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VOICE IMPROVEMENT USING ADAPTIVE FILTER

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ABSTRACT

The removal of noise from speech signals has applications ranging from cellular communications to front ends for speech recognition systems. In this paper, an optimal estimate of adaptive filtering using least mean algorithm has been implemented for the observed noisy speech. The algorithm yields better results in noise reduction with significantly less distortions and artificial noise.

In this paper, it gives the concept of speech enhancement in a practical approach, using different speech enhancement algorithms. Extraction of high resolution information signals is important in all practical applications. The Least Mean Square (LMS) algorithm is a basic adaptive algorithm has been extensively used in many applications as a consequence of its simplicity and robustness. In this paper we present a novel adaptive filter for de-noising the speech signals based on unbiased and normalized adaptive noise reduction (UNANR) algorithm. The UNANR model does not contain a bias unit, and the coefficients are adaptively updated by using the steepest-descent algorithm. The adaptive filter essentially minimizes the mean-squared error between a primary input, which is the noisy speech, and a reference input, which is either noise that is correlated in some way with the noise in the primary input or a signal that is correlated only with speech in the primary input. To measure the ability of the proposed implementation, signal to noise ratio improvement (SNRI) is calculated.

Keywords- Adaptive filtering, Digital signal processing (DSP), LMS, NLMS.

INTRODUCTION

Digital signal processing (DSP) has been a major player in the current advancements such as noise filtering, system identification, and voice prediction. Standard DSP techniques, however, are not enough to solve these problems quickly and obtain acceptable results [2]. Adaptive filtering techniques must be implemented to promote accurate solutions and a timely convergence to that solution. Speech is most primary human communication for that reason there exists a big trend to increase & improve telecommunication. However, the background noise is an important handicap. If it is joined with other distortion, it can seriously damage the service quality. The acoustical environment is defined as a set of transformation that affects the speech signal, since the moment it leaves speakers mouth until it is in digital form. There are among others, two main sources of distortion are acoustic noise & channel distortion. Acoustic noise is like a fan running in the background, a door slam, a conversion among others it is in our common daily life. It can be stationary or non-stationary. Stationary noisy is one made by a computer fan or air conditioning it has a spectral power density that does not change over time. Non stationary noise caused by door slam radio, TV voices has statistical properties that change over time. A signal captured with speaker close to the microphone has a little noise & reverberation. However if the microphone is far from the speakers mouth it can pick up a lot of noise and reverberation. Channel distortion can be caused by the frequency response of a microphone, the presence of an electrical signal of the local loop of a telephone line etc. Reverberation caused by the reflection of acoustic waves of the walls and other objects can also dramatically alters the speech signal[3].The presence of background noise in speech significantly reduces the intelligence of speech noise reduction or speech enhancement algorithms. These algorithms are used to suppress such background noise and improve the perceptual quality with intelligibility of speech. Removing various type of the noise and the inherent complexities of the speech noise reduction techniques usually have a trade-off between the amount of noise removal & speech distortion introduce due to processing of the speech signal. Several techniques have been proposed for this purpose in the area of speech enhancement, like Adaptive filtering method using LMS, UNR algorithms. The performance of these techniques depends on the quality & intelligibility of the processed speech signal.

LITERATURE SURVEY

a. Sambur M. ITT, Nutley N. J. [2] described that a novel constrained-stability least-mean-squares algorithm for filtering speech sounds is proposed in the adaptive noise cancellation problem. It is based on the minimization of the squared Euclidean norm of the weight vector change under a stability constraint over the a posteriori estimation errors. To this purpose, the Lagrangian methodology has been used in order to propose a nonlinear adaptation in terms of the product of differential input and error.

b. M. Chakraborty and H. Sakai,[7] in their paper, the author applied a FAP algorithm on adaptive noise cancellation setup. The simulation results were compared with the classical adaptive filters, such as LMS, NLMS, and RLS algorithms, for attenuating noise in speech signals. In each algorithm, the mean square error and the output of filter were presented. The simulation results show that the convergence rate of this algorithm is comparable with the RLS algorithm. Also, the optimum values of the FAP algorithm were calculated through experiments. In this algorithm, the number of iterations to be performed at each new sample time is a user selected parameter giving rise to an attractive and explicit tradeoff between convergence/tracking properties and computational complexity.

c. Sayed A. Hadei, M. lotfizad [4] studied in many application of noise cancellation, the changes in signal characteristics could be quite fast. This requires the utilization of adaptive algorithms, which converge rapidly. Least Mean Squares (LMS) and Normalized Least Mean Squares (NLMS) adaptive filters have been used in a wide range of signal processing application because of its simplicity in computation and implementation. The Recursive Least Squares (RLS) algorithm has established itself as the ultimate adaptive filtering algorithm in the sense that it is the adaptive filter exhibiting the best convergence behavior.

