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# An Adaptive Algorithm for Sequential Adaptive Predictive Coding of Speed Signals.

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# AN ADAPTIVE ALGORITHM FOR SEQUENTIAL ADAPTIVE PREDICTIVE CODING OF SPEECH SIGNALS

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ABSTRACT:

Various methods have been proposed for adapting the coefficients of digital lattice filters used in linear predictive speech coding systems The most common of these is the stage-by-stage algorithm based on the least mean square (LMS))method.

In this paper a new sequential adaptive algorithm referred to as "end-point" method is introduced. A comparison study between the stage-by-stage and the "end-point" has been carried out by computer simulation. The preliminary results showed that the "end-point" provides higher convergence rate and less misadjustment in mean-square error over the stage-by-stage method.

## INTRODUCTION:

The use of linear prediction for spectral analysis and vocal tract estimation has been widely accepted in the speech processing field. Although the Autocorrelation and Covariance methods [ 1 ] are well established in this area, their computational complexity has led to a search for alternative methods which may be more convenient for real-time applications. These involve the adaptation of the coefficients of a non-recursive digital filter on a sample-by-sample basis, i.e, a small adjustment is made each time a new speech sample is obtained. The aim is to keep the filter output minimised in mean-square value and spectrally flat so that low-bit rate encoding techniques can be adopted for efficient transmission. Since the inverse of the adaptive filter is used to reconstruct the original speech at the receiver, a further requerment is that this inverse filter is stable,i.e, that the adaptive filter is minimum phase.

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The most straight forward sample-by-sample adaptation method is probably the LMS algorithm [ 2 ] using a ladder or 'tapped delay line' type of digital filter structure. However, this method can lead to difficulties with respect to the minimum phase requrement. Alternative methods based on lattice type structure have been proposed [3,4,5] . Lattice filters of the type shown in Fig. 1 have the important property that minimum phase is guaranteed when all the multiplier coefficients k are less than one in modulus, and that the forward and backward errors ( $f_i$ , $b_i$ for i= 1,2,3,.......M-1) are all minimised in mean square value when the output e(n) is similarly minimised. The forward and the backward errors at each stage of the lattice filter are given by

$$f_i(n) = f_{i-1}(n) + k_i\, b_{i-1}(n)$$
$$b_i(n) = b_{i-1}(n-1) + k_i\, f_{i-1}(n-1) \qquad \ldots\ldots (1)$$

Application of the noisy 'steepest descent' gradient method used in the LMS algorithm [ 2 ], to sequentially minimise the mean square value of the output e(n) of an mth order lattice filter requires the vector $\underline{K}$ of the lattice coefficients to be updated, on receipt of each new speech sample, by the formula

$$\underline{K}^{(n+1)} = \underline{K}^{(n)} - 2\mu_e\, e(n)\, \underline{G}(n) \qquad \ldots\ldots(2)$$

where

$$\underline{G}(n) = \left[\frac{\partial e(n)}{\partial k_1}\ \frac{\partial e(n)}{\partial k_2}\ \frac{\partial e(n)}{\partial k_3} \ldots\ldots \frac{\partial e(n)}{\partial k_M}\right]^T \ldots\ldots(3)$$

$\underline{G}(n)$ is the gradient vector evaluated at time n and $\mu_e$ is a 'step size' as defined in [ 2 ] . Calculation of $\underline{G}(n)$ is not as straightforward as for ladder-type filters. From Fig. 1, the output e(n) is given in terms of the input S(n) as:

$$e(n) = S(n) + \sum_{i=1}^{M} k_i\, b_{i-1}(n) \qquad \ldots\ldots(4)$$

Hence, as all signals $b_i$ with $i \geq j$ are dependent of $k_j$ :

$$\frac{\partial e(n)}{\partial k_j} = b_{j-1}(n) + \sum_{i=j+1}^{M} k_i \frac{\partial b_{i-1}(n)}{\partial k_j} \qquad \ldots\ldots(5)$$

The evaluation of $\underline{G}(n)$ by equation (5) for each speech sample is clearly impractical in computational terms, especially as the calculation should involve the correction of the signals $b_i(n)$ after each adjustement to $\underline{K}$.

