Adaptive Filtering with Averaging in Noise Cancellation for Voice and Speech Recognition

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Abstract – In many applications of noise cancellation the changes in signal characteristics could be quite fast. This requires the utilization of adaptive algorithms, which converge rapidly. From this point of view the best choice is the recursive least squares (RLS) algorithm. Unfortunately this algorithm has high computational complexity and stability problems. In this contribution we present an algorithm based on adaptive filtering with averaging (AFA) used for noise cancellation. The main advantages of AFA algorithm could be summarized as follows. It has high convergence rate comparable to that of the RLS algorithm and at the same time low computational complexity and possible robustness in fixed-point implementations. The algorithm is illustrated on car and office noise added to speech data.

I. INTRODUCTION

The purpose of this contribution is to study the application of a new algorithm based on adaptive filtering with averaging in noise cancellation problem.

It is well known that two of most frequently applied algorithms for noise cancellation [1] are normalized least mean squares (NLMS) [2], [3], [4] and recursive least squares (RLS) [5], [6] algorithms. Considering the two algorithms, it is obvious that NLMS algorithm has the advantage of low computational complexity. On the contrary, the high computational complexity is the weakest point of RLS algorithm but it provides a fast adaptation rate. Thus, it is clear that the choice of the adaptive algorithm to be applied is always a tradeoff between computational complexity and fast convergence.

In the present work we propose a new adaptive algorithm with averaging applied for noise cancellation. The conducted extensive experiments with different types of noise reveal its robustness maintaining fast convergence and at the same time keeping the computational complexity at a low level.

II. ADAPTIVE NOISE CANCELLATION

Fig. 1 shows the classical scheme for adaptive noise cancellation using digital filter with finite impulse response (FIR). The primary input consists of speech $s(n)$ and noise $n_2(n)$ while the reference input consists of noise $n_1(n)$ alone. The two noises $n_1(n)$ and $n_2(n)$ are correlated and $h_i(n)$ is the impulse response of the noise path. The system tries to reduce the impact of the noise in the primary input exploring the correlation between the two noise signals. This is equivalent to the minimization of the mean-square error $E[e^2(n)]$ where

$$e(n) = s(n) + n_2(n) - n_3(n) \qquad (1)$$

Having in mind that by assumption, $s(n)$ is correlated neither with $n_2(n)$ nor with $n_1(n)$ we have

$$E[e^2(n)] = E[s^2(n)] + E[n_2(n) - n_3(n)]^2. \qquad (2)$$

In other words the minimization of $E[e^2(n)]$ is equivalent to the minimization of the difference between $n_2(n)$ and $n_3(n)$. Obviously $E[e^2(n)]$ will be minimal when $n_3(n) \approx n_2(n)$ i.e. when the impulse response of the adaptive filter closely mimics the impulse response of the noise path.

The minimization of $E[e^2(n)]$ can be achieved by updating the filter taps $w_i(n)$. Most often NLMS and RLS algorithms are used. In Tables 1 and 2 are summarized the steps required for adaptive noise cancellation scheme depicted in Fig. 1.

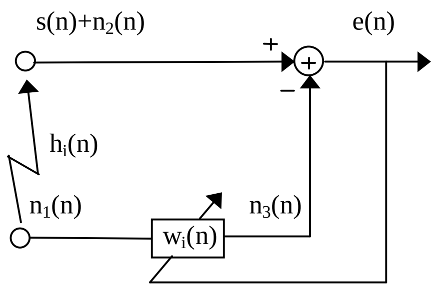

Fig. 1. Adaptive noise cancellation scheme.

Table 1. NLMS algorithm.

Noise estimation:
$n_3(n) = \sum_{i=0}^{N} w_i(n)\, n_1(n-i)$
N – filter order
Error estimation:
$e(n) = s(n) + n_2(n) - n_3(n)$
Coefficients update:
$w_i(n+1) = w_i(n) + \mu \dfrac{e(n)\, n_1(n-i)}{\sum_{i=0}^{N} n_1^2(n-i)}$
for $0 \le i \le N$

Table 2. RLS algorithm.

