Importance and relevance of the scientific contents

Almost any book in the adaptive systems literature [1],[3],[6] refers to the interference surpression configuration, based on correlation properties (Fig. 1). Amongst the most important applications of this configuration, we recall line echo surpression, acoustic echo surpression, ambiental noise reduction, interference reduction via adaptive beamforming in smart antenna systems.

The basic configuration is based on the assumption that two signals are available:

- primary signal, $x(n)+v(n)$, resulted as the useful signal $x(n)$ affected by the additive perturbation, $v(n)$;
- secondary signal, $u(n)$, correlated with the perturbation. We also assume that the useful signal is totally uncorrelated with $u(n)$ and $v(n)$.

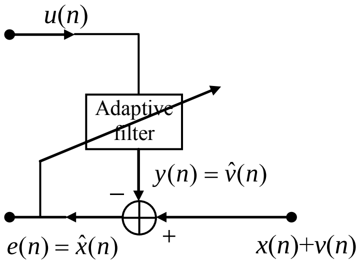

Fig. 1. Adaptive filter in interference surpression configuration

A characteristic of this configuration is the existence of an external signal $x(n)$ of significant value, that should not affect the adaptive algorithm. The main goal is to restore the useful signal. Theoretically, the adaptive filter fed with the input signal $u(n)$ and with the desired signal $d(n)=x(n)+v(n)$ is supposed to generate an estimate of the perturbation, $y(n)=\hat{v}(n)$, which further subtracted from the primary signal leads to an estimate of the useful signal. This mechanism works perfectly based on Wiener-Hopf optimal theory. Assuming that the relation between $u(n)$ and $v(n)$ may be expressed through MA modelling, which corresponds to the practical applications of this configuration

$$v(n)=\mathbf{h}^H\mathbf{u}(n) \tag{1}$$

where

$\mathbf{h}=[h_0,h_1,\ldots,h_{N-1}]^H$

$\mathbf{u}(n)=[u(n),u(n-1),\ldots,u(n-N+1)]^T$

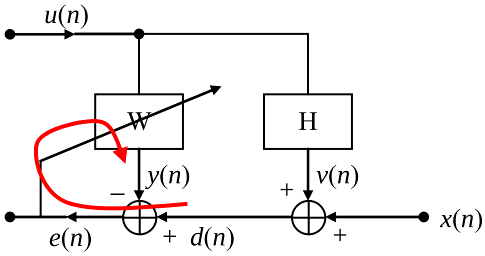

Fig. 2. Adaptive interference supresser based on MA modelling

Assume a FIR filter, having the weight taps

$$\mathbf{w}=[w_0,w_1,\ldots,w_{N-1}]^H$$

The optimal filter is given by Wiener-Hopf equation[1],[3],[6]

$$\mathbf{R}\mathbf{w}_{opt}=\mathbf{p} \tag{2}$$

where

$$\mathbf{R}=E\left\{\mathbf{u}(n)\mathbf{u}^H(n)\right\} \tag{3}$$

is the autocorrelation matrix and

$$\mathbf{p} = E\left\{\mathbf{u}(n)d^*(n)\right\} \tag{4}$$

is the correlation vector between the input and the desired signals.

But

$$\begin{aligned}\mathbf{p} &= E\left\{\mathbf{u}(n)d^*(n)\right\} = E\left\{\mathbf{u}(n)\left(x^*(n)+v^*(n)\right)\right\} = E\left\{\mathbf{u}(n)x^*(n)\right\} + E\left\{\mathbf{u}(n)v^*(n)\right\} = \\ &= E\left\{\mathbf{u}(n)v^*(n)\right\} = E\left\{\mathbf{u}(n)\mathbf{u}^H(n)\mathbf{h}\right\} = \mathbf{Rh}\end{aligned} \tag{5}$$