A true steepest descent approach is therefore not feasible. Alternative methods [3,5] aim to minimise $E\{e(n)^2\}$ indirectly, on a stage-by-stage basis, by minimising the expectations of $b_i(n)^2$ and $f_i(n)^2$ at each stage of the filter. For the lattice filter shown in Fig. 1, $E\{b_i(n)^2\} = E\{f_i(n)^2\}$ for all i, and hence it suffices to minimise $E\{f_i(n)^2\}$ for each stage by the noisy steepest descent method, i.e, at each stage i :

$$k_i^{(n+1)} = k_i^{(n)} - \mu_s^i \frac{\partial}{\partial k_i} ( f_i(n)^2 ) = k_i^{(n)} - 2\mu_s^i f_i(n)\, b_{i-1}(n) \quad .........(6)$$

where $\mu_s^i$ is the ith step size for the stage-by-stage method.

As an adaptive algorithm, equation (6) is as convenient for the lattice as equation (2) is for the ladder . The aim of this paper is to discuss some of the disadvantages of this stage-by-stage method and to compare it with an equally convenient alternative, referred to as the " end-point " method.

## END-POINT UPDATING:

The end-point adaptation method , originally proposed by Zaki and Cheetham [6] is to apply equation (2) with the gradient vector $\underline{G}(n)$ taken to be

$$\underline{G}(n) = [b_o(n) \quad b_1(n) \; .........\; b_{M-1}(n)]^T \quad ........(7)$$

Comparing equation (7) with equation (6) shows the end-point method to be equivalent in computational complexity to the stage-by-stage method. Although not true steepest descent, the end-point method may be justified as a means of updating $\underline{K}$ in such a way that $e(n)^2$ as calculated from equation (4) assuming fixed $b_i$ samples, is reduced for the current input sample. The dependence of the $b_i$ signals on $\underline{K}$ is disregarded since they are not recalculated during the adaptation process each time $\underline{K}$ is updated.

## EXPERIMENTAL RESULTS:

A series of experiments was carried out by simulation on a 1906s computer to investigate the convergence behaviour of both stage-by-stage and end-point updating algorithms for stationary input signals. As shown in Fig.2, a coloured noise is generated by exciting a fixed all-pole recursive filter with Gaussian noise of zero mean and unit variance. The output from the all-pole fixed filter was passed through the adaptive lattice filter whose coefficients were set initially to zero. The adaptive filter was allowed to update its coefficients on a sample-by-sample basis for a periode of 5000 samples. After each block of 25 samples the current set of adaptive filter coefficients was transferred to a non-adaptive filter (copy filter). The same coloured noise as that exciting the adaptive filter was passed through this copy filter for 200 samples in order to produce an estimate of $E\{e(n)^2\}$ . Ensemble average learning curves which are obtained from 25 individual learning curves are shown in Fig. 3. The optimum value of the mean-square error, as given by the level of the average power of the Gaussian noise is also indicated. For convenience of presentation, the values of the mean-square error and the optimum mean-square error are all normalised to the mean-square value of the output from the fixed filter.

From Fig.3, it can be seen that although the rate of convergence for both methods is roughly the same, the misadjustment obtained after the learning curves approached a constant level (90 iteration), was found to be 51.76% and 6.67% for stage-by-stage and end-point respectively. To explain this higher misadjustment from stage-by-stage the coefficient tracking for both methods was monitored during adaptation. Fig. 4, shows the sample-by-sample coefficient tracking capability for both methods after 2000 samples from the starting point. It can be seen that the sample-by-sample variations in the coefficients obtained from stage-by-stage are much higher than the variations of the coefficients obtained from the end-point method after equilibrium had been approached.

In a different comparison study, the first experiment was repeated using the same fixed value of $\mu_e$ for end-point and a vector of different values of $\mu_s$ for each stage of the lattice in a stage-by-stage algorithm. Fig. 5, shows the ensemble average learning curves for both methods and the corresponding values of $\mu$ used. It can be seen here that the stage-by-stage updating algorithm requires as many as 130 iteration to give similar misadjustment as the end-point method after 90 iteration.

## CONCLUSION:

The end-point updating algorithm has been demonstrated as being superior to the stage-by-stage in a series of experiments.

1- When values of $\mu$ are set to equalise the rate of convergence for both methods,
  a) the end-point performs better than the stage-by-stage since the latter results in a higher excess mean-square error once convergence is reached.
  b) the variation in the coefficients around their equilibrium is much higher for stage-by-stage than for the end-point.

