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Adaptive Noise Cancelation in Speech Signals

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ADAPTIVE NOISE CANCELATION IN SPEECH SIGNALS

POTLAČOVANÍ ŠUMU V ŘEČOVÝCH SIGNÁLECH POMOCÍ ADAPTIVNÍCH METOD

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CONTENTS

1 THE MAIN OBJECTIVES OF THE THESIS

In this thesis we try to achieve three goals: **to analyze**, **to develop** and **to apply** adaptive algorithms for noise cancelation in speech signals. By *analyzing* a structure and performance of conventional adaptive algorithms such as the NLMS and the RLS we want to reveal the strong parts and the weaknesses of these methods and understand the crucial parts of the adaptive process. By *developing* new concepts and improving the existing methods we try to ameliorate the overall performance and achieve better results in nontypical conditions. For this purpose we specify several conditions and criteria (rate of convergence, computational complexity, residual error level, ability to track sudden changes of parameters) in a way to determine which method yields the best results. Finally, we try to test the adaptive methods in certain *applications* that are often encountered in the field of speech communications. This includes system identification, background noise suppression and inverse filtering.

We have successfully developped a new algorithm named OSS (Optimal Step-size Strategy) which is essentially a gradient adaptive algorithm using orthogonality principles. We provide a mathematical description of the OSS concept and present results of several experiments that we conducted to estimate its performance.

2 THE SCOPE OF CHAPTERS

In this article we begin our discussion by a short review of the speech enhancement methods that are known in literature up to date. First, we provide a short introduction into the problem of speech enhancement. Then we describe some well-known non-adaptive techniques that have been successfully developped and implemented in several practical applications.

In the second part we develop the concept of adaptive noise cancelation and describe in detail two widely used methods, the **NLMS** (Normalized Least Mean Squares) and the **RLS** (Recursive Least Squares). These methods serve as a reference during the rest of the thesis. Therefore, we conduct several experiments to estimate their performance in terms of the convergence rate and computational complexity.

In the third part we address the issue of modifying the NLMS and the RLS method with the aim to improve the performance. Several algorithms have been proposed in literature so far to improve either the rate of convergence, the robustness, the immunity against impulsive noise, the numerical stability or the complexity. In this part we discuss only few methods including the SPSA-LMS, our own modification to the method of NLMS.

In the key part of this article we propose a novel approach to the problem of speech enhancement. It is named **OSS** (Optimal Step-Size) and it is a stochastic gradient adaptive algorithm based on the method of APA (Affine Projection

Algorithm). The algorithm has been developped with the aim to improve the performance of the conventional methods in nonstationary environments. After providing a description of the mathematical concept of the proposed method several experiments are made to evaluate its performance and compare the results with conventional methods.

3 THE STATE OF THE ART

There are numerous approaches to the problem of speech enhancement existing in literature today . This thesis deals with only adaptive methods but in fact there are also many successful nonadaptive methods. Therefore, in the first part of this chapter we focus on them. We describe their principles and provide some remarks on their performance.

In the second part we turn to conventional adaptive methods. We concentrate on two well-known algorithms, the NLMS (Normalized Least Mean Square) and the RLS (Recursive Least Squares). It is of interest to understand the mathematical concept of these methods since it provides a motivation to the research of a new approach, namely the OSS (Optimal Step-Size). We present some experimental results and discuss their performance in terms of convergence rate and computational complexity.

In the last part we address the issue of modifying adaptive techniques. The idea of these methods is to modify either the NLMS or the RLS algorithms in order to achieve better results in certain specific situations. The objectives are usually lower rate of convergence, higher numerical stability, greater robustness, lower complexity, etc.

3.1 NONADAPTIVE SPEECH ENHANCEMENT TECHNIQUES

3.1.1 Spectral subtraction

The spectral subtraction method is probably the most popular single-channel noise suppression technique used in real-world applications. The basic idea is to estimate the amount of additive noise in a noisy speech signal and *subtract* it out in the frequency domain. The method was first proposed by Boll [1][2] in 1979 and later

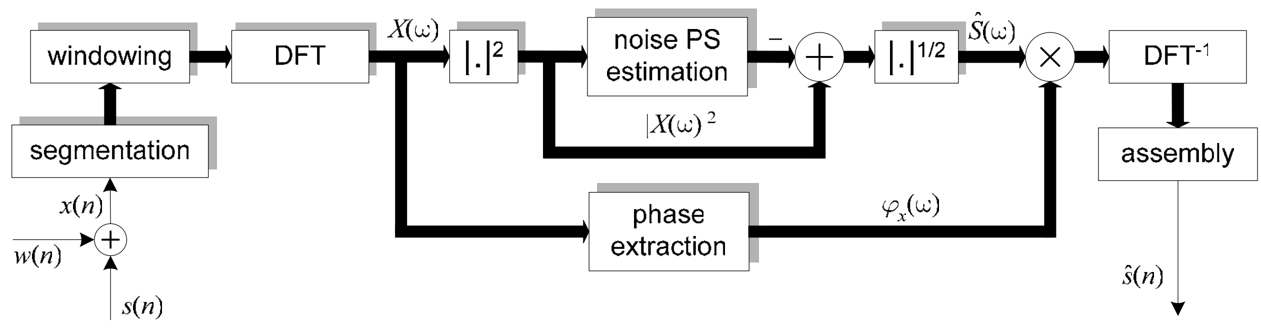

Fig. 3.1: Schematic structure of the spectral subtraction

expanded and generalized by McAulay and Malpass [3] in 1980 who performed spectral subtraction in power domain. In this method it is assumed that the additive noise is uncorrelated with the speech signal. The principle of the method is best explained on the schematic diagram in Fig. 3.1.

The noisy speech signal $x(n)$ is transformed into frequency domain by the DFT transform. Its phase is stored for later use. The subtraction is carried out in the power spectral domain. The power spectrum of the noise itself, $|W(\omega)|^2$ is calculated during periods of speech inacivity. After the subtraction, the signal is transformed back into the time domain by using an inverse DFT transform. For this purpose there is the stored information about the phase $\varphi_x(\omega)$. The whole spectral subtraction method may be described by the following equation

$$\hat{S}(\omega) = \left[\max\left(\left|X(\omega)\right|^2 - k\left|W(\omega)\right|^2, 0\right)\right]^{1/2} . e^{j\varphi_x(\omega)}, \tag{3.1}$$

in which $k > 1$ is used to overestimate the noise level to account for its variance. The max(.) function ensures that the result after subtraction is positive. A major drawback of the above method is that it introduces a distortion, called "musical artifacts" to the enhanced speech signal $\hat{s}(n)$. It has been found that by applying a noise floor according to Berouti et. al. [4] one can eficiently reduce this annoying distortion.

The spectral subtraction method is a single-channel method which does not involve any adaptive principles. Its advantage is inherent simplicity with relatively low computational complexity. The main drawback, though challenged in derived methods, is the introduction of musical artifacts and nonlinear distortion.

3.1.2 Iterative Wiener filtering

The structural concept of Wiener filtering of a noisy speech signal is similar to the spectral subtraction. However, the basic idea here is to minimize the diference between the estimated speech $\hat{s}(n)$ and the uncorrupted speech $s(n)$ in the optimal sense. The criterion used is the minimum mean-square error (MMSE)

$$\xi = \mathrm{E}\left\{\left(s(n) - \hat{s}(n)\right)^2\right\}, \tag{3.2}$$

where both $s(n)$ and $\hat{s}(n)$ are assumed to be long-term stationary and $\mathrm{E}\{.\}$ is an expectation operator. An optimal filter (most often referred to as a *non-causal Wiener filter*) that would be able to achieve the minimum of the MMSE function is given [5] by

$$H(\omega) = \frac{\left|S(\omega)\right|^2}{\left|S(\omega)\right|^2 + \left|W(\omega)\right|^2}, \tag{3.3}$$

where the quantities are the same as in section 3.1.1. However, since neither $S(\omega)$ nor $W(\omega)$ are known we must use their estimates. The estimate of the noise spectrum is obtained in periods of speech inactivity, i.e. in the same way as in the spectral subtraction method. The clean speech spectrum is estimated iteratively using the output of the filter. That is

$$\hat{S}^{(i)}(\omega) = H^{(i)}(\omega) X(\omega) \tag{3.4}$$

and the Wiener filter is updated by

$$H^{(i+1)}(\omega) = \frac{\left|\hat{S}^{(i)}(\omega)\right|^2}{\left|\hat{S}^{(i)}(\omega)\right|^2 + \left|\hat{W}(\omega)\right|^2} \tag{3.5}$$

The iterative Wiener filtering approach has been first proposed by Hansen and Clements [5]. It was found that the algorithm converges to a steady state, in which the MMSE function achieves its minimum. There are numerous modifications existing in literature each of which trying to improve the performance of the basic method described above.

3.1.3 Estimation maximization (E-M) approach

This approach, proposed by Dempster et. al. [6] uses the theory of probability to solve a so-called maximum likelihood (ML) problem or the maximum aposteriori (MAP) problem. These two problems are related to the speech enhancement by a quantity called *log-likelihood function* which is defined as

$$L(\theta) = \log \sum_{\mathbf{x}} \left(\mathcal{P}(\mathbf{s}|\mathbf{x},\theta) \mathcal{P}(\mathbf{x}|\theta) \right) \tag{3.6}$$

where θ is a parameter vector, $\mathbf{x}$ is a noisy speech vector and $\mathbf{s}$ is a clean speech vector. Usually the clean speech signal is estimated from the noisy speech signal using an autoregressive (AR) model. Therefore, the paramaters θ are the AR coefficients of the model, i.e.

$$\theta = \{a_1, a_2, \ldots, a_p\} \tag{3.7}$$

and p is usually between 10 and 20. Thus the objective is to *maximize* the conditional logarithmic probability (3.6). It can be interpreted as maximizing the probability of observing a clean speech vector $\mathbf{s}$ given the knowledge of a noisy speech vector $\mathbf{x}$ and the state of the AR model θ.

