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DOUBLE TALK ACOUSTIC ECHO CANCELLATION BY USING ADAPTIVE FILTER

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Abstract: This paper proposes a step size control method capable of steadily cancelling acoustic echo resisting double talk. The method is characterized by applying a sub-adaptive filter to the control. The step size and number of taps of the sub-adaptive filter are larger and fewer than those of the main adaptive filter used for cancelling the acoustic echo, respectively. Accordingly, the sub-adaptive filter can reduce the residual echo more rapidly than the main adaptive filter. The method applies the step size calculated using the residual echo to the main adaptive filter, and thereby, quickly and steadily reduces the acoustic echo. This paper finally verifies that the proposed method can provide almost the same convergence speed as that obtained by applying a fixed large step size to the main adaptive filter.

Key words: Double talk, acoustic Echo, Adaptive Filter, Step Size.

I. INTRODUCTION

In acoustic echo canceller systems, the coefficients of adaptive filter are disturbed by two factors. One is the power fluctuation of far end talker's signal used for estimating the coefficients. This disturbance, however, can be easily prevented by applying the block length control to the estimation. Another is the superposition of near end talker's signal on the acoustic echo, called double talk. The deterioration by this superposition is generally prevented by pausing the estimation during the double talk. This means that the exact and quick detection of the superposition is requisite to the prevention. Many double talk detection methods have been hence studied.

On the other hand and methods capable of steadily estimating the coefficients without pausing the estimation even during the double talk. The methods, however, have the drawback that the convergence speed of the coefficients is extremely slow while the estimation error is large.

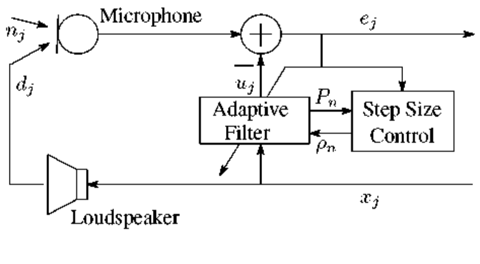

Figure 1: Configuration of conventional system.

This paper hence proposes a new step size control method capable of providing higher convergence speed than the methods. In this new method, the variable step size given to the main adaptive filter cancelling the acoustic echo is adjusted using the residual echo provided by another adaptive filter, called sub-adaptive filter in this project. The fixed step size and number of taps of the sub-adaptive filter are larger and fewer than those of the main adaptive filter; accordingly, the residual echo decreases more rapidly than that provided by the main adaptive filter.

The variable step size thereby increases quickly; consequently, the main adaptive filter can swiftly reduce the acoustic echo. This paper also verifies that the proposed method can provide almost the same convergence speed as that obtained by applying a fixed large step size to the main adaptive filter.

In this configuration, the coefficient vector of the adaptive filter, H_n is estimated using the following block implementation adaptive algorithm,

$$H_{n+1}= H_n + \rho_0 \sum_{j=nj+1}^{(n+1)j} e_j x_j \Big/ \sum_{j=nj+1}^{(n+1)j} x_j^t x_j \dashrightarrow (1)$$

Where x_j is the reference signalling vector, e_j is the residual echo, ρ_j is a constant called step size, j and n denotes sample time index and block number, respectively. This algorithm can guarantee that the estimation error decreases to it is satisfied, where Q_0 is the power of environmental noise γ_{ij},

$$C_0 = \frac{\rho_0}{2}\frac{Q_0}{P_0} * I \dashrightarrow (2)$$

When the block is extended until the relation,

$$\rho_0 = \sum_{j=nj+1}^{(n+1)j} x_j^t x_j \geq P_0 \dashrightarrow (3)$$

is the reference signal power, and is the number of taps of the adaptive filter. The threshold P_0 , can be easily estimated using

$$C = \frac{\rho}{2}\frac{Q}{P} * I \dashrightarrow (4)$$

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By applying this block length control method to the coefficient vector can be continuously estimated even when the reference signal power is low. In this control method can be more over rewritten as this equation also shows that the estimation error can be kept at C_0 if the step size is controlled as at a constant maximizing the convergence speed. The sub-adaptive filter can accordingly reduce the residual echo more quickly than the main adaptive filter.

On the other hand, the sub-adaptive filter cannot sufficiently cancel the acoustic echo d_j . The proposed system adds the echo replica synthesized using the latter half taps of the main adaptive filter, u_j^b to u_j^c, and subtracts it from the

$$\rho = \frac{2\,C_0 P_0}{Q_n} \dashrightarrow (5)$$

$$Q_n \approx \frac{\sum_{j=nj+1}^{(n+1)j} e_j^2}{j} \dashrightarrow (6)$$

When the near end talker's signal increases Q_0 to Q_n . However, it is difficult to estimate Q_n increased by the near end talker's signal. Proposes to approximate it to be this estimation naturally delays the estimation of H_n, be-cause e_j involves the residual echo, which is large after the echo path change. This paper hence proposes a new method estimating Q_n.