ADAPTIVE FILTER

A. Overview of Adaptive Filter:

The earliest work on adaptive filters may be traced back, during which time a number of researchers were working independently on theories and applications of such filters. From this early work, the least-mean-square algorithm emerged as a simple, yet effective algorithm for the design of adaptive transversal (tapped-delay-line) filters. The LMS algorithm is a pattern-recognition machine known as the adaptive linear element, commonly referred to as the 'Adaline'. The LMS algorithm 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 weight. Let denote the tap-weight vector of the LMS filter, computed at iteration (time step) N. The adaptive operation of the filter is completely described by the recursive equation (assuming complex data) is the tap-input vector, the desired response, and μ is the step-size parameter. A more efficient method is to use an adaptive filter. By such a device we mean one that is self-designing in that the adaptive filter relies for its operation and a recursive algorithm which makes it possible for the filter to perform satisfactorily in an environment where complete knowledge of the relevant signal characteristic is not available.

An Adaptive process, which involves the automatic adjustment of the tap weight of the filter in accordance with the estimation error. Thus the combination of these two processes working together constitutes a feedback loop around the LMS algorithm, as illustrated in fig 1. First we have a transversal filter, around which the LMS algorithm bur is built; this component is responsible for performing the filtering process. Second we have a mechanism for performing the adaptive control process on the tap weight of the transversal filter, hence the designation "adaptive weight control mechanism" in fig 3.1.We have used a hot over the symbols for the tap-weight vector to distinguish it from the value obtained by using the steepest descent algorithm. Equivalently, we may write the result in the form of three basic relations as follows

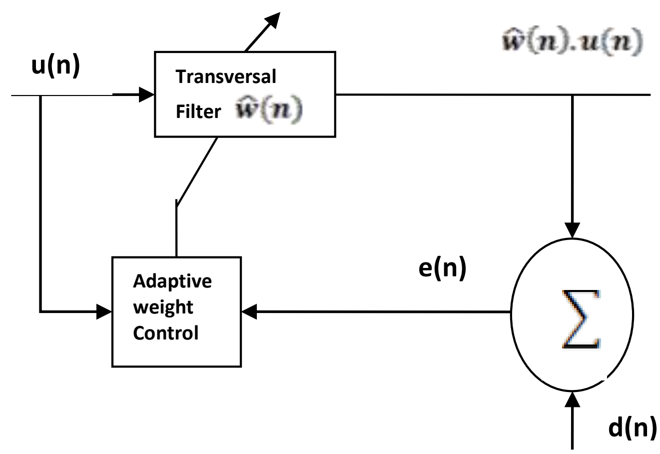

Figure1 Basic block diagram of Adaptive Processing

$\widehat{W}(n+1) = \hat{w} + \mu\, u(n)e^{*}(n)$ --

- Filter output: $Y(n) = \hat{w}(n).u(n)$ ----- (1)
- Estimation error: $E(n) = d(n) - y(n)$ ----- (2)
- Tap-weight adaptation:

$\widehat{W}(n+1) = \hat{w} + \mu\, u(n)e^{*}(n)$ ---------- (3)

Equation (3.1) and (4.2) define the estimation error *e(n)* the computation of which is based on the current estimate of the tap-weight vector $\hat{w}(n)$. Note that the second term $\mu u(n)\ e^{*}(n)$, on the right-hand side of equation (3.3) represents the correlation that is applied to the current estimate of the tap-weight vector, $\hat{w}(n)$. The interactive procedure is started with an initial guess $\hat{w}(0)$.

sThe algorithm described by equation (3.1) to (3.3) is the complex form of the adaptive least-mean-square (LMS) algorithm. At each iteration or time update, it also requires knowledge of the most recent values *u(n)*, *d(n)* & *w(n)*.