2- When values of $\mu$ are set to equalise the misadjustment, the rate of convergence of the end-point algorithm far exceeds the rate of convergence of the stage-by-stage algorithm.

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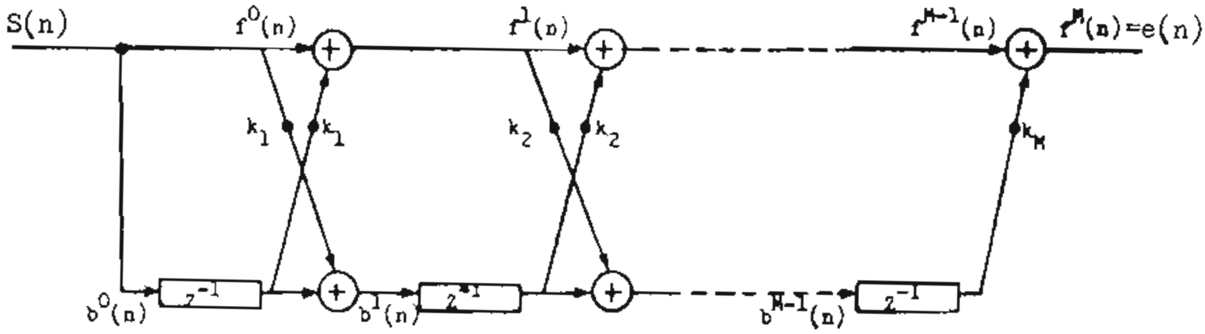


Fig. 1 lattice Structure Prediction Filter Of Order M.

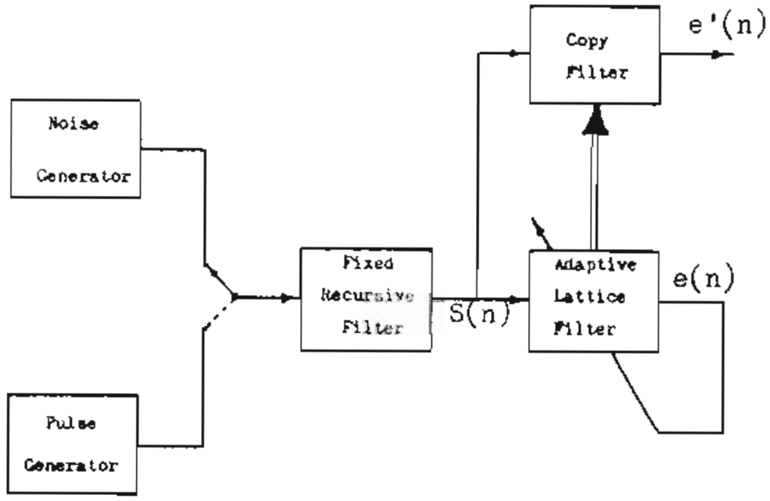


Fig. 2 Block Diagram For The Experimental Study.

$$\text{Misadjustment(MA)} = \frac{\text{Excess Mean-Square Error ( EMSE )}}{\text{Optimum Mean-Square Error}} \%$$

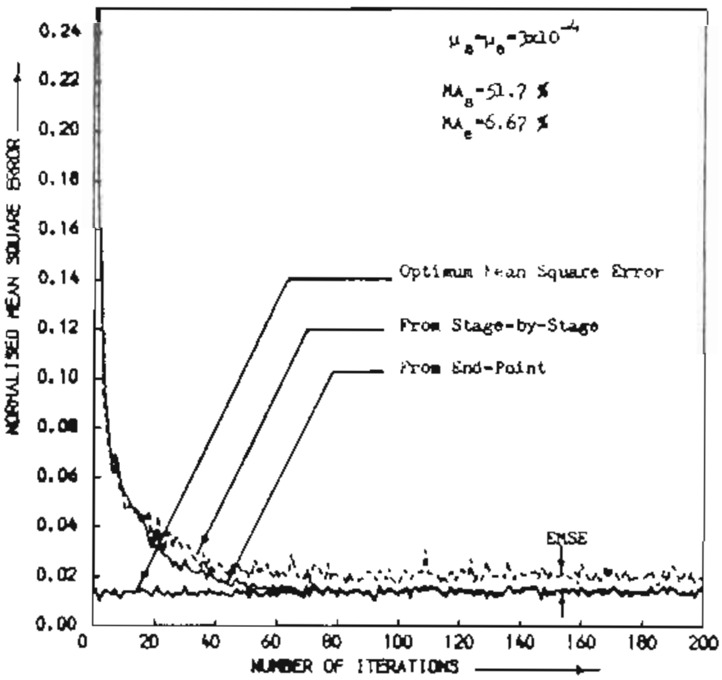


Fig. 3, Ensemble Average Learning Curves From Both Stage-by-stage and End-point Methods.