II. PROBLEM STATEMENT

Teleconferencing systems employ acoustic echo cancellers to reduce echoes that result from coupling between the loudspeaker and microphone. To enhance the sound realism, two- channel audio is necessary. However, in this case (stereophonic sound) the acoustic echo cancellation problem is more difficult to solve because of the necessity to uniquely identify to acoustic paths. We explain these problems in detail and give an interesting solution which is much better than previously know solutions. The basic idea is to introduce a small nonlinearly into each channel that has the effect of reducing the inter channel coherence while not being noticeable for speech due to self masking

2.1. Adaptive Filter

Adaptive digital Filters have been used for several decades to model systems whose properties are a priori unknown. Pole-zero modelling using an output error criterion involves finding an optimum point on a (potentially) multimodal error surface, a problem for which there is no entirely satisfactory solution. In this chapter we discuss previous work on the application of genetic-type algorithms to this task and describe our own work developing an evolutionary algorithm suited to the particular problem

Discrete-time (or digital) filters are ubiquitous in today’s signal processing applications. Filters are used to achieve desired spectral characteristics of a signal, to reject unwanted signals, like noise or interferers, to reduce the bit rate in signal transmission, etc.

- What is adaptive filter

The notion of making filters adaptive, i.e., to alter parameters (coefficients) of a filter according to some algorithm, tackles the problems that we might not in advance know, e.g., the characteristics of the signal, or of the unwanted signal, or of a systems influence on the signal that we like to compensate. Adaptive filters can adjust to unknown environment, and even track signal or system characteristics varying over time.

- Signal Processing and Adaptive Filters

Digital Signal Processing (DSP) is used to transform and analyze data and signals that are either inherently discrete or have been sampled from analogue sources. With the availability of cheap but powerful general-purpose computers and custom-designed DSP chips, digital signal processing has come to have a great impact on many different disciplines from electronic and mechanical engineering to economics and meteorology.

In the field of biomedical engineering, for example, digital filters are used to remove unwanted 'noise' from electrocardiograms (ECG) while in the area of consumer electronics DSP techniques have revolutionized the recording and playback of audio material with the introduction of compact disk and digital audio tape technology.

The design of a conventional digital signal processor, or filter, requires a priori knowledge of the statistics of the data to be processed. When this information is inadequate or when the statistical characteristics of the input data are known to change with time, adaptive filters are employed.

Adaptive filters are employed in a great many areas of telecommunications for such purposes as adaptive equalization, echo cancellation, speech and image encoding, and noise and interference reduction. Adaptive filters have the property of self-optimization. They consist, primarily, of a time varying filter, characterized by a set of adjustable coefficients and a recursive algorithm which updates these coefficients as further information concerning the statistics of the relevant signals is acquired.

A desired response d (n), related in some way to the input signal, is made available to the adaptive filter. The characteristics of the adaptive Filter are then modified so that its output y (n), resembles d (n) as closely as possible. The difference between the desired and adaptive filter responses is termed the error and is defined as

$$e(n) = y(n) - d(n) \dashrightarrow (7)$$

Ideally, the adaptive process becomes one of driving the error, e (n) towards zero. In practice, however, this may not always be possible and so an optimization criterion, such as the mean square error or some other measure of fitness, is employed. Adaptive filters may be divided into recursive and non-recursive categories depending on their inclusion of a feedback path.

The response of non-recursive or finite impulse-response (FIR) filters is dependent upon only a finite number of previous values of the input signal. Recursive, or infinite impulse-response (IIR) filters, however, have a response which depends upon all previous input values, the output being calculated using not only a finite number of previous input values directly, but also one or more previous output values. Many real-world transfer functions require much more verbose descriptions in FIR than in recursive form.

The potentially greater computational efficiency of recursive filters over their non-recursive counterparts is, however, tempered by several shortcomings, the most important of which are that the filter is potentially unstable and that there are no wholly satisfactory adaptation algorithms.

There are two main types of adaptive IIR filtering algorithms, which diver in the formulation of the prediction error used to assess the appropriateness of the current coefficient set during adaptation. In the equation-error approach the error is a linear function of the coefficients. Consequently the mean square error is a quadratic function of the coefficients and has a single global minimum and no local minima.

This means that simple gradient-based algorithms can be used for adaptation. However in the presence of noise (which is present in all real problems) equation-error based algorithms converge to biased estimates of the filter coefficients .The second approach, the output-error formulation, adjusts the coefficients of the time-varying digital filter directly in recursive form. The response of an output-error IIR filter is characterized by the recursive difference equation:

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- AEC scheme using an adaptive filter

Acoustic echo cancellation (AEC) is a classical application of adaptive filters to cancellation of acoustic echoes appearing in communication channels as depicted in Fig. 2. In particular, AEC is very effective in cancelling the acoustic echoes in such systems as telecommunications, internet telephony and audio and video conferencing system.

However, since acoustic echoes can be produced from the open-air acoustic path between a loudspeaker and a microphone in hands-free full-duplex communication systems, communication quality may be severely degraded due to those echoes. For that purpose, some AEC systems have been increasingly proposed recently. Furthermore, computationally efficient adaptive algorithms also have been developed to reduce computational cost of the corresponding AEC systems.

