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Adaptive System for Engine Noise Cancellation in Mobile Communications

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Original scientific paper

An adaptive system, which provides engine noise cancellation for hands-free cellular phones is developed. The system employs a cascade of three second-order adaptive notch/bandpass filters based on Gray-Markel lattice structure. This structure defines the high stability of the adaptive system. A Newton type algorithm is used for updating the filter coefficients that determines fast adaptation. In addition a new algorithm using adaptive filtering with averaging (AFA) is developed. The main advantages of AFA algorithm could be summarized as follows: high convergence rate comparable to that of the recursive least squares (RLS) algorithm and at the same time low computational complexity. The presented adaptive system for engine noise cancellation could improve considerably the speech intelligibility of hands-free cellular phones.

Key words: adaptive algorithms, digital filters, noise reduction

1 INTRODUCTION

The hands-free operation of the telephone system when driving a car provides indisputable advantages. There are, however, three main obstacles that have to be overcome in order to design such a system: the high level of the ambient noise in the vehicle compartment due to the engine, tires and wind; the acoustic echo interference and the high sound volume of the car audio system as shown in Figure 1.

While the car stereo system might be switched off during the use of the telephone, the other two sources of disturbances are always presented and their characteristics are changed quite rapidly. The engine noise depends on the car speed and the sound isolation between the engine and the compartment while the acoustic feedback – on the head position of the driver, the number of the passengers inside the car, the sound absorption of the interior and so on. Thus it is clear that an efficient suppression of these disturbances is possible only by applying an adaptive system. The most popular system against the engine and all ambient noises is known for more than 25 years [1] but it requires multiple reference microphones and a complicated processing. The acoustic echo cancellation problem is also widely investigated [2] but most of the results are valid for low noise environments like conference rooms or offices. An entirely new approach to fight against all sources of disturbances was proposed in [3]. The system developed in [3] incorporates also the car audio and is called an »integrated system«. That system is very efficient and its only weak point is the very complicated adaptive filter (nonrecursive of 256 order) for suppression of the engine noise. In this paper a new adaptive system for this purpose is proposed and its performance is investigated. This system may be incorporated in the »integrated system« [3] or could be used in some simpler implementations including also acoustic echo suppression.

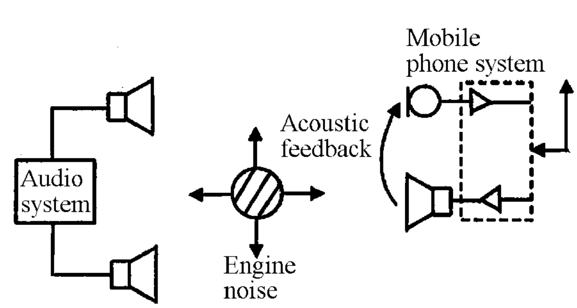

Fig. 1 Disturbances inside the car

Also it is well known that two of most frequently applied algorithms for noise cancellation [4] are normalized least mean squares (NLMS) [5] and recursive least squares (RLS) [6, 7] 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 reveal its robustness maintaining fast convergence and at the same time keeping the computational complexity at a low level.

2 ADAPTIVE SYSTEM FOR ENGINE NOISE CANCELLATION

The approach here is that instead of using multiple microphones to pick up the noises the reference signal for the adaptive filter is obtained throughout calculations based on the engine speed controlled by the motor revolutions per minute (RPM). Although the engine noise might be quite wide-band, there are a limited number of dominant sinusoidal signals that carry most of the noise energy. It was found [3] that these sine-wave signals are usually no more than three and their frequencies are integral multiples of the fundamental harmonic frequency defined by RPM. Once the noise around these frequencies is suppressed, the noise power after the microphone will be considerably reduced without distorting the speech signal.

The adaptive system has to meet the following requirements:

- to adapt as fast as possible to the changes of the engine RPM;
- to preserve the speech signal from distortions.

The second requirement suggests the application of narrow-band notch filters each one centered at some of the dominant frequencies and ensuring enough narrow bandwidth. In [3] these notch filters are realized using a FIR structure of 256 order.

The first requirement (concerning the speed of adaptation) could be met much easier by using an IIR instead of FIR filter. IIR filters are usually avoided because they create a lot of stability problems. So if some (at least conditionally) stable adaptive IIR structures are available, they will meet easier both requirements and additionally will decrease sharply the price because narrow-band filters might be of second order.