Noise estimation:
$n_3(n) = \sum_{i=0}^{N} w_i(n)\, n_1(n-i)$
N – filter order
Error estimation:
$e(n) = s(n) + n_2(n-d) - n_3(n)$
Covariance update:
$P(n) = P(n-1) - \dfrac{P(n-1)\, N_1(n)\, N_1^T(n) P(n-1)}{1/\delta + N_1^T(n) P(n-1)\, N_1(n)}$
Gain update:
$K(n) = \dfrac{P(n-1)\, N_1(n)}{1/\delta + N_1^T(n) P(n-1)\, N_1(n)}$
Coefficients update:
$w_i(n) = w_i(n-1) + k_i(n)e(n)$
for $0 \le i \le N$
$0<\delta<1$ $P(0) = \alpha I$ α large

III. NOISE CANCELLATION WITH AVERAGING

As mentioned in the introduction, for application where the fast convergence rate is vital, NLMS algorithm is not applicable. The more complex RLS algorithm maintains a good rate of adaptation but the prize to be paid is an order-of-magnitude increase in complexity. Moreover RLS algorithm is known to have stability issues [7] due to the recursive covariance update formula (see Table 2). In this section we introduce a new adaptive algorithm applied for noise cancellation based on adaptive filtering with averaging.

We start with defining the problem in the following manner. To recursively adjust the filter coefficients, so that the mean-square error is minimized, a standard algorithm for approximating the vector of filter coefficients can be written as

$$W(n+1) = W(n) - a(n)N_1(n)e(n) \tag{3}$$

where

$W(n) = [w_0(n), w_1(n),\ldots, w_N(n)]^T$ is the coefficients vector,

$N_1(n) = [n_1(n), n_1(n-1),\ldots, n_1(n-N)]^T$ is the input vector and $a(n)$ is a sequence of positive scalars as $a(n)\to 0$ for $n\to\infty$.

In (3) the estimation error can be given by

$$e(n) = s(n) + n_2(n) - N_1^T(n)W(n). \tag{4}$$

The equation (3) could be transformed through taking the averages of W:

$$W(n+1) = W(n) + \frac{1}{n^\gamma} N_1(n)e(n) \tag{5}$$

$$\overline{W}(n) = \frac{1}{n}\sum_{k=1}^{n} W(k)$$

$$1/2<\gamma<1$$

The analysis presented in [8] shows that such an algorithm could be unstable in the initial period. In order to improve the stability we undergo the second step, namely to average not only trough the approximation sequence but also through the observed signals N_1 and e. This leads us to an adaptive algorithm with averaging (AFA):

$$\overline{W}(n) = \frac{1}{n}\sum_{k=1}^{n} W(k)$$

$$W(n+1) = \overline{W}(n) + \frac{1}{n^\gamma}\sum_{k=1}^{n} N_1(k)e(k) \tag{6}$$

$$1/2<\gamma<1$$

The required steps for the utilization of an AFA algorithm in noise cancellation problem are presented in Table 3.

Considering Table 3 it could be concluded that first, the averaging here does not create additional burden since the terms $\overline{w_i}(n)$ and $\overline{n_1 e_i}(n)$ can be recursively computed from their past values. Second, the algorithm does not use the covariance matrix, so there is no need of covariance estimate. This implies low computational complexity and escape from stability issues related to P(n).

Table 3. AFA algorithm.

Noise estimation:
$n_3(n) = \sum_{i=0}^{N} w_i(n)\, n_1(n-i)$
N – filter order
Error estimation:
$e(n) = s(n) + n_2(n) - n_3(n)$
Coefficients update:
$\overline{w_i}(n) = \frac{1}{n}\sum_{k=1}^{n} w_i(k)$
$\overline{n_1 e_i}(n) = \sum_{k=1}^{n} n_1(k-i)e(k)$
$w_i(n+1) = \overline{w_i}(n) + \frac{1}{n^\gamma}\overline{n_1 e_i}(n)$
for $0 \le i \le N$ and $1/2<\gamma<1$

IV. EXPERIMENTAL RESULTS

In this section we assess the performance of the proposed AFA algorithm for noise cancellation.

The LMS, RLS and AFA algorithms are implemented according to the steps presented in Tables 1-3 as for the LMS algorithm - μ= 0.02, for the RLS algorithm - δ= 0.98 and for the AFA algorithm - γ = 0.5.

First, the original speech (the word "home") is corrupted with office noise (SNR=6dB) and the results after noise cancellation are shown in Fig. 2. Second, an experiment with car noise (SNR=0dB) is conducted and the results for different algorithms are presented in Fig. 3 (here the original speech is the word "return").

