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Noise Suppression in Speech Signals Using Kalman Filtering

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ABSTRACT

This paper deals with the speech enhancement, when a corrupted speech signal with an additive noise is the only information available for processing. Kalman filtering is known as an effective speech enhancement technique in which speech signal is usually modeled as autoregressive (AR) process and represented in the state-space domain. In this paper, Kalmanfilter based linear predictive coding method (LPC) is used for adaptive estimation of the speech and noise AR parameters.

Keywords*: *Additive Noise, Speech Enhancement , State–Space domain, Auto regressive parameters, Linear Predictive Coding.

I. INTRODUCTION

Speech enhancement is an area of signal processing where the objective is improving the pleasantness of the speech signals. Enhancing of speech deteriorated by noise is the most vital field of enhancement. The necessary methods for enhancing of speech are the removal of hidden noise, echo cancellation and also introducing the particular frequenciesinto the speech signal. We will focus on the suppressing of hidden noise after discussing what the other existed methods are all about.In this paperKalman filter algorithm along with linear predictive coding(LPC)method is used to reduce the background noise and to estimate the parameters of speech signal.Linear predictive coding(LPC) is defined as a digital method for encoding an analog signal in which a particular value is predicted by a linear function of the past values of the signal. At aparticular time n,the speech sample s(n)is represented as a linear combination of the past samples. The most important aspect of LPC is the linear predictive filter which allows the value of the next sample to be determined by a linear combination of previous samples.

II. NOISY SPEECH MODEL

The speech signal S(t) and the additive noise N(t) are modeled as the mth-order order and nth-order AR processes:

$$S(i)=\sum_{k=1}^{m}c_k S(i-k)+X(i) \quad (1) \qquad N(i)=\sum_{l=1}^{n}d_l N(i-l)+Y(i) \quad (2) \qquad Z(i)=S(i)+N(i) \quad (3)$$

S(i) is the i^{th}sample of the speech signal

N(i) is the i^{th} sample of the additive noise

Z(i) is the i^{th} of the observation

c_k is the k^{th} AR speech model parameter

d_l is the l^{th} AR noise model parameter

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X(i) and Y(i) are uncorrelated Gaussian white noise sequences.This system can be represented by the following state space model:

p(i) = F p(i − 1) + q(i) (4)

z(i) = H p(i) (5)

Where, p(i) is the (m + n) × 1 state vector

q(i) is the (m+ n) × 1 vector

F is the (m + n) × (m + n) transition matrix

$$F=\begin{bmatrix} F_S & 0 \\ 0 & F_N \end{bmatrix} \quad F_S=\begin{bmatrix} 0 & 1 & \dots & 0 \\ 0 & 0 & 1 & 0 \\ \vdots & \ddots & \ddots & \vdots \\ c_m & \dots & \dots & c_1 \end{bmatrix} \quad F_N=\begin{bmatrix} 0 & 1 & \dots & 0 \\ 0 & 0 & 1 & 0 \\ \vdots & \ddots & \ddots & \vdots \\ d_l & \dots & \dots & d_1 \end{bmatrix}$$

III.AUTOREGRESSIVE PROCESS &ESTIMATION OF AR PARAMETERS

Autoregressive is a stochastic process used in statistical calculations in which future values are estimated based on a weighted sum of past values. The autoregressive process of order n is denoted AR(n) is defined by

$x_t=\sum_{r=1}^{n}\varphi_r x_{t-r}+\varepsilon_t$ (6) where φ$_1$, . . . , φ$_r$ are fixed constants and { ε_t } is a sequence of independent (or uncorrelated) random variables with mean 0 and variance σ^2.

The AR (1) process is defined by

$$x_t=\varphi_1 x_{t-1}+\varepsilon_t \quad (7)$$

To find its auto covariance function we make successive substitutions, to get

$$x_t=\varepsilon_t+\varphi_1\varepsilon_{t-1}+\varphi_1^2\varepsilon_{t-2}+\dots \quad (8)$$

The fact that { x_t } is second order stationary follows from the observation that E (x_t) = 0 and that the auto covariance function can be calculated as follows:

$$\gamma_0=\sigma^2/(1-\varphi^2) \quad (9)$$

The Yule–Walker equations provide several routes to estimating the parameters of an AR (*p*) model, by replacing the theoretical co-variances with estimated values.

$$x_t=c+\sum_{i=1}^{p}\varphi_i x_{t-i}+\varepsilon_t^* \quad (10)$$

Here predicted of values of x_t would be based on the *p* future values of the same series. This way of estimating the AR parameters is due to Burg,and is called the Burg method.

