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A NEW ADAPTIVE LINE SPECTRAL PAIR FILTER FOR

LINEAR PREDICTION OF SPEECH

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طريقة جديدة لتـهايؤ مرشح ازواج خطوط الطيف تـستخــدم
في التوقع الخطي للاشارات الصوتيـــة

خلاصــــــة :

ارسال الاشارات الصوتية بطريقة الشفرة ذو النبضات الثنائية يحتاج الى اتساع مدى كبير جـــــدا •
ولتقليل اتساع المدى استخدمت طرق عديدة منها طريقة التوقع الخطي المتباين • أو طريقة معامــــلات
الارتباط الجزئي (PARCOR) حيث يمكن التعبير عن الاشارات الصوتية بعدد معين من المعاملات التـــــي
تحتاج في تشفيرها الى عدد قليل من النبضات الثنائية • وقد أثبتت طريقة معاملات الارتباط الجزئـــــي
جدواها عن ما سبقها من الطرق في تحليل واعادة تركيب الاشارات الصوتية وذلك عن معدل نبضات ثنائيـــــة
أكثر من ٢٤٠٠ نبضة/ثانية • ولكن اذا قلّ عدد النبضات المستخدمة عن ذلك فان الاشارات الصوتية المستقبلة
تصبح غير واضحة وغير طبيعية • ولهذا السبب استحدثت طريقة ازواج خطوط الطيف لكونها تحتاج الـــــى
عدد أقل من النبضات الثنائية لتشفيرهـــا •

هذا البحث يقدم مرشح متـباين جديد لاستنتاج معاملات ازواج خطوط الطيف مباشرة من عينــــــات
الاشارات الصوتية المتتالية • وقد أثبتت تجارب المحاكاة باستخدام الحاسب الآلي أن الطريقة المستحدثـــــة
لها معدل تقارب أعلى ونسبة خطأ أقل من ما سبق نشره في هذا المجــــــال •

ABSTRACT:

Analysis/synthesis of speech by PARCOR method is proved to be advantageous over other methods previously developed for bit rates above 2.4 kbps. However, if the bit rate is reduced below this value, reconstructed speech becomes unclear and unnatural. Line spectral pair (LSP) coefficients were thus introduced as alternative representations of linear prediction parameters for low-bit rate speech coding. This paper presents a least-mean-square (LMS) type adaptive LSP filter for directly calculating the LSP coefficients on sample-by-semple basis. The algorithm proposed here is shown to have higher convergence rate and lower misadjustment as compared to other algorithms.

INTRODUCTION:

The use of linear prediction for spectral analysis and vocal tract parameters estimation has been widely accepted in the speech processing field. Although, the autocorrelation and covariance methods [1,2] 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 updating 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 speech at the receiver, a further requirement is that this inverse filter is stable, i.e., that the adaptive filter is minimum phase.

Sequential adaptation methods [3] have the advantage of computational simplicity as is required for real-time applications, while being still capable of following the time varying nature of the speech to an acceptable degree of accuracy. In the past, sequential adaptive linear prediction was implemented with tapped-delay line or ladder structure digital filter [4,5,6,7]. However, adaptive ladder filters have been reported to suffer from slow convergence and sensitivity to round-off noise in practical finite word length applications. To overcome these problems an adaptive lattice structure digital filter was introduced [8,9,10]. The lattice structure filter, which may be interpreted as a realisation of the Levinson-Durbin algorithm [11], has many advantageous properties and has found wide applications in signal processing, spectral estimations, and speech analysis. The lattice structure is an orthogonalising filter which transforms the original observations into two orthogonal sequences of forward and backward prediction errors, both spanning the same space as that of the original data. The parameters of the lattice filter, known as partial correlation coefficients (PARCOR), provide an alternative representation of the ladder coefficients. Lattice filters have the important property that a minimum phase is guaranteed when all the PARCOR coefficients are less than one in modulus and that the forward and backward errors at each stage are all minimised in mean square value when the output is similarly minimised (orthogonality property [1]). The PARCOR estimates may be obtained from the exact least squares lattice or the gradient lattice methods, which iteratively update the estimates as each new data sample becomes available [8,9,10].

