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Implementation of acoustic echo cancellation system onTMS3206713DSK

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***ABSTRACT* - Acoustic echo cancellation (AEC) isan essential part of a hands-free system to eliminate acoustic echo received by a microphone. Acoustic echo cancellers are necessary in applications such as hands-free telephony, speakerphones, mobile phones, car kits, desktop communication, audio and video conferencing, voice command, desktop dictation, speech recognition, and many more. This paper implements an Acoustic Echo Canceller System on TMS320C67xx DSK. The main modules of this echo canceller are an adaptive Filter System employing NLMS (Normalized Least Mean Square) algorithm, a Double-Talk Detector (DTD) and a Non-Linear Processor (NLP). The adaptive filter based on NLMS algorithm is an FIR filter suitable tap length to cancel the echo sufficiently. In place of NLMS based adaptive system, VSS (variable step size) NLMS algorithm and Modified NLMS algorithm based adaptive system is to be implemented on the DSP and the performances of both are to be evaluated and compared.**

INDEX TERMS- Adaptive filters, normalized leastmean square (NLMS), variable step-size NLMS, (NLMS) TMS320C67xx DSK.

I. INTRODUCTION

The rapid growth of technology in recent decades has changed the whole dimension of communications. In such a situation, the use of a regular loudspeaker and a high-gain microphone, in place of a telephone receiver. If a communication is simply between two fixed telephones, then only the electrical echo occurs. However, the development of hands-free teleconferencing systems gave rise to another kind of echo known as an acoustic echo. The acoustic echo is due to the coupling between the loudspeaker and microphone.
Adaptive cancellation of acoustic echoes has become very important. The main modules of this echo canceller are an Adaptive Filter System employing various adaptive methods like Normalized Least Mean Square algorithm NLMS, Variable Step Size NLMS (VSS-NLMS) , a Double-Talk Detector and a Non-Linear Processor.

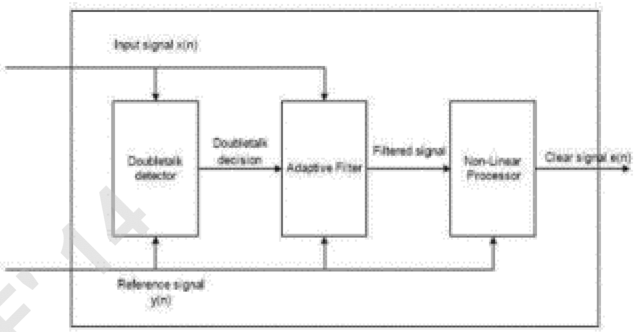


Fig 1: Block Diagram of a Generic Echo Canceller

The paper is organized as follows. Section II describes the AEC Implementation, section III, IV describes the Adaptive filter method, Double talk detection. Experimental results are given in section V while VI concludes the paper.

II. AEC IMPLEMENTATION

The conceptual block diagram illustrating the

Operation of the AEC algorithm is shown in Fig. **2.**

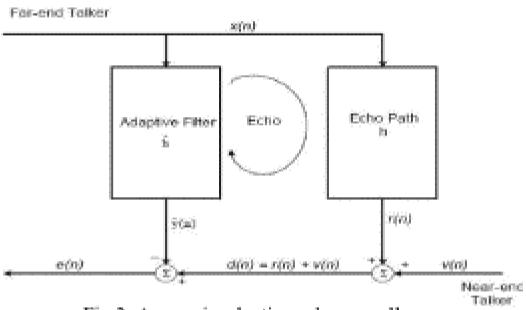


Fig 2. A generic adaptive echo canceller

leads to increasing amount of uncancelled echoes. It sometimes occurs that a well-working echo canceller leaves The estimated echo, yˆ (n), is generated by passing the reference input signal, x (n), through the adaptive filter, hˆ (n) that will ideally match the transfer function of the echo through the adaptive filter, hˆ (n) that will ideally match the transfer function of the echo path, h(n). The echo signal, r(n), is produced when x(n) passes through the echo path. The echo r(n) plus the near-end talker or disturbance signal, v(n), constitute the desired response, for the adaptive canceller. The two signals x(n) and r(n) are correlated since the latter is obtained by passing $x(n)$ through the echo path. The error signal $e(n)$ is given by