IV. KALMAN FILTER ALGORITHM

The Kalman filter is a mathematical procedure which operates through a prediction and correction mechanism. In essence, this algorithm predicts a new state from its previous estimation by adding a correction term proportional to

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the predicted error. In this way, this error is statistically minimized. This filter is the main algorithm to estimate dynamic systems specified in state-space form.Itis an optimal recursive data processing algorithm. A feature is called optimum if the Kalman filter incorporates all the information provided. It processes all the measurements available, regardless the precision,toestimate the current value of the interest variables using knowledge of the system.

The algorithm works in a two-step process. In the prediction step, the Kalman filter produces estimates of the current state variables,along with their uncertainties.in the correction step It processes based on present input and previously calculated estimate using weighted average.

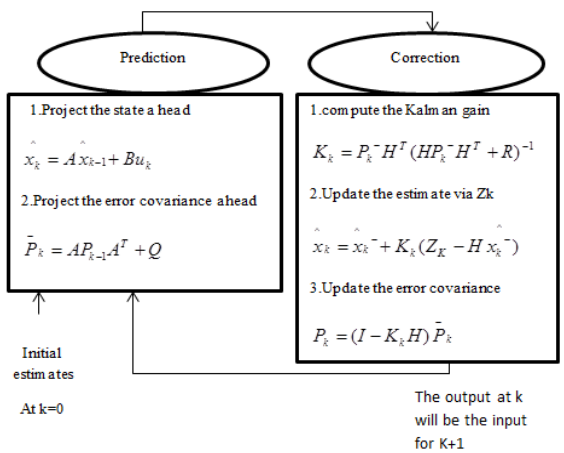

Fig 1:Complete Vision of Kalman Filter

Kalman filter algorithm consists of three matrices known as Prediction Matrix,Measurement Matrix ,Updated Co-Variance Matrix.prediction is related to the forecasting side of information processing.

$$\hat{X}_{K/K-1} = F_K \hat{X}_{K-1/K-1} + B_K U_K \quad (11)$$

$$P_{K/K-1} = F_K P_{K-1/K-1} F^T + Q_K \quad (12)$$

Measurement matrix is used to estimate position. $\bar{Z}_T = C\bar{X}_T$ (13)

Where, $C = \begin{bmatrix}1 & 0\end{bmatrix}\begin{bmatrix} POS_T \\ VEL_T \end{bmatrix} = [POS_T]$ In probability theoryand statistics, a covariance matrix is a matrix whose element in the i, j position is the covariance between the i th and j th elements of a random vector. $\bar{P} = \mathrm{cov}(I - KC)(X_T - \bar{X}_T) + \mathrm{cov}(KVT)$ (14) $K = C^T P^T \bar{S}^{-1}$ (15)

Where K is the kalman gain.

A.COVARIANCE

The covariance between two variables can be defined as

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COV(X,Y)=E[(X-E[X])(Y-E[Y])] (16)

V. SIMULATION RESULTS

The approach was tested using a speech signal and an additive noise. The speech signals are taken from the AURORA database and the noise signal is the additive random noise. Noise covariance values are initialized with 0.1 and tested till 0.4.and LPC polynomial order is taken from 4 to 16.The below table 1 shows the Mean square error values of few speech signals for different noise covariance values.Table 2 shows the Mean square error calcuted for different polynomial order of the LPC system.