Line spectral pair (LSP) coefficients have been proposed by Itakura et al [12] and Honda and Itakura [13] as an alternative representation of linear predictive coding (LPC) speech parameters for sub-band coding techniques with dynamic bit allocation in each sub-band. These LSP coefficients are preferred to other LPC parameters, such as ladder and PARCOR coefficients because of their closer relationship to the spectrum of the speech being coded and their uniformly distributed sensitivity to quantisation effects across the frequency spectrum.

Calculation of LSP coefficients in the above method [12,13] involves autocorrelation analysis based on a block of stored speech samples followed by an arithmetic conversion procedure which includes the location of zeros in Fourier sine and cosine series. Recently, Cheetham [14] has introduced an adaptive LSP even order filter updated by LMS algorithm, where the end-point error is used for gradient estimation.

In this paper, a new updating algorithm for the even-order LSP adaptive filter is introduced. The algorithm does not require any calculation of autocorrelation parameters or matrix manipulation. Moreover, it provides higher convergence rate and lower misadjustment than the algorithm referenced in [14].

LINE SPECTRAL PAIR ANALYSIS:

As stated previously, PARCOR analysis/synthesis method reaches the lowest bit rate of 2400 bps. If the bit rate falls below this value, synthesised speech degrades rapidly. The LSP method was thus investigated [13] to maintain speech quality at lower bit rates. The PARCOR coefficients

are essentially parameters operating in the time-domain, whereas the LSP are parameters functioning in the frequency-domain. Therefore, the LSP parameters are advantageous in that the distortion they produce is smaller than that of the PARCOR coefficients even when they are roughly quantised and linearly interpolated [15].

For the linear prediction model shown in Fig. 1, the transfer function in Z-transform notations is given as:
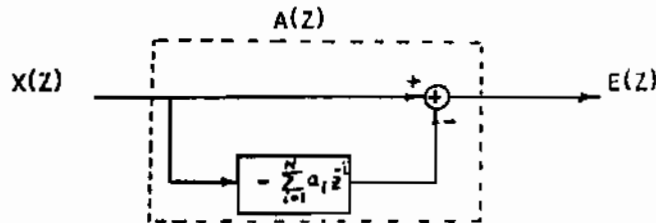

Fig. 1, Linear Prediction (All-Zero) Model.

$$E(Z)/X(Z) = 1 + \sum_{i=1}^{N} a_i Z^{-i}$$

$$= 1 + a_1 Z^{-1} + a_2 Z^{-2} + \ldots\ldots + a_N Z^{-N} \tag{1}$$

where N is the order of the prediction filter, and $\{a_i, i=1,2,\ldots N\}$ are the predictor coefficients. The linear prediction model in Fig.1, may be realised using all-zero lattice structure filter shown within the dotted lines in Fig.2. This filter has forward and backward error outputs labelled $f_N(n)$ and $b_N(n)$ respectively. The forward prediction error $f_i(n)$ at stage i is given as:
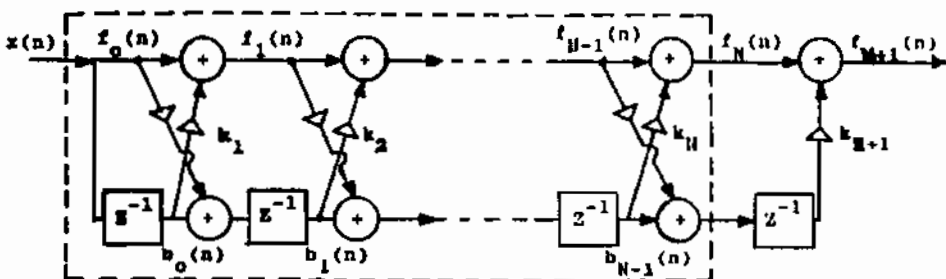
$$f_i(n) = f_{i-1}(n) + k_i b_{i-1}(n) \tag{2}$$

Fig. 2, Lattice Filter Structure with Augmented Stage.