$$e(n) = d(n) - \hat{y}(n).$$

In the ideal case, $e(n) = v(n)$, which represents the case when the adaptive echo canceller is perfect. Adaptive echo cancellers also face the problem of double talking when both near and far end speakers talk simultaneously. If double talk occurs, the system may try to adjust the adaptive filter parameters to imperfectly cancel the near-end talker signal. This will result in making large corrections to the estimated echo path, $\hat{h}(n)$, in an attempt to mimic h. In order toavoid this possibility the coefficients in the adaptive filter must not be updated as soon as double talking is detected as illustrated in Fig 3. there is still a possibility of changes occurring in the echo channel during the time that the echo canceller is not updated, which the residual echo. The goal of the nonlinear processor is to block this small unwanted signal if the signal magnitude is lower than a certain small threshold value during single talking..

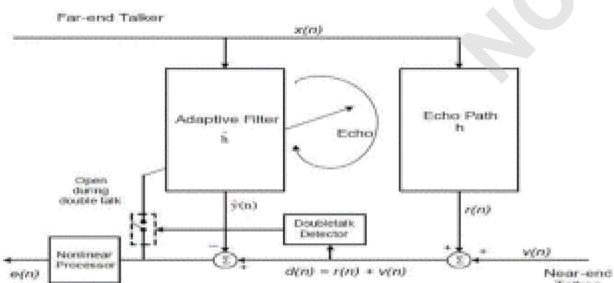
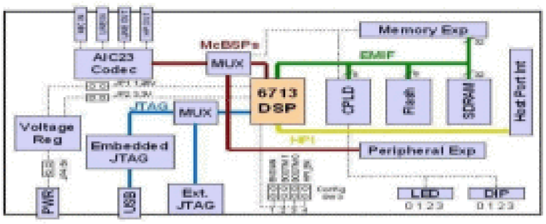


Fig3: Echo Canceller with Doubletalk Detector and Nonlinear Processor

A. IMPLEMENTATION

The hardware implementation of the noise suppression system is done using TMS320C67xx shown as below:



The C6713™ DSK builds on TI's industry-leading line of low cost, easy-to-use DSP Starter Kit (DSK) development boards. The high-performance board features the TMS320C6713 floating-point DSP. Capable of performing 1350 million floating-point operations per second (MFLOPS), the C6713 DSP makes the C6713 DSK the most powerful DSK development board.

some residual uncancelled echo. In such a case, a nonlinear processor is used to remove

The DSK is USB port interfaced platform that allows efficiently developing and testing applications for the C6713. The DSK consists of a C6713-based printed circuit board that will serve as

a hardware reference design for TI s customers products. With extensive host PC and target DSP software support, including bundled TI tools, the DSK provides ease-of-use and capabilities that are
attractive to DSP engineers. The code we developed

takes the noisy speech signal through the „line in terminal of the DSK and the processed output comes out through the speakers or headphones

which are connected to the line out terminal of the DSK.

III. DOUBLE TALK DETECTOR

The proposed DTD algorithm implemented in the present project form an error vector with its initial values equal to zero. Keep the new error sample calculated as the difference between the original echo and output of the adaptive FIR filter of AEC, on the top of the error vector like what we do for the signal vector. Find the norm of the error vector i.e. calculate the error energy or variance. If the error norm is less than a minimum threshold value (say EPSILON = 0.000001), then make the error norm equal to that value to not to let the norm of the error vector equal to zero or a too low value.If the norm of the error vector is less than 0.1 times the norm of the signal vector, which happens when near end speaker is silent, then the effective step size is made equal to step size μ times inverse of the norm of the signal vector as what is done in the NLMS based AEC.If the norm of the error vector is more than 0.1 times the norm of the signal vector, which happens when near end speaker is speaking, then the step size is made equal to the product of step size μ and the inverse of the four times of the sum of the input vector and the error vector norms. Filter coefficient update is done using the update step-size modified in accordance with depending upon whether single talk or double talk scenario. After filter update, the NLP is implemented if the double talk is not detected. This algorithm is simple, robust and is very quick in determining the presence of double talk or not. In the simulation, initially single talk situation exists and after a specified duration, near speech signal which is smaller in length to the far end signal is added to the echo thus error signal contains a mixture of residual echo and the near end speech signal. After the near end speech signal is over, again the far end signal alone remains and the error signal containing only the residual echo is observed.