Table 1 :Mean Square Error for different Noise covariances

Noise Covariance	Mean Square Error		
	Sp01.wav	Sp02.wav	Sp03.wav
0.1	0.6971	0.8724	0.7628
0.2	0.6731	0.8612	0.7558
0.3	0.6585	0.8545	0.7552
0.4	0.6485	0.8495	0.7565

Results for sp01.wav signal :

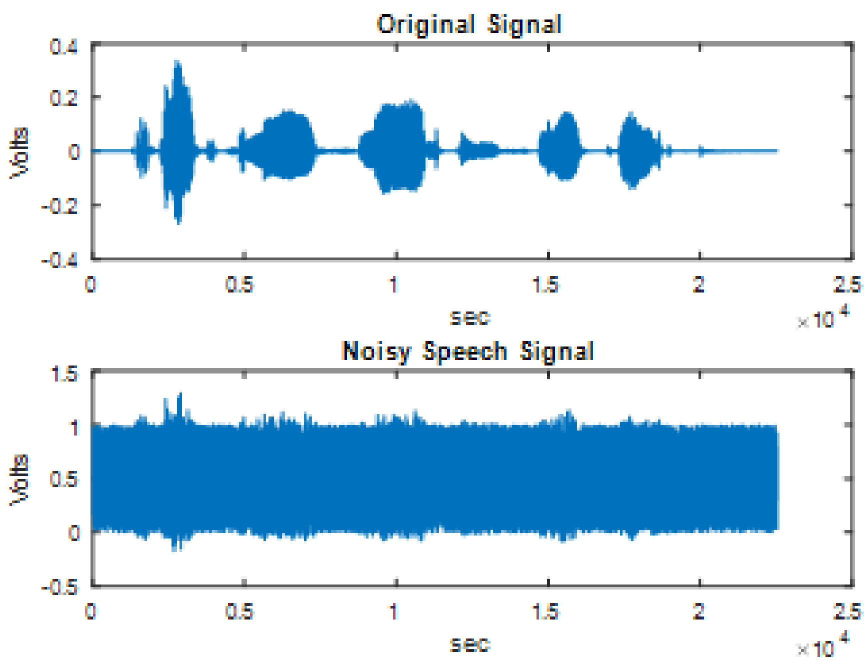

Fig 2 :Original & Noisy speech signals

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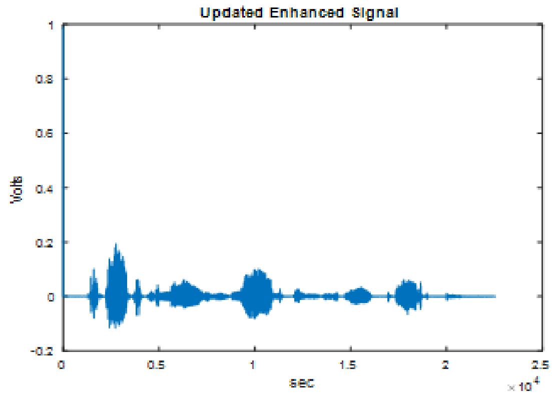

Fig 3: Updated Enhanced signal

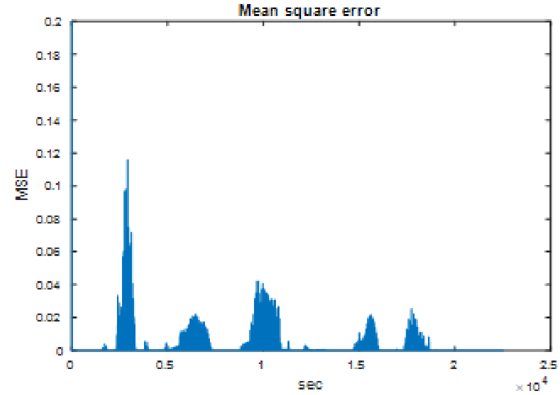

Fig 4: Mean Square Error

Table 2 :Mean Square Error for different LPC system Order

LPC System Order	Mean Square Error		
	Sp01.wav	Sp02.wav	Sp03.wav
4	4.713 x10^3	4.884 x10^3	2.869 x10^3
8	4.699 x10^3	4.814 x10^3	2.783 x10^3
12	4.694 x10^3	4.813 x10^3	2.769 x10^3
16	4.689 x10^3	4.811 x10^3	2.744 x10^3

Results for sp01.wav signal :

