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Adaptive Filter for Removal of Impulsive Noise and Its Comparison with LMS Algorithm

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ABSTRACT
Adaptive filters are used in digital signal processing and have many applications such as echo cancellation, noise cancellation, system identification, prediction. They are mainly used whenever the statistical characteristics of the signal is said to be non-stationary in nature. Coefficients of adaptive filter are continuously and automatically adapted to given signal in order to get desired response and improve the performance. Impulsive noise is the most damaging type of noise which destroys complete information so it becomes necessary to remove it. In this paper an adaptive algorithm is proposed to remove impulsive noise and it is compared with standard LMS algorithm. This method gives satisfactory results.
***Keywords* –**Adaptive filter, Impulsive noise, Simulink, coefficients, LMS algorithm.

I. INTRODUCTION

There are many digital signal processing applications in which second order statistics cannot be specified. It includes channel equalization, echo cancellation and noise cancellation. For such applications filters with adjustable coefficients are used. Filters with fixed coefficients are suitable when characteristics of signal and noise are stationary or known. They are not applicable when characteristics of signal & noise vary with time. An adaptive filter has an adaptive algorithm that is meant to monitor the environment & vary the filter transfer function accordingly. There are many adaptive algorithms but most of them assume that the adaptive system obtains an error following the Gaussian distribution. However the noise encountered is more impulsive than actually predicted by a Gaussian distribution. For this reason many adaptive algorithms robust to impulsive noise are developed for proper operation of filter [6]-[8]. Impulsive noise is most damaging type of noise so adaptive filtering is used to remove it.The brief theory of system identification method is given. Detailed algorithm description for impulsive noise removal is given. Results with included noise and after its suppression are shown. The paper is organized as follows. Section II describes scheme of an adaptive filter. Section III describes basic LMS filter. A modified algorithm is given in Section IV and simulation results are shown in section V.

II. ADAPTIVE FILTER

The Adaptive filters are time-varying since their parameters are continuously updated in order to meet a performance criterion.

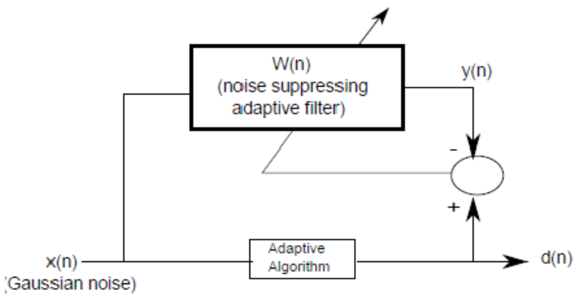

Fig.1. system identification

Here, x(n) is an input of adaptive filter, y(n) is output of adaptive filter, d(n) is the desired response and estimation error is given as e(n)=d(n)-y(n). An adaptive system consists of two modules, adaptive system and adaptive algorithm. Adaptive system calculates the output signal in response to the input and generates an estimation error by comparing output with the desired response. Adaptive algorithm adjusts the filter parameters automatically according to the estimation error so that the adaptive system output and desired signal are equal [2].

The adaptive algorithm used to suppress impulse noise is based on a system identification application with impulse noise contribution [1]. In this system input signal x(n) is applied to both adaptive filter and unknown system. The output of the unknown system d[*n*] becomes the output of the entire system. After convergence the adaptive filter output

$y[n]$ will approximate d[n] in an optimum (usually least mean squares) sense. The output of the adaptive filter y(n) is subtracted from the output of the unknown system resulting in a desired signal d(n). The resulting difference is an error signal e(n) is used to manipulate the filter coefficients of the adaptive system trending towards an error signal of zero.

III. LMS ALGORITHM

It was derived by Widrow and Hoff. It is a stochastic gradient algorithm in that it iterates each tap weight of the transversal filter in the direction of the instantaneous gradient of the squared error signal with respect to the tap weighting question.

The weights are updated according to

$$W(n+1)=w(n)+\mu e(n)\, x^*(n) \qquad (1)$$

Where x(n) is input vector, w(n+1) is value of new weight at time n+1, w(n) is value of old weight at time n. μ is the step size and its value is chosen between $0 \le \mu \le 2/\lambda max$. The larger step sizes make the coefficients to fluctuate more and eventually become unstable.

$e(n)=d(n)-y(n)$, Where $y(n)= \Sigma w_n(k)x^*(n-k)$.

This algorithm is most popular due to its simplicity. Its main drawback is convergence is slow due to step size restriction which depends on the Eigen value of the autocorrelation matrix of the input signals.