So that the Wiener-Hopf solution is

$$\mathbf{w}_{opt} = \mathbf{h} \tag{6}$$

leading to

$$y(n) = \mathbf{w}_{opt}^H\mathbf{u}(n) = \mathbf{h}^H\mathbf{u}(n) = v(n) \quad \Rightarrow \quad e(n) = x(n) \tag{7}$$

so $x(n)$ and $v(n)$ are correctly separated. The separation was possible based on the uncorrelation property

$$E\left\{\mathbf{u}(n)x^*(n)\right\} = \mathbf{0} \tag{8}$$

As a matter of fact, adaptive algorithms do not implement the statistical average operator, so that this operation mode will most probably malfunction in both LMS and RLS cases.

For LMS algorithms, the coefficients update based on the weel known equation:

$$\mathbf{w}(n+1) = \mathbf{w}(n) + \mu\mathbf{u}(n)e^*(n) \tag{9}$$

During the adaption process, the error signal $e(n)$ must decrease, so that coefficients update variation also decreases once entering a convenrgence phase. In this case, the decrease of $e(n)$ is basically limited, because it has to asimptotically tend to $x(n)$. In such situations, it is very possible that a divergence may occur.

The occurence of such phenomena was first emphasized by the echo canceller specialists In Fig. 3, such a canceller is presented, where we denoted with H the echo path and the adaptive filter is W.

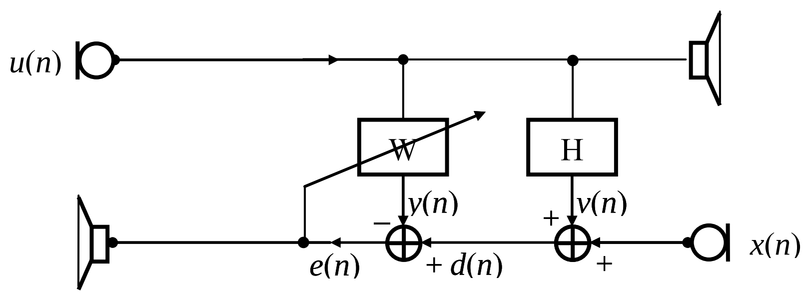

Fig. 3. Compensatorul adaptiv de ecou

In the left side, we have the *far-end user*, and in the right side, *the near-end user*. The imperfection of the 2 to 4-line differential transformers, a line echo occurs leading to an input return loss of the signal $u(n)$ through the system H to the far-end user. According to the G168 ITU-T recommendation, this echo has to be reduced under certain limits. This is achieved in each equipment by using the adaptive filter W. Also, an acoustic echo phenomenon may occur in a hands-free systembetween the speaker and the microphone of the near-end user. In the above configuration, the adaptive filter reduces the echo as long as the near-end signal is absent. When $x(n)$ is present and has significant values, the „double-talk" phenomenon occurs, and based on the afore remarks, the algorithm diverges. The solution is to freeze the adaptive process during double-talk. A double-talk detector is thus needed, which operates based on an averaging process and therefore it cannot react instantaneously. [12] This delay may be enough to lead the adaptive filter in a diverging state. Another solution may consist in using a variable update factor μ [8][10][11]. This should start with a rather large update step to achieve a fast-enough convergence speed. Then this step should decrease to reduce the sensitivity in oredr to avoid the divergence tendencies when the external signal is present. Moreover, this solution relies on an *unpersistent excitation* at near-end (there are quiet periods, when the adaptive process may converge). This assumption may not be valid if the near-end user is in a noisy environment.

When dealing with a permanent excitation, one may operate with a very small updating factor at the expense of a small converence speed.

