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Adaptive Filter for Event-Based Signal Extraction

Original scientific paper

This paper introduces a new adaptive filter structure for a class of event-based signals corrupted by quasi-periodic noise. The event driven adaptive filter emerges from Widrow's adaptive filter, exploiting specific properties of event-based signals such as unpredictable time appearance and limited time duration. This filter can be used when reference input to Widrow's filter, which essentially has to be correlated to the noise, is unavailable, but is known for a fact that it is quasi-periodic. Experimental tests verify improved filter performance of the proposed solution.

Key words: adaptive filter, event detection, LMS, quasi-periodic additive noise, RLS, spheric signal

1 INTRODUCTION

Event-based signals are quite common in many natural and physical systems and applications. Their property is limited time duration and unpredictable, random time appearance. Those signals may be corrupted by noise due to imperfection of the measurement system. A common form of noise that appears in many electronic systems is quasi-periodic, additive noise such as that which comes from power lines.

An example of an event-based signal is the electromagnetic radiation from lightning discharge [1–3], further referred to as a spheric signal. These signals are used in a variety of meteorological [3] and upper atmospheric [7] remote sensing applica-

tions. The accuracy of these remote sensing techniques is determined partly by the degree to which noise can be removed. An example of the measured signal, (Figure 1, top) contains a spheric signal (Figure 1, bottom) corrupted by additive noise (Figure 1, middle). This noise comes from nearby power line electromagnetic fields at 60 Hz (in the U.S.) and odd harmonic components. Both, noise and spheric signal are unknown. The goal of this work is to develop new adaptive methods in signal processing to get the spheric signal from measured signal.

If a simple notch filter, or high-pass filter is applied, the output spheric signal would be distorted because its' frequency spectrum overlaps with the spectrum of the noise. It is shown that adaptive filters can get undistorted output signal even if the frequency spectrums of the noise and desired output signal overlap [4]. This property makes adaptive signal processing a promising approach in this case study.

Figure 2 shows Widrow's adaptive filter [5]. A signal s is transmitted over a channel to a sensor that also receives a noise n_0 uncorrelated with the
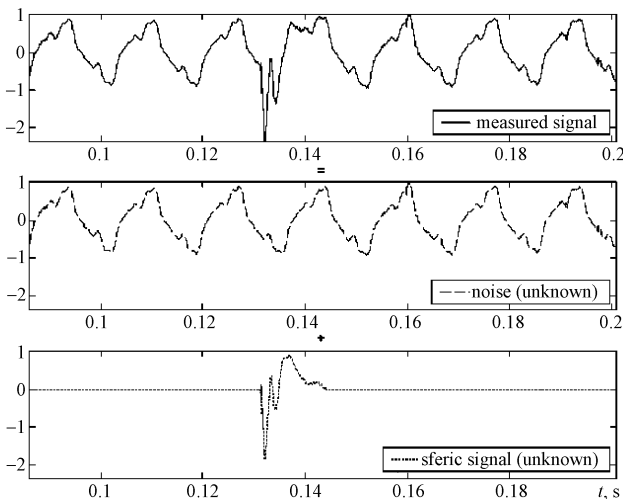

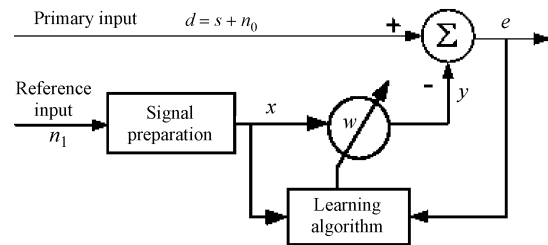Fig. 1 Measured signal = noise + spheric signal

Fig. 2 Widrow's adaptive filter

signal. The combined signal and noise $s + n_0$ form the primary input to the filter. A second sensor receives a noise n_1 uncorrelated to the signal but correlated in some unknown way with the noise n_0. This sensor provides the reference input to the filter. The noise n_1 is filtered to produce an output y that is close replica of n_0. This output is subtracted from the primary input $s + n_0$ to produce the system output $e = s + n_0 - y$ [4].

