7$ dB	$SSNR_{w1}=18,2$ dB	$SSNR_{w2}=3,1$ dB	$SSNR_{w3}=-1,8$ dB
$M=10$ %	$\mu_1=5,9 \times 10^{-3}$ ; $M=12$ $d=0,172$	$\mu_1=6,4 \times 10^{-3}$ ; $M=146$ $d=0,407$	$\mu_1=5,4 \times 10^{-3}$ ; $M=144$ $d=0,591$	$\mu_1=4,09 \times 10^{-3}$ ; $M=3$ $d=0,538$
$M=20$ %	$\mu_2=1,08 \times 10^{-2}$ ; $M=11$ $d=0,21$	$\mu_2=1,18 \times 10^{-2}$ ; $M=146$ $d=0,304$	$\mu_2=1 \times 10^{-2}$ ; $M=37$ $d=0,349$	$\mu_2=7,5 \times 10^{-3}$ ; $M=2$ $d=0,33$
$M=30$ %	$\mu_3=14,996 \times 10^{-3}$ ; $M=77$ $d=0,228$	$\mu_3=1,63 \times 10^{-2}$ ; $M=129$ $d=0,249$	$\mu_3=1,38 \times 10^{-2}$ ; $M=4$ $d=0,23$	$\mu_3=1,04 \times 10^{-2}$ ; $M=2$ $d=0,261$

**Table 9** Calculation of distance  $d$  for the set of the filter length  $M=21$  and step size factor  $\mu$  with  $SSNR_a=6,7$  dB (the LMS adaptive noise canceller was implemented on the TMS320C6713 DSK, (first iteration)).

settings of factor $\mu$ (implemented on the TMS320C6713 DSK)	$\mu=1 \times 10^{-12}$	$\mu=1 \times 10^{-10}$	$\mu=1 \times 10^{-8}$
calculation of distance values $d$ (in MATLAB)	$d=4,27 \times 10^{-1}$	$d=3,48 \times 10^{-1}$	$d=8,97 \times 10^{-2}$
settings of the filter length $M$	$M=21$	$M=21$	$M=21$

**7 Using the LMS adaptive noise canceller in voice communication with a control Bus system**

The proposed method with the DTW criterion was used for optimal settings parameters of the LMS adaptive noise canceller, implemented on the TMS320C6713 DSK, applied in voice communications with the control Bus system (Fig. 7). The control Bus system was used in the application of visualization operational control of the technical functions of the building with the visualization software Promotic.

Software My Voice, linked with software Promotic (Fig. 7), was used for the speech recognition in voice communication with the control Bus system. By use of the software My Voice operational technical functions in the buildings can be done through voice control. In voice communication with the control Bus system were used voice commands, for example switch on/off lights, increase of temperature, decrease of temperature, reducing of temperature by **one** degree Celsius, turn on/off **boiler**.

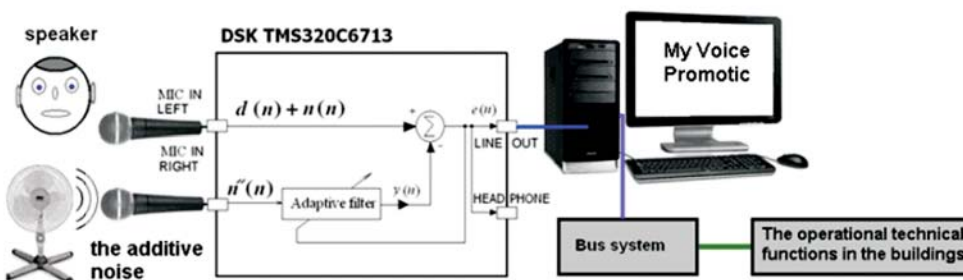
In the Czech language were used the following voice commands: "rozsvítit/zhasnout světla", "zvýšit teplotu", "snížit teplotu", "snížit teplotu o 1 °C" ("teplota minus jedna"), "zvýšit teplotu o 1 °C" ("teplota plus **jedna**") "zapnout/vypnout **bojler**") etc.