The output signal is recorded and is observed using the WAVOSAUR software. It can be observed that there exists no divergence of the residual echo during the double talk period and also the convergence time of the residual echo, after the near end speech signal ends, is

IV. ADAPTIVE FILTER

The below given figure shows the block diagram for the adaptive filter method

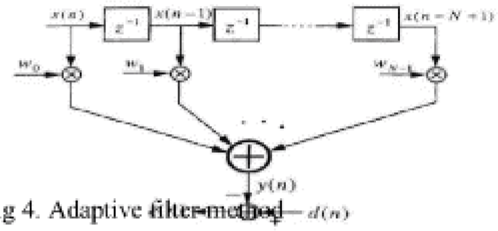


Fig 4. Adaptive filter method

The second class are known as Recursive Least Squares (RLS) adaptive filters.

A. NORMALISED LEAST MEAN SQUARE ALGORITHM

.The normalized least mean square algorithm (NLMS) is an extension of the LMS algorithm which bypasses this issue by selecting a different step size value, μ(n), for each iteration of the algorithm. This step size is proportional to the inverse of the total expected energy of the instantaneous values of the coefficients of the input vector **x**(n).

Initial Condition	$0<\mu_n\le 2$ $x(0)=w(0)=[0,\cdots,0]^T$ γ = a small constant
For each instant of time, k = 1, 2, ···, compute	
Filter output:	$y(k)=x(k)^T w(k)$
Estimation Error:	$e(k)=d(k)-\hat{y}(k)$
Tap-Weight Adaptation:	$w(k+1)=w(k)+\dfrac{2\mu_n}{\gamma+x^T(k)x(k)}e(k)x(k)$

Table: Implementation of the NLMS algorithm

B. VARIABLE STEP-SIZE (VSS) ALGORITHMS

Method 1: The purpose of a variable step-sizenormalized LMS filter is to solve the dilemma of fast convergence rate and low excess MSE. In the past two decades.

Given the input vector **X***k*, the Euclidean norm of the input vector $\|\mathbf{X}_k\|^2$, the NLMS algorithm with fixed step size, μ, for adjusting the adaptive echo canceller's coefficients at time instant k is defined as follows:

$$\mathbf{w}_{k+1}=\mathbf{w}_k+\mu e_k\frac{\mathbf{x}_k}{\|\mathbf{x}_k\|^2},$$

Where the error ek is defined as $ek = dk + nk - \mathbf{X}^T_k \mathbf{w}k, dk$is

Here w represents the coefficients of the FIR filter tap weight vector, x(n) is the input vector samples, z^{-1} is a delay of one sample period, y(n) is the adaptive filter output, d(n) is the desired echoed signal and e(n) is the estimation error at time n. The aim of an adaptive filter is to calculate the difference between the desired signal and the adaptive filter output, e(n). This error signal is fed back into the adaptive filter and its coefficients are changed algorithmically in order to minimize a function of this difference, known as the cost function. In the case of acoustic echo cancellation, the optimal output of the adaptive filter is equal in value to the unwanted echoed signal the various methods can be divided into two groups based on their cost functions. The first class are known as Mean Square Error (MSE) adaptive filters, they aim to minimize a cost function equal to the expectation of the square of the difference between the desired signal d(n), and the actual output of the adaptivefilter

$$\xi(n)=E\left[e^2(n)\right]=E\left[(d(n)-y(n))^2\right]$$

the desired value and$nk$is theadditive noise. In this work, the fixed step size μ in (1) is made variable and is updated according to the following recursion:

$$\mu_k=\mu_{k-1}-\frac{\rho}{2}\frac{\partial e_k^2}{\partial\mu_{k-1}},$$

Which can be transformed, after substituting Equation (1), to the form:

$$\mu_k=\mu_{k-1}+\rho e_k e_{k-1}\frac{\mathbf{x}_k^T\mathbf{x}_{k-1}}{\|\mathbf{x}_{k-1}\|^2},$$