For example, affine projection (AP) algorithms were reported, which yield faster convergence speed than the least-mean squares (LMS) methods and also requires much lower computational complexity than the recursive least-squares (RLS) method. However, if the AP order increases, higher computational burden can be required for a matrix inversion or even stability problems may occur. To solve those problems, the Gauss-Seidel pseudo affine projection (GS-PAP) algorithm was suggested in. However, the performance of the GS-PAP algorithm may not be so good particularly when a non-unity step-size is chosen. In, a GS-PAP with variable step-size, called variable step-size PAP (VSS-PAP) algorithm, was proposed for linear AEC systems.

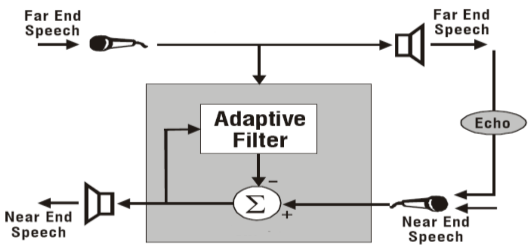

Figure 2: AEC scheme using an adaptive filter

Also, the variable step-size Gauss-Seidel pseudo affine projection (VSSGS-PAP) algorithm was reported, being robust to near-end signal variations in a double-talk situation. In case of nonlinear AEC systems, Volterra filtering approaches were suggested, whereby the linear relation between system kernels and the system output is utilized, making it possible to extend conventional linear approaches further to nonlinear AEC.In this paper, we propose a new nonlinear AEC, employing adaptive 3rd-order Volterra filtering with a VSSGS-PAP algorithm. The proposed approach is robust even to near-end signal variations, yielding stable nonlinear AEC performance and faster convergence than conventional Volterra AEC methods.

2.2. Sub-Band implementation of Adaptive non linear filter

The nonlinear filter we can regard each channel in Fig.2 as a linear filter without extra consideration concerning the spectral outgrowth. As a result, we can extend the linear sub-band adaptive filter techniques to develop an adaptive sub-band nonlinear filter based on the multi-channel structure.

The configuration of the developed sub-band adaptive nonlinear filter is shown in Fig. 3. If one interprets this figure as a nonlinear AEC configuration, the far-end signal and so is the reference signal provided to the adaptive nonlinear filter, which in this case would usually be speech.

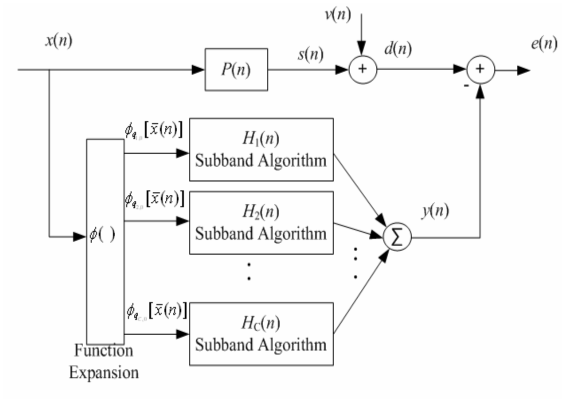

Figure 3: Sub-band adaptive function expansion nonlinear filter based on multi-channel configuration

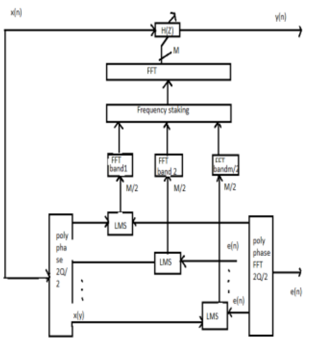

Figure 4: Delay less sub-band adaptive linear filter based on the Morgan configuration

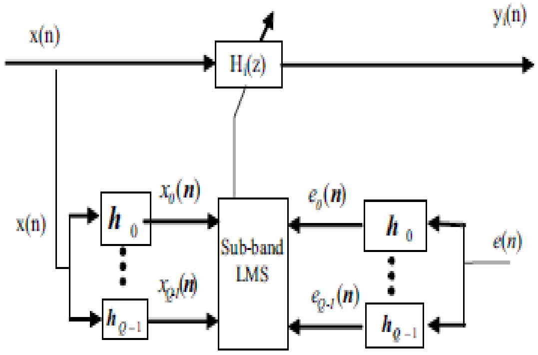

Figure 5: Delay less sub-band adaptive linear filter based on the De Brunner configuration

The conventional linear sub-band adaptive filters induced delay in the signal path through the introduction of the sub-band filters into that path. This delay limits the application of AEC. Morgan et al proposed the delay less sub-band adaptive linear filter as shown in Figure 4. In that configuration, the coefficients for each sub-band are updated independently and then combined through an FFT to yield the broadband coefficients.