The algorithm may work iteratively. Let's assume the state of the model in *k*th state is denoted as θ_k and the corresponsing likelihood function as $L(\theta_k)$. It can be shown that by applying Jensen's inequality [7], we may improve $L(\theta_k)$ by taking the parameters

$$\begin{aligned}
\theta_{k+1} &= \arg\max_{\theta} \left\{ \sum_{\mathbf{x}} \mathcal{P}(\mathbf{x}|\mathbf{s},\theta_k) \log \mathcal{P}(\mathbf{s}|\mathbf{x},\theta) \mathcal{P}(\mathbf{x}|\theta) \right\} \\
\theta_{k+1} &= \arg\max_{\theta} \left\{ \mathrm{E}_{\mathrm{x}|s,\theta_k} \left[\log \mathcal{P}(\mathbf{s},\mathbf{x}|\theta) \right] \right\}.
\end{aligned} \tag{3.8}$$

The E-M algorithm consists of applying the following two steps:

- *E-step*: determine the conditional expectation $\mathrm{E}_{\mathrm{x}|s,\theta_k}\left[\log \mathcal{P}(\mathbf{s},\mathbf{x}|\theta)\right]$
- *M-step*: maximize this expression with respect to θ.

The algorithm is known to be iteratively convergent [8] since in each iteration we improve the log-likelihood function (3.6). This method has been first applied by Lim and Oppenheim [9] for parameter estimation of speech degraded by additive background noise. The general problem of statistical speech enhancement may also be solved within a fully Bayesian framework which has been extensively studied and applied by Vermaak et al. [10].

3.2 CONVENTIONAL ADAPTIVE METHODS

Historically, the concept of adaptive signal processing evolved from techniques developed to enable adaptive control of time-varying systems. In the 1960s, mainly due to work of Bernard Widrow and his colleagues [11], it began to be recognized as a separate category in digital signal processing.

Adaptive systems refer to systems that are able to efectively change their own parameters and thereby "adapt" to the changes of the environment in which they operate. In this chapter we review some basic properties of adaptive systems and adaptive algorithms. We concentrate mainly on the NLMS (Normalized Least Mean Squares) algorithm and the RLS (Recursive Least Squares) algorithm as these two methods represent a reference for the other methods.

3.2.1 NLMS (Normalized Least Mean Square) method

The basic NLMS algorithm belongs to the group of stochastic gradient methods developped by Bernard Widrow et al. [11] in 1960. The adaptive system may be best described using the schematic diagram in Fig. 3.2. In this scheme $x(n)$ represents an

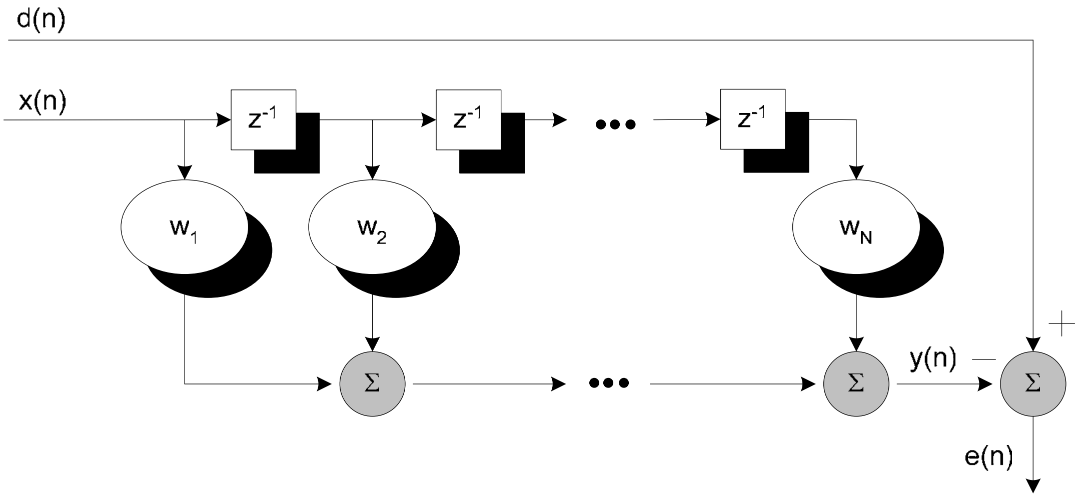

Fig. 3.2: Block diagram of an adaptive filter (tapped-delay line)

input signal to the filter, $d(n)$ is the desired output signal, $y(n)$ is the filter output and $e(n)$ is the error signal. The number of coefficients is usually denoted as N. The output of the filter can be expressed as

$$y(n) = \mathbf{w}^T(n)\mathbf{x}(n) \tag{3.9}$$

where

$$\mathbf{w}(n) = \left[w_1(n), w_2(n), \ldots, w_N(n)\right]^T \tag{3.10}$$

is the vector of filter coefficients (tap-weight vector) and

$$\mathbf{x}(n) = \left[x(n), x(n-1), \ldots, x(n-N+1)\right]^T \tag{3.11}$$

is the input vector. In the NLMS algorithm the tap-weight vector is updated in every iteration according to the following equation

$$\mathbf{w}(n+1) = \mathbf{w}(n) + \frac{\mu}{\left\|\mathbf{x}(n)\right\|^2}\mathbf{x}(n)e(n) \tag{3.12}$$

In (3.12), μ is called a step-size parameter and it controls the rate of convergence and stability. The state of the adaptive process may be characterized by a single function, called *cost function* (objective function). In the case of the NLMS algorithm, the cost function is the MSE (Mean Square Error). The function is defined as