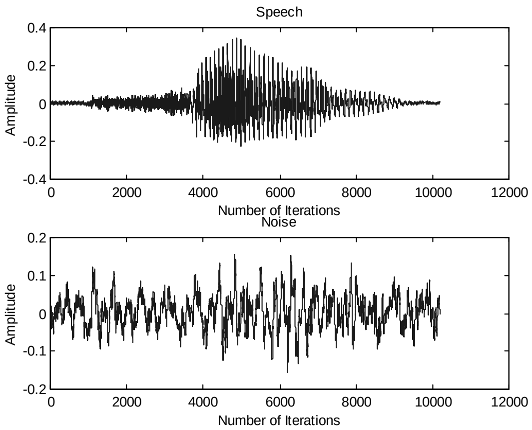

Fig. 2a. The signals for the experiment with office noise.

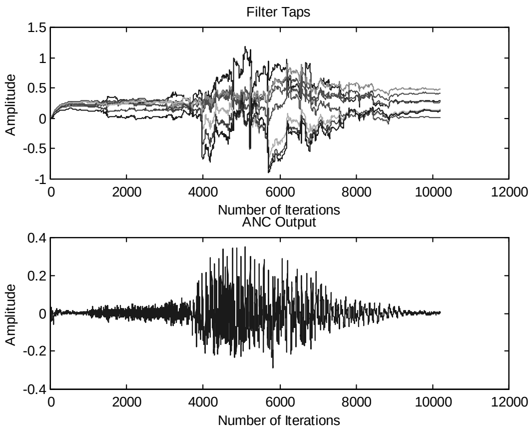

Fig. 2b. The NLMS algorithm – office noise.

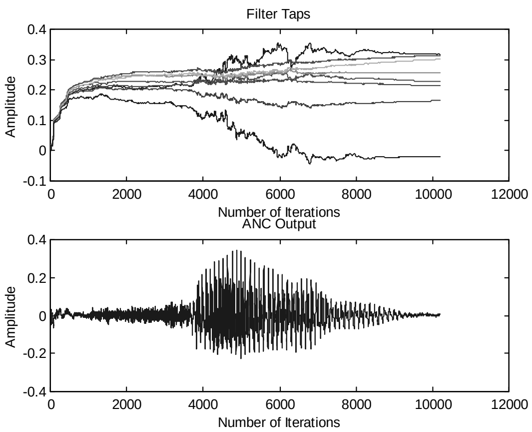

Fig. 2c. The RLS algorithm – office noise.

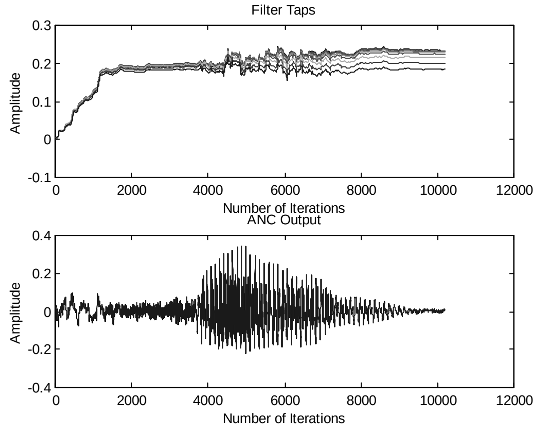

Fig. 2d. The AFA algorithm – office noise.

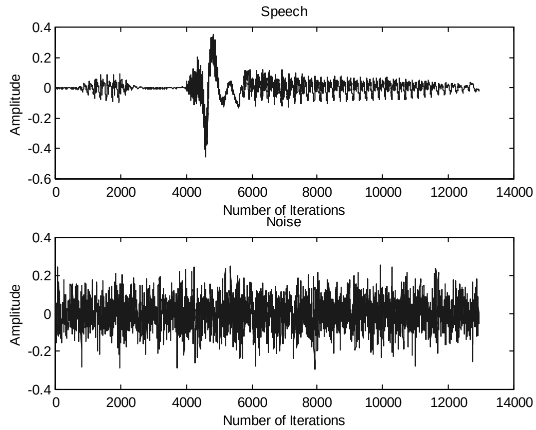

Fig. 3a. The signals for the experiment with car noise.

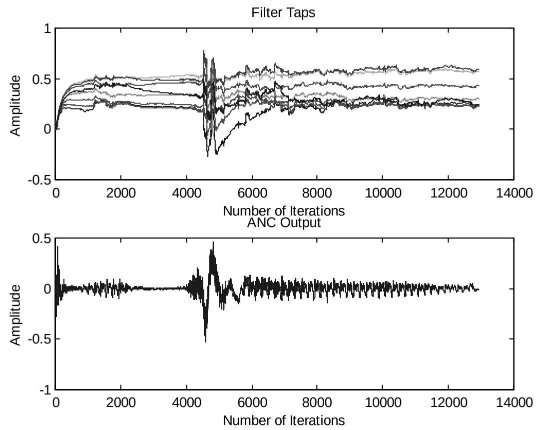

Fig. 3b. The NLMS algorithm – car noise.