The Morgan configuration can greatly reduce the computational complexity when the linear system has a large order. However, in order to have a good approximation for each sub-band frequency response, each sub-band needs to have at least 4 coefficients. Also, to increase the convergence speed, at least 4 sub-bands are required. These limit the application of the Morgan sub-band configuration to applications with large-order channels. De-Brunner et. all. introduced another configuration for the sub-band adaptive linear filter as shown in Figure 5 that directly updates the broadband coefficients based on all sub-band signals. Without up sampling and down-sampling, the De Brunner configuration has no limitations on the adaptive filter order; however, the computational complexity will increase as the number of channels increases. In the multi-channel implementation of the nonlinear filter, different channels usually have different lengths for fixed memory nonlinear models.

Here, we proposed a new sub-band adaptive nonlinear filter by combining the two delay less sub-band configurations. This means that when the order of the channel is less than 64, we can implement the De Brunner configuration; otherwise, we implement the Morgan configuration. As a result, we combine Figs. 4, 5 and 4, to yield our proposed sub-band adaptive nonlinear filter. By sub-band decomposition, we can decrease the Eigen value spread in each sub-band, and each sub-band can be updated using different step sizes. As a result, the convergence speed is greatly improved, and especially for coloured inputs such as speech.

2.3 Applications of Adaptive Filters

Two possible application scenarios of adaptive filters are given in figure 6, system identification and inverse filtering. For system identification the adaptive filter is used to approximate an unknown system. Both the unknown system and the adaptive filter are driven by the same input signal and the adaptive filter coefficients are adjusted in a way, that the output signal resembles the output of the unknown system, i.e., the adaptive filter is used to approximate the unknown system.

For inverse modelling or equalization the adaptive filter is used in series with the unknown system and the learning algorithm tries to compensate the influence of the unknown system on the test signal u[n] by minimizing the (squared) difference between the adaptive filters output and the delayed test signal.

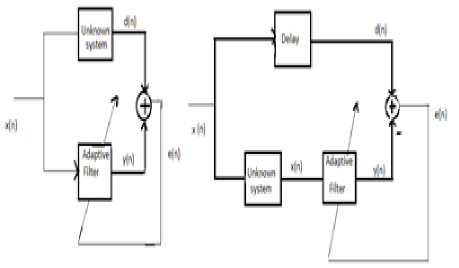

Figure 6: Two applications of adaptive filters: System identification (left) and inverse modelling/ equalization (right)

Applications of adaptive filters further include the adaptive prediction of a signal, used for example in ADPCM4 audio coding, adaptive noise or echo cancellation, and adaptive beam-forming (shaping of the acoustic/radio 'beam' transmitted/received by an array of loudspeakers/microphones/antennas).

III. MATHEMATICAL MODEL

a. Proposed Method for Performance

- Step size control method

A good step-size control algorithm will prevent repetition or escape from areas near roots or minima from happening. At the same time, however, when steps based on the model function are appropriate, the step-size control algorithm should not restrict them, otherwise the convergence rate of the algorithm would be compromised. Two commonly used step-size control algorithms are "line search" and "trust region" methods.

In a line search method, the model function gives a step direction, and a search is done along that direction to find an adequate point that will lead to convergence. In a trust region method, a distance in which the model function will be trusted is updated at each step. If the model step lies within that distance, it is used; otherwise, an approximate minimum for the model function on the boundary of the trust region is used. Generally the trust region methods are more robust, but they require more numerical linear algebra.

3.1.1. Adaptive Step-size Control

The control function examines the proposed change to the solution produced by a stepping function and attempts to determine the optimal step-size for a user-specified level of error.

3.1.2. Step-Size Control using Sub-ADF

Optimal step-size parameter:

An optimal step-size parameter when the input signal of the adaptive filter is white Gaussian noise is expressed as follows,

$$\alpha_{opt}(n) = \frac{E\{\epsilon^2(n)\}}{E\{e^2(n)\}} = \frac{E\{\epsilon^2(n)\}}{E\{\epsilon^2(n)\}+E\{w^2(n)\}} \quad \text{-->(8)}$$

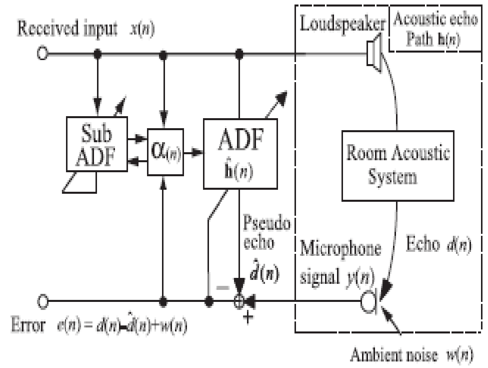

Figure 7: Structure of the AEC.

Where e (n) is the error signal and α_{opt} (n) is decreased with time so that an estimate error ε (n) becomes small. In addition, if the acoustic echo path changes, the AEC can track the change because the step-size parameter is increased according to the increase of the estimate error. On the other hand, the step-size parameter is suddenly decreased when the ambient noise w (n) is increased due to double talking. However, it is impossible to applied to above equation to the real system because the estimate error ε (n) is unknown in the real system and the expectation operation is used in above equation. Hence, the estimate error must be approximately calculated in some way.

3.1.3. Controlling the step-size

Noise which is not correlated with the excitation signal x (k) will not disturb the adaption as the adaption in the FLMS algorithm is performed along the cross-correlation between the error vector e (k) and the loudspeaker signal x (k). In real-time applications the general assumption that these signals are not correlated with each other does not hold due to the limited length of the observation interval.