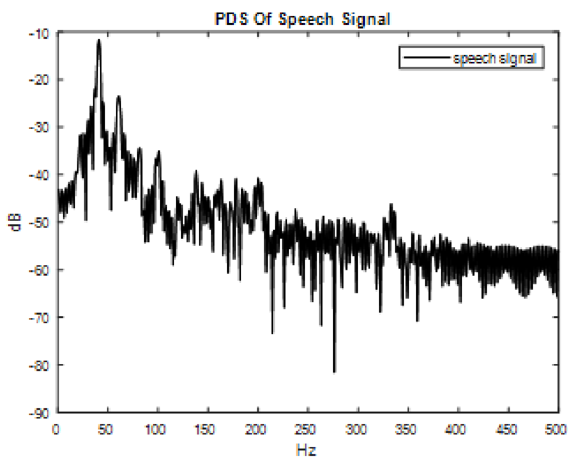

Fig 5 : Power Spectral Density of Speech Signal

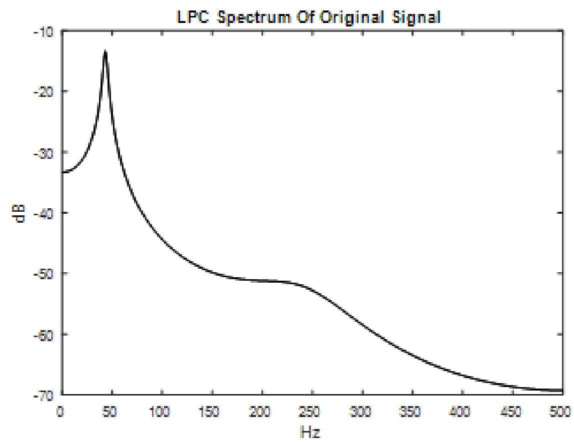

Fig 6 : LPC Spectrum of Original Signal

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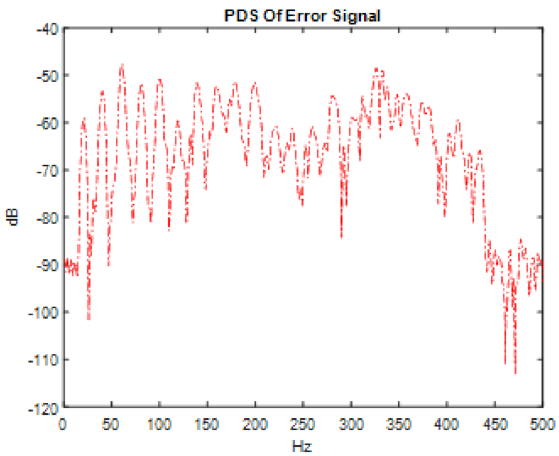

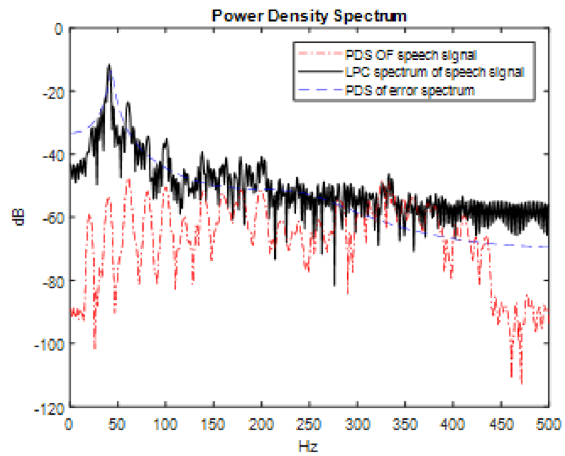

Fig 7 : Power Spectral Density Of Error Signal **Fig 8 : Power Density Spectrum**

VI. CONCLUSION

In this paper kalman filter based linear predictive coding methodis used to estimate the speech and noise AR parameters. Standard speech signals sp01.wav, sp02.wav, sp03.wav, sp04.wav are taken from the Aurora data base for analysis.The performance is measured based on polynomial order and noise covariance.Mean square error is estimated in terms of noise covariance and polynomial order. It is observed that MSE is reduced when noise covariance is varying from 0.1 to0.4 and LPC polynomials are taken from 4 to 16 factor,which improves the quality of the estimated signal.

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