Thus, for the three dominant engine noise frequencies only three second-order sections would be enough. Fortunately such stable second-order notch sections could easily be obtained using second-order allpass sections as shown in Figure 2.

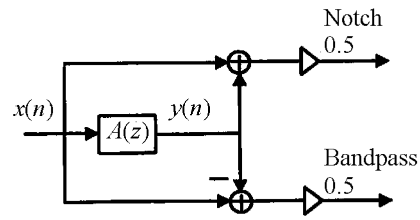

Fig. 2 Second-order notch/bandpass section

Actually the notch transfer function is obtained at the upper output while the narrow-band bandpass transfer function is produced at the other output (Figure 2).

The realizations based on the structure shown in Figure 2 are widely investigated [8] and they are famous with two important advantages:

- they are structurally real lossless bounded (RLB) and the mirror-image symmetry of the poles and zeros of the allpass section is independent of the multiplier coefficients quantization;
- they have extremely low pass sensitivity as their transfer functions are real lossless bounded [8].

Many allpass sections permit structurally LBR realization but the lattice Gray-Markel circuit [9] (Figure 3) offers an additional advantage. When this circuit is used in the structure shown in Figure 2 it becomes possible to control independently the notch frequency and the bandwidth of the filter. Thus if the allpass transfer function is

$$A(z) = \frac{k_2 + k_1(1+k_2)z^{-1} + z^{-2}}{1 + k_1(1+k_2)z^{-1} + k_2 z^{-2}} \tag{1}$$

then k_1 controls the notch frequency ω_0 while k_2 is related to the bandwidth BW via

$$k_1 = -\cos\,\omega_0 \tag{2}$$

$$k_2 = \frac{1 - \tan(BW/2)}{1 + \tan(BW/2)}. \tag{3}$$

But, on the other hand, BW is directly connected to the distance from the pole to the unity-circle.

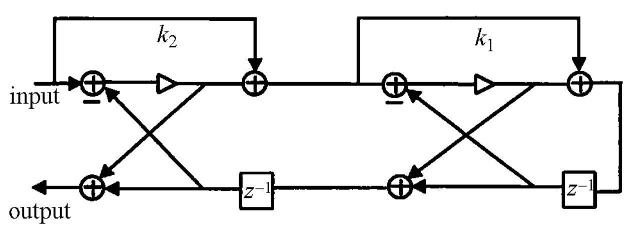

Fig. 3 Second-order lattice Gray-Markel circuit realizing allpass function A(z)

So, if we use the structure shown in Figure 2 as an adaptive filter applying the allpass circuit depicted in Figure 3 we may fix BW and thus fixing k_2 we make the distance from the pole to the unity-circle constant. But it means that with this constraint we obtain an adaptive IIR notch/bandpass filter free of stability problems. Adapting k_1 we may shift the notch frequency ω_0 around the unity-circle.

Using the basic structure shown in Figure 2 and the constraint mentioned above, the final arrangement of our system is presented in Figure 4. The system will work in the following manner: each second-order notch section will remove one of the dominant frequencies using an appropriate adaptive algorithm. As shown in Figure 4 we propose to update only the coefficients k_{11}, k_{12} and k_{13} while k_2 is a priori determined from equation (3). Thus we can reduce considerably the number of computations and can guarantee that the adaptive structure will be stable during the adaptation.