As a consequence the additive noise and the local speech will lead to misalignment or even divergence of the algorithm. One way to avoid the misalignment is to control the step-size α (k) of the algorithm depending on the power of the additive local signals. We subdivide the frequency domain in bins and use the coherence between the microphone signal α (k) and the excitation signal x (k) to estimate this power in each corresponding bin.

3.1.4. Frequency Selective Step-Size Control

The spectral properties of the excitation speech signal x (k) and the additive speech and environmental noise signals n (k) can differ significantly. Thus the impact of the additive signals on the adaption of the adaptive filter can be very different in the different spectral regions.

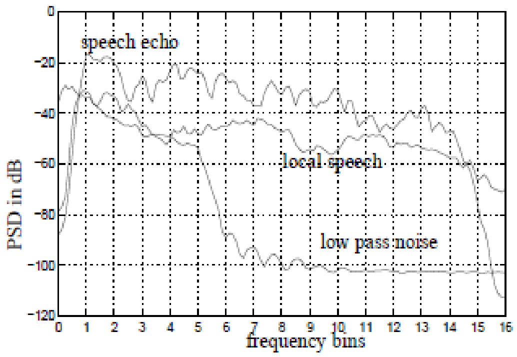

Figure 8: Power spectral density (PSD) of echo

A frequency-selective adaption control allows to continue the adaption on a high rate in frequency bins which are not affected by noise and to slow down in frequency bins with high noise levels. This will lead to an improved impression in listening tests independent of the achieved system distance between the LEM system g (k) and the cancellation filter h (k) In frequency bins with a high noise level, where adaption is not possible, the noise will mask the echoes, whereas in frequency bins without noise the adaption can be continued and the echo's will be cancelled.

The most popular step-size control algorithms use an estimate of the system distance Ë normalized to .dB at start-up to control the step-size. The limited frequency resolution of the estimate does not allow a frequency selective adaption control; furthermore these algorithms make sophisticated mechanisms necessary to detect LEM system changes.

3.1.5. Adaptive Step size Control for Runge-Kutta

A good ODE integrator should exert some adaptive control over its own progress, making frequent changes in its step size. Usually the purpose of this adaptive step size control is to achieve some predetermined accuracy in the solution with minimum computational effort. Many small steps should tiptoe through treacherous terrain, while a few great strides should speed through smooth uninteresting countryside. The resulting gains in efficiency are not mere tens of percents or factors of two; they can sometimes be factors of ten, a hundred, or more. Sometimes accuracy may be demanded not directly in the solution itself, but in some related conserved quantity that can be monitored. Implementation of adaptive step size control requires that the stepping algorithm signal information about its performance, most important, an estimate of its truncation error. In this section we will learn how such information can be obtained.

Adaptive Step size Control for Runge-Kutta the calculation of this information will add to the computational overhead, but the investment will generally be repaid handsomely. With fourth-order Runge-Kutta, the most straightforward technique by far is step doubling. We take each step twice, once as a full step, then, independently, as two half steps. How much overhead is this, say in terms of the number of evaluations of the right-hand sides? Each of the three separate Runge-Kutta steps in the procedure requires 4 evaluations, but the single and double sequences share a starting point, so the total is 11. This is to be compared not to 4, but to 8 (the two half-steps), since step size control aside we are achieving the accuracy of the smaller (half) step size. The overhead cost is therefore a factor 1.375.

b. Block Length Control

Traditionally, block-length has been used as a proxy for end to end delay since block-codes are easier to understand than non-block codes. This turns out to be correct when there is no feedback since the dominant error events turn out to involve the channel's behaviour between when the message is made available to the encoder and when it is needed at the decoder. When feedback is allowed, block-codes are unable to really exploit it. For memory less symmetric channels, not only is the capacity not increased with feedback, but the sphere-packing bound remains essentially unchanged and so no significant improvements in error probability are possible in the high rate regime of greatest interest.

When the latency is only constrained on average, then the variable block-length story of shows that feedback can significantly lower the probability of error without much impact on the average delay. Either way, the architectural message from block-codes seems to remain: with or without feedback, to get the best probability of error, aggregate your messages and use the longest block length you can afford given your latency constraint. Yet even when end-to-end delay is desired, this project shows that non block codes can provide a tremendous reduction in the probability of bit error if feedback is allowed.

The role of the sphere-packing (volume) bound is played by the uncertainty focusing bound in giving the fundamental limit on what is asymptotically possible in the limit of large delays. The dominant error events involve a mixture of past and future channel behaviour and the resulting bound is also achievable with feedback for erasure channels and any channel with strictly positive feedback zero-error capacity.

The codes that achieve the focusing bound hint at an architectural message that is different from that provided by traditional fixed-length block-coding. When feedback is available, the messages should be of moderate size. Long enough, but not a length comparable to the target end-to-end latency itself. Feedback should be used to adapt the block-lengths as needed and do flow-control on the instantaneous rate of information transfer.

