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Noise Cancellation in DSSS by Using Adaptive LMS Filter in Fractional Domine Methods

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ABSTRACT:- Adoptive filter techniques are used for noise cancellation in speech signal. The voice carrying DSSS signal are normally corrupted by noise and the voice signal and noise signal are found to time variant. In such a citation adaptive filtering becomes very relevant. A blocked Adoptive LMS (BLMS) algorithm has been developed in this paper for the cancellation of noise in Direct Spread Spectrum System (DSSS). The application of BLMS algorithms based on adoptive filters in fractional domain on DSSS voice signal indicate an significant improvement in the noise suppression by 0.46 dB. The BLMS algorithms developed is found to be efficient and simple to adopt for applications.

KEYWORDS: Adaptive noise cancellation (ANC), LMS Algorithm, Adaptive filtering. Direct Spread Spectrum System (DSSS).

I. INTRODUCTION

The development of Industrial equipment such as engines, transformers, compressors etc demands acoustic noise cancellation. The conventional techniques such as enclosures, boundaries and silencers are adopted for acoustic noise cancellation will significantly reduce the undesirable noise signal [1][2]. Foe low frequency applications the techniques mostly used for noise cancellation are not very effective and highly-priced. Mechanical vibration generates different types of noise which creates serious issues in verbal communication and electronic devices. Signal processing techniques can be used for reducing the effect of acoustic noise and for extracting, improving, storing, and transmitting information signals.

The design of adoptive filters will have constraints as they do not have constant filter coefficients and no priori expertise. The filters with adjustable parameters and adopts to the signal environment is referred to as adaptive filter. Adaptive filter change their coefficients to reduce an error signal and may be realized as Finite Impulse Response (FIR) filter. Infinite Impulse Response (IIR) filters in transform domain [4]. The most commonly used form of adaptive filter is the transverse filter using Least Means Square (LMS) algorithm [5].

Fractional domine like FFT has received lot of attention for making improvements on approach to AIC tools. This idea was forwarded by V.Namias [9] and extensively applied in adaptive signal processing field. FFT represents single variable and the pass domine problems are solved by FFT Filtering algorithm 10]. The accelerated process of knowledge conversion with the aid of superimposing a pseudo random (PN) sequence on each information bit, the data can be spread over a wide bandwidth and not susceptible to interference. Wide band interference in direct-sequence code division has more than one access in communications, [11, 12]. The direct – sequence spreading of the signal increases the bandwidth of the transmitted message and easy to monitor the message. While monitoring jammers within the time–frequency (TF) domain, the TF-situated domain applied before dispreading increases the robustness to interference [13]. The FFT of a signal of chirp can be interpreted as a rotation in the time-frequency plane. The FFT relationship with time-frequency representation has been presented [14].

Adaptive filters employ least mean squares (LMS) algorithms and the adaptation is normally realized in time domain [8, 9]. The multi- aspect chirp-form indicators, [15] suggests that in the fractional Fourier domain the modified sign of insufficiently in long commentary periods. To remove an unwanted



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signal an appropriate Least Mean Square (LMS) algorithm adaptive filter can be designed. The LMS algorithm begins with an assumption that the weight vector is zero at the start. As the iteration continues, the error is minimized until its top-rated degree.

In the present paper the noise is treated as undesirable signal independent of the noise generating media such as electrical, acoustic, vibration etc. The adaptive algorithms can be applied to all kinds of noise independent of the noise source.

The adoptive noise cancellation algorithm is aimed to send the corrupted signal through a filter that tends to suppress the noise without affecting the signal at the same time. The filter adapts to the signal for the changes with noise. This means that the filter does not require a priori expertise of signal or noise trends. An adaptive noise cancellation (ANC) method efficiently attenuates the low frequency noise. The FIR filters is probably the most practical and commonly used for adaptive filtering

A cellular verbal exchange receiver must have a wider frequency range and real time signal processing capabilities. An adaptive digital filter is option that can improve the receiver sensitivity under for low SNR condition. Adaptive filters can process information without prior knowledge of the signal environment of the acquired signals. The adaptive digital filters with high speed data processing have become an effective tool for signal processing with noise suppression.