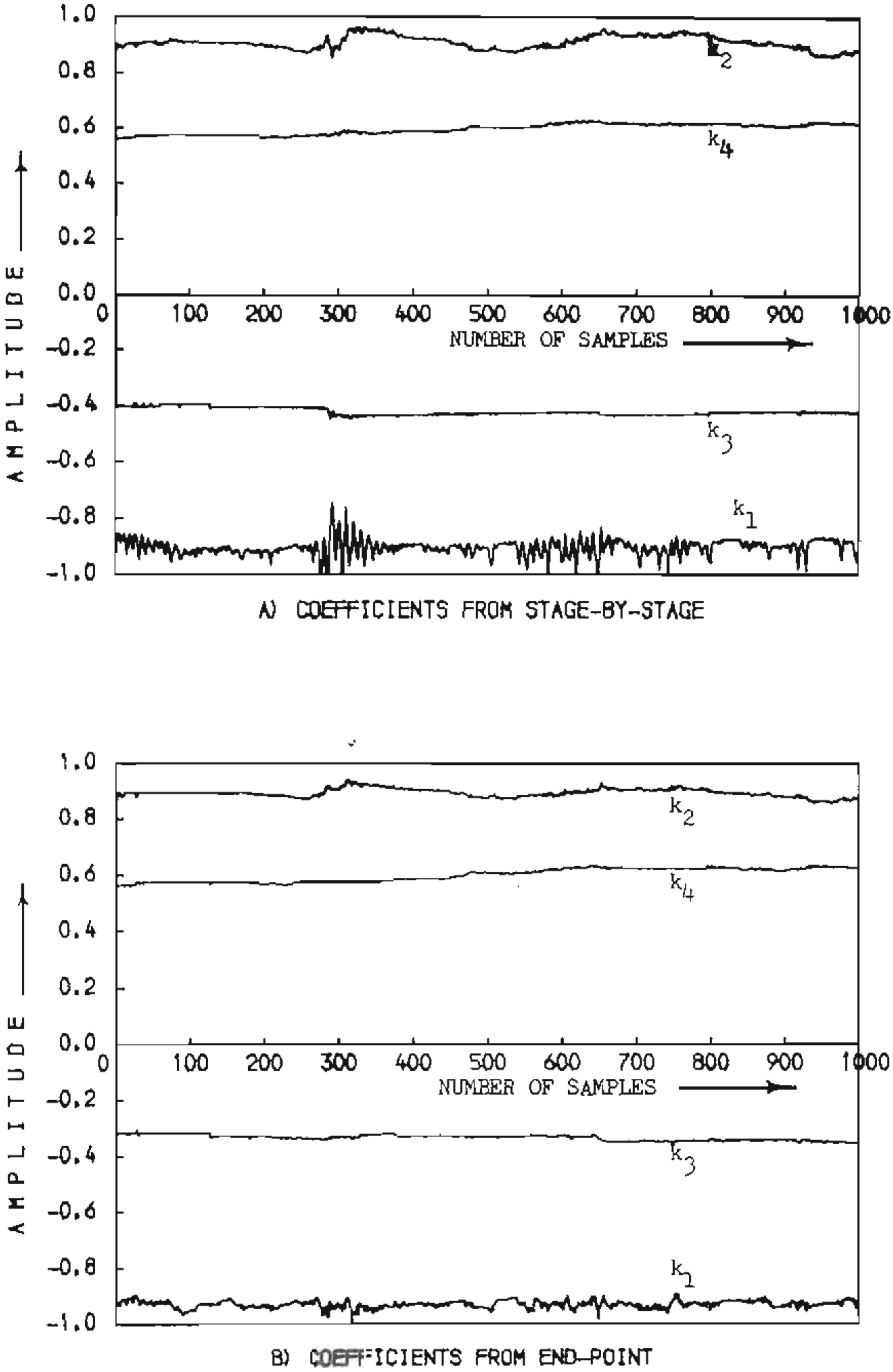


Fig. 4, Coefficient Tracking From A) Stage-by-Stage And B) End-Point For Random Noise Excitation($\mu_s=\mu_e=3x10^{-4}$).