An interpretation of the new results in the context of remote stabilization problems is found in where it is shown how to leverage noiseless, but low rate, feedback to make more effective use of a higher-capacity noisy feedback channel in order to stabilize an unstable system in closed loop. The basic code construction used to show achievability of the focusing bound for channels with strictly positive zero-error capacity is then extended in to generic channels. While not attaining the focusing bound itself, the codes of do beat the sphere packing bound with fixed delay in the high-rate regime.

The core ideas of are also explored in the context of lossless source coding in .The point-to-point setting is considered in and the source-coding counterpart of the uncertainty focusing bound is developed. Feedback is irrelevant and the dominant error events turn out to involve the source behaviour before the symbol in question arrived at the encoder. This is used to show that optimal block codes are quite bad from the perspective of fixed end-to-end delay constraints when used over fixed-rate noiseless channels.

Instead moderate sized. fixed-to-variable length codes with their output rate smoothed using a FIFO queue with deterministic service times asymptotically achieve the best possible trade-off between fixed deadlines and the probability of error. The case of side-information at the decoder is considered and an upper bound on the reliability function with delay is derived by considering error events due to atypically bad side information between the time of symbol arrival and when it is required at the decoder.

This bound turns out to be tight for certain symmetric cases. Put together, these results make precise Shannon's intriguing comment at the close of the duality between source and channel coding can be pursued further and is related to a duality between past and future and the notions of control and knowledge. Thus we may have knowledge of the past and cannot control it; we may control the future but have no knowledge of it.

i. Fixed-length

The fundamental lower-bound on error probability comes from the sphere-packing or volume bound, and this bound is also known to be achievable at high rates by random-coding. Reliable communication is not possible if during the block, the channel acts like one whose capacity is less than the target rate. For block codes this idea immediately gives the following bound on the exponential error probability:

$$E^{+}(R) = \quad \text{infmax}_{\vec{r}}\, D(G\|P|\vec{r}) \dashrightarrow (9)$$

Even with causal noiseless feedback, there is no way around this bound because channel capacity does not increase with feedback for memory less channels. Without feedback, the bound can be tightened to the form traditionally known as the sphere-packing bound.

$$E_{SP}(\text{R})=\max_{\vec{r}} \min_{G:I(\vec{r},G)\le R} D(G\|P|\vec{r}) \dashrightarrow (10)$$

For symmetric channels, the optimizing codeword composition ~r is always uniform and

$$E_{SP}(\text{R}) = \text{E}^{+}(\text{R}). \dashrightarrow (11)$$

An alternate form for E_{SP}(R) is given by:

$$E_{SP}(\text{R})=\max_{\rho>0}[E_0(\rho) - \rho R] \dashrightarrow (12)$$

with the Gallager function $E_0(\rho)$ defined as

$$E_0(\rho)=\max_{\vec{q}} - \ln \textstyle\sum_y \sum_x qxpx,y^{\frac{1}{1=\rho}} \dashrightarrow (13)$$

Note that for symmetric channels, it suffices to use a uniform ~q while optimizing. Also, since the random-coding error exponent is given by

$$E_r(\rho)=\max_{0<\rho\le 1} E_0(\rho) - \rho R \dashrightarrow (14)$$

It is clear that the sphere-packing bound is achievable, even without feedback, at rates close to C since for those rates, <1 optimizes both expressions. The points on the sphere packing bound where > 1 are also achievable by random coding if the sense of .correct decoding. is slightly relaxed. Rather than forcing the decoder to emit a single estimated codeword, list-decoding allows the decoder to emit a list of guessed code words. The decoding is considered correct if the true codeword is on the list. Decoding a random code with list size has exponent:

$$E_{r1}\ (\text{R})=\max_{0<\rho\le l}[Eo(\rho) - \rho R] \dashrightarrow (15)$$

is achievable. At high rates (where the maximizing is small), there is no benefit from relaxing to list-decoding, but it makes a difference at low rates.

3.2.2 Variable-length

Without feedback, a variable-length mode of operation is impossible since the encoder has no way to know if the channel is behaving typically or atypically. With noiseless feedback, the length of the codeword can be made to vary based on what the channel has done so far. As long as that variation depends only on the received channel symbols.

The proposed error exponent for variable-length channel codes divided the negative log of the probability of block error by the expected length E [N] of an average rate R variable-length code that attains the probability of error.

$$E_{r1}(\bar{R})=\lim_{e\to 0} -\frac{\ln(\epsilon)}{E[Ne]} \dashrightarrow (16)$$

Burnashev gave the upper bound to this exponent by using martingale arguments treating the ending of a block as a stopping time.

$$E_{r1}(\bar{R}) = C_1(1-\frac{\bar{R}}{C}) \dashrightarrow (17)$$

where C is the Shannon capacity of the channel and

$$C_1 = \max_{i,k} D\big(P(.|i)\|P(.|k)\big) = \max_{i,k} \sum_l Pil \ln\frac{Pil}{Pkl} \dashrightarrow (18)$$

represents the maximum divergence possible between channel output distributions given choice of two input letters. This bound is also achievable by using a repeat-until-success scheme. The relevant flow-control. Information is carried by confirm/deny messages sent by the encoder telling the decoder whether or not it is going to repeat the block or not.