IV. NEW ADAPTIVE ALGORITHM

Adaptive filters are based on minimization of a certain cost function. The most widely cost function is the mean square error. This cost function implicitly assumes the error produced by the adaptive system to be Gaussian. In many real world problems the noise encountered is more impulsive than that predicted by a Gaussian distribution. An obvious option is to use a different cost function. A well known alternative, based on robust statistics is the use of a convex combination of cost functions of the form J(n)=E(|e(n)^r|, where r is a parameter and n denotes discrete time. The main drawback of this type of function is the choice of the optimal values of r.

We have chosen the cost function

$$J(n) = \frac{\log\,[\cosh\,(\beta . e(n))]}{\beta} \qquad (2)$$

Where β controls the concavity in the cost function about the origin and the sensitivity to large outliers in the value of e(n)[3]. By using the Delta rule for the update of the coefficients,

$$w_{n+1} = w_n + \mu . \tanh[\beta . e(n)] \qquad (3)$$

In equation (3) proposed cost function is noise-robust.

The hyperbolic tangent saturates to ±1 for extreme values.

The contribution of the outliers in e(n) to the coefficient updates is limited and easily controlled with β. This equation is easy for hardware implementation.

$\tanh(\beta \cdot e(n))$

$$= \begin{cases} \mathrm{sign}(e(n)), & \text{if } |e(n)| > 1/\beta \\ -e(n).|e(n)|.\beta^2+2\beta.e(n), & \text{if } |e(n)| \le 1/\beta \end{cases} \quad (4)$$

Therefore, the update of the algorithm coefficients in (3) is given by,

$$w_{n+1} = \begin{cases} w_n + \mu\,.\mathrm{sign}\,[e(n)].x_n, & \text{if } |e(n)|>1/\beta \\ w_n + \mu\,[2\beta-\beta^2.\,|e(n)|]e(n)\,x_n & \text{if } |e(n)|\le 1/\beta \end{cases} \quad (5)$$

The value of β can be modified iteratively according to the evolution of the error in the learning process. We have taken the classical threshold of three standard deviations to consider a pattern as an outlier. Moreover, since tanh(|β|) =|0.96|, i.e., a value close to unity, the parameter β can be obtained as follows:

$$\beta = \frac{3}{m+3.\sigma} \qquad (6)$$

Where m is the mean value of the error signal and σ is its standard deviation [3]. This threshold for the outliers is modified providing different levels of immunity to impulsive noise. The calculation process for updating coefficients requires the values of e(n), β and μ. Most of the applications in adaptive filtering have zero mean signals. When the number of samples is high, the value of m can be rounded to zero. A fixed value for β is not necessary as it controls the outlier immunity. The standard deviation or its square (the variance) can used to estimate the value of β [9]. Thus, in equation (6) β can be approximated as $1/\sigma^2$. This simplifies calculation of β.

$$\sigma^2(n) = \frac{n-1}{n}.\sigma^2(n-1) + \frac{1}{n-1}(e(n)-m)^2 \qquad (7)$$

Calculation of y(n) is done according to following equation. In this case L=9.

$$y(n) = \sum_{k=0}^{m-1} x(n-k).w_n(k) \qquad (8)$$

The estimation error can be calculated as e(n)=d(n)-y(n). This is nothing but difference between desired response and output of an adaptive filter. Again equation (7) can be approximated for high number of samples as

$$\sigma^2(n) = 0.95.\sigma^2(n-1) + \frac{e^2(n)}{n} \qquad (9)$$

The next step is calculation of next sample coefficients which is calculated according to (5) substituting value of β.

V. RESULTS AND DISCUSSION

Adaptive filter system which is robust to impulsive noise is described here. Simulation is done using MATLAB simulink. It was tested on a system identification application with impulsive noise contribution. Here x(n) is the stimulus signal given directly to both unknown system and adaptive filter. The unknown system is an FIR filter. Signal corrupted with noise, desired signal and filtered signals are shown in both figures which show system's effectiveness. Nowadays, the use of FPGAs is increasing. They combine main advantages of DSP and ASIC processors, since they provide both a programmable and a dedicated hardware solution. So this algorithm can be used further for hardware implementation.

Fig.2. Simulation of ECG signal corrupted with impulsive noise and its suppression using LMS algorithm

Fig.3. Simulation of ECG signal corrupted with noise and its suppression using new approach.

VI. CONCLUSION

A new adaptive filter approach is described here and compared with the standard LMS algorithm. Simulations validate effectiveness of the new adaptive algorithm which gives satisfactory and smooth results. This algorithm can be applied in any system having impulsive noise to increase accuracy and efficiency and its hardware implementation can also be done.

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