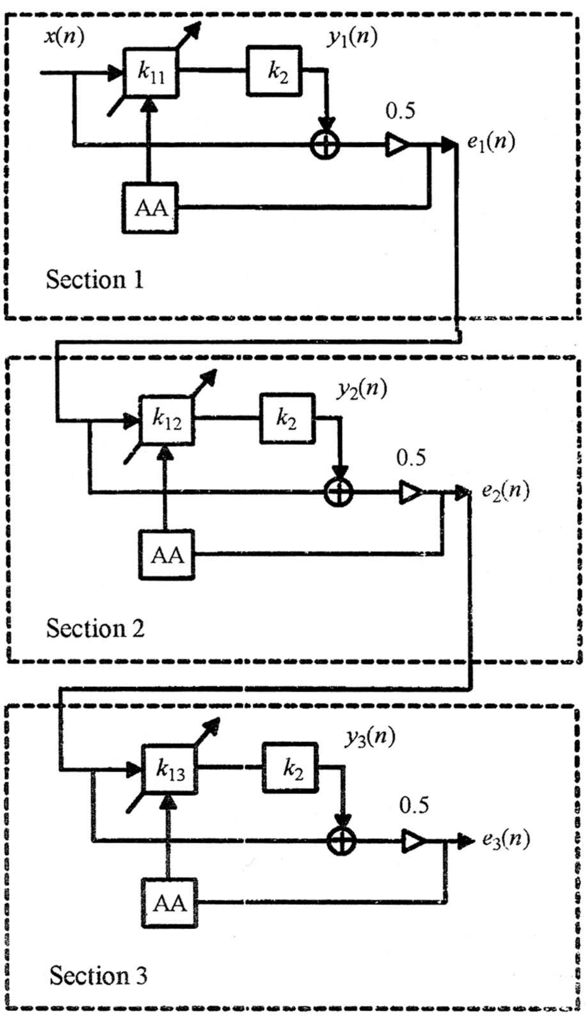

Fig. 4 Adaptive system for engine noise cancellation

The error signal for each second-order adaptive notch section (Figure 4) is formed as

$$e_i(n) = 0.5[e_{i-1}(n) + y_i(n)] \tag{4}$$

for $i = 1$ to 3 and $e_0(n) = x(n)$.

We select to apply a Newton type adaptive algorithm (AA) for updating the filter coefficients of the adaptive system shown in Figure 4. The advantages of such an algorithm are:

- an algorithm based on Newton method can be used successfully when the mean square error $\mathrm{MSE} = \mathrm{E}[e^2(n)]$ has local minima [1];
- applying Newton method we can reduce considerably the time of adaptation.

The equation of Newton method [10] can be described as

$$K(n+1) = K(n) - \mu R^{-1}(n)\nabla(n) \tag{5}$$

where $K(n)$ is the weight vector, $\nabla(n)$ is the gradient vector, $R(n)$ is the correlation matrix and μ is the step of adaptation.

But equation (5) cannot be used directly for adaptation of the coefficients $k_{11}(n)$, $k_{12}(n)$ and $k_{13}(n)$. It is necessary to get appropriate estimations for the gradient vector and the correlation matrix. A suitable choice of estimation for $\nabla(n)$ is

$$\hat{\nabla}(n) = \frac{\partial e^2(n)}{\partial K(n)} = 2e(n)\frac{\partial y(n)}{\partial K(n)}. \tag{6}$$

As shown in (6) we use the square error $e^2(n)$ instead of the mean square error $E[e^2(n)]$. Such estimation has been used successfully with least mean squares (LMS) algorithm [1].

The estimation of the correlation matrix can be formed using the method of sliding window [11]. This method is very suitable for tracking of signals with changeable characteristics because of its finite memory. Using the method of sliding window and having in mind that the correlation matrix for each adaptive notch filter (Figure 4) will have only one element we get

$$r_i(n) = \frac{1}{M}\sum_{s=0}^{M-1}\left[y_i'(n-s)\right]^2 \tag{7}$$

where $y_i'(n)$ is the derivative of $y(n)$ with respect to the coefficient subject of adaptation.

In equation (7) M is the size of the sliding window and its value was found to be 200 as a result of computer simulations.

Substituting (6) and (7) in (5) we get

$$k_{1i}(n+1) = k_{1i}(n) - \mu r_i^{-1}(n) y_i'(n) e_i(n) \tag{8}$$

for $i = 1$ to 3.

Equation (8) describes an adaptive algorithm based on Newton method, which can be used for adjusting the coefficients of the adaptive system shown in Figure 4.

In order to ensure the stability of the adaptive algorithm we should set the range of the step size μ. We use the results reported in [12]:

$$0 < \mu < \frac{K}{\mathrm{Trace}(R)}, \tag{9}$$

or in a more convenient form:

$$0 < \mu < \frac{K}{L\sigma^2}. \tag{10}$$

In our case σ^2 is the power of signal $y'(n)$, L is filter order and K is a constant depending on the statistical characteristics of the input signal. In most of practical situations K is approximately equal to 0.1.

3 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 [13] due to the recursive covariance update formula. 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

$$W(n+1) = W(n) - a(n)X(n)e(n) \tag{11}$$

where

- $W(n) = [w_0(n),\ w_1(n), \ldots,\ w_N(n)]^T$ is the coefficients vector,
- $X(n) = [x(n),\ x(n-1), \ldots,\ x(n-N)]^T$ is the input vector and
- $a(n)$ is a sequence of positive scalars as $a(n) \to 0$ for $n \to \infty$.