and the backward prediction error at stage I is expressed as:

$$b_i(n) = b_{i-1}(n-1) + k_i \, f_{i-1}(n-1) \qquad (3)$$

where

$$f_0(n) = x(n)$$

$$b_0(n) = x(n-1)$$

and $\{k_i, \; i=1,2,......N\}$ are the PARCOR coefficients. The transfer function between the forward output error $f_i(n)$ of stage I and the input $x(n)$ can be expressed as:

$$F_i(Z) = F_{i-1}(Z) + k_i B_{i-1}(Z) \qquad (4)$$

Similarly, the transfer function between the backward output error $b_i(n)$ of stage I and the input $x(n)$ is given as:

$$B_i(Z) = Z^{-1}[\; B_{i-1}(Z) + k_i F_{i-1}(Z) \;] \qquad (5)$$

where

$$F_0(Z) = 1 \qquad \text{and} \qquad B_0(Z) = Z^{-1}$$

Let us now assume that the lattice filter shown in Fig.2, is augmented by an extra stage with $k_{N+1} = \pm 1$ to produce an output $f_{N+1}(n)$. It is easy to show that all the zeros of the augmented filter lie on the unit circle in the Argand Z-plane [1]. This condition ($k_{N+1} = 1$) corresponds to the case where the air flow is completely reflected at the glottis in the vocal tract model represented by PARCOR coefficients [16]. In other words, this condition corresponds to the completely open or closed termination condition. The actual boundary condition at the glottis is, however, the sequence of opening and closing, as a function of vocal cord vibrations. Since the boundary condition at the lips in the PARCOR analysis is a free field ($k_0 = -1$) [16], the present boundary condition sets the absolute values of the reflection coefficients to 1 at both ends of the vocal tract. This means that the vocal tract acoustic system becomes a lossless system which completely shuts in the energy. Therefore, the quality factor Q at each resonance mode in the acoustic tube becomes infinite, and a pair of delta function-like resonance characteristics (a pair of line spectra) which corresponds to each boundary condition at the glottis are obtained. The number of resonances are 2N.

Let P(Z) and Q(Z) be the transfer functions obtained for the augmented filter when $k_{N+1} = -1$ or $+1$ respectively. Hence:

$$P(Z) = F_{N+1}(Z) = F_N(Z) - B_N(Z) \qquad (6)$$

and

$$Q(Z) = F_N(Z) + B_N(Z) \qquad (7)$$

Although P(Z) and Q(Z) are both (N+1)st. order polynomial expressions, P(Z) has inversely symmetrical coefficients whereas Q(Z) has symmetrical

coefficients. Using Eqs. (6) and (7) we get

$$F_N(Z) = [\ P(Z) + Q(Z)\ ]/2 \qquad\qquad (8)$$

Note that $F_N(Z)$ is the same transfer function $A(Z)$ in Eq. (1).

From the recursive equations (4) and (5), we have

$$F_1(Z) = F_0(Z) + k_1 B_0(Z)$$
$$= 1 + k_1\ Z^{-1}$$

$$B_1(Z) = Z^{-1}[B_0(Z) + k_1 F_0(Z)]$$
$$= Z^{-(1+1)} F_1(Z^{-1})$$

$$F_2(Z) = F_1(Z) + k_2 B_1(Z)$$
$$= 1 + k_1(1+k_2)Z^{-1} + k_2 Z^{-2}$$

$$B_2(Z) = Z^{-1}[B_1(Z) + k_2 F_1(Z)]$$
$$= Z^{-(1+2)} F_2(Z^{-1})$$

Continuing the above manipulation, a general expression can be obtained for $B_N(Z)$ as:

$$B_N(Z) = Z^{-(N+1)} F_N(Z^{-1})$$
$$= Z^{-(N+1)} + a_1 Z^{-N} + \ldots\ldots + a_N Z^{-1}$$

or

$$B_N(Z) = Z^{-(N+1)} A(Z^{-1}) \qquad\qquad (9)$$

Applying Eq.(9) into Eqs. (6) and (7), then

$$P(Z) = A(Z) - Z^{-(N+1)} A(Z^{-1}) \qquad\qquad (10)$$

and

$$Q(Z) = A(Z) + Z^{-(N+1)} A(Z^{-1}) \qquad\qquad (11)$$

Now, if N is assumed to be even, P(Z) and Q(Z) can be factorised as:

$$P(Z) = (1 - Z^{-1}) \prod_{i=1}^{N/2} (1 + c_i\ Z^{-1} + Z^{-2}) \qquad\qquad (12)$$

and

$$Q(Z) = (1 + Z^{-1}) \prod_{i=1}^{N/2} (1 + d_i\ Z^{-1} + Z^{-2}) \qquad\qquad (13)$$

where

$$c_i = -2 \cos \theta_i \qquad\qquad (14)$$

$$d_i = -2 \cos \psi_i \qquad\qquad (15)$$

and θ_i, ψ_i for $i = 1,2,\ldots\ldots\ldots N/2$ are the Line Spectral Pair coefficients. Note that the factors $(1 - Z^{-1})$ and $(1 + Z^{-1})$ are found by using $P(1)=0$ and $Q(-1)=0$ in Eqs. (10) and (11).

Since $A(Z) = [P(Z) + Q(Z)]/2$, the LSP coefficients θ_i, ψ_i can be used instead of $\{a_i, i=1,2,\ldots\ldots N\}$ to characterise the transfer function $A(Z)$ of the prediction filter in Fig.1. When $A(Z)$ is minimum phase, as stated previously, the zeros of $P(Z)$ and $Q(Z)$ are interlaced around the unit circle with

$$0 < \psi_1 < \theta_1 < \psi_2 < \theta_2 < \ldots\ldots < \psi_{N/2} < \theta_{N/2} < \pi \qquad (16)$$

Furthermore, this interlacing is a necessary and sufficient condition for the stability of the all-pole synthesis model $1/A(Z)$.

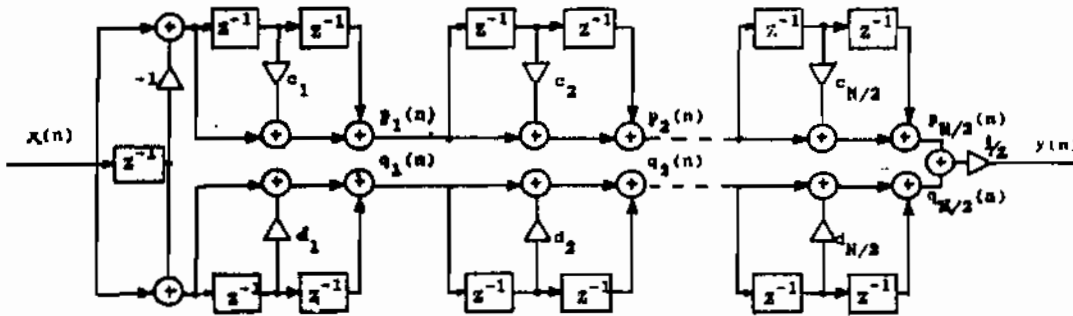A line spectral pair filter structure derived from Eqs. (8), (12) and (13) is shown in Fig. 3 for even order N.

Fig. 3, Line Spectral Pair (LSP) All-Zero Filter Structure.

THE UPDATING ALGORITHM

In the filter structure shown in Fig. 3, $P(Z)$ and $Q(Z)$ are realised by cascades of non-recursive second order filter sections. This filter has an output error signal $y(n)$ and two error signals $p_i(n)$ and $q_i(n)$, $i=1,2,\ldots N/2$ at the output of each section. The output $y(n)$ may be expressed as:

$$y(n) = [p_{N/2}(n) + q_{N/2}(n)]/2 \qquad (17)$$

where $p(n)$ and $q(n)$ are calculated recursively as:

$$p_i(n) = p_{i-1}(n) + c_i \, p_{i-1}(n-1) + p_{i-1}(n-2) \qquad (18)$$

$$q_i(n) = q_{i-1}(n) + d_i \, q_{i-1}(n-1) + q_{i-1}(n-2) \qquad (19)$$

and

$$p_0(n) = x(n) - x(n-1)$$

$$q_0(n) = x(n) + x(n-1)$$

Now, the aim is to adjust the multiplier coefficients (c_i, d_i, $i=1,2,....N/2$) of the filter in Fig. 3 so that the minimum mean square value of $y(n)$ is reached. This minimisation process may be achieved by means of a sequence of local minimisation algorithms, one for each section. The LMS algorithm [4] is proposed to update the filter coefficients so that the output at each stage is minimised. That is, an iterated change in the coefficients in the direction of the negative gradient of $p_i^2(n)$ and $q_i^2(n)$, $i=1,2,....N/2$ is performed until the minimum mean square value of $y(n)$ is achieved.