The adaptive filter, general concept is shown in Figure 3 where x is reference input recursive vector [5]. The filtered signal is calculated by (1).

$$e_j = d_j - \sum_{i=1}^{N} x_{j-i+1} \cdot w_i. \qquad (1)$$

In cases when reference input is either unavailable for measurement or is not correlated enough with noise component in primary signal, Widrow's adaptive filter can not be used. In this work a new adaptive filter structure is introduced in order to overcome these difficulties for a class of event-based signals corrupted by quasi-periodic additive noise. This filter structure is called event driven adaptive filter and will be further elaborated.
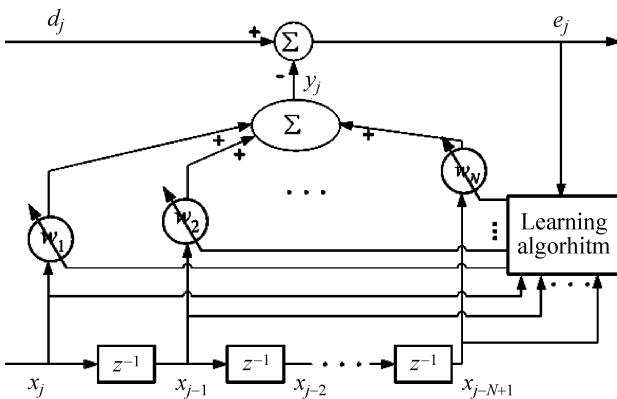

Fig. 3 Adaptive filter, general concept, with x as a recurrent vector

2 EVENT DRIVEN ADAPTIVE FILTER

The paper proposes an event driven adaptive filter for estimation of event-driven signals from measured signals containing the desired signal and quasi-periodic noise. The idea is essentially to first estimate the noise via adaptive filter whose coefficients are not updated during the short time slots when the desired signal is present in the measured signal, and then to subtract the so obtained estimated noise from the measured signal.

A. Event-based Signal Properties

A signal (Figure 1 top) that contains a spheric signal corrupted by additive noise is acquired by a low frequency magnetic field sensor in Duke University. Note that while this is a synthetic signal generated by adding a known signal to measured background noise, it is essentially identical to the recorded signal plus noise. The spheric signal (Figure 1 bottom) belongs to a class of event-based signals with following properties:

– Unpredictable time appearance t_j.

– Limited time duration, Δ_{AFT}.

– Average appearance frequency f is low so that

$$1/f \gg \Delta_{\mathrm{AFT}} \qquad (2)$$

This property implies that spheric signal is present in average 1–5 % of time, and in the rest 95–99 % is equal to zero.

– Amplitude and time response shape of two spheric signals may be considerably different.

Noise that comes from power line interference (60 Hz and odd harmonics) also has some useful properties that can be exploited:

– Noise signal is quasi-periodic i.e. changes in amplitude and shape are slow. Within few periods noise signal can be considered periodic, as seen on Figure 1 middle.

– Due to (2) noise signal takes 95–99 % of time in measured signal.

Figure 4 represents typical measured signal segment. Parameters required for event driven adaptive filter are clearly marked in the figure.
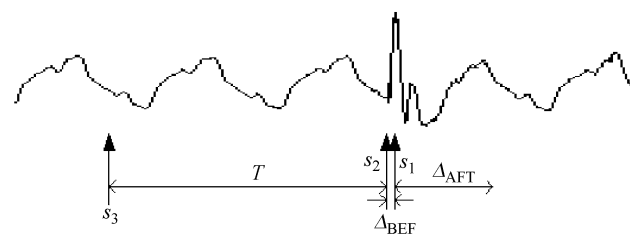

Fig. 4 Measured signal segment with parameters required for event driven adaptive filter

Δ_{AFT} – maximum spheric signal duration after detection

T – integer factor of lowest noise signal period

s_3 – measured signal value at time t_3 where $t_3 = t_2 - T$

s_2 – measured signal value at time t_2

s_1 – measured signal value at time t_1

Spheric signal appearance can be detected by a simple comparator. Time when the detection takes place is t_1. Because of some slew rate spheric signal actually appears Δ_{BEF} before it is detected, at time $t_2 = t_1 - \Delta_{\mathrm{BEF}}$.
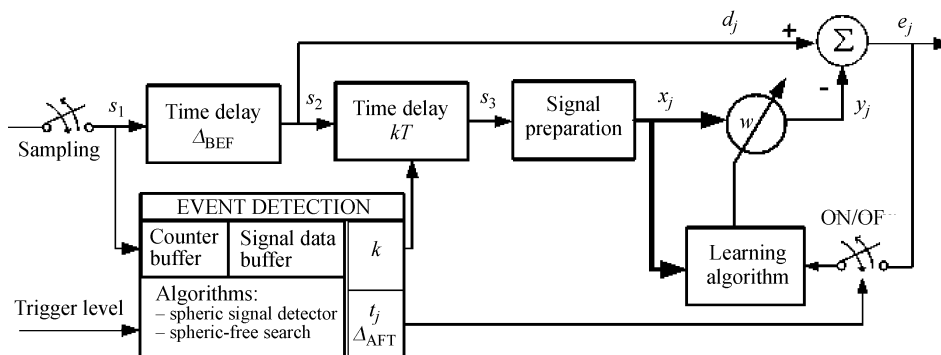
Fig. 5 Event driven adaptive filter block diagram

B. Event Driven Adaptive Filter Structure

A new method in data processing and filtering is developed to take advantage of signal properties cited in A. We call this method event-driven adaptive filter, which is described in Figure 5. and Figure 7. The block-diagram of event-driven adaptive filter in Figure 5 shows signal flow. A brief description of each block will be given.