$$J_w = \mathrm{E}\left\{e^2(n)\right\} \tag{3.13}$$

It depends on the square of the tap-weight vector and therefore it is common to

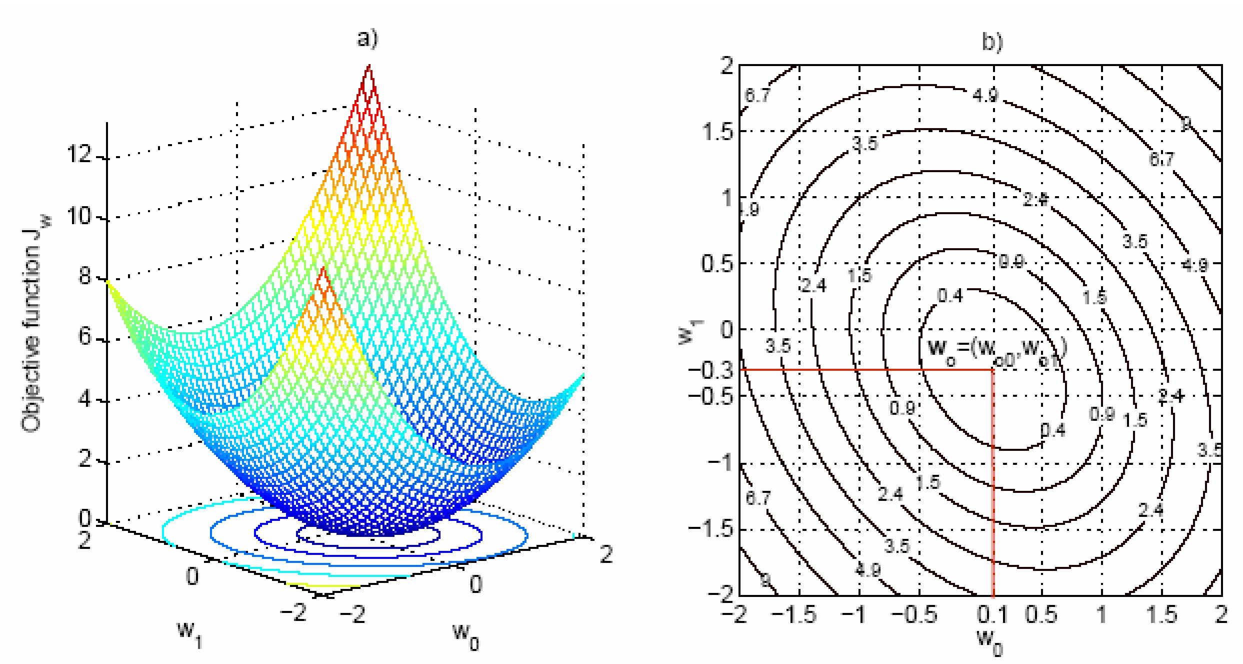

Fig. 3.3: (a) MSE cost function for the case of $N = 2$, (b) MSE contour plot

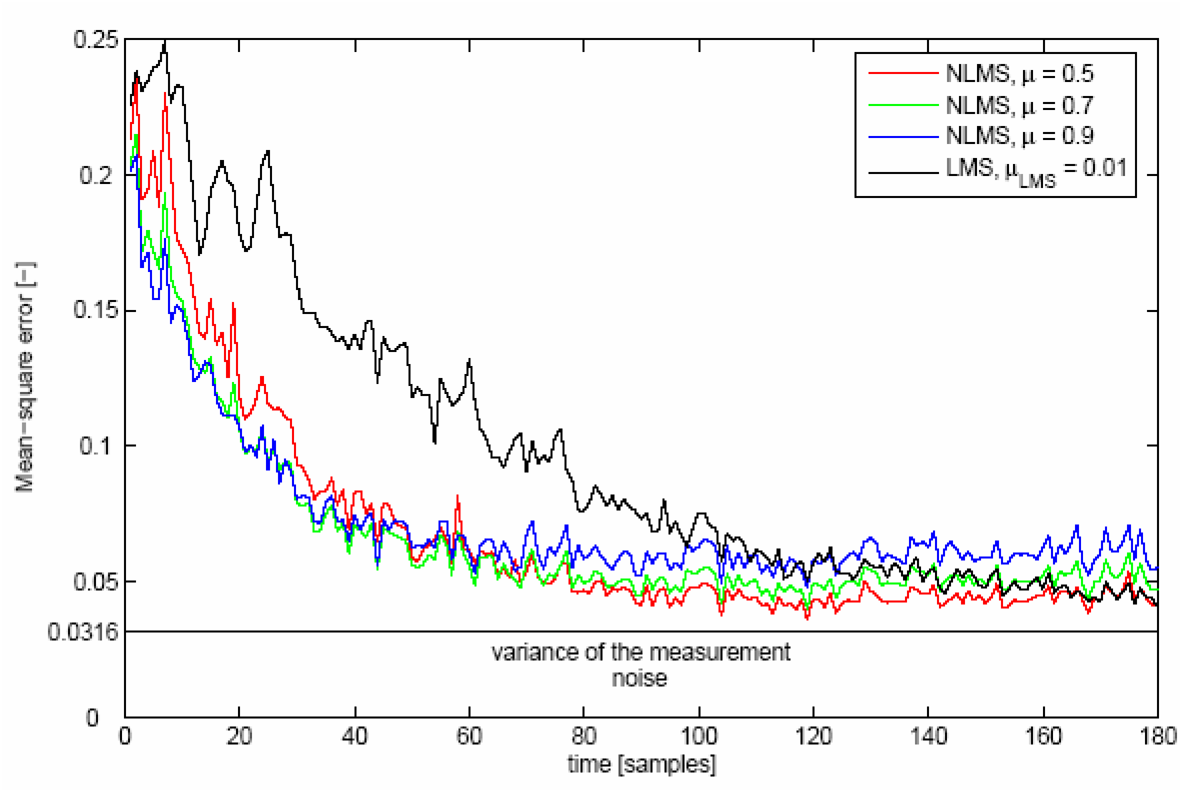

Fig. 3.4: Convergence behavior of the NLMS algorithm for different step sizes

visualize the cost function as an *elliptical paraboloid* (see Fig. 3.3).

Here are some results of the convergence rate analysis that we conducted in order to evaluate the performance of the NLMS method. We employed this method to solve the *system identification problem*. The objective is to find a transfer function of an unknown system that has been aplied to an input signal $x(n)$. The output of the system is denoted as $d(n)$ and serves also as the desired output for the adaptive filter. Thus, when the adaptive system converges to its steady state its coefficients represent the transfer function of the unknown system. The input signal is the white noise with a level of 0dB and the output of the unknow system $d(n)$ is corrupted by an additive white noise (measurement noise) with a level of -15dB. The results of the analysis are shown in Fig. 3.4.

3.2.2 RLS (Recursive Least Squares) method

As an alternative to the stochastic gradient method, such as the NLMS, there is another class of algorithms suitable for speech enhancement applications, the *least squares methods*. The RLS method, a representative of this class, does not make use of the stochastic nature of signals. Instead it applies some recursive principles to obtain averages of parameters which are of stochastic (noisy) character. In particular, it establishes an input correlation matrix

$$\mathbf{\Phi}(n)=\sum_{i=1}^{n}\lambda^{(n-i)}\mathbf{x}(i)\mathbf{x}^{T}(i) \tag{3.14}$$

and a cross-correlation vector

$$\mathbf{z}(n)=\sum_{i=1}^{n}\lambda^{(n-i)}\mathbf{x}(i)d(i) \tag{3.15}$$

In both equations, i.e. (3.14) and (3.15) it is assumed that the data prior to time $n=1$ are zero (prewindowing method). The correlation matrix $\mathbf{\Phi}(n)$ and the cross-correlation vector $\mathbf{z}(n)$ may be calculated resursively

$$\begin{aligned}\mathbf{\Phi}(n)&=\lambda\mathbf{\Phi}(n-1)+\mathbf{x}(n)\mathbf{x}^{T}(n)\\ \mathbf{z}(n)&=\lambda\mathbf{z}(n-1)+\mathbf{x}(n)d(n).\end{aligned} \tag{3.16}$$

In the RLS algorithm the tap-weight vector $\mathbf{w}(n)$ is updated in every iteration using the following equation

$$\mathbf{w}(n)=\mathbf{w}(n-1)+\mathbf{k}(n)\xi(n) \tag{3.17}$$

where $\xi(n)$ is the a-posteriori estimation error calculated as

$$\xi(n)=d(n)-\mathbf{x}^{T}(n)\mathbf{w}(n-1) \tag{3.18}$$

and $\mathbf{k}(n)$ is a so-called *gain vector* defined as [12]

$$\mathbf{k}(n)=\frac{\lambda^{-1}\mathbf{\Phi}^{-1}(n-1)\mathbf{x}(n)\mathbf{x}^{T}(n)\mathbf{\Phi}^{-1}(n-1)}{1+\lambda^{-1}\mathbf{x}^{T}(n)\mathbf{\Phi}^{-1}(n-1)\mathbf{x}(n)}. \tag{3.19}$$

From (3.19) it is clear that it would be necessary to calculate the inverse correlation matrix $\mathbf{\Phi}^{-1}(n)$. This operation would be computationally very intensive and would probably cause the RLS method be inatractive for the developpers. Fortunately, Householder [13] found that it may be calculated recursively as

$$\mathbf{\Phi}^{-1}(n)=\lambda^{-1}\mathbf{\Phi}^{-1}(n-1)-\lambda^{-1}\mathbf{k}(n)\mathbf{x}^{T}(n)\mathbf{\Phi}^{-1}(n-1). \tag{3.20}$$

In Fig. 3.1 there is a signal flow graph of the tap-weight update equation (3.17) and the a-posteriori error equation (3.18).

We also conducted several experiments to estimate the convergence behavior of the RLS algorithm in the same way as for the NLMS algorithm. The objective of the

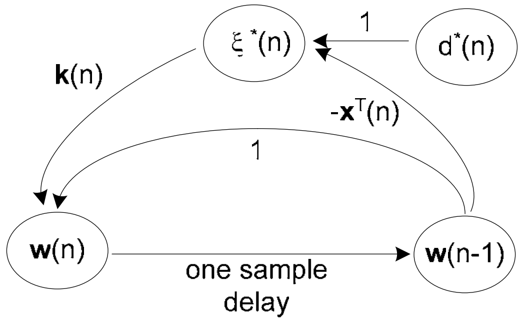

Fig. 3.5: Signal flow graph of the RLS tap-weight update equation

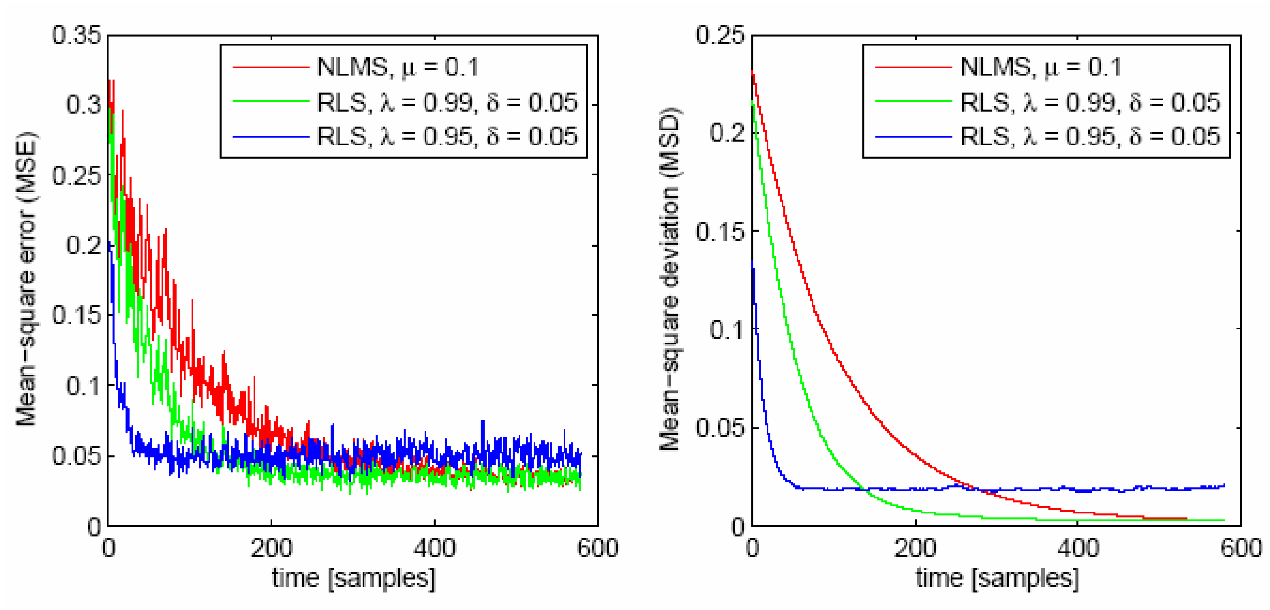

Fig. 3.6: Convergence rate analysis of the RLS algorithm, (a) MSE, (b) MSD

experiment is to identify an unknown system which is a low-pass FIR filter with the order of 20. Therefore, the number of tap-weights in the adaptive filter is set to 20 and the identification should be accurate.