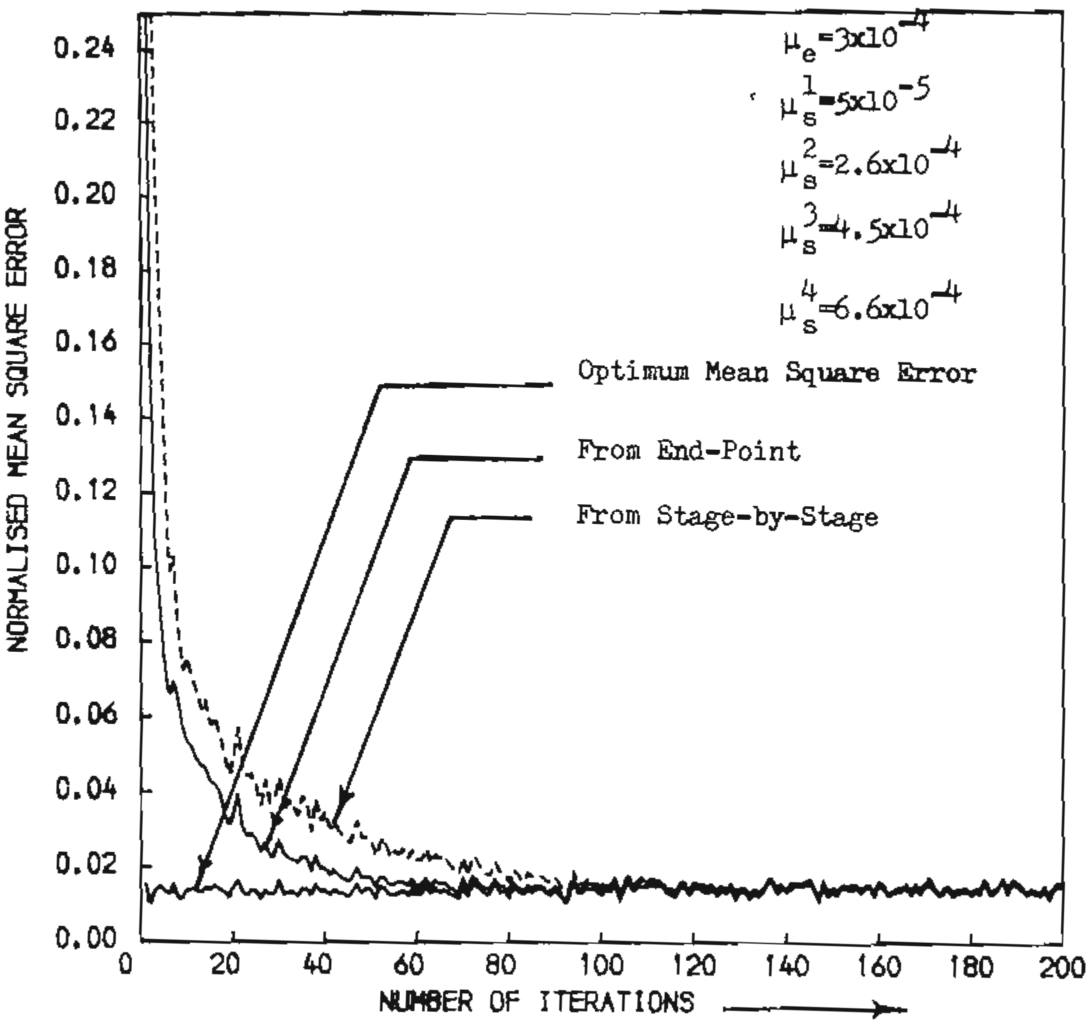


Fig. 5 , Ensemble Average Learning Curves For Both Stage-by-Stage With Vector Of $\mu_s$ And End-Point With Fixed Value Of $\mu_e$ .