Event-driven adaptive filter takes only one input – the measured signal (primary input, d) and gives at the output estimated spheric signal clear of noise. Primary input is being sampled giving s_1 and delayed for Δ_{BEF} giving s_2. The reason of this Δ_{BEF} time delay block will be explained later. As the second, reference input, the additionally delayed primary input is used. s_2 is delayed for kT seconds where k is integer equal or greater than 1 and T is one of the integer factors of 60 Hz signal period, preferably $T = 2*(1/60)$ (s) and once being set, should not be changed.
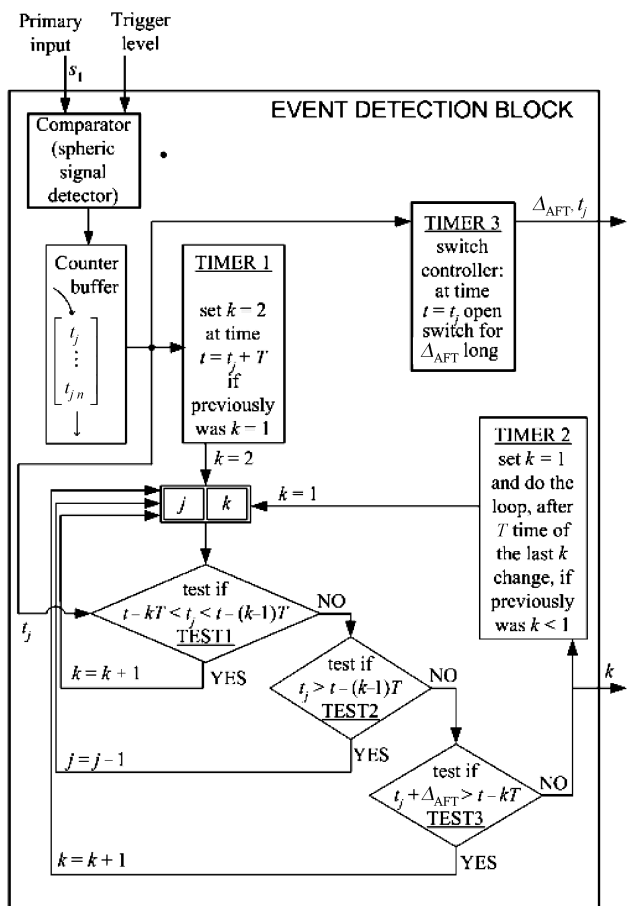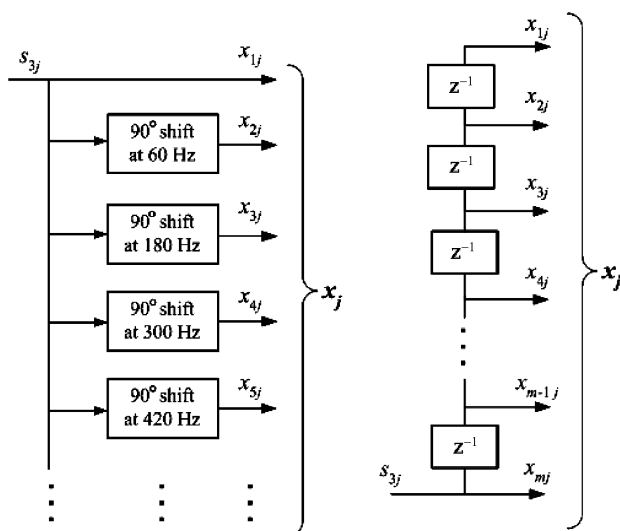

a. adaptive notch filter at multiple frequencies

b. adaptive noise canceller, general concept

Fig. 6 Signal preparation block options

Fig. 7 Event detection block

Signal s_3 is delayed for an integer number of 1/60 seconds after signal s_2. Since the noise signal is quasi-periodic, in this way reference input is close approximate of the noise component in primary input. Integer number k is being selected during the filtering process in a way that s_3 contains no spheric signal. This is done by the EVENT DETECTION block, Figure 7. The signal preparation block defines which one of the adaptive filter structures

is selected, see Figure 6 (namely, a. adaptive notch filter at multiple frequencies, or b. adaptive noise canceler, general concept). In the presentation signal preparation block in Figure 6b is used.

The vector product of x_j and w is the noise estimate y_j which is subtracted from s_2 giving the output e_j. To improve the output signal, the weights update is paused in those times t while $s_2(t)$ contains spheric signal. This is approximately 1–5 % of total time. This is also done by event detection block.