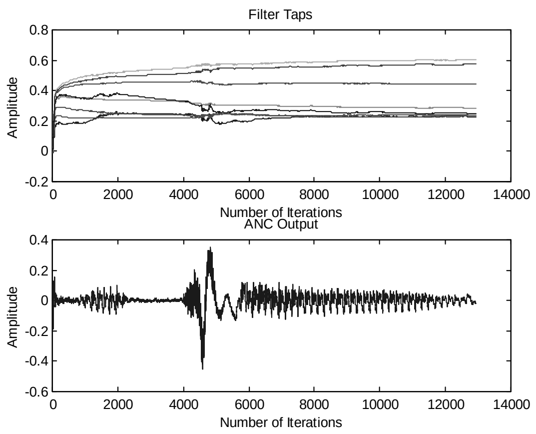

Fig. 3c. The RLS algorithm – car noise.

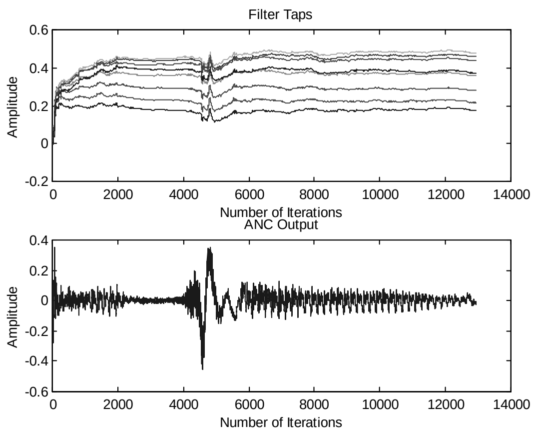

Fig. 3d. The AFA algorithm – car noise.

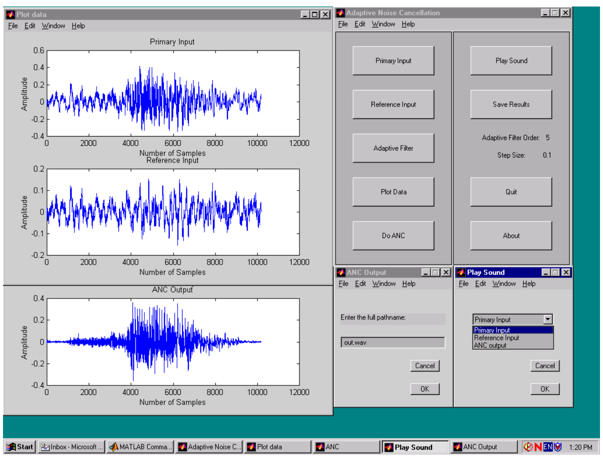

Fig. 4. Graphical user interface for adaptive noise cancellation.

Comparing the results of the different algorithms it is clear that RLS and AFA outperform NLMS algorithm. The last shows a high deviation in its coefficients that results in poorer performance.

A MatLab package with graphical user interface (GUI) (see Fig. 4) is available on the WWW from http://divcom.otago.ac.nz/infosci/KEL/CBIIS.html.

The program can be used in off-line applications. The signals from primary and reference microphone have to be previously recorded in .wav files. The order of the adaptive filter, the step size and the initial values of filter taps are controlled via the interface. At the output the user may see the plotted filter taps and the speech after noise reduction, listen to the different signals used in the process of adaptive noise cancellation and save the free of noise speech in a .wav format file.

V. CONCLUSIONS

The main goal of this paper is to investigate the application of an algorithm based on adaptive filtering with averaging in noise cancellation problem. Here the main concern is to achieve a high convergence rate in order to meet the requirements imposed by applications where the changes in signal characteristics could be quite rapid. In this aspect the obtained results show that the AFA algorithm is very promising. Its main advantages could be summarized as follows:

- high adaptation rate, comparable to that of the RLS algorithm;
- low computational complexity and possible robustness in fixed-point implementations.

The method is applicable for real word applications of Automated Speech Recognition Systems (ASRS):

- noise suppression in ASR in a car environment;
- noise suppression in ASR in office environment;
- noise suppression in ASR in a plane.

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