For convenience of presentation, a section of LSP filter in Fig. 3 is shown in Fig. 4. Applying the LMS algorithm to this filter section, then c_i and d_i multipliers can be updated as:
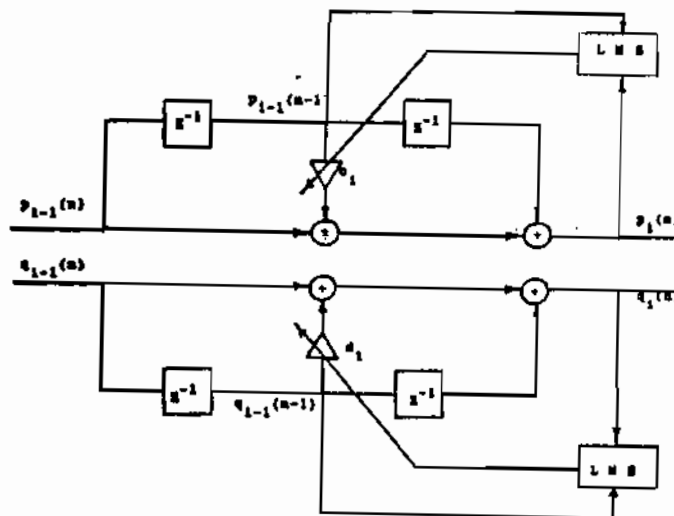

Fig. 4, A Section of LSP Filter With
LMS Updating Algorithm.

$$c_i(n+1) = c_i(n) - \mu \partial p_i^2(n)/\partial c_i(n) \qquad (20)$$

and

$$d_i(n+1) = d_i(n) - \mu \partial q_i^2(n)/\partial d_i(n) \qquad (21)$$

where μ is a step size controls stability and rate of convergence of LMS algorithm. Applying Eqs. (18) and (19) into Eqs. (20) and (21) yields,

$$\partial p_i^2(n)/\partial c_i(n) = 2 \, p_i(n) \, p_{i-1}(n-1)$$

and

$$\partial q_i^2(n)/\partial d_i(n) = 2 \, q_i(n) \, q_{i-1}(n-1)$$

Therefore, the stage-by-stage LMS updating algorithm for the adaptive LSP digital filter becomes

$$c_i(n+1) = c_i(n) - 2 \, \mu \, p_i(n) \, p_{i-1}(n-1) \qquad (22)$$

and

$$d_i(n+1) = d_i(n) - 2 \, \mu \, q_i(n) \, q_{i-1}(n-1) \qquad (23)$$

To maintain minimum phase condition, it must be ensured that the condition

$$-2 < d_1 < c_1 < d_2 < c_2 < \ldots < d_{N/2} < c_{N/2} < 2 \qquad (24)$$

is satisfied at all times. This condition is equivalent to Eq. (16) stated previously. If the LMS algorithm in Eqs. (22) and (23) is applied to the adaptive LSP filter shown· in Fig. 3, to minimise the mean square value of $y(n)$ for a section of speech applied at the input, the LSP coefficients θ_i, ψ_i for $i=1,2,...N/2$ may be obtained by means of an inverse cosine look-up table.