A key element of the event-driven adaptive filter is EVENT DETECTION block, Figure 7. The input to the event detection block is the primary input which is compared with a constant trigger level. The time when a spheric signal is detected is stored in counter buffer. Those times are called counts or count times. Spheric signal cannot be detected at the very moment it appears, because of the finite onset slope of the signal. This is why there is a Δ_{BEF} time delay block in Figure 5. The adaptive filter weights update has to stop sometime before spheric signal takes place, and can start being updated again when spheric signal has passed, after Δ_{AFT}. This is done by TIMER 3, switch controller, Figure 7. Switch controller works as follows: at time $t = t_j$ open switch for Δ_{AFT} long. TIMER 1 and TIMER 2, together with decision parallelograms in event detection blocks are parts of the spheric free search algorithm, Figure 7. This algorithm searches for time segment of length T of measured signal in which no spheric signal is present, giving integer k at output. Note that TIMER 1 once started counting up to T cannot be interrupted by new t_j count, while TIMER 2 can be interrupted by k change and TIMER 3 can be interrupted by new t_j count.

A clear description of *Event detection block* in signal processing is shown in Table 1. A time frame of 0.4 second of measured signal is a random specimen taken out of 10^8 seconds recorded data in total. In this time frame four events appear. Events can be differed as four peaks that arise from quasi-periodic noise signal. Times of their appearances are marked as t_5, t_6, t_7 and t_8. Signal s_2 corresponds to the *primary input*, d while s_3 corresponds to the *reference input*, n_1 to the Widrow's filter. Table 1 shows step-by-step signal processing in *Event detection block* where right column shows position of signals s_2 and s_3 in critical moments when some actions or decisions have to be made. Those actions or decisions are defined in left column. Note that position of s_2 constantly increases in real time. The essence role of the *Event detection block* is to find proper position for reference input s_3 so that it fulfils two conditions; to be delayed for an integer factor of lowest noise signal period T and to contain no spheric signal.

3 LEARNING ALGORITHM

Two learning algorithms for weights update are tested and compared, least mean square (LMS) and recursive least square (RLS). LMS is the simplest learning algorithm to implement, but the convergence rate is rather slow. The weight LMS update is as follows [4, 6]:

$$w_{j+1} = w_j + 2\mu e_j x_j. \tag{3}$$

This algorithm does not require squaring, averaging or differentiation. Starting with an arbitrary initial weight vector, the algorithm will converge in the mean and will remain stable as long as the parameter μ is greater than 0 but less than the reciprocal of the largest eigenvalue λ_{max} of the matrix R.

$$0 < \mu < \frac{1}{\lambda_{max}} \tag{4}$$

where R is reference input correlation matrix, whose elements are defined as

$$R = E(x(i,j), x(k,j)) \tag{5}$$

where $E(.)$ is expectation operator.