METHODOLOGY

A. LMS Algorithm (LMS Filtering**)**

There are many algorithms used to adjust the coefficients of the digital filter in order to match the desired response as well as possible. The LMS Algorithm is the more successful of the algorithms because it is the most efficient in terms of both storage requirement and indeed computational complexity. Similar to the steepest descent approach on which the LMS algorithm is based upon, the basic LMS algorithm updates the filter coefficients after every sample [2].The simplicity of the LMS algorithm and ease of implementation means that it is the best choice for many real-time systems. There are also other LMS based algorithms, which include the complex LMS, the block LMS algorithm and the Time sequenced LMS algorithm.

B. UNANR Algorithm (UNANR Filtering)

It present a novel unbiased and normalized adaptive noise reduction (UNANR) system to suppress non stationary noise in speech signals using the frame work of [8] and [9]. The UNANR learning rate demonstrate that the adaptive noise-reduction system that includes the UNANR model can effectively eliminate random noise in speech recordings, leading to a higher SNR improvement than that with the same system using the popular least-mean-square (LMS) filter. To prove the ability of UNANR we compared its functioning with LMS and NLMS based realizations. The UNANR model of the system performs the function of adaptive noise estimation.

The adaptation process of the UNANR model is designed to modify the coefficients that get convolved with the reference input in order to estimate the noise present in the given speech signal. Such a goal can be achieved by optimizing the UNANR coefficients according to the steepest-descent algorithm.

C. The Steepest –Descent Method

The surface of the mean square output error of an adaptive FIR filter, with respect to the filter coefficients, is a quadratic bowl-shaped curve, with a signal global minimum that corresponds to the LSE filter coefficients. Fig 4.2 illustrates the steepest-descent [3] search for the minimum mean square error coefficient. The search is based on taking a number of successive downward steps in the direction of negative gradient of the error surface. Starting with a set of initial values, the filter coefficients are successively updated in the downward direction, until the minimum point, at which the gradient is zero, is reached.

for the minimum error point

The steepest-descent adaptation method can be expresses as

$$w(n+1) = w(n) + \mu \{\delta E[e^2 (n)] / \delta w(n)\} \qquad \text{---(4)}$$

Where is μ the adaptation step size

and $e(n) = x(n) – w^T(n)y(n)$.

The gradient of the mean square error function is given by

$$\{\delta E[e^2 (n)] / \delta w(n)\} = - 2 r_{yx} + 2R_{yy} w(n) \qquad \text{----------(5)}$$

where $r_{yx} = y(n)x(n)$ and $R_{yy} = y(n)y^T(n)$

Substituting equation (4.3.2) in (4.3.1) we get

$$w(n+1) = w(n) + \mu [-2 r_{yx} + 2R_{yy}w(n)]$$

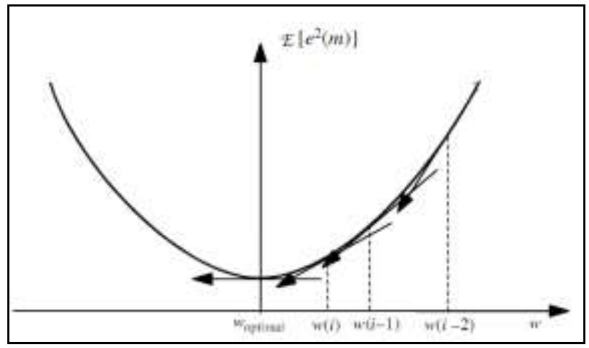

Fig 2 Gradient search of mean square error of surface

Vector-valued adaptation step size: Instead of using a single scalar-valued adaptation step size, μ we can use a vector-valued adaptation step size, $\mu = [\mu 0, \mu 1, \mu 2, \mu 3, \ldots\ldots, \mu_{p-1}]$, with each filter coefficients, w_k, having its own adaptation step size, μ_k.

The requirement that an adaptive filter has to satisfy is to find a solution for its tap-weight vector. In general, this procedure is quite straight forward. However it presents serious computation difficulties, especially when the filter contains a large number of tab weights & when the input data rate is high.