The results of the experiment are shown in Fig. 3.6. The MSD (Mean Square Deviation) function is defined as

$$D_w = \mathrm{E}\left\{\left\|\mathbf{w}(n) - \mathbf{w}_o\right\|^2\right\}, \tag{3.21}$$

where $\mathbf{w}_o$ is the optimal solution in which the MSD function is zero. We see that the RLS algorithm exhibits better convergence compared to the NLMS. This is exemplified for example by the MSD curves in (b) where for $\lambda = 0,99$ both methods achieve the same level of steady-state error but the speed of convergence of the RLS method is approximately twice as better.

4 ALTERNATIVE STOCHASTIC GRADIENT ALGORITHMS

The popularity of the NLMS and the RLS methods led to several practical modifications. The goal is obviously to improve the performance of these methods under certain specific requirements. In most cases the objectives are to improve the rate of convergence, to increse the robustness, to improve the immunity against impulsive noise or to decrese the computational complexity.

In this chapter we present several methods that we analyzed and tested in the intial phase of our research. The fundamentals of these methods are either known in literature or found experimentally. We try to investigate the performance of these methods under inconventional conditions, such as speech input, abrupt change of parameters or high level of noise. The aim is not to provide an extensive analysis or comparison of methods but to show that certain changes of algorithms may lead to better results.

We discuss several simple methods derived from the NLMS algorithm, such Leaky LMS, Dead-Zone LMS or Median LMS. We also propose our own modification to the NLMS algorithm using stochastic perturbations which we named SPSA-LMS. We provide some experimental results and discuss the performance of these methods.

4.1 LEAKY-LMS

The possible sensitivity to round-off errors and other disturbances exists in the NLMS algorithm due to the fact that (3.12) is essentially an integrator. An introduction of a small "leakage" to the tap-weight vector

$$\mathbf{w}(n+1) = (1-\alpha\gamma)\mathbf{w}(n) + \alpha\mathbf{x}(n)e(n), \tag{4.1}$$

should protect the algorithm against such numerical problems. The parametr γ is called the leakage factor and it is chosen such that $\alpha\gamma$ is grater than but close to 0. The leakage provides an additional degree of stability. However, by applying the leakage, (4.2) no longer corresponds to an MSE estimation problem. The objective function minimized by the Leaky-LMS is given by

$$J(\mathbf{w}) = |e(n)|^2 + \gamma\|\mathbf{w}(n)\|^2 \tag{4.2}$$

The Leaky-LMS algorithm does not only help to solve the numerical problems of the NLMS method. It is also useful for improving the convergenmce properties when the input signal is correlated (e.g. the voiced parts of speech signals). In this case the convergence would be slow due to an ill-conditioned input correlation matrix [12].

4.2 DEAD-ZONE LMS

Small values of the error signal $e(n)$ may represent disturbances or noise but may also result from numerical instability. The Dead-Zone Least Mean Squares (DZ-LMS) is designed to mitigate the problems of round-off errors. The algorithm applies a dead-zone nonlinearity and stops updating the tap-weight vector when the error signal falls below some predefined threshold. The dead-zone nonlinearity is defined as

$$g(x) = \left\{ \begin{matrix} x-d, & x > d > 0 \\ 0, & -d < x < d \\ x+d, & x < -d \end{matrix} \right\}, \tag{4.3}$$

where d is a threshold. When the nonlinear function $g(x)$ was applied to the error signal $e(n)$ of the NLMS algorithm, the tap-weight update equation (3.12) would become

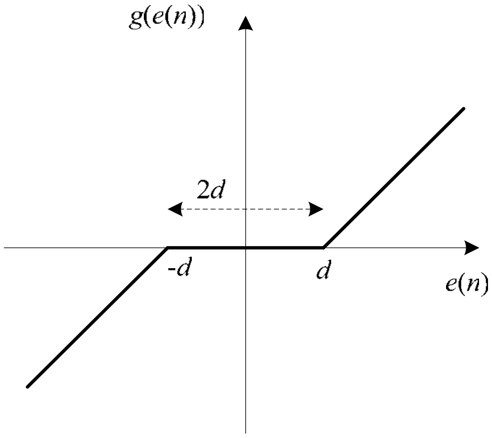

Fig. 4.1: Nonlinear function "dead zone" used in the DZ-LMS algorithm

$$\mathbf{w}(n+1) = \mathbf{w}(n) + \alpha \mathbf{x}(n) g(e(n)), \tag{4.4}$$

The "dead-zone" nonlinear function has the shape shown in Fig. 4.2.

4.3 SIGNED-ERROR LMS, SIGNED-DATA LMS AND SIGNED-SIGNED LMS

Although the NLMS algorithm is very simple and computationally efficient there is an effort to reduce the complexity of this popular method even more. This is a motivation that lead to the research of signed variants of the NLMS method. The idea is to replace the multiplication operation in (3.12), which is computationally intensive, by a more simple operation such as shifting or addition. It is noteworthy to remark that today's DSP processors are able to perform multiplication operation at the same rate as addition or shifting. Thus, for several applications these algorithms have lost their attractivity. Nevertheless, the possibility to have a low-complex adaptive method is still an issue of concern that will persists for several decades.

In all of the signed variants of the NLMS algorithm, the sgn(.) function is used to replace the multiplication operation [14]. The function is defined as ordinarily

$$\operatorname{sgn}(x) = \begin{cases} 1, & x > 0 \\ 0, & x = 0 \\ -1, & x < 0 \end{cases}. \tag{4.5}$$

The sgn(.) function (4.5) can be applied either to the error signal $e(n)$ (Signed Error Least Mean Squares (SE-LMS)), the input data $x(n)$ (Signed Data Least Mean Squares (SD-LMS)) or both (Signed Signed Least Mean Squares (SS-LMS))

$$\begin{aligned} &\text{SE-LMS:} \quad \mathbf{w}(n+1) = \mathbf{w}(n) + \mu . \operatorname{sgn}(e(n)) \mathbf{x}(n) \\ &\text{SD-LMS:} \quad \mathbf{w}(n+1) = \mathbf{w}(n) + \mu . e(n) \operatorname{sgn}(\mathbf{x}(n)) \\ &\text{SS-LMS:} \quad \mathbf{w}(n+1) = \mathbf{w}(n) + \mu . \operatorname{sgn}(e(n)) \operatorname{sgn}(\mathbf{x}(n)). \end{aligned} \tag{4.6}$$

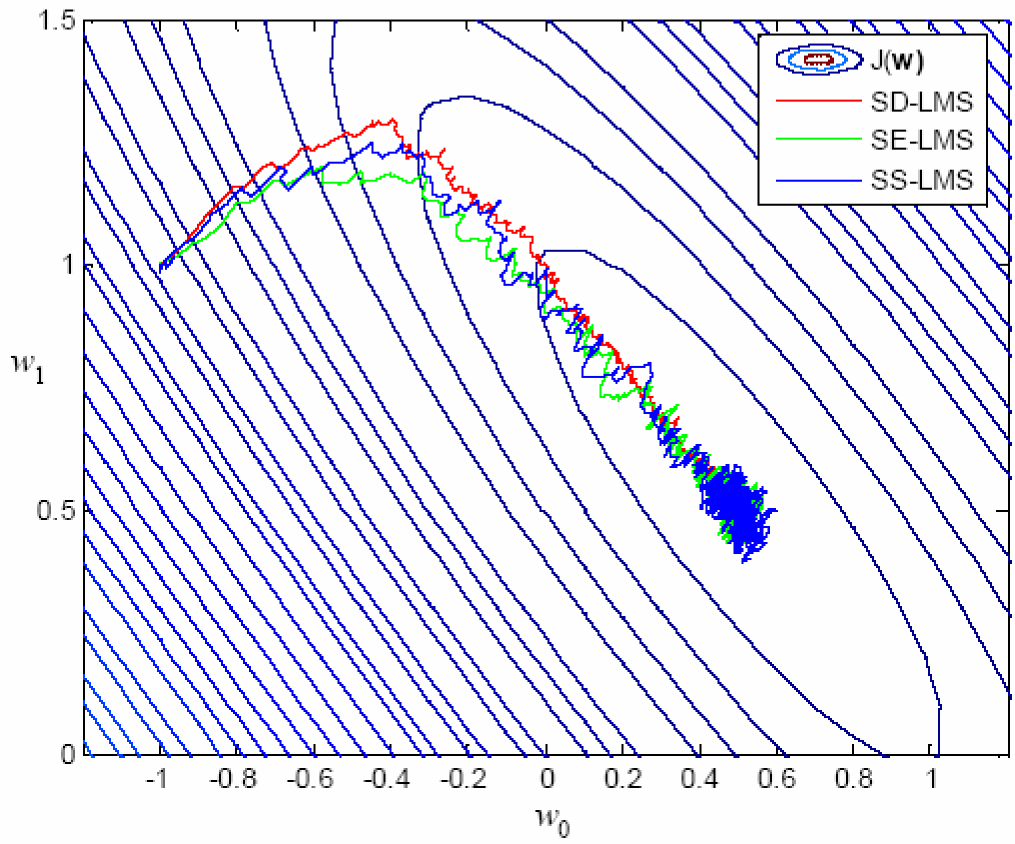

Fig. 4.2: Convergence performance of the signed algorithms - comparison

It is an intuitive feeling that the gradient estimates of the SE-LMS and the SS-LMS may become rather chaotic. This has also been approved by Classen and Mecklenbrauker [15] who noticed that the directions of the updates can be significantly diferent from the true gradient direction. In the worst case which is when signed data sgn(x(n)) are used instead of the true data, there is a possibility of divergence and instability. Therefore, caution must be taken when employing these methods in practise since they work only in specific environments. A precise analysis is not provided in this thesis and interested readers are referred to e.g. [16].