The convergence rate can be controlled by parameter μ. If μ is small, convergence is slower, and if μ is closer to its upper limit, weights will converge faster.
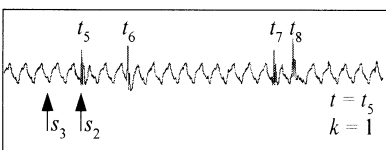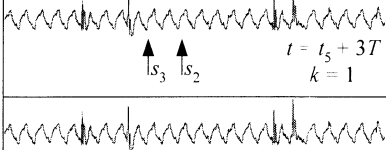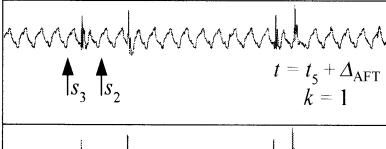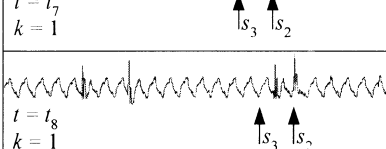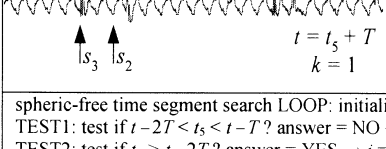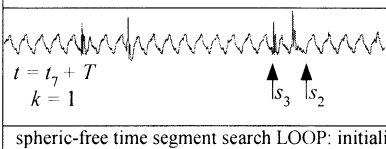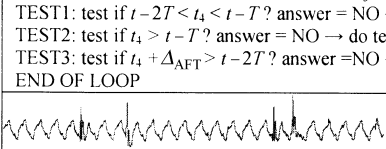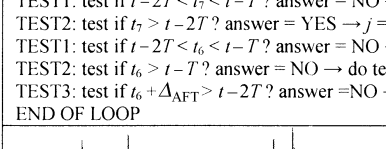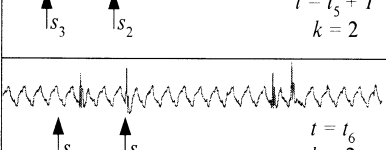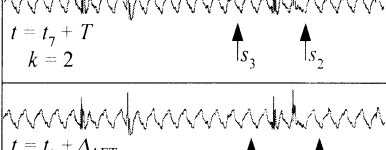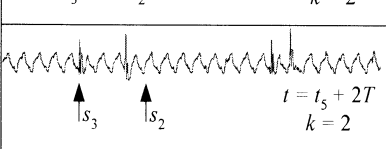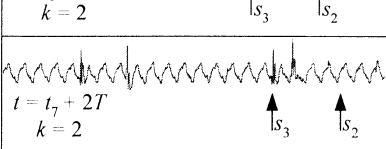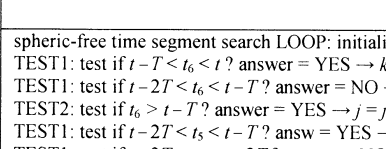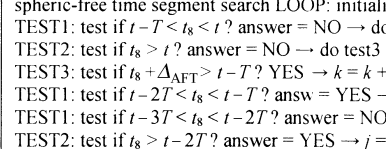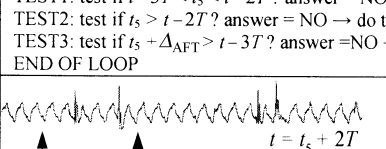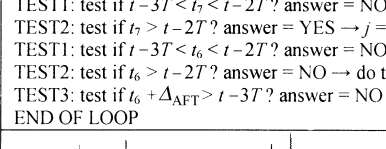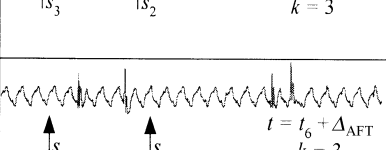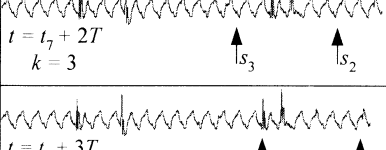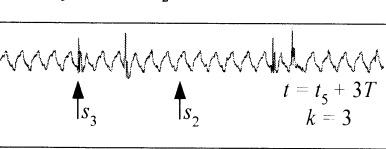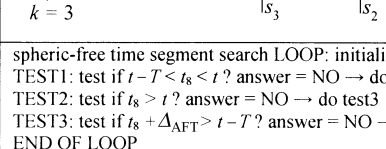
The RLS learning algorithm is time consuming, but the convergence rate is much faster compared to LMS. The weight RLS update is as follows [6]:

$$
\begin{aligned}
&P = \delta^{-1} \cdot \text{eye}(N+1) \\
&w = \text{zeros}(N, \text{length}(t)) \\
&\text{for } j = N+1 : \text{length}(t) \\
&\quad u = x(j:-1:j-N) \\
&\quad pipi = u^T \cdot P \\
&\quad kal = pipi^T / (\lambda + pipi) \cdot u \\
&\quad \alpha = d(j) - w(:, j-1) \cdot u \\
&\quad w(:, j) = w(:, j-1) + kal \cdot \alpha \\
&\quad P = (P - kal \cdot pipi) / \lambda \\
&\text{end}
\end{aligned} \tag{6}
$$

Learning in progress can be seen and compared in Figure 8 and Figure 9 for both, LMS and RLS.

Due to a very small duty-cycle of the event-signal, the weights updated by LMS are primarily determined by the background noise signal. Without ON/OFF switch the event signal would cause only momentary change of the weights, as seen in Figure 8, that would affect the output after the event signal. The weights converge again to a new stable