In (11) the estimation error can be determined by equation (4). Then the expression (11) could be transformed through taking the averages of $W(n)$:

$$W(n+1) = W(n) + \frac{1}{n^\gamma} X(n)e(n) \tag{12}$$

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

$$\frac{1}{2} < \gamma < 1.$$

The analysis presented in [14] 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 $X(n)$ and $e(n)$. This leads us to an adaptive algorithm with averaging (AFA):

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

$$W(n+1) = \overline{W}(n) + \frac{1}{n^\gamma}\sum_{k=1}^{n} X(k)e(k) \tag{13}$$

$$\frac{1}{2} < \gamma < 1.$$

Considering equation (13) it could be seen that 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.

4 EXPERIMENTAL RESULTS

The performance of the developed adaptive system for engine noise cancellation is assessed by computer simulations. The input signal $x(n)$ (Figure 4) is a sum of engine noise and speech signal. The engine noise is defined by three dominant frequencies according to Reference [3]. The step of adaptation μ is set to 0.01 in order to provide a fast convergence and k_2 is 0.969 to reduce the speech distortions.

Figure 5 shows the original speech and Figure 6 depicts the noise-corrupted speech. In Figure 7 the speech after noise cancellation is presented. The adaptive system demonstrates a fast adaptation rate at about 100 iterations. Figure 8 presents the trajectories of the filter coefficients. In this experiment the capability of the system to track the changes in noise signal is tested as the dominant frequencies shift from 0.1, 0.2 and 0.4 at the beginning to 0.14, 0.23 and 0.36.

Table 1 shows the improvement in SNR as a result of the application of the developed adaptive system. The obtained results are comparable to these of the conventional adaptive noise canceller (ANC) [15] but our system is faster and simpler to implement.