It turns out that the rate just determines how many channel uses are left over for the flow-control messages and the variable block-coding reliability is purely a function of that proportion.

3.2.3. Double talk

Acoustic echoes are major sources of annoyance in hands-free communications, where the presence of coupling from the far-end signal (loudspeaker) to the near-end signal (microphone) would result in undesired acoustic echo. A reliable acoustic echo canceller (AEC) should include good solutions to the problems of estimating the echo path and double-talk detection. When the near-end speech s (n) and far-end speech x (n) occur simultaneously, the so-called double-talk (DT) mode, the adaptation of the adaptive filter will be severely disturbed by the near-end signal. Therefore, a dependable double-talk detector is required to decide whether it enters DT mode.

If so, the AEC has to either slow down or freeze the adaptation of the adaptive filter to prevent it from divergence. In hands-free communications, the movement of objects or people produce changes in the acoustic echo paths and it has introduced a more difficult problem for double-talk detector (DTD). The DTD might treat the double-talk situation as echo path change. Consequently, the adaptive filter will keep updating and result in the divergence of the system. On the other hand, the DTD may declare an echo-path change as DT mode. It is important for the DTD to efficiently differentiate between echo path change and DT mode.

3.2.4 Double Talk detection based on normalized Cross Correlation

An acoustic echo canceller electrically models the path from the loudspeaker to the microphone by an adaptive filter. By exciting the adaptive filter with the signal from the remote side, or far-end, an echo replica is generated. The echo replica is subtracted from the microphone signal, resulting in an echo-cancelled speech for transmission. Double-talk, when the far-end and the near-end speech (NES) simultaneously exist, sometimes causes fatal degradation in echo cancellation because of the interference by the near-end speech.

Therefore, coefficient adaptation should be disabled during double-talk periods. Double-talk detection plays a key role in the overall performance and is carried out based on various measures. The most basic algorithm for double-talk detection is the one originally developed by Geigel .

When the maximum of past samples multiplied by 0.5 is greater than the current microphone signal, double-talk is declared. The factor of 0.5 is based on the fact that a loss of 6 dB is typical in the case of network echo cancellation. Although it is simple with reasonable performance, it cannot be directly applied to acoustic echo cancellation where a characteristic of the echo path is unknown in advance.

A more sophisticated algorithm by Ye et al. It utilizes cross-correlation of the reference signal and the error. Only when the correlation is non-zero, coefficient adaptation is carried out based on the fact that such a cross correlation becomes zero after convergence. However, because the acoustic echo path keeps more or less changing, cross-correlation is likely to take a non-zero value and adaptation is performed even when the NES is present.

Therefore, it is not suitable for acoustic echo cancellation. G¨ ansleret al. proposed an algorithm based on coherence between the reference and the microphone signal. However, its drawback is insufficient normalization of the coherence. As a result, a threshold heavily depends on the signal statistics and the echo-path characteristics. To perform double-talk detection with a fixed threshold, Benesty et al. proposed a technique based on normalized cross-correlation of the echo and the microphone signal. Although it exhibits good performance in most cases, it still has insufficient detection capability in the presence of noise, as the already mentioned algorithms. Acoustic echo cancellers are more exposed to open environment than network echo cancellers. Therefore, it is important to pay attention to noise contaminating the echo and the NES. This paper presents a noise-robust double-talk detection algorithm based on normalized cross-correlation and a noise offset.

The noise offset that is estimated from the echo cancelled signal alleviates undesirable influence by the background noise existing in the microphone signal.

A detection threshold of the new normalized cross-correlation is adaptively controlled based on the echo-to-NES ratio (ENR). The next section reviews double-talk detection based on normalized cross-correlation.

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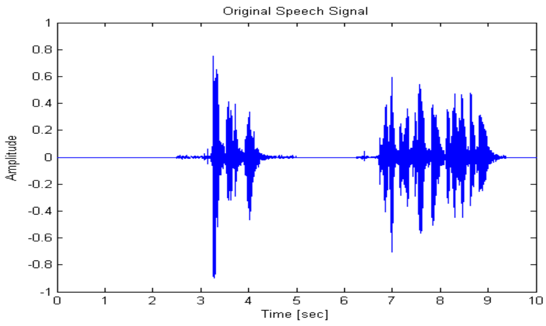
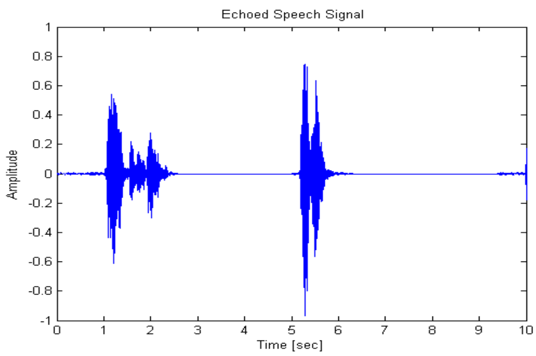
IV. EXPERIMENTAL RESULTS AND PERFORMANCE EVALUATION