Table 1 Event detection block signal processing, a case study

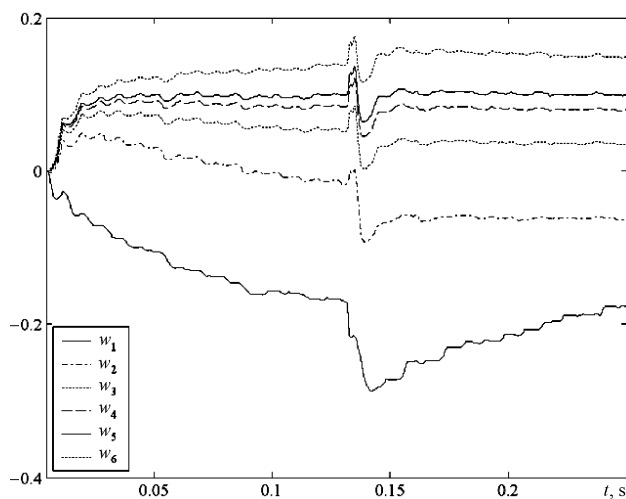| Diagram	Description
t_5 t_6 t_7 t_8; $t = t_5$; $k = 1$; s_3, s_2	count detected – write t_5 to buffer –TIMER 3 turns switch OFF –TIMER 1 starts counting
$t = t_5 + \Delta_{\text{AFT}}$; $k = 1$; s_3, s_2	TIMER 3 turns switch back ON
$t = t_5 + T$; $k = 1$; s_3, s_2	$t = t_5 + T$ and $k = 1$ activates TIMER 1 output: $k = 2$, do the LOOP
spheric-free time segment search LOOP: initialization: $k = 2, j = 5$ TEST1: test if $t - 2T < t_5 < t - T$? answer = NO → do test2 TEST2: test if $t_5 > t - T$? answer = YES → $j = j - 1 = 4$, do test1 TEST1: test if $t - 2T < t_4 < t - T$? answer = NO → do test2 TEST2: test if $t_4 > t - T$? answer = NO → do test3 TEST3: test if $t_4 + \Delta_{\text{AFT}} > t - 2T$? answer = NO → put k to output ($k = 2$) END OF LOOP	
$t = t_5 + T$; $k = 2$; s_3, s_2	LOOP output: $k = 2$ k change initiates TIMER 2 to start counting
$t = t_6$; $k = 2$; s_3, s_2	count detected – write t_6 to counter buffer –TIMER 3 turns switch OFF
$t = t_5 + 2T$; $k = 2$; s_3, s_2	T milliseconds has passed after last k change. This activates TIMER 2 output: $k = 1$ and do the LOOP
spheric-free time segment search LOOP: initialization: $k = 1, j = 6$ TEST1: test if $t - T < t_6 < t$? answer = YES → $k = k + 1 = 2$, do test1 TEST1: test if $t - 2T < t_6 < t - T$? answer = NO → do test2 TEST2: test if $t_6 > t - T$? answer = YES → $j = j - 1 = 5$, do test1 TEST1: test if $t - 2T < t_5 < t - T$? answ = YES → $k = k + 1 = 3$, do test1 TEST1: test if $t - 3T < t_5 < t - 2T$? answer = NO → do test2 TEST2: test if $t_5 > t - 2T$? answer = NO → do test3 TEST3: test if $t_5 + \Delta_{\text{AFT}} > t - 3T$? answer = NO → put k to output ($k = 3$) END OF LOOP	
$t = t_5 + 2T$; $k = 3$; s_3, s_2	this t time is the time when the k change has been made, TIMER 2 starts counting now at $t = t_5 + 2T$
$t = t_6 + \Delta_{\text{AFT}}$; $k = 3$; s_3, s_2	TIMER 3 turns switch back ON
$t = t_5 + 3T$; $k = 3$; s_3, s_2	TIMER 2 output activates, set $k = 1$ and do the LOOP
spheric-free time segment search LOOP: initialization: $k = 1, j = 6$ TEST1: test if $t - T < t_6 < t$? answer = NO → do test2 TEST2: test if $t_6 > t$? answer = NO → do test3 TEST3: test if $t_6 + \Delta_{\text{AFT}} > t - T$? answer = NO → put k to output ($k = 1$) END OF LOOP	
$t = t_5 + 3T$; $k = 1$; s_3, s_2	LOOP output $k = 1$
$t = t_7$; $k = 1$; s_3, s_2	count detected –write t_7 to buffer –TIMER 3 turns switch OFF –TIMER 1 is counting
$t = t_8$; $k = 1$; s_3, s_2	count detected – write t_8 to counter buffer –switch already OFF
$t = t_7 + T$; $k = 1$; s_3, s_2	$t = t_7 + T$ and $k = 1$ activates TIMER 1 output: $k = 2$ and do the LOOP
spheric-free time segment search LOOP: initialization: $k = 2, j = 7$ TEST1: test if $t - 2T < t_7 < t - T$? answer = NO → do test2 TEST2: test if $t_7 > t - 2T$? answer = YES → $j = j - 1 = 6$, do test1 TEST1: test if $t - 2T < t_6 < t - T$? answer = NO → do test2 TEST2: test if $t_6 > t - T$? answer = NO → do test3 TEST3: test if $t_6 + \Delta_{\text{AFT}} > t - 2T$? answer = NO → put k to output ($k = 2$) END OF LOOP	
$t = t_7 + T$; $k = 2$; s_3, s_2	LOOP output $k = 2$ k change initiates TIMER 2 start counting
$t = t_8 + \Delta_{\text{AFT}}$; $k = 2$; s_3, s_2	TIMER 3 turns switch back ON
$t = t_7 + 2T$; $k = 2$; s_3, s_2	TIMER 2 output activates, set $k = 1$ and do the LOOP
spheric-free time segment search LOOP: initialization: $k = 1, j = 8$ TEST1: test if $t - T < t_8 < t$? answer = NO → do test2 TEST2: test if $t_8 > t$? answer = NO → do test3 TEST3: test if $t_8 + \Delta_{\text{AFT}} > t - T$? answer = NO → do test1 TEST1: test if $t - 2T < t_8 < t - T$? answ = YES → $k = k + 1 = 3$, do test1 TEST1: test if $t - 3T < t_8 < t - 2T$? answer = NO → do test2 TEST2: test if $t_8 > t - 2T$? answer = YES → $j = j - 1 = 7$, do test1 TEST1: test if $t - 3T < t_7 < t - 2T$? answer = NO → do test2 TEST2: test if $t_7 > t - 2T$? answer = YES → $j = j - 1 = 6$, do test1 TEST1: test if $t - 3T < t_6 < t - 2T$? answer = NO → do test2 TEST2: test if $t_6 > t - 2T$? answer = NO → do test3 TEST3: test if $t_6 + \Delta_{\text{AFT}} > t - 3T$? answer = NO → put k to output ($k = 3$) END OF LOOP	
$t = t_7 + 2T$; $k = 3$; s_3, s_2	LOOP output $k = 3$ k change initiates TIMER 2 start counting again
$t = t_7 + 3T$; $k = 3$; s_3, s_2	TIMER 2 output activates, set $k = 1$ and do the LOOP
spheric-free time segment search LOOP: initialization: $k = 1, j = 8$ TEST1: test if $t - T < t_8 < t$? answer = NO → do test2 TEST2: test if $t_8 > t$? answer = NO → do test3 TEST3: test if $t_8 + \Delta_{\text{AFT}} > t - T$? answer = NO → put k to output ($k = 1$) END OF LOOP	
$t = t_7 + 3T$; $k = 1$; s_3, s_2	LOOP output $k = 1$