We evaluated the convergence performance of all signed algorithms discussed above and the results are shown in Fig. 4.3.

4.4 SIMULTANEOUS PERTURBATION STOCHASTIC APPROXIMATION (SPSA)

In this section we propose a new adaptive method based on the NLMS algorithm. It is called the SPSA-LMS (Simultaneous Perturbation Stochastic Approximation). The principle of stochastic approximaion has been developed by J. C. Spall in 1988 [17] and was primarily intended for use in nonlinear control applications.

4.4.1 The principle of simultaneous perturbation

In the conventional NLMS algorithm the tap-weight adjustment is carried out accoring to the *stochastic gradient vector*

$$\mathbf{g}(n) = \mathbf{x}(n)e(n). \tag{4.7}$$

This vector is noisy and it has certain variance. Therefore, the convergence process is also noisy which can be seen for example in *Fig. 3.4*. The algorithm considered here uses a more accurate estimate of the gradient vector and its convergence process is therefore less noisy.

Suppose we have an access to the objective function $J_w(n)$. The state of the adaptive filter is represented by the tap-weight vector $\mathbf{w}(n)$ at time *n*. If we conducted two measurements of the objective function at small distances from $\mathbf{w}(n)$ we could calcualte a differnce between them as

$$\Delta J_w(n) = J\left(\mathbf{w}(n) + c(n)\boldsymbol{\Delta}(n)\right) - J\left(\mathbf{w}(n) - c(n)\boldsymbol{\Delta}(n)\right) \tag{4.8}$$

where $\boldsymbol{\Delta}(n)$ is an *N*-dimensional vector consisting of random values and $c(n)$ controls its variance. The vector $\boldsymbol{\Delta}(n)$ is called the *perturbation* and since all elements of the tap-weight vector are perturbed at the same time it is *simultaneous perturbation*. We see that $\Delta J_w(n)$ has been calculated using two measurements at the distances $\pm c(n)\boldsymbol{\Delta}(n)$ from the tap-weight vector.

Every element of the gradient vector is calculated using the following equation

$$g_i\left(\mathbf{w}(n)\right) = \frac{\Delta J_w(n)}{2c(n)\Delta_i(n)}, \quad i = 1, 2, \ldots, N\,. \tag{4.9}$$

It is clear that the gradient vector calcualted using (4.8) and (4.9) is still noisy and has its variance but it is more accurate than the gradient vector used in the NLMS algorithm. A drawback of using the stochastic perturbation principle is that an exact objective function must be known in advance.

The SPSA method uses the following tap-weight update equation

$$\mathbf{w}(n+1) = \mathbf{w}(n) + a(n)\mathbf{g}\left(\mathbf{w}(n)\right). \tag{4.10}$$

where $a(n)$ is called a variable step-size parameter and it substituted the constant λ that has been used in the NLMS algorithm. Thus, in every iteration the step-size is different.

4.4.2 The configuration of parameters

Ideally, the perturbation vector $\boldsymbol{\Delta}(n)$ would be generated by Monte Carlo simulations [18]. However, this is not practical and a Bernoulli generator giving an outcome of ± 1 is used instead. The chance for each outcome is 50%. Spall [18] also notes that random vectors from uniform or normal distribution is not allowed since it violates some regularity principles.

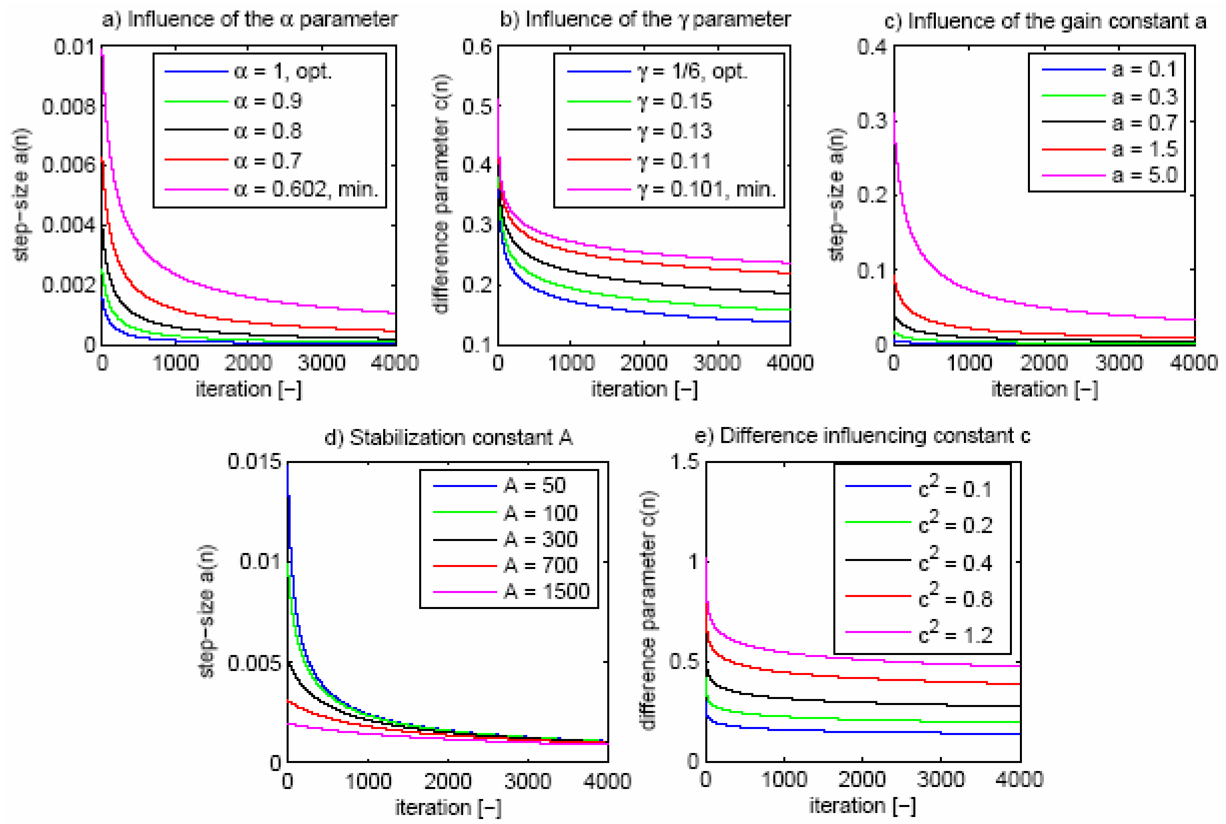

Fig. 4.3: Influence of various parameters on sequences $a(n)$ *and* $c(n)$

The choice of the sequences $a(n)$ and $c(n)$ has a profound effect on the performance of the SPSA method. However, there exist only heuristic analyses as to what type of sequence sould be used. The most popular choice seem to be

$$
\begin{aligned}
a(n) &= \frac{a}{(A+n+1)^{\alpha}} \\
c(n) &= \frac{c}{(n+1)^{\gamma}}
\end{aligned}
\tag{4.11}
$$

where $\alpha = 0{,}602$ and $\gamma = 0{,}101$. The constant a assures sufficient noise suppression near the solution $\mathbf{w}_o$. The optimal choice of a is obtained by experimental evaluation. The choice of c determines the distance of the current estimate of the tap-weight vector from the perturbed one. It is best to set c to a level approximately equal to the standard deviation of the measurement noise in Jw . An accurate value is not necessary. The constant A is typically not discussed in literature but Spall [18] has shown that it may improve the stability of the SPSA algorithm in early iterations. It allows to use a larger a in the numerator of (4.11) and therefore more aggressive steps in early iterations. After certain amount of time A may become insignificant against n and its impact will be minimized. The character of the sequences $a(n)$ and $c(n)$ and the impact of the constants α, γ, a, c and A are shown together in Fig. 4.8.