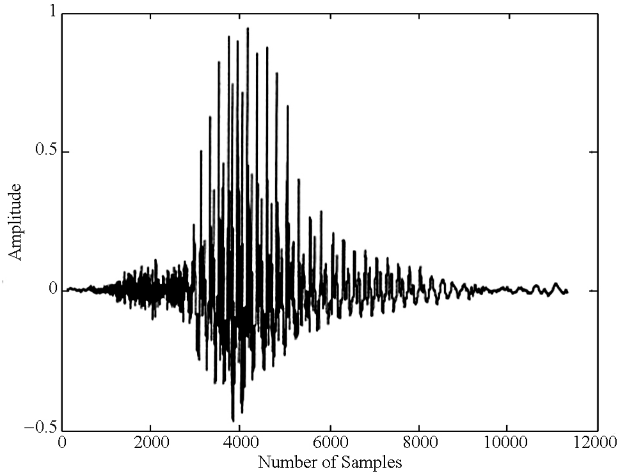

Fig. 5 Original speech

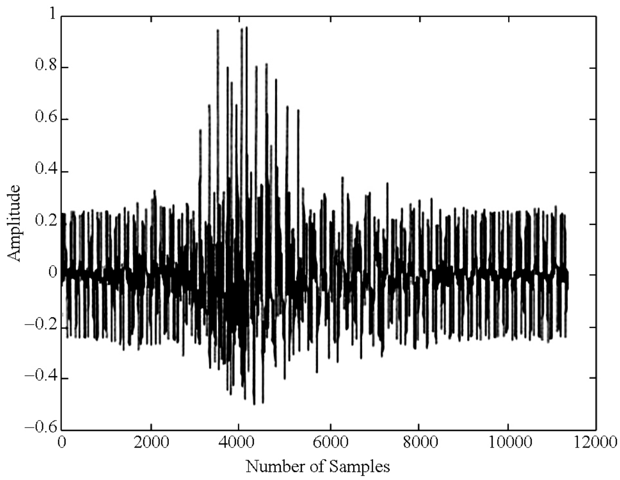

Fig. 6 Noise-corupted speech

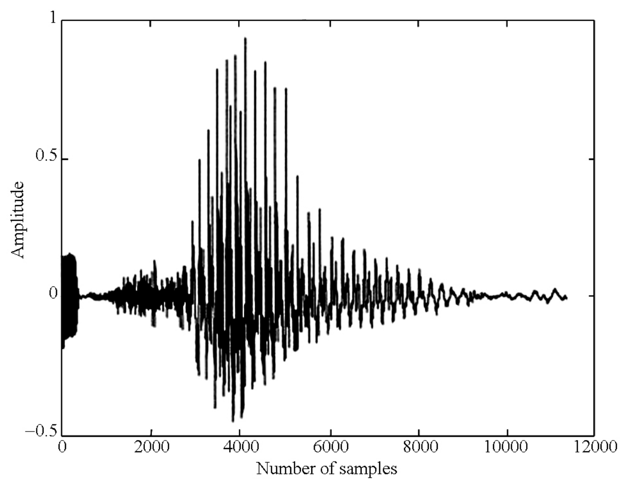

Fig. 7 Speech after noise cancellation

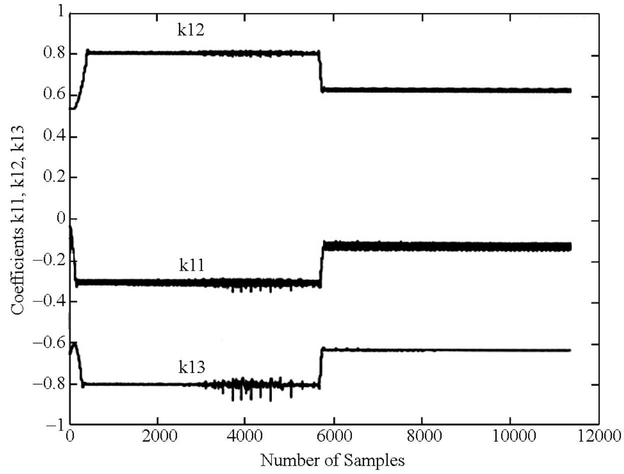

Fig. 8 Trajectories of the filter coefficients

Table 1 **SNR before and after Noise cancellation**

Proposed System	Before	After	SNR Gain
SNR(dB)	0	11.2	11.2
SNR(dB)	3	13.5	10.5
ANC	Before	After	SNR Gain
SNR(dB)	0	10	10

We also assess the performance of the proposed AFA algorithm for noise cancellation. The NLMS, RLS and AFA algorithms are implemented as for the NLMS algorithm $-\mu = 0.02$, for the RLS algorithm $-\delta = 0.98$ and for the AFA algorithm $-\gamma =$ $= 0.5$.

The original speech (the word »return«) is corrupted with car noise (SNR = 0 dB) and the results for different algorithms after noise cancellation are shown in Figures 9–12.