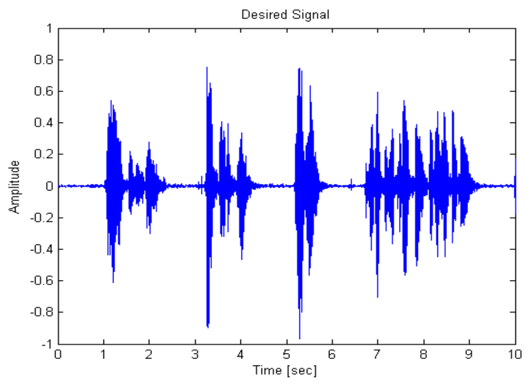
Step 1: Original Speech Signal



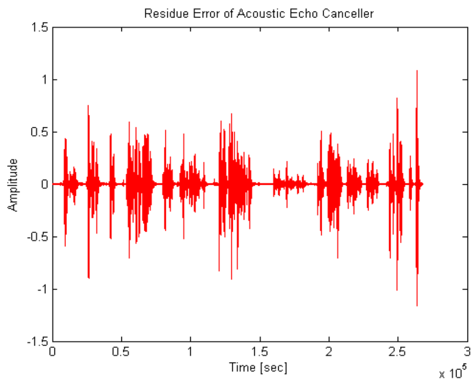
Step 2: Echoed Speech Signal



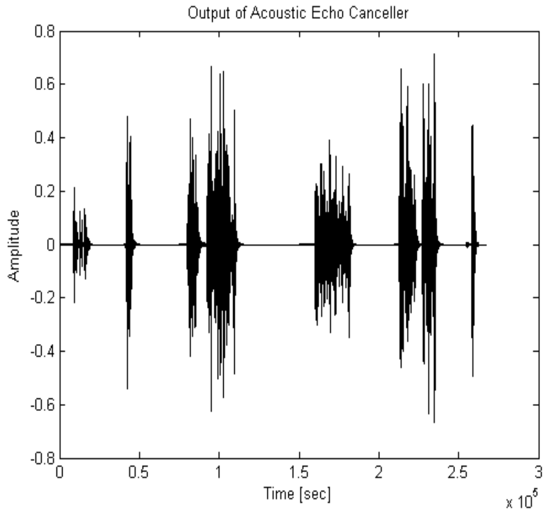
Step 3: Desired Speech Signal



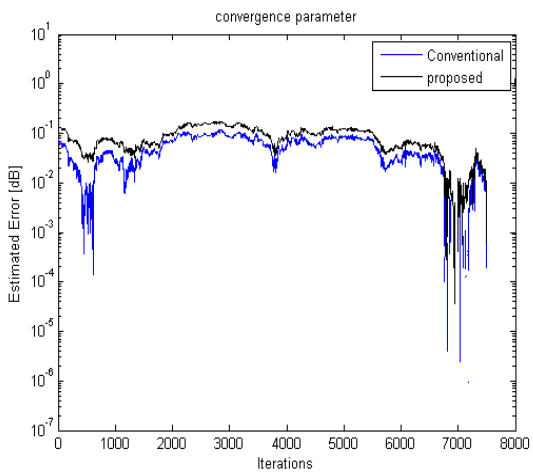
Step 4: Residue Error of Acoustic Echo Canceller



Step 5: Output of Acoustic Echo Canceller



Step 6: Convergence Parameter



Step 7: Convergence Property of Proposed Method

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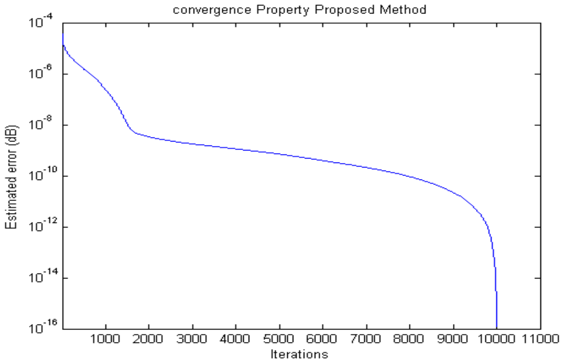

V. CONCLUSIONS

A VSS-APA suitable for AEC applications has been derived in this paper. The basic idea of the classical APA, i.e., to cancel posterior errors, was modified within the proposed algorithm in order to take into account the existence and the non-stationary of the near-end signal. Moreover, the case when the under-modelling noise is present was also considered. The variable step-size formula of the proposed algorithm resulted in a unified manner, requiring no additional parameters from the acoustic environment. The simulation results performed in an AEC context sustain the theoretical findings; accordingly, the gain is twofold. First, due to its nonparametric nature and simplicity, the proposed VSS-APA is very suitable in practice. Second, as compared to other APAs, it was found to be more robust to near-end signal variations like the increase of the background noise or double-talk. Concerning the last scenario, the VSS-APA can be combined with a simple Geigel DTD in order to enhance its performance. This is also a low complexity practical solution, taking into account that in AEC applications, more complex DTDs or robustness techniques are involved.

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