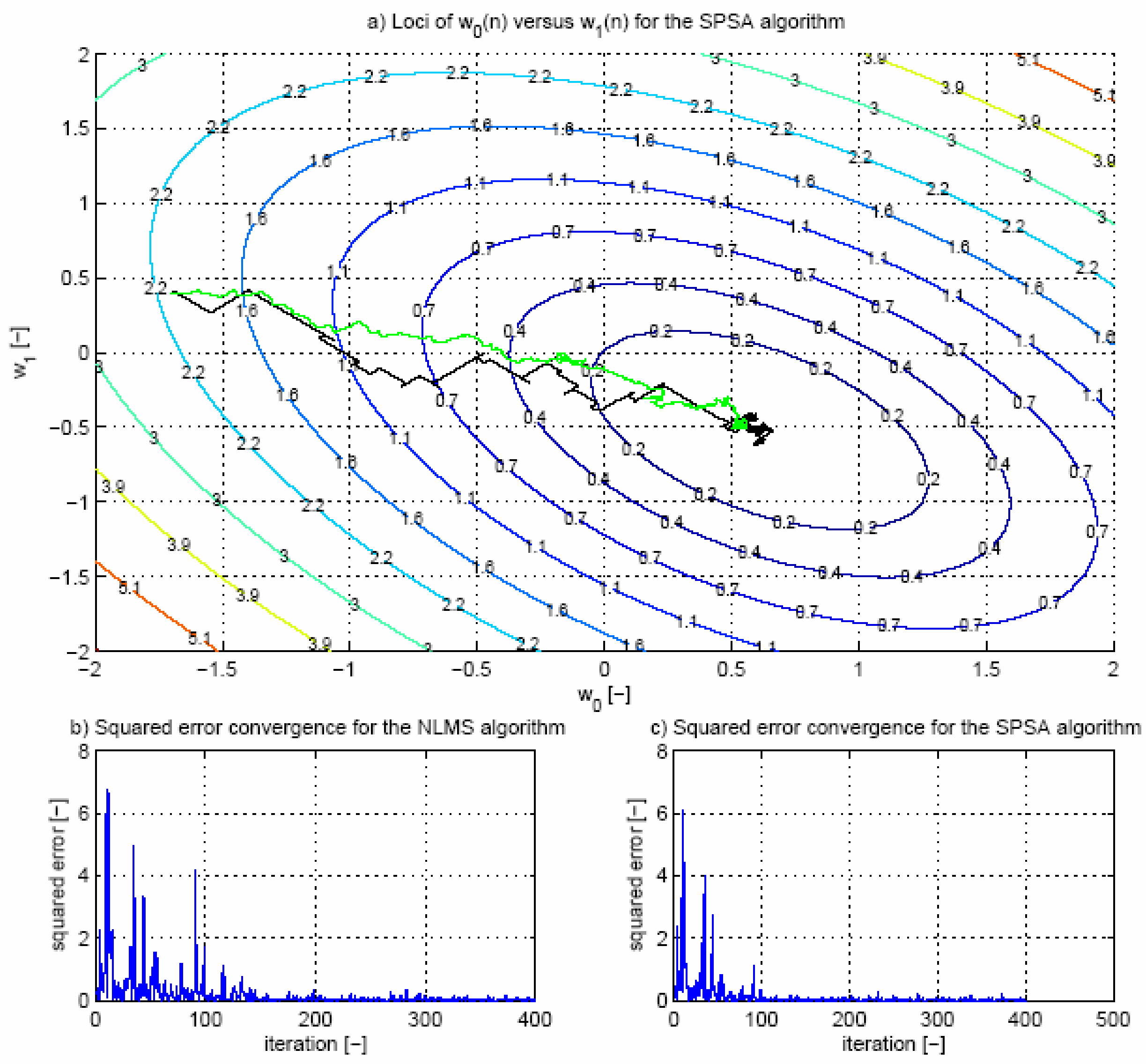

Fig. 4.4: Convergence analysis of the SPSA algorithm and comparison with the NLMS, (a) contour plot of the tap-weight vector movement, (b),(c) MSE functions

4.4.3 Convergence performance

We evaluate the performance of the SPSA algorithm on the application of system identification, i.e. the same experimental system as for the NLMS algorithm. As an input, however, we use the colored noise signal, obtained by filtering the white noise signal thourgh a 20th order low-pass FIR filter. The unknown system is a 2nd order FIR filter with the coefficients $w_o = [0,6125; -0,5124]$.

First we illustrate the the SPSA tap-weight vector movement. We will compare this movement to that of the NLMS algorithm for the case of $N = 2$, i.e. for 2 tap weights. On the countour plot in Fig. 4.4 we see how the SPSA and the NLMS algorithms try to approach the optimal point of the objective function. It is clear that the updates of the SPSA algorithm take place in exactly 2^N directions. The parameters of the algorithms were set to achieve the highest possible rate of convergence while maintaining the variance of the steady-state excess error under 0,05.

In the lower part of Fig. 4.4 we see the MSE functions of both methods. It can be deduced that the convergece performance of the SPSA method is clearly better than that of the NLMS method. We may also notice a noisy charactyer of the function with alternating peaks and valleys. This is due to the colored noise input.

5 OPTIMAL STEP-SIZE (OSS) STRATEGY

In chapters 3 and 4 we have shown some adaptive algorithms that may be employed to solve the speech enhancement problem. In experiments conducted we analyzed the performance of these methods in terms of convergence rate and steady-state error level. The partial conclusions that we came to may be summarized as follows. The NLMS method and its derivatives have all a very low computational complexity. On the other side, their rate of convergence and also the steady-state error level is sometimes poor compared to the method of RLS, which is more complex. In section 4.4 we proposed a novel stochastic gradient approach based on the SPSA principle. This method uses a variable step-size in every iteration. The problem is that it is necessary to know some parameters in advance which is impractical in real-time applications. However, the idea of applying a variable step motivated our research into a new class of adaptive algorithms, which we call Optimal Step-Size (OSS).

In this chapter we describe the optimal step-size strategy and develop an OSS-LMS algorithm. We compare its performance with the methods of NLMS and RLS which are considered as a reference. Finally, we show some experimental results in a typical speech enhancement applications.

5.1 MATHEMATICAL DESCRIPTION

5.1.1 The idea of the OSS method

We start our description with the objective function of the conventional LMS algorithm (3.13) which can be written in terms of the tap-weight vector [12]

$$J_w = \sigma_d^2 - \mathbf{w}^T\mathbf{p} - \mathbf{p}^T\mathbf{w} + \mathbf{w}^T\mathbf{R}\mathbf{w}\,, \tag{5.1}$$

where σ_d^2 is the variance of the desired output signal and $\mathbf{R}$ and $\mathbf{p}$ are the input correlation matrix and the cross-correlation vector, respectively, defined as

$$\begin{aligned}\mathbf{R} &= \mathrm{E}\left\{\mathbf{x}(n)\mathbf{x}^T(n)\right\}\\ \mathbf{p} &= \mathrm{E}\left\{\mathbf{x}(n)d(n)\right\}.\end{aligned} \tag{5.2}$$

In the stochastic gradient approach, the tap weights of the _lter are updated along the noisy gradient vector which is calculated as

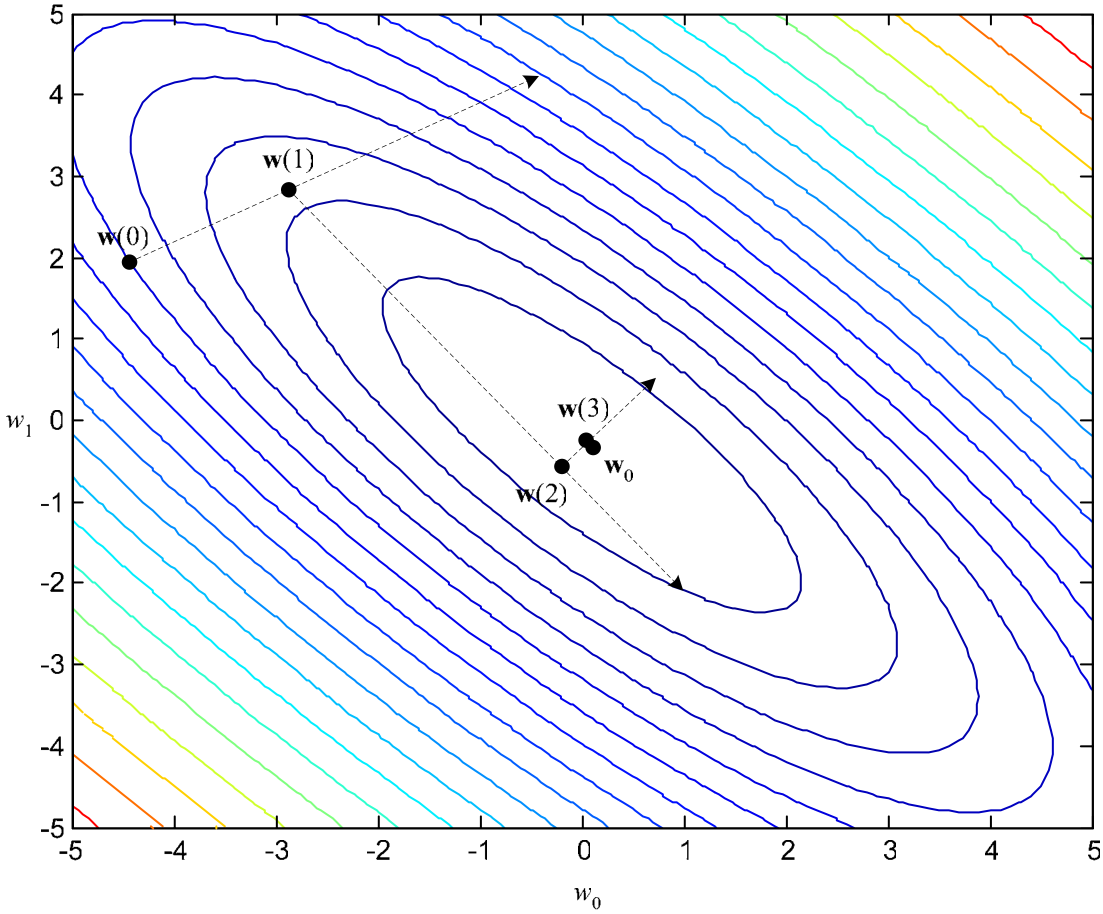

Fig. 5.1: The principle of the OSS strategy

$$\nabla J_w = -2\mathbf{x}(n)e(n) \tag{5.3}$$

Thus, it uses the instantaneous values of the input correlation matrix and the cross-correlation vector. In every step the tap-weight vector is moved in a direction determined by the noisy gradient vector. The length of the movement is controlled by a fixed step-size parameter μ.

We propose to calculate the step-size in such a way that the tap weights will be moved to a position where the objective function will achieve its local minimum value. This is called the *optimal step-size*. The line along which the movement is carried out is calculated in advance using an averaged correlation matrix and an averaged cross-correlation vector. The situation is explained in Fig. 5.1 for the case of 2 tap weights. If the gradient vector was known precisely the solution would be reached N steps exactly. This is not the practical case, however.