II. LEAST MEAN SQUARE ALGORITHM

The least-mean-square (LMS) algorithm can be used in adaptive signal processing It is known for its simplicity and steady-state performance Consider in general an N -tap filter, with the weight vector W(n) at time instant as denoted in fig.1

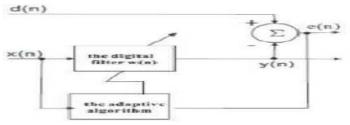


Fig .1 Adaptive LMS algorithm

The estimated signal is given by , $w(n) = [w_1(n)w_2(n) \dots w_1(n - N + 1)]^T \dots 1$ Let the input sequence be $x(n) = [w_1(n)w_2(n) \dots w_1(n - N + 1)]^T$ be its representation containing the past N samples of $\{x(N)\}$. The filter output $y(n) = w^T(n) x(n)$ and it follow a desired signal d(n). The estimated error e(n) is defined by

$$\mathbf{e}(\mathbf{n}) = \mathbf{d}(\mathbf{n}) - \mathbf{y}(\mathbf{n}) \dots \dots 2$$

After estimating the gradient vector we get a relation by which we can update the tap weight vector recursively as: $w(n + 1) = w(n) + \mu[d * (n)w(n)].....3$

Where μ is the step – size parameter

 $\mu^{h}(n)$ = Hermit of a matrix u

d * (n) =Complex Conjugate

We may write the result in the form of three basic relations as follows:

1. Filter output: $y(n) = w^h(w)u(n)$

2. Estimation error or error signal: e(n) = d(n) - y(n)

3. Tap weight adaptation: $w(n + 1) = w(n) + \mu u(n)e^{*}(n)$

The estimated error e(n) is defined by Equations (1) and (2). The computation e(n) is based on the current estimate of the tap weight vector W(n). Note that the second term, u(n)e * (n) on the right hand side of equation (3) represents



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the adjustments that are applied to the current estimate of the tap weight vector W(n). The iterative procedure is start with an initial guess W(0). The algorithm described by equations (1) and (2) is the complex form of the adaptive least mean square (LMS) algorithm. At each iteration or time update, this algorithm requires knowledge of the most recent values u(n), d(n)w(n)

III. NOISE CANCELLATION

-the basic concepts adoptive noise cancellation is shown in figure 2.

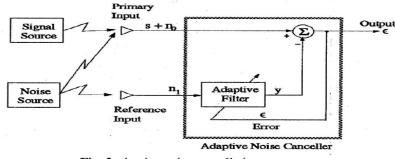


Fig .2.adaptive noise cancellation concept

A signal **s** is transmitted over a channel to a sensor that also receives a noise n_0 uncorrelated with the signal. The primary input is combination of both signal and noise $s + n_0$. A second sensor receives a noise n_1 uncorrelated with the signal but correlated with the noise n_0 . This sensor provides the reference input. This noise n_1 is filtered to produce an output y that is as close n_0 . This output of the adaptive filter is subtracted from the primary input $s + n_0$ to produce the system output. $z = s + n_0 - y$

The reference input processed by an adaptive filter is also shown in figure 2. An adaptive filter automatically adjusts its own impulse response. Adjustment is accomplished through an algorithm. The filter can operate under changing conditions and can readjust itself continuously to minimize the error signal.

In noise cancelling systems the practical objective is to produce a system output $z = s + n_0 - y$ that is a best fit in the least squares sense to the signal *s*. This is achieved by output feedback to the adaptive filter and adjusting the filter through an LMS adaptive algorithm to minimize total system output power. In an adaptive noise cancelling system, the system output serves **as** the error signal for the adaptive process. The prior knowledge of the signal **s** or of the noises n_0 and n_1 would be necessary before the filter could be designed to produce the noise cancelling signal **y**.

Assume that s, n_0 , n_1 and y are statistically stationary and have zero means. Assume that s is uncorrelated with n_0 and n_1 , and suppose that n_1 is correlated with n_0 . The output.

$$Z = s + n_0 - y \dots 4$$

 $z - s = n_0 - y \dots 5$

Adapting the filter to minimize the total output power is causing the output \mathbf{z} to be a best least squares estimate of the signal \mathbf{s} . The output \mathbf{z} will contain the signal \mathbf{s} plus noise. From (5), the output noise is given by $(n_0 - y)$. Since minimizing $E[z^2]$ minimizes $E[(n_0 - y)^2]$ minimizing the total output power minimizes the output noise power.



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Since the signal in the output remains constant, minimizing the total output power maximizes the output signal to noise ratio

$$E\left[z^2\right] = E\left[s^2\right]$$

When

$$E\left[\left(n_0-y\right)^2\right]=0$$

At $y = n_0$ and z = s

Minimizing the output power causes the output signal to be perfectly noise free.