It seems more tempting to use RLS-based algorithms which perform a temporal averaging, replacing the statistical averaging operator with

$$E\{\bullet\} \to \sum_{i=1}^{n} \lambda^{n-i} \{\bullet\}$$

where the averaging factor (algorithm memory) is given by $\lambda \in (0,1]$. Experimental research easily show that for a rather small λ, the output signal may become null. For larger values, solely a diminishing of the ideal output signal $x(n)$ may occur. This happens because a $x(n)$ component appears at the adaptive filter output. The phenomenon is vaguely described or studied in literature. We also remark an abnormal behavior of the adaptive algorithm, which nulls not only the component correlated with the input, but also the useful signal $x(n)$. This phenomenon has been first presented by our team under the term of "residual leakage thorugh the error signal" (the red path in Fig.2) and is not, by far, enough known or studied. When the values of λ are large (close to 1), then the algorithm behaves normally and this somehow explains the interest that we believe should be accorded to the RLS-based algorithms in order to solve the problem of a permanent excitation. This fenomenon should not be confused with another leakage fenomenon, generated by the correlation of $x(n)$ and $u(n)$ .A lot of questions remain unanswered such as:

What means a sufficiently large λ? What influences this value? Is there a way to relate this phenomenon to λ?

Our research studies show a deeply non-linear dependence. Is this fenomenon dependent on the frequency domain (laedind to the idea of linear distortions)? A larger value for λ (large memory, long-term averaging) may lead to a slower convergence.The initial convergence may be corrected if properly choosing the initialization parameters [4], but what happens with the tracking ability in a non-stationary medium? Would a variable forgetting factor λ represent a viable solution? If so, what would be the variation formula?A RLS-based approach also raises serious implementation issues, taking into account the much larger arithmetic complexity with respect to LMS-based algorithms. This also leads to serious issues related to the finite precision representation of the numbers. The high dynamic range of the variables in this algorithm, especially for high λ, may create overflows or stallings when some parameters are rounded to 0, freezing the algorithm [5],[7],[14].

11.2. Project objectives

1. To achieve a deep analysis of the phenomenon occuring in the "interference surpression" configuration, meaning an adaptive configuration with secondary external signal.
2. To give a precise characterization of the residual signal leakage through the error signal for RLS-based algorithms.
3. To give solutions for a non-permanent excitation. It is expected that such solutions exist for LMS algorithms with variable step size, bringing better solutions with respect to the current ones.
4. On the practical aspect, this could mean algorithms with superior performances for line echo adaptive cancelers or for acoustic echo (hands-free systems, teleconference systems etc.)
5. To give solutions for permanent excitation. Obviously, these can be used also for non-permanent excitation, but it may lead to very complex solutions. Our target is RLS-based algorithms family.
6. The previous aspect may further extend to adaptive noise surpression systems and to adaptive antenna systems with automatic beamforming.
7. To analyze the performances of the proposed algorithms, in the context of the target application classes.
8. To analyze aspects related to the practcical implemenattion of the algorithms in finite-precision. We target the fixed point implementation.
9. To effectively implement the proposed algorithms on two different platforms: digital signal processors (DSPs) and field programmable gate arrays (FPGAs).
10. To perform lab measurements in order to evaluate the performances and the compliance with the existing standards if applicable.

The team will develop an intensive dissemination activity, targeting to obtain a broad recognition of the contributions in the field of the project and on the other side, to find potential partners in the economic field, interested in a technology transfer process.

11.3. Research methodology

The approach takes two different situation into account, given by two different classes of applications:

- The case when the external signal in non-permanent (tha case of echo cancellers in rather less noisy environments)
- The case when the external signal is permanent (the case of noise surpressers or line enhancers, adaptive beamformers for interference reduction)

In order to analyze specific phenomenons that lead to malfunctions in the presence of the external signal in the studied adaptive configuration (objectives 1 and 2), we target an experimental approach, based on Matlab simulations, but we also target an analytical approach. For instance, in order to emphasize the leakage phenomenon in the RLS algorithm, a possible starting point, proposed by us in [17] could be the following.