5.1.2 Calculation of the optimal step

As mentioned in the introduction, the optimal step-size is calculated in every iteration. Let us assume the weight adjustment is carried out according to the following equation

$$\mathbf{w}(n+1)=\mathbf{w}(n)+r_0(n)\mathbf{t}(n), \tag{5.4}$$

where t(n) represents a vector along which the optimal step $r_o(n)$ is searched for. Unless otherwise specified, from now on, we will omit the time index n from the quantities that depend on it. Then, in every iteration we perform the following minimization

$$r_0=\min_r\left(\frac{\partial J_w}{\partial r}\right). \tag{5.5}$$

By substituting (5.1) to (5.3) we recognize that the partial derivative consists of the following three terms

$$\frac{\partial J_w}{\partial r}=-\frac{\partial}{\partial r}\left(\mathbf{w}^T\mathbf{p}\right)-\frac{\partial}{\partial r}\left(\mathbf{p}^T\mathbf{w}\right)+\frac{\partial}{\partial r}\left(\mathbf{w}^T\mathbf{R}\mathbf{w}\right). \tag{5.6}$$

The variance of the desired response σ_d^2 does not depend on r and thus its derivative is zero. The first term of (5.6) may be written as

$$\begin{aligned}\frac{\partial}{\partial r}\left(\mathbf{w}^T\mathbf{p}\right)&=\frac{\partial}{\partial r}\left\{\left[\mathbf{w}+r\mathbf{t}\right]^T\mathbf{p}\right\}\\&=\mathbf{t}^T\mathbf{p}.\end{aligned} \tag{5.7}$$

The second term is similar to the first one and its derivative is therefore

$$\frac{\partial}{\partial r}\left(\mathbf{p}^T\mathbf{w}\right)=\mathbf{p}^T\mathbf{t}. \tag{5.8}$$

The last term of (5.6) is calculated as

$$\begin{aligned}\frac{\partial}{\partial r}\left(\mathbf{w}^T\mathbf{R}\mathbf{w}\right)&=\frac{\partial}{\partial r}\left(\left[\mathbf{w}+r\mathbf{t}\right]^T\mathbf{R}\left[\mathbf{w}+r\mathbf{t}\right]\right)\\&=\mathbf{t}^T\mathbf{R}\mathbf{w}+\mathbf{w}^T\mathbf{R}\mathbf{t}+2r\mathbf{t}^T\mathbf{R}\mathbf{t}.\end{aligned} \tag{5.9}$$

By substituting (5.7), (5.8) and (5.9) to (5.6) we get

$$\frac{\partial J_w}{\partial r}=-\mathbf{t}^T\mathbf{p}-\mathbf{p}^T\mathbf{t}+\mathbf{t}^T\mathbf{R}\mathbf{w}+\mathbf{w}^T\mathbf{R}\mathbf{t}+2r\mathbf{t}^T\mathbf{R}\mathbf{t}. \tag{5.10}$$

In order for a function to achieve its minimum point, its derivative must be equal to zero. Thus, by setting (5.10) to zero we may calculate the optimal step-size r_o as

$$\begin{aligned}r_o&=\frac{1}{2}\frac{\mathbf{t}^T\left(\mathbf{p}-\mathbf{R}\mathbf{w}\right)+\left(\mathbf{p}^T-\mathbf{w}^T\mathbf{R}\right)\mathbf{t}}{\mathbf{t}^T\mathbf{R}\mathbf{t}}\\&=\frac{\mathbf{t}^T\left(\mathbf{p}-\mathbf{R}\mathbf{w}\right)}{\mathbf{t}^T\mathbf{R}\mathbf{t}}.\end{aligned} \tag{5.11}$$

From the last equation we may recognize that the second term closely resembles the gradient vector ∇J_w which is defined as

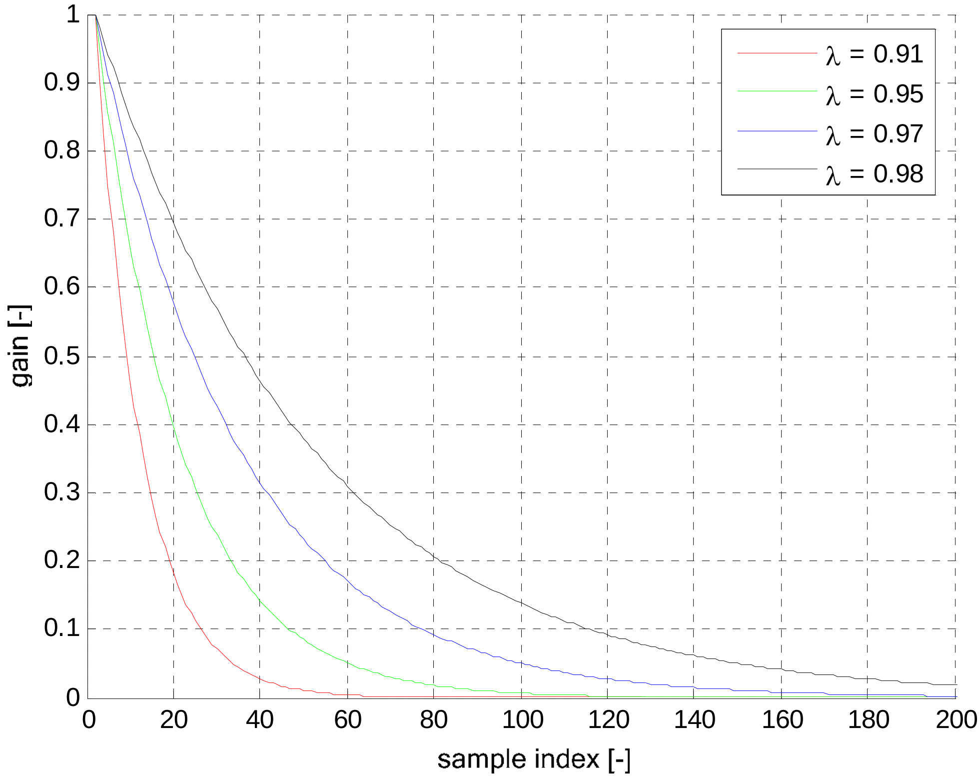

Fig. 5.2: Impulse response of the exp. averaging filter for various values of λ

$$\nabla J_w = -2\mathbf{p} + 2\mathbf{R}\mathbf{w} . \tag{5.12}$$

Using (5.12) we may rewrite (5.11) as

$$r_o = \frac{1}{2} \frac{\mathbf{t}^T \nabla J_w}{\mathbf{t}^T \mathbf{R} \mathbf{t}} . \tag{5.13}$$

5.1.3 Tap-weight update

By substituting (5.13) back to (5.4), we obtain the OSS tap-weight update equation

$$\mathbf{w}(n+1) = \mathbf{w}(n) - \frac{1}{2} \frac{\mathbf{t} \nabla J_w \mathbf{t}}{\mathbf{t}^T \mathbf{R} \mathbf{t}} . \tag{5.14}$$

The OSS strategy does not require any a priori knowledge of the characteristics of the input data. Moreover, it is not controlled by any parameters that would have to be set before adaptation. The convergence rate, however, is still subject to the character of the input signal, especially its eigenvalue spread. This will be illustrated by the results of experimental analyses given further in the next section.

5.2 EXPONENTIAL AVERAGING AND REGULARIZATION

The OSS weight adjustment process (5.14) requires the knowledge of the correlation matrix **R** and the cross-correlation vector **p**. Since instantaneous values of these quantities are stochastic with high variance, we propose to apply *exponential averaging* to improve the estimates over time

$$\begin{aligned}\mathbf{R}(n+1) &= \lambda\mathbf{R}(n) + (1-\lambda)\mathbf{x}(n)\mathbf{x}^T(n)\\ \mathbf{p}(n+1) &= \lambda\mathbf{p}(n) + (1-\lambda)\mathbf{x}(n)d(n),\end{aligned} \tag{5.15}$$

where λ is so-called *forgetting factor*. It determines the amount of memory the averaging filter has and how many past samples it uses. It is chosen in the range $0<\lambda<1$ and the closer it is to one the less past samples it uses. The introduction of exponential averaging requires the input signal to be stationary and ergodic. We know that the speech signal is stationary only in a short interval not longer than few milliseconds. This corresponds to setting the forgetting factor to

$$\lambda < 1 - \frac{1}{F_s t_d}, \tag{5.16}$$

where F_s is a sampling frequency and t_d is the chosen interval of stationarity. The averaging filter's impulse response is shown in Fig. 5.2.

If the algorithm is close to its steady state, the optimal step-size calculation becomes numerically instable. The reason is that near the optimal point the gradient vector will have low energy and the division in (5.14) will no longer be accurate. A solution to this problem may be the *regularization*. Regularization, as we known it from the literature of linear algebra, helps in overcoming the problems with ill-conditioned matrices [19]. The key is to strengthen the values on the main diagonal of a given matrix by adding a small constant, i.e.

$$\mathbf{A}_r = \mathbf{A} + \delta\mathbf{I}, \tag{5.17}$$

where I is an identity matrix. We propose a different, slightly modified, method of regularization. We add a small constant δ to the whole denominator term in (5.14), i.e.

$$\mathbf{w}(n+1) = \mathbf{w}(n) - \frac{1}{2}\frac{\mathbf{t}\nabla J_w \mathbf{t}}{\delta + \mathbf{t}^T\mathbf{R}\mathbf{t}}, \tag{5.18}$$

The value of δ is subject to various numerical considerations and a thorough analysis would be necessary. Practically, the value of δ determines the length of the step near the optimal point w_o.