Fig. 8 LMS algorithm weights update
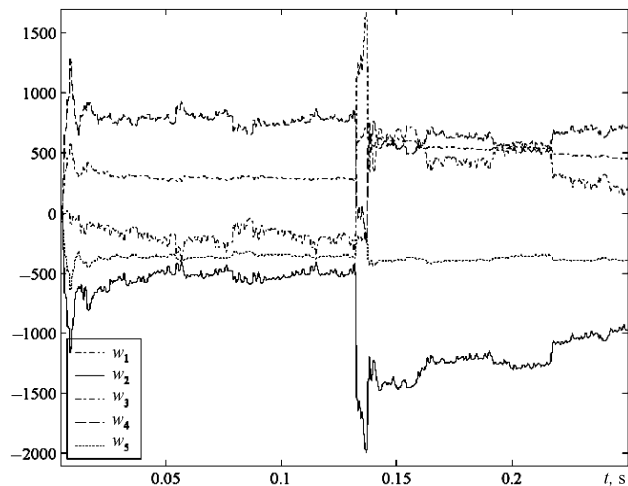
Fig. 9 RLS algorithm weights update

value before the next event signal. Due to the quasi stationary properties of the background signal, rather small adaptation step size μ could be used, thus reducing the effects of event signals on the weights estimation.

However, due to event signal unpredictable time appearance property it is likely possible that multiple event-signals appear in relatively short time thus increasing its duty-cycle. In this case, stopping the weight update, that is done by ON/OFF switch in Figure 5, improves the background elimination compared to simple prediction without any inhibition.