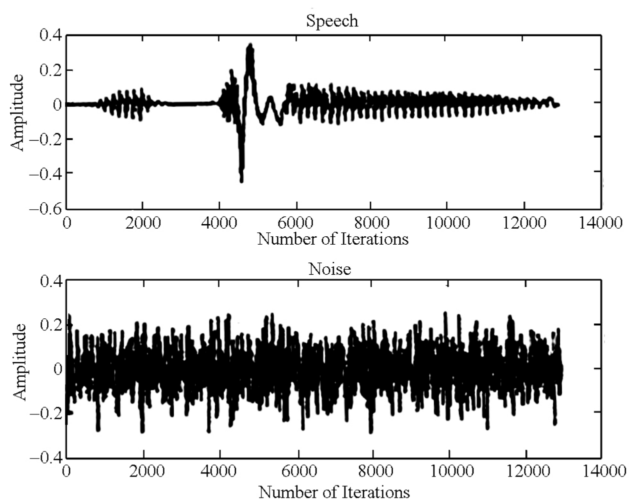

Fig. 9 Speech and noise signals

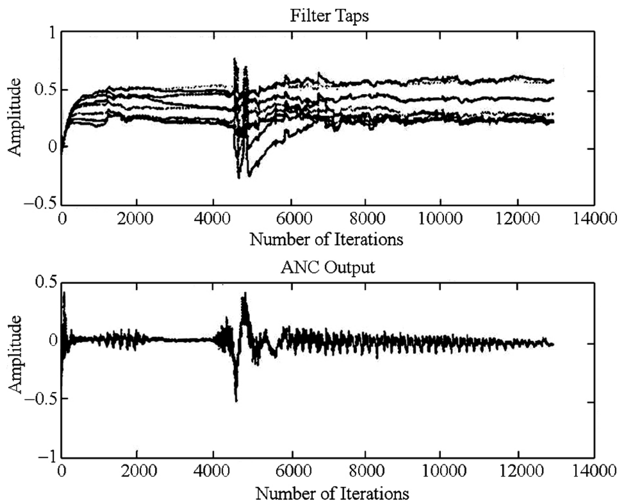

Fig. 10 NLMS algorithm

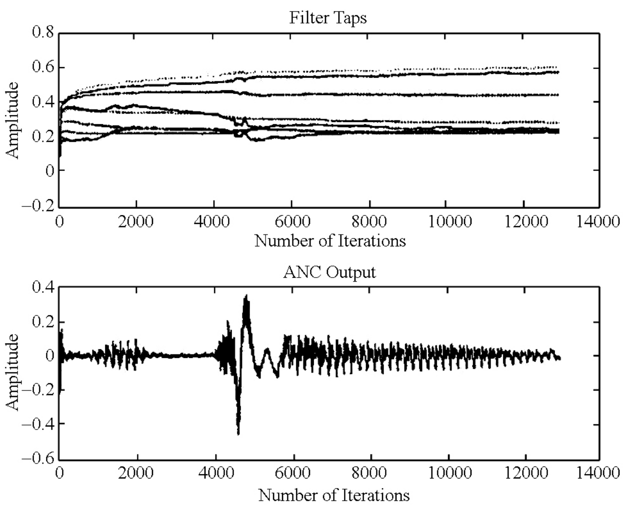

Fig. 11 RLS algorithm

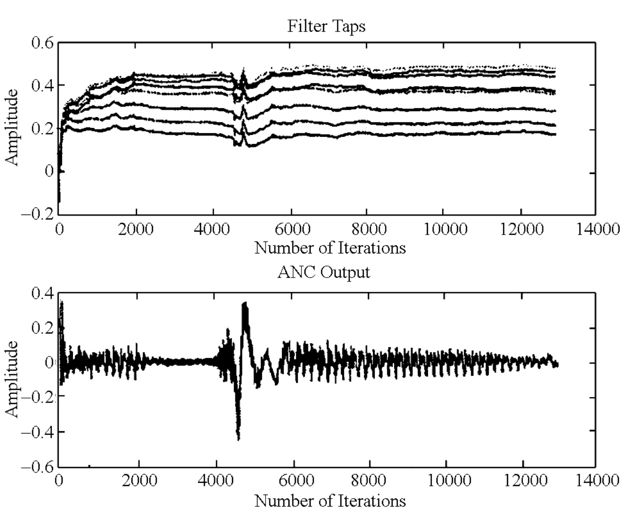

Fig. 12 AFA algorithm

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.

5 CONCLUSIONS

A very efficient adaptive system based on IIR structure for engine noise cancellation is proposed in this contribution. The main advantages of the presented realization are:

- the adaptive system has a very good time of adaptation (about 100 iterations);
- the system is very simple, flexible and has low computational complexity;
- the second-order lattice structures are stable during the adaptation that defines the high stability of the adaptive system for engine noise cancellation.

In addition a new algorithm based on adaptive filtering with averaging is developed. The obtained results are very promising. The adaptive algorithm combines high adaptation rate and low computational complexity.

The proposed system for engine noise cancellation could improve considerably the speech intelligibility of the hands-free cellular phones.

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Adaptivni sustav za poništavanje utjecaja šuma motora na mobilne komunikacije. Razvijen je adaptivni sustav koji poništava utjecaj šuma motora pri korištenju mobitela bez uporabe ruku. Sustav koristi kaskadu koja se sastoji od tri adaptivna filtra drugog reda s karakteristikom pojasnog propusta ili pojasne brane zasnovana na Gray-Markel rešetkastoj strukturi. Ta struktura osigurava veliku stabilnost adaptivnog sustava. Za određivanje koeficijenata filtra primijenjen je algoritam Newtonovog tipa. Ovaj algoritam osigurava brzu adaptaciju. Dodatno je razvijen novi algoritam koji koristi adaptivno filtriranje s usrednjavanjem (AFA). Glavne su prednosti AFA algoritma velika brzina konvergencije usporediva s brzinom konvergencije rekurzivnog algoritma najmanjih kvadrata (RLS) te niska kompleksnost izračunavanja. Prikazani adaptivni sustav za poništavanje utjecaja šuma motora mogao bi značajno poboljšati razumljivost govora pri korištenju mobitela bez uporabe ruku.

Ključne riječi: adaptivni algoritmi, digitalni filtri, smanjenje šuma

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