Where the parameter ρ is a small positive constant that controls the adaptive behavior of the step-size sequence μk and T denotes transpose operation. Accordingly, the coefficients of the VSS-NLMS echo canceller will be updated according to a variable step-size NLMS (VSS-NLMS) algorithm given by [8]:

$$\mathbf{w}_{k+1}=\mathbf{w}_k+\mu_k e_k\frac{\mathbf{x}_k}{\|\mathbf{x}_k\|^2},$$

Where the variable step size parameter is confined to the following limits [8]:

$$\mu_k=\begin{cases}\mu_{max} & \text{if } \mu_k>\mu_{max}\\ \mu_{min} & \text{if } \mu_k<\mu_{min}\\ \mu_k & \text{otherwise,}\end{cases}$$

and μmin, μmax are chosen to satisfy the convergence requirements of the NLMS algorithm with fixed step size, that is $0<\mu min<\mu max<2$.

Method 2: Another type of VSS algorithms hastime-varying regularization parameter that is fixed in the conventional å-NLMS filters.

1. GNGD algorithm - The GNGD belongs to the family of time-varying regularized VSS algorithm. The filter coefficient vector is updated as

$$\mathbf{w}(n+1)=\mathbf{w}(n)+\frac{\mu_c}{\|\mathbf{x}(n)\|^2+\varepsilon(n)}e(n)\mathbf{x}(n),$$

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Where μ_c a fixed step size and the regularization

$$\varepsilon(n) = \varepsilon(n-1) - \rho\mu_c \frac{e(n)e(n-1)\mathbf{x}^T(n)\mathbf{x}(n-1)}{(\|\mathbf{x}(n-1)\|^2 + \varepsilon(n-1))^2},$$

2. RR-NLMS Algorithm - Choi's RR-NLMS algorithm is a modified version of GNGD. The regularization parameter is updated as

$$\varepsilon(n) = \varepsilon(n-1) - \rho\mu_c \frac{e(n)e(n-1)\mathbf{x}^T(n)\mathbf{x}(n-1)}{(\|\mathbf{x}(n-1)\|^2 + \varepsilon(n-1))^2},$$

Where sgn(x) represents the sign function, and $\varepsilon_{\min}$ is a parameter needs tuning.

3. GSER Algorithm -The GSER updates $\mathbf{w}(n)$ as follows where a fixed step size and the regularization parameter is $\varepsilon(n)$ is recursively calculated as

$$\varepsilon(n) = \varepsilon(n-1) - \rho\mu_c \frac{e(n)e(n-1)\mathbf{x}^T(n)\mathbf{x}(n-1)}{(\|\mathbf{x}(n-1)\|^2 + \varepsilon(n-1))^2},$$

Where ρ an adaptation parameter is needs tuning, and the initial value $\varepsilon(0)$ has to be set as well.

IV. EXPERIMENT RESULTS

Figure shows the far-end speech and the microphone signals used in the simulation and the resulting error signal after AEC. In this section, we present the comparison results of several experiments of VSSLMS VS-NLMS , GNGD [9], RR-NLMS ,GSER.

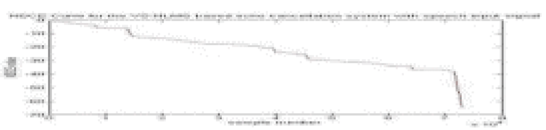

Fig. 5, NSCE curves of variable step-size algorithms in time-invariant system case.

Fig. 6. NSCE curves of GSER variable step-size algorithms in time-invariantsystem case.

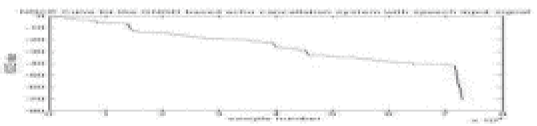

Fig. 6. NSCE curves of gngd variable step-size algorithms in time-invariantsystem case.

Fig7.NSCE curves of variable step-size algorithms in time-varying system

Fig. 8., NSCE curves of variable step-size algorithms in time-varying system Case

Fig. 9., NSCE curves of RR basedvariable step-size algorithms in time-varying system

V. CONCLUSION

The implementations are to be done using TMS320C6713DSK for each AEC and the performances have to be evaluated for comparison. Many variable step-size NLMS algorithms have been proposed to achieve fast convergence rate, rapid tracking and presented a Performance comparison by means of extensive simulation. According to the simulation GSER have the best performance in both time-invariant and Time-varying systems

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