For this experiment were chosen Czech words as voice commands "**jedna**" and "**bojler**". The aim of this experiment was to determine the success of the recognition of selected voice commands ("bojler", "jedna") with additive noise, by the use of software My Voice in voice communication with the control Bus system, with subsequent conditions:

- a) in the case partial use of the proposed method with settings of optimal parameters ( $M, \mu$ ) of the LMS adaptive noise canceller, (as voice command was used of the isolated Czech word "bojler", ("boiler")) and
- b) in the case without partial use of the proposed method, without settings of optimal parameters ( $M, \mu$ ) of the LMS adaptive noise canceller (as voice command was used of the isolated Czech word "jedna", ("one")).

ad a) The voice command "bojler" was used for simulation of turning on/off of the boiler (Fig. 8). Conditions of this experiment were following:

1. 100× was spoken voice command "bojler" without the LMS adaptive noise canceller implemented on the TMS320C6713 DSK.
- **measurement 1** without additive noise 99 % successful speech recognition,
  - **measurement 2** with additive noise 81 % successful speech recognition.



**Figure 7** Implementation of the LMS adaptive noise canceller for the voice communications with the control Bus system.

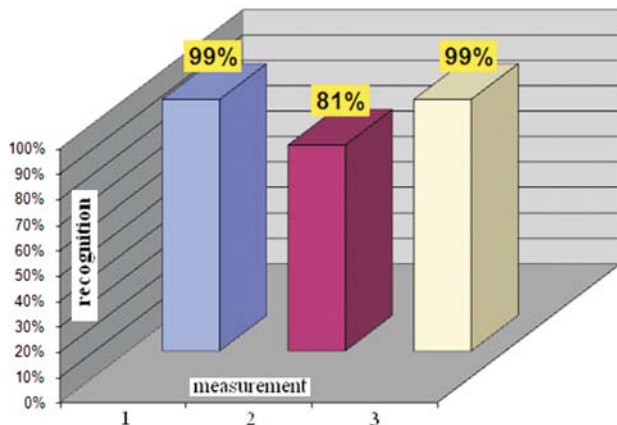


Figure 8 Evaluation of recognition of isolated Czech word - voice command "bojler" (boiler) with software MyVoice.

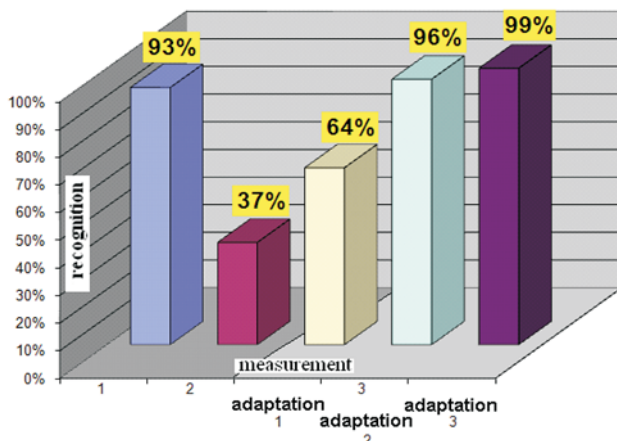


Figure 9 Evaluation of recognition of isolated Czech word - voice command "jedna" (one) with software MyVoice.

2. 100× was spoken voice command "bojler" with the LMS adaptive noise canceller implemented on the TMS320C6713 DSK with partial use of the proposed method

- **measurement 3** with additive noise 99 % successful speech recognition.

ad b) The isolated word "jedna" (one) was used as part of voice command for increasing of temperature +1 °C (Fig. 9). Conditions of this experiment were the following:

1. 100× spoken voice command "jedna" without the LMS adaptive noise canceller implemented on the TMS320C6713 DSK

- **measurement 1** without additive noise 98 % successful speech recognition,
- **measurement 2** with additive noise 37 % successful speech recognition.

2. 100× spoken voice command "jedna" with the LMS adaptive noise canceller implemented on the TMS320C6713 DSK without partial use of the proposed method

- **measurement 3** with additive noise  
**1 adaptation** of the LMS adaptive noise canceller (100× spoken voice command "jedna") 64 % successful speech recognition,

**2 adaptation** of the LMS adaptive noise canceller (100× spoken voice command "jedna") 96 % successful speech recognition,

**3 adaptation** of the LMS adaptive noise canceller (100× spoken voice command "jedna") 99 % successful speech recognition.