EXPERIMENTAL RESULTS:

A series of experiments was carried out by simulation on an IBM Pc computer to investigate the convergence behaviour of adaptive lattice [3], adaptive LSP end-point introduced in [14], and adaptive LSP introduced in this paper (stage-by-stage updating). A speech-like signal was generated by exciting a fixed all-pole recursive .filter with Gaussian noise of zero mean and unit variance. The poles of the recursive filter were chosen at 0.9 EXP($\pm$j π/4) and 0.8 EXP($\pm$j π/2). The output from the fixed filter was passed through the three adaptive filters mentioned above with initial coefficient values set to zero. The adaptive filters were allowed to update their coefficients on a sample-by-sample basis for a period of 100 samples. This experiment was repeated 70 times, and an ensemble average learning curve is calculated from the 70 individual learning curves. Figures 5, 6, and 7 show the learning curves for adaptive lattice, adaptive LSP [14], and adaptive LSP stage-by-stage for the same value of step size μ. In each figure, it is shown also the optimum mean-square-error, measured as ensemble average for the variance of the Gaussian noise. It can be seen that the convergence time for both lattice and LSP end-point is almost the same (73 iterations), whereas the convergence time for LSP stage-by-stage is only 35

iterations. In other words, the algorithm introduced   here is more than two times faster than the other two.
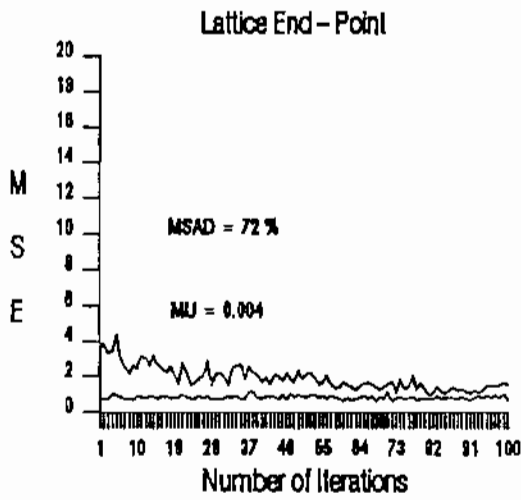

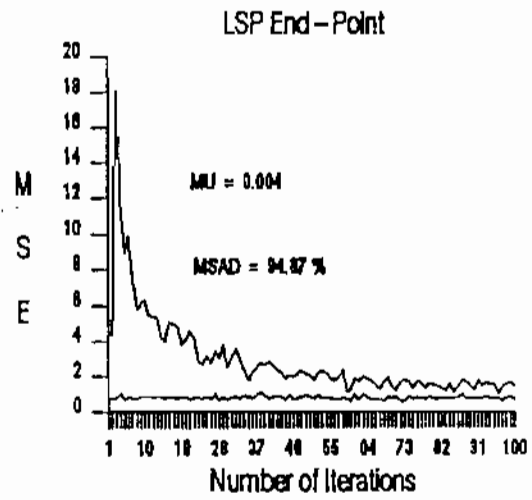Fig. 5, Learning Curve for Adaptive Lattice [3].

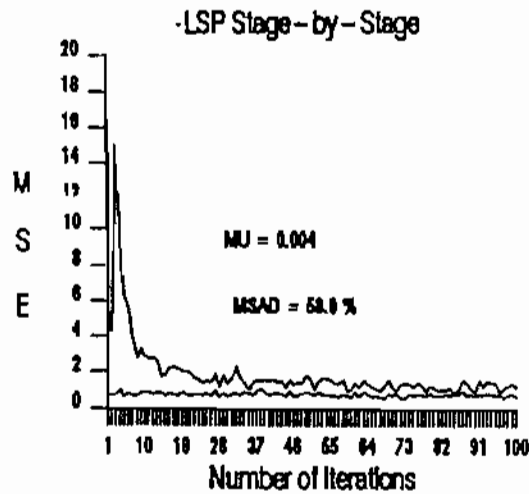Fig. 6, Learning Curve for Adaptive LSP [14].

Fig. 7, Learning Curve for Adaptive LSP Introduced In this Paper.

Moreover, the misadjustment defined as:

$$MSAD = \frac{Mean\ Square\ Error\ (MSE)\ -\ Optimum\ MSE}{Optimum\ MSE}\ \%$$

Is found to equal 72% for lattice, 94% for LSP end-point, and 58.9% for LSP stage-by-stage. For convenience of comparison, Fig. 8, shows a smoothed version of the learning curves In Figs. 5, 6, and 7 together.
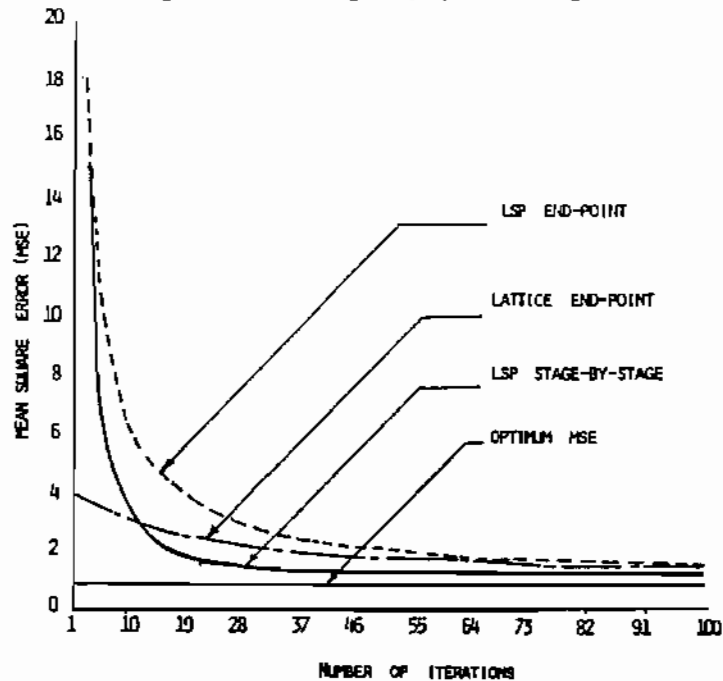

Fig. 8, Comparison of Learning Curves for Three
Adaptive Filters.

In the following part, two sets of experiments were conducted to study the effect of quantisation noise on the performance of the adaptive LSP stage-by-stage filter Introduced in this paper. The speech-like signal output from the fixed all-pole filter mentioned before was passed through the adaptive filter with initial coefficient values set to zero. In the first set of these experiments, the filter was allowed to update its coefficients $\{c_i, d_i,\ i=1,2,...,N/2\}$ for a period of 100 samples. For each sample, the coefficients were updated, quantised, and passed to the adaptive filter to estimate the error signal required for the next update. Again, each experiment was repeated 70 times, and ensemble average learning curves were obtained for 12 bits and 10 bits word-length. In the second set of experiments, the LSP coefficients $\{\theta_i, \psi_i,\ i=1,2,...,N/2\}$ were calculated for each sample by Inverse cosine of the updated coefficients $\{c_i, d_i,\ i=1,2,...,N/2\}$. The cosine of a quantised version of the LSP coefficients $\{\theta_i, \psi_i,\ i=1,2,...,N/2\}$ was then obtained and passed to the adaptive filter to

estimate the error signal required for the next update. Ensemble average learning curves for 12 bits and 10 bits word-length were obtained from 70 individual learning curves as mentioned previously.

Figs. 9 and 11 show the learning curves obtained when the coefficients $\{c_i, d_i, i=1,2,...,N/2\}$ were quantised and Figs. 10 and 12 show the corresponding curves when the LSP coefficients $\{\theta_i, \psi_i, i=1,2,...,N/2\}$ were quantised. Comparing these figures with Fig. 7, it can be seen that the convergence rate is almost unchanged. However, a small increase in the misadjustment is noticed in all cases. The increase in misadjustment obtained when the coefficients $\{c_i, d_i, i=1,2,...,N/2\}$ were quantised is marginally higher than that obtained when the LSP coefficients $\{\theta_i, \psi_i, i=1,2,...,N/2\}$ were quantised. Note that there are rounding-off errors in the calculation of cosine and inverse cosine procedure. However, quantisation of $\{\theta_i, \psi_i, i=1,2,...,N/2\}$ provides better performance than quantisation of $\{c_i, d_i, i=1,2,...,N/2\}$. This confirms the theory stating that the LSP coefficients are less sensitive to quantisation errors than any other time-domain coefficients.
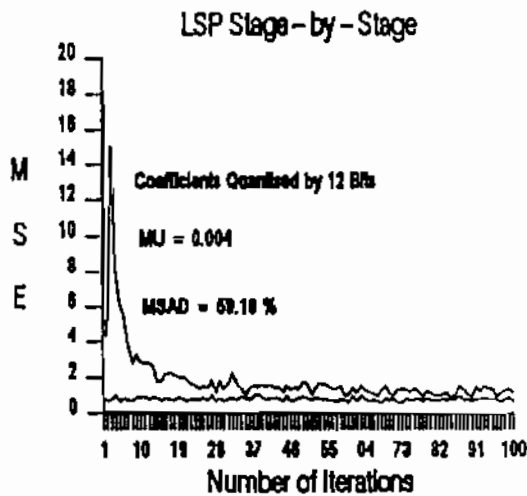