5.3 EXPERIMENTAL ANALYSIS

In the experiment, the objective is to model a transfer function of an unknown FIR filter using the OSS strategy (the same as usually). As the input, we use the colored noise signal (white noise passed through a 20th order LP FIR with $f_c = 0.3$). In Fig. 5.3 we see the MSD function between the coeficients of the model and the unknown filter. We see that in the first half of the experiment the OSS method achieves the fastest convergence time, better than that of the RLS and the NLMS. The RLS method, in addition, has the lowest steady-state MSD of approximately

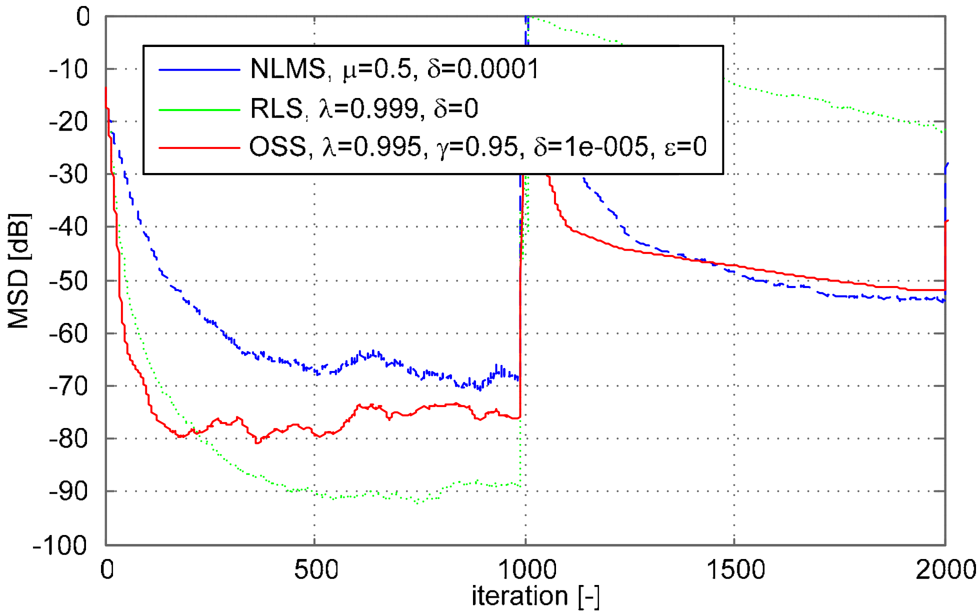

*Fig. 5.3: MSD function of the OSS method, compared with the NLMS and the RLS. In the middle of the experiment (i.e. when n=*1000*) the coeficients of the unknown FIR filter are reversed.*

-90dB. After the changeover of coeficients, the OSS method still continues to achieve the best convergence time, followed by the NLMS and the RLS.

The ability of the OSS method to model the impulse response of an unknown system is depicted in Fig. 6.1. In (a) we can see the impulse response of the unknown system, in (b) we see its magnitude spectrum and in (c) we see the model's impulse response and its time evolution. We may recognize that it closely fits the original in a few iterations. We may also notice a sudden change of the response in the beginning of the second half of the experiment. This reflects the algorithm's ability to track sudden changes of parameters of the unknown system.

6 CONCLUSION

In this thesis we have presented some adaptive algorithms for noise cancelation in speech signals. We have explored diferent ways to improve the performance of the conventional methods. We have also proposed a novel approach that we named the Optimal Step-Size (OSS) algorithm. The proposed method provides comparable to better convergence than the widely used NLMS and RLS algorithms, especially in certain applications. We have verified the performance of the proposed method by conducting several experiments with some results presented in this article.

During the development of the OSS method we first analyzed the structure and the performance of the two well-known methods, the NLMS and the RLS. We revealed the strong points and the weaknesses of these methods (convergence rate, complexity, level of the steady-state error) and we established some objectives for

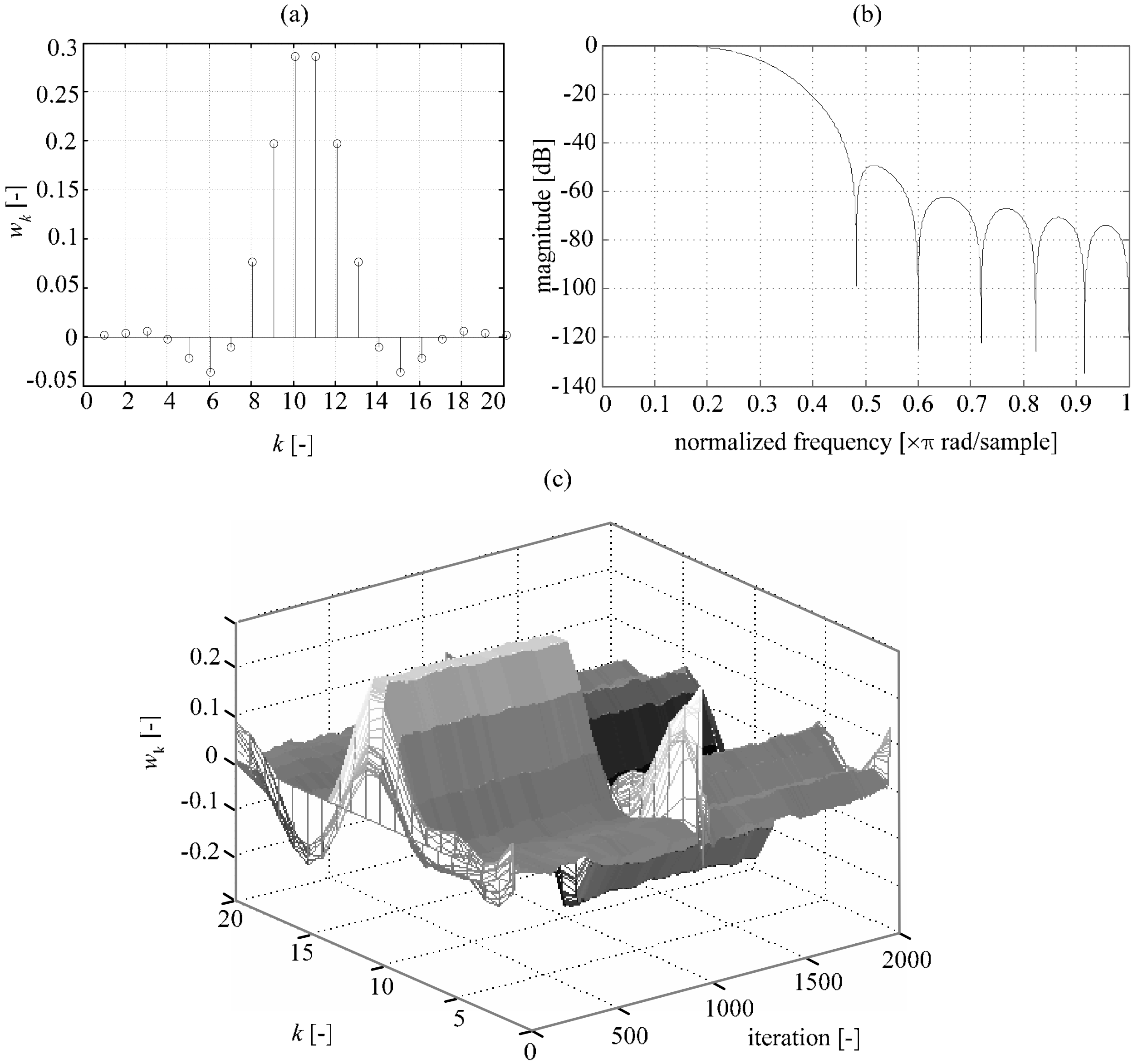

Fig. 6.1: (a) Impulse response of the unknown filter, (b) the magnitude spectrum, (c) 3D evolution of the filter coefficients.

the proposed algorithm. We came to a conclusion that the new method should represent a meaningful compromise between the stochastic gradient concept and the least squares concept. Then we presented some alternative approaches including the SPSA method, a modification to the NLMS algorithm.

Motivated by some new approaches with variable step-size that were recently published in literature we began our work on optimal step-size methods. In this article we have presented the mathematical concept of the OSS method including the exponential averaging principle and the regularization principle. From the experiments that we conducted with the OSS method we present some results for the problem os system identification. We proved that the OSS method was comparable to the conventional methods in terms of convergence speed and level of error in steady state. In a few cases it was even better.

In the future work we propose to conduct a subjective listening test with a group of 20-50 independent listeners. The speech signals should comprise different languages spoken by male and female speakers. It would be best to conduct a statistical test, such as Perceptual Evaluation of Speech Quality (PESQ), Mean Opinion Score (MOS) or MUlti Stimulus test with Hidden Reference and Anchors (MUSHRA) to evaluate the overall quality of speech rather than intelligibility or clearness. We also propose to continue with the mathematical concept of the OSS method. There is a challenge to integrate the OSS principle into the RLS concept. This would lead to an OSS-RLS algorithm which could be another way of how to increase the performance of the adaptive algorithm.

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BIOGRAPHY

Vladimír Malenovský was born in Nové Zámky (Slovakia) on February 23, 1978. He studied at Brno University of Technology, Faculty of Electrical Engineering and Computer Science from 1995 to 2001, where he received his Eng. diploma in 2001. After his studies he worked as a research engineer in ASTP s.r.o in Brno. He was involved in several projects including development and implementation of communication systems in bandsaw distributors. From 2003 to 2006 he did a Ph.D. research at the Department of Telecommunications at Brno University of Technology. In 2005 he joined the Speech and Audio Processing Group at the University of Sherbrooke in Canada where he will continue to work after the graduation. His research interests are primarily in the area of signal and speech processing and speech coding.

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