In the RLS algorithms, the statistical averaging operator is replaced with a temporal weighted average

$$E\{\bullet\} \to \sum_{i=1}^{n} \lambda^{n-i}\{\bullet\} \tag{1}$$

Where the weighting factor $\lambda \in (0,1]$ describes the algorithm memory. Then, the Wiener-Hopf equation becomes

$$\sum_{i=1}^{n} \lambda^{n-i}\mathbf{u}(i)\mathbf{u}^{H}(i)\mathbf{w}_{opt} = \sum_{i=1}^{n} \lambda^{n-i}\mathbf{u}(i)(v^{*}(i)+x^{*}(i)) = \sum_{i=1}^{n} \lambda^{n-i}\mathbf{u}(i)v^{*}(i) + \sum_{i=1}^{n} \lambda^{n-i}\mathbf{u}(i)x^{*}(i) \tag{2}$$

For λ close to 1 and for a large n

$$\lim_{n\to\infty} \frac{1}{n}\sum_{i=1}^{n} \lambda^{n-i}\mathbf{u}(i)x^{*}(i) \cong E\left\{\mathbf{u}(n)x^{*}(n)\right\} = 0 \Rightarrow \sum_{i=1}^{n} \lambda^{n-i}\mathbf{u}(i)\mathbf{u}^{H}(i)\mathbf{w}_{opt} \cong \sum_{i=1}^{n} \lambda^{n-i}\mathbf{u}(i)v^{*}(i) = \sum_{i=1}^{n} \lambda^{n-i}\mathbf{u}(i)\mathbf{u}^{H}(i)\mathbf{h} \tag{3}$$

$$\Rightarrow \quad \mathbf{w}_{opt} \cong \mathbf{h}$$

and $e(n) = x(n)$ as in the ideal case.

On the other hand, for a small value of λ, $\lambda^{k} \cong 0$ for $k \geq n_0$, so that:

$$\sum_{i=1}^{n} \lambda^{n-i}\{\bullet\} \cong \sum_{i=n-n_0+1}^{n} \lambda^{n-i}\{\bullet\} \tag{4}$$

The normal equation becomes in this case

$$\sum_{i=n-n_0+1}^{n} \lambda^{n-i}\mathbf{u}(i)e^{*}(i) = \mathbf{0} \tag{5}$$

Which is a homogenous system of N equations with n_0 unknown variales, $e(i)$, $i = \overline{n-n_0+1,\ n}$. If $n_0 < N$, the system admits the trivial solution

$$e(i) = 0 \quad \text{for} \quad i = n-n_0+1,\ldots,n \tag{6}$$

leading to

$$y(n) = \mathbf{w}^{H}(n)\mathbf{u}(n) = x(n) + v(n) \tag{7}$$

This fact confirms the experimental remark mentioned above: the adaptive algorithm not only that it cancels the component which is correlated with the input, but also the useful signal, $x(n)$. This approach explains the phenomenon, but only takes the extreme situations into account: small λ and λ close to 1. It also suggests a relation between the minimum necessary value for λ for a correct operation of the algorithm and the filter order, without explaining it.

About the 3rd goal, the solution must be searched in the LMS/NLMS family with variable step size. An analytical approach must be found, starting from an alternative expression of the cost function, which takes the external signal into account. Mainly, a continuously decreasing step size during the convergence phase is necessary, whilst returning to higher values when changing the echo path.

For the 4th goal, we will perform simulations involving Matlab environment in the conditions contained in the G168 ITU-T recommendations.

For the 5th goal, different algorithms from RLS family will be analyzed. This is linked to the 8th objective. Several issues related to values of λ close to 1, regarding the convergence speed and the tracking ability, but also the dynamic range of the parameters that become crucial and important at this point. A starting point could be [18], in where we propose a slightly modified version of the cost function.

Performances will be analyzed with two methods: via simulations (7th objective), which alledgely lead to solutions acceptable for implementation and via measurements (objective 10).

Implementation will be made on two different platform types: digital signal processors, using Star Core (Freescale) – based boards and the CodeWarrior software package and on Field Programmable Gate Arrays, based on VHDL design, using Mentor Graphics packages.

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