4 SIMULATION RESULTS

In Figure 10 bottom, the simulation results of event driven adaptive filter using the RLS learning algorithm show good match between unknown spheric signal and filter output. The RLS weights update in fast convergence. Essentially all of the quasi-harmonic noise has been successfully removed without altering the shape of the desired signal. Note that simple notch filtering would distort significantly the desired signal. The broadband noise that remains in the output signal is small and can be handled in the signal analysis that follows.
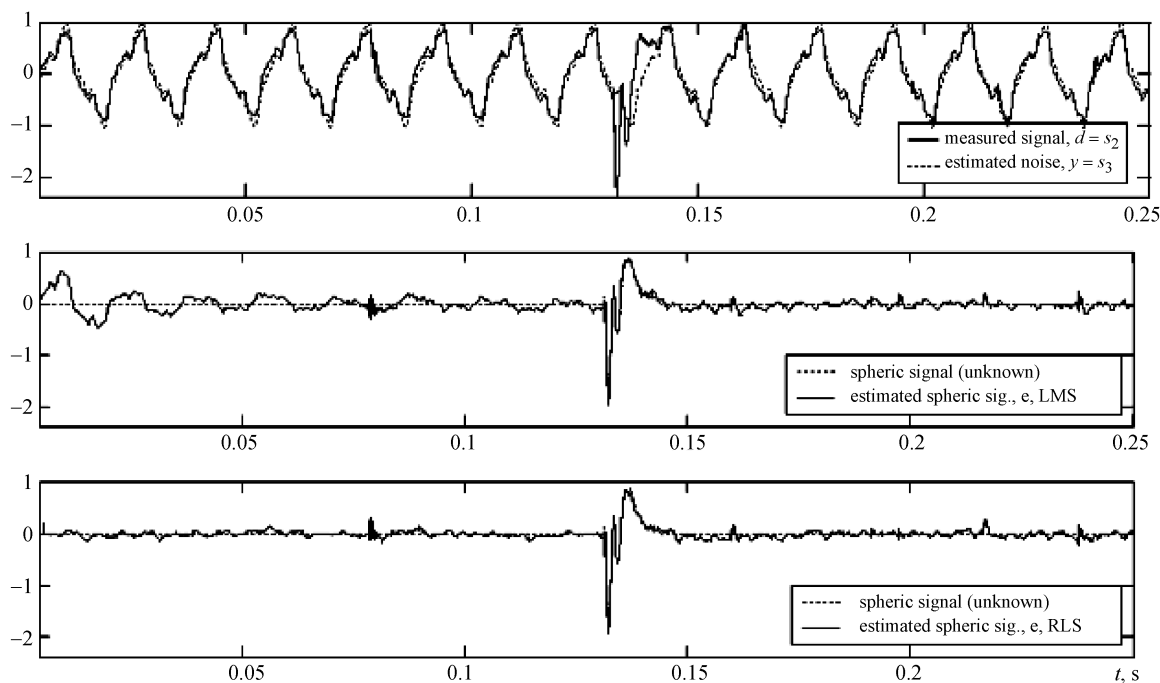

Fig. 10 Event driven adaptive filter simulation results

Event driven adaptive filter may encounter problem of small undetectable spheric signals. Events that are small in amplitude may appear in input signal s_1. If not detected in *Event detection block* those spheric signals are treated as noise and are present in both s_2 and s_3 with kT time shift in s_3. Both s_2 and s_3 contribute to the output signal e_j resulting in output signal e_j having twice as many undesired, small, undetectable spheric signals. This can be overcome by adding a high-pass filter in front of *Event detection block*.

REFERENCES

[1] S. Cummer, M. Stanley, **Submillisecond Resolution Lightning Currents and Sprite Development: Observations and Implications**. Geophysical Research Letters, v. 26, p. 3205, 1999.

[2] S. A. Cummer, U. S. Inan, T. F. Bell, C. P. Barrington-Leigh, **ELF Radiation Produced by Electrical Currents in Sprites**. Geophysical Research Letters, v. 25, p. 1281, 1998.

[3] S. A. Cummer, S. A. Inan, U. S. Inan, **Measurement of Charge Transfer in Sprite-Producing Lightning Using ELF Radio Atmospherics**. Geophysical Research Letters, v. 24, p. 1731, 1997.

[4] B. Widrow, J. R. Gloverr, J. M. McCool, et al., **Adaptive Noise Cancelling: Principles and Applications**, Proc. IEEE, vol 63, pp. 1692–1716, 1975.

[5] B. Widrow, S. D. Stearns, **Adaptive Signal Processing**. Prentice-Hall, Englewood Cliffs, N. J., 1985.

[6] M. H. Hayes, **Statistical Digital Signal Processing and Modeling**. Georgia Institute of Technology,1996.

[7] S. A. Cummer, U. S. Inan, **D Region Ionospheric Remote Sensing Using VLF Radio Atmospherics**, Radio Science, v. X, p. X, 1998.

Adaptivni filtar za ekstrakciju signala pogonjenog događajem. U ovom radu predstavljen je novi tip adaptivnog filtra za klasu signala pogonjenih događajem onečišćenih sumirajućom, pseudoperiodičnom smetnjom. Adaptivni filtar pogonjen događajem nastaje razvojem iz Widrowog adaptivnog filtra, iskorištavajući specifična svojstva signala pogonjenih događajem kao što su nepredvidiv trenutak pojave signala i njegovo vremenski ograničeno trajanje. Ovaj filtar se može primijeniti kada je referentni ulaz u Widrow filtar, koji treba biti koreliran sa smetnjom, nedostupan, ali je sa sigurnošću poznato da je pseudoperiodičan. Eksperimentalni rezultati potvrđuju napredna svojstva predloženog rješenja.

Ključne riječi: adaptivni filtar, detekcija događaja, LMS, pseudoperiodična sumirajuća smetnja, RLS, elektromagnetski signal atmosferskog pražnjenja

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