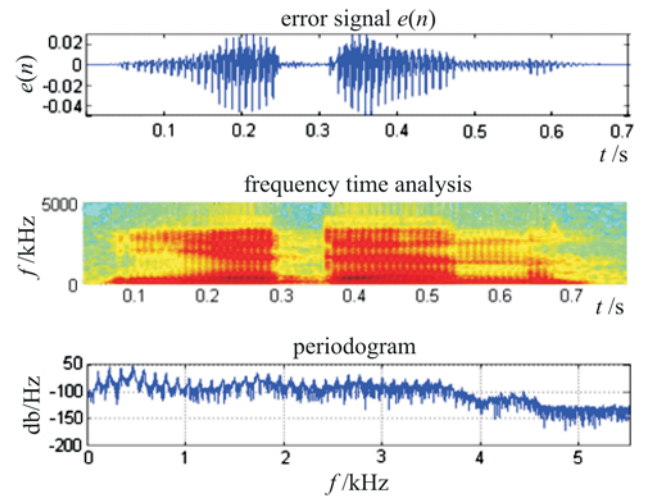


Figure 10 The error signal  $e(n)$  from the LMS adaptive noise canceller, implemented on the TMS320C6713 DSK ( $M = 21$ ,  $\mu = 10^{-8}$ ,  $d = 8.97 \times 10^{-2}$ ,  $SSNR = 6,7$  dB, (first iteration cycle), word **was recognized** (Tab. 9).

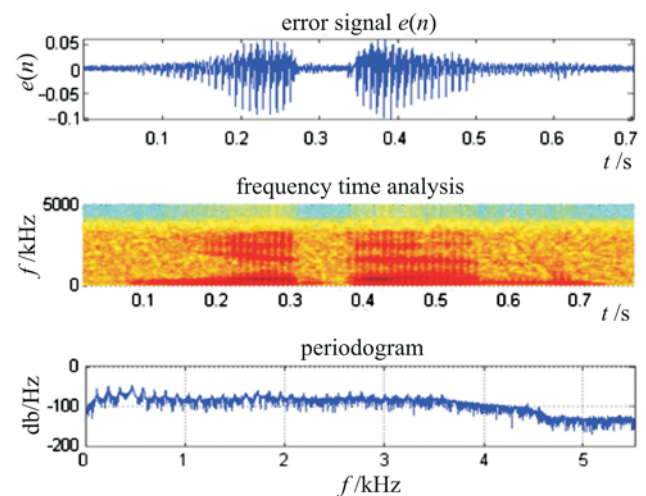


Figure 11 The error signal  $e(n)$  from the LMS adaptive noise canceller implemented on the TMS320C6713 DSK ( $M = 21$ ,  $\mu = 10^{-12}$ ,  $d = 0,427$ ,  $SSNR = 6,7$  dB, (first iteration cycle), word **was not recognized** (Tab.9).

## 8 Conclusion

In experimental section of this paper was described the way of using of the proposed method in variations of the adaptive filter with the LMS algorithm in application of suppressing noise from the speech signal by simulations in MATLAB software. The proposed method was partially used in the practical implementation of the LMS adaptive noise canceller on the TMS320C6713 DSK. This implementation was used in voice communication with Bus system for controlling of operating – technical functions in buildings. Application of variations of the LMS adaptive filter for voice communications with control system are also suitable for manufacturing technologies for on-line quality control e.g. [14, 15, 16, 17] and for analysis fo material properties for rapid prototyping.

## Acknowledgments

This paper has been supported by the VŠB TU grant No. SP2011/12. The authors are thankful for the support.