IV. BLOCK LMS (BLMS) ALGORITHM

Let the BLMS based adaptive filter input sequence be x(n), which is divided into non-overlapping blocks of length P each by means of a serial to parallel converter The block of data produced are sent to an FIR filter of length N, one block at a time. After the collection of each block of data samples the tap weights of the filter are updated, The adaption of the filter proceeds on a block-by-block basis

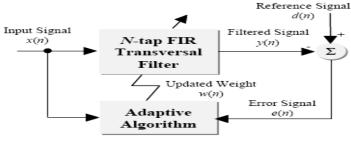


Fig.3. BLMS algorithm

An schematic of the adaptive filter is shown in Figure 3, where d(n) is a desired response, y(n) is the actual output of a programmable digital filter driven by a reference input signal x(n), and the error e(n) is the difference between d(n) and y(n). The function of the adaptive algorithm is to adjust the digital filter coefficients to minimize the mean-square value of e(n)

$$W(i + 1) = W(i) + \mu[RW - P]$$
(6)

Where,

$$R = \frac{1}{L} \sum_{r=0}^{L-1} x(iL+r) x^{t}(iL+r)$$
$$P = \frac{1}{L} \sum_{r=0}^{L-1} x(iL+r) d(iL+r)$$

L is the Block length, R is the autocorrelation matrix and P, cross correlation vector. The weight update equation is,

The

Output is

$$y(iL + r) = W^{t}(i)x(iL + r)....(9)$$

is



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Than intervals block representation BI,

The step size in intervals representation IS

$$BI = \frac{2}{4L\mu_B\lambda_{max}}$$
$$BI = \frac{2}{4\mu_B\lambda_{max}}$$
$$0 < \mu_B < \frac{2}{L\lambda_{max}}$$

Step is bounded as

Results and discussion

-To demonstrate the application of the BLMS algorithm for noise suppression in a acoustic signal an typical input voice signal selected for the analysis is shown in figure 4.It may be noted that the voice signal is associated with significant noise.

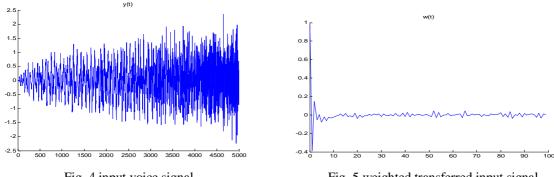
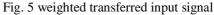
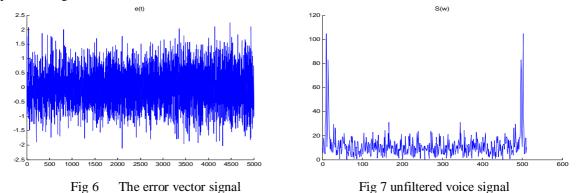


Fig .4 input voice signal



The correspond weighted transferred input signal derived from of the BLMS algorithm using equation 6 is shown in figure 5. The range of estimated weighted signals corresponding to input voice signal without filtering. The error vector derived from equation 8 of the BLMS algorithm is plotted in figure 6. The figure shows the maximum errors present in the input voice signals.



The unfiltered voice signal s(w)with noise derived from equation 9 of the BMLS algorithm is shown in figure 7. The figure indicates clearly the extent of noise present in the input voice signal.

The final noise supressed out out signal derived from equation 9 of the BLMS algorithm is shown in figure 8. It is evident from the figure 5 and 6 that there is a significant noise supression in the input voice signal ~ 0.48 dB.



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Fig. 8 Noise supressed out put signal

The results of the analysis on the input voice signal clearly indicates that the adoptive filter BLMS algorithms applied for the noise supression show an improvement in the noise supression ~0.46 dB is a very efficient technique for the supression of noise in DSSS voice signals

V. CONCLUSIONS

The following conclusions can be drawn from the results presented

- (1) The adoptive filters in fractional domain can be effectively used for suppression of noise in the DSSS voice signals
- (2) The BLMS algorithms developed for adoptive filters and the corresponding equations can be used for deriving input signal, estimated weighted signal, noise signal and final noise suppressed output signal.
- (3) The adoptive filters in fractional domain and BLMS algorithms are found to be efficient method for suppression of noise in voice DSSS signals to the extent of ~0.46 dB.

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