RESULT

In this system, we are showing result for 12 speech samples with their different noise levels. As shown in the table below with their signal to noise ratio:

Speech Sample	Before Filtering (SNR in dB)	After using LMS	After Filtering using UNR
Sample-I	28.4973	PSNR = 42.9626 dB	PSNR = 49.7032dB
		RMSE = 0.00011	RMSE = 5.0629e-
		Time = 0.2249 sec	Time = 0.6411 sec
Sample-II	17.5264	PSNR = 30.519dB	PSNR = 37.132 dB
		RMSE = 0.000433	RMSE = 0.000202

		Time = 0.21238 sec	Time = 0.62172 sec
Sample-III	23.2201	PSNR = 33.8718 dB	PSNR = 41.9642 dB
		RMSE = 0.000257	RMSE = 0.000101
		Time = 0.22212 sec	Time = 0.62613 sec
Sample-IV	10.2964	PSNR = 20.8513 dB	PSNR = 27.5632 dB
		RMSE = 0.000877	RMSE = 0.000404
		Time = 0.24031sec	Time = 0.63726 sec
Sample-V	.SNR = 1.6915	PSNR = 16.7419 dB	PSNR = 22.8644 dB
		RMSE = 0.002251	RMSE = 0.001112
		Time = 0.20378 sec	Time = 0.63142 sec
Sample-VI	14.5179	PSNR = 29.0258 dB	PSNR = 35.7243dB
		RMSE = 0.000547	RMSE = 0.000253
		Time = 0.18804 sec	Time = 0.63392 sec
Sample - VII	4.6015	PSNR=34.139dB	PSNR=41.84dB
		RMSE=0.00720	RMSE=0.0029
		Time=0.864 sec	Time=2.93 sec
Sample – VIII	37.7152	PSNR=62.135dB	PSNR=69.61dB
		RMSE=0.00020	RMSE= 8.783e-
		Time=0.834 sec	Time=2.99sec
Sample – IX	37.2245	PSNR=56.47dB	PSNR=70.80dB
		RMSE=0.00045	RMSE=8.782 e-0
		Time=0.814 sec	Time=2.91sec
Sample –X	4.8129	PSNR=31.99dB	PSNR=41.49dB
		RMSE=0.0170	RMSE=0.0057
		Time=0.851 sec	Time=2.88sec
Sample -XI	38.5362	PSNR=58.42dB	PSNR=69.35dB
		RMSE=0.00030	RMSE=8.282 e-
		Time=0.870 sec	Time=2.88sec
Sample - XII	38.1859	PSNR=61.74dB	PSNR=71.238Db
		RMSE=0.00026	RMSE=8.783 e-

Results are calculated by using Least Mean Square (LMS) and Unbiased Normalized Adaptive Noise Rejection (UNANR) filters.

The filtering process is carried out by using adaptive filters with algorithm LMS and UNANR methods. Hence, we measure different parameters like Peak signal to noise ratio (PSNR), Root mean square error (RMSE), Time (Conversion rate). After evaluation, we analyze that the improvement after filtering by UNANR method is better than LMS filtering method. The improvement of PSNR is approximately 50% of LMS filtering. Due to this improvement the RMSE is less in UNANR than LMS filter.

CONCLUSION

In this paper, the concept of adaptive digital filtering is introduced by conveying an everyday application in echo cancellation in the telephone system. The LMS filter algorithm and UNANR model is introduce as the main adaptive algorithm in the time domain and its operation is examined. An alternative representation of signals in the frequency domain is then introduced, which allows the convolution of two signals to be calculated in a much more efficient manner. The cost of transforming the signals to and from the frequency domain must be accounted for however and for short filter impulse responses it is too high to allow frequency domain filtering replace time domain filtering. From this paper we conclude that the signal to noise ratio of filtered speech is much higher than the noisy speech signal and the convergence rate of LMS algorithm compared to UNR algorithm is also high.

FUTURE SCOPE

There are many possibilities of expanding this project in particular investigation of its implementation using integer arithmetic leading to possibilities for efficient hardware implementation. Further investigation of the adaptive equalizer implementation could also be carried out. Analysis of the computational savings and the benefits obtained by using an adaptive filter in the frequency domain as opposed to the time domain in a real world application where the impulse response is relatively long would certainly be worth some investigation.

In future, the person which driving car, automotive vehicle can receive the incoming call and make the communication of speech. We also use the different filters with variety of filtering algorithms use for speech enhancement. It is regretted that due to time constraints full investigation in the area of further applications such as hands free telephony was not completed, however there was time to investigate adaptive equalization and it was found that the frequency domain adaptive filter would indeed be applicable here if the impulse response was sufficiently long. Regrettably, there was no time for investigation of the algorithm using integer implementation either.

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