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## References

- [1] Farhang – Borounjy, B. Adaptive Filters, Theory and applications, John Wiley & Sons, Chichester 2005, ISBN 0-471-98337-3, pp. 139-168.
- [2] Poularikas, D. A.; Ramadan, M. Z. Adaptive filtering primer with MATLAB, Taylor & Francis Group, 2006, ISBN 0-8493-7043-4, pp. 101-122.
- [3] Jan, J. Číslicová filtrace, analýza a restaurace signálů, nakladatelství VUTIUM, Brno, 2002, ISBN 80-214-1558-4 (2. uprav. vydání), pp. 287-308.
- [4] Hayikín, S.; Widrow, B. Least – Mean – Square Adaptive Filters, WILEY INTERSCIENCE A JOHN WILEY & SONS, New Jersey 2003, ISBN 0-471-21570-8
- [5] Černocký, J. Zpracování řečových signálů – studijní opora, <http://www.fit.vutbr.cz/study/courses/ZRE/public/>, VUT Brno, (5.3.2011)
- [6] Hayikín, S. Adaptive filter theory, PRENTICE HALL, New Jersey 2002, ISBN 0-13-090126-1, pp. 231-258
- [7] Uhlíř, J.; Sovka, P.; Pollák, P.; Hanžl, V.; Čmejla, R. Technologie hlasových komunikací, nakladatelství ČVUT Praha 2007, ISBN 978-80-01-03888-8, pp. 75-165
- [8] [http://en.wikipedia.org/wiki/Dynamic\\_time\\_warping](http://en.wikipedia.org/wiki/Dynamic_time_warping) (8.3.2011)
- [9] Sovka, P.; Pollák, P. Vybrané metody číslicového zpracování signálů, vydavatelství ČVUT, Praha, 2003, ISBN 80-01-02821-6, pp. 89-94
- [10] Vaňuš, J. Voice communication with control system, Dissertation thesis, VŠB TU Ostrava, 2010
- [11] Widrow, B.; Walach, E. Adaptive Inverse Control: A Signal Processing Approach, Published by John Wiley & Sons, Inc., Hoboken, New Jersey 2008. ISBN 978-0-470-22609-4, pp. 59-87.
- [12] Vaňuš, J. Application of optimal settings of the LMS adaptive filter for speech signal processing, IMCSI Technology, Wisła 2010, Poland, ISBN 978-83-60810-27-9, pp. 767-774.
- [13] Chassaing, R.; Reay, D. Digital Signal Processing and Applications with the TMS320C6713 and TMS320C6416 DSK, John Wiley & Sons, Inc. New Jersey 2008, ISBN 978-0-470-13866-3, pp. 319-353.
- [14] Valíček, J.; Hloch, S. Using the acoustic sound pressure level for quality prediction of surfaces created by abrasive waterjet. // International Journal of Advanced Manufacturing Technology, 48, 1-4(2010), pp. 193-203
- [15] Valíček, J. et al. An investigation of surfaces generated by abrasive waterjets using optical detection. // Strojnicki vestnik-Journal of mechanical engineering. vol. 53, (2007), pp. 224-232.
- [16] Valíček, J.; Hloch, S. Optical measurement of surface and topographical parameters investigation created by abrasive waterjet. // International Journal of Surface Science and Engineering, 3, 4(2009), 360-373. DOI: 10.1504/IJSURFSE.2009.027421.
- [17] Valíček, J.; Hloch, S.; Kozak, D. Surface geometric parameters proposal for the advanced control of abrasive waterjet technology. // The International Journal of Advanced Manufacturing Technology, 41, 3-4(2009), 323-328.
- [18] Hloch, S. et al. Using waterjet in reverse logistic operations in discarded munitions processing // Tehnicki vjesnik-Technical gazette. 18, 2(2011), pp. 267-271.
- [19] Pilipovic, A.; Raos, P.; Sercer M. Experimental analysis of properties of materials for rapid prototyping. // International Journal of Advanced Manufacturing Technology, 40, 1-2 (2009), pp. 105-115.
- [20] Ivandić, Z.; Ergić, T.; Kljajin, M. Welding robots kinematic structures evaluation of based on conceptual models using the potential method. // Tehnicki Vjesnik - Technical Gazette, 16, 4(2009), pp. 35-46.
- [21] Hreha, P. et al. Water jet technology used in medicine. // Tehnicki Vjesnik - Technical Gazette, 17, 2(2010), pp. 237-240.
- [22] Gaćeša, B.; Milošević-Mitić, V.; Maneski, T.; Kozak, D.; Sertić, J. Numerical and experimental strength analysis of fire-tube boiler construction. // Tehnicki Vjesnik - Technical Gazette, 18, 2(2010), pp. 237-242.

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