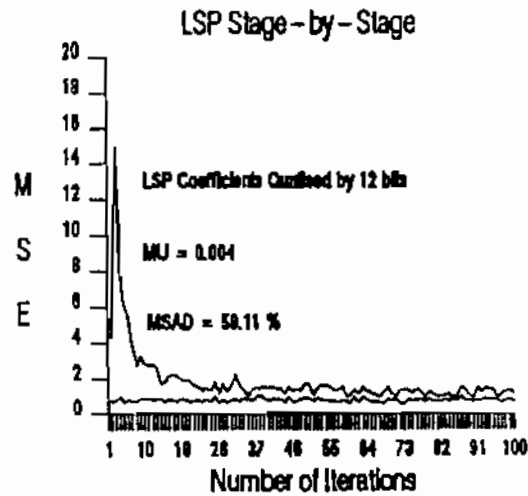Fig. 9, Learning Curve when c'^s and d'^s are Quantised with 12 Bits.

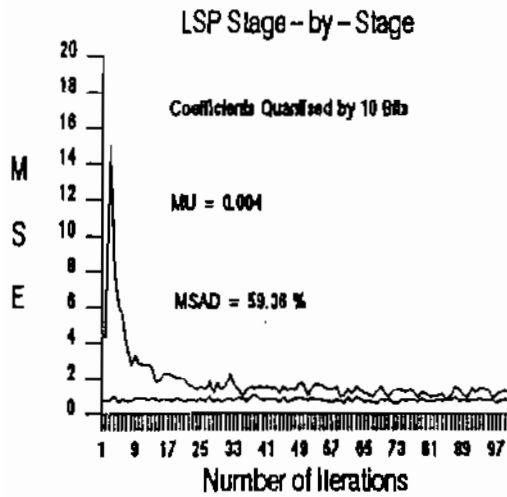Fig. 10, Learning Curve when θ'^s and ψ'^s are Quantised with 12 Bits.

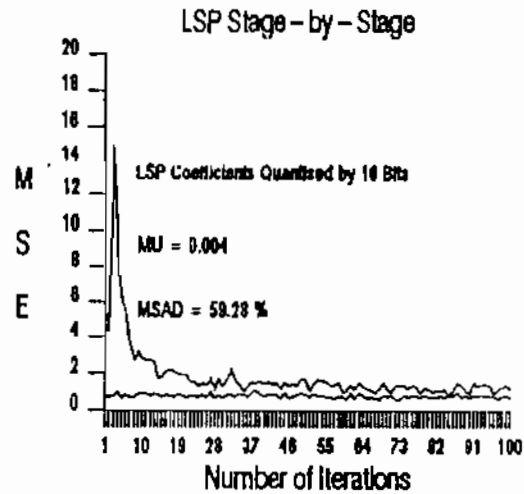Fig.11, Learning Curve when c'' and d' are Quantised with 10 Bits.

Fig.12, Learning Curve when θ' and ψ' are Quantised with 10Bits

CONCLUSIONS:

In this paper, a new method of updating the line spectral pair adaptive filter is presented. The method is based on sample-by-sample updating for the coefficients of the LSP filter. The residual signal at the output of each stage is used instead of the end-point residual used previously by other researchers. The new method has been demonstrated as being superior to other methods in a series of experiments.

Under finite word-length. condition, the algorithm is found to be stable and the convergence rate is not sensitive to quantisation error. However, a slight increase in the misadjustment is noticed. The increase in misadjustment due to quantisation of the LSP coefficients is less than that due to quantisation of the filter coefficients.

Applications of the algorithm introduced here in linear prediction of speech is now in progress and will be published latter.

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