Innovative Approach to the Generation of Reverberation Time Series and Echo Detection Algorithm

S. Balayya
Assistant Professor, Department of ECE, Wellfare Institute of Science Technology and Management,
Visakhapatnam, Andhra Pradesh, India

Abstract— An approach to the generation of time series and echo detection algorithms is presented and demonstrated. The SONAR system transmits pulses of acoustic signals to detect the target under the sea surface. The transmitted waves are reflected off objects in their paths, creating echoes that return to the vessel and are picked up by the sonar equipment. The received signal consists of echo signal, reverberated signal and noise signal. Echo is made when sound hits the target and bounces back. Reverberation is delayed repetition of sound reflected from the sea surface and bottom. The desired echo signal and reverberation have same characteristics, because of this it is very difficult to separate echo from the reverberation. The computer simulated reverberation time series are of high quality, in that they are accurate representations of those which would result from an actual sonar system(transmit/receive and horizontal/vertical beam patterns; pulse type, shape, length, and power; frequency and sampling rate),platform(speed and depth),and environment(wind speed and direction, backscattering strengths, and propagation loss).The time series approach utilizes recent developments in linear spectral prediction research in which the spectra of stochastic process are modelled as rational functions and algorithms are used to efficiently compute optimal estimates of coefficients which specify the spectra. The approach taken in this paper is to detect echo signal in two steps . In the first part the expected reverberation spectra for all beams are predicted. In the second part time series is generated from the expected spectra.

Keywords— Active sonar, Reverberation, Autoregressive model, Reverberation spectrum, pre-whiten

I. INTRODUCTION

SONAR is an acronym for sound navigation and ranging .sonar is a system that uses transmitted and reflected underwater sound waves to detect and locate submerged objects or measure the distance of underwater target. In sonar, the sound was generated by projector, through the sea to the target and returned as echoes to a hydrophone which converts these acoustic signals to electric signals. The electric output of hydrophone is amplified to a control or display device to accomplish the purpose for which the sonar system was intended. A sonar systems, equipments and devices are said to be active when the sound is purposely generated by one of the system component called the projector. The sound waves generated by the projector travel through the sea to the target and are returned as sonar echoes to a hydrophone which converts sound into electricity. The simplest active sonar w have an omni directional projector and hydrophone .Its detection performance is given by the allowable two way propagation loss i.e. from projector to target and back to hydrophone. Practical active sonar will have directional transmit and receive arrays.

Sonar Reverberation (and radar clutter) has been modeled in a variety of ways and for a diversity of applications. Expected reverberation power (intensity) level models are perhaps the most common**.** In these, the expected reverberation power level at the input, output, or some intermediate point in the sonar (radar) system is estimated as a function of the environmental and system parameters. The models are useful in evaluating system performance for signal processing approaches which depend primarily upon power level, such as single beam energy detectors and matched filters. As systems increase in complexity, making use of multiple beams, platform motion, and complex coherent signal processing, power level alone is an insufficient parameter to describe the interfering effects of reverberation..

II. TIME SERIES MODELING

Recent developments in linear spectral prediction (UP) techniques allow stochastic processes to be modeled in a straightforward manner. Common time series models of sampled stochastic processes, which are basic to many LSP techniques, include autoregressive (AR), moving average (MA), and autoregressive moving average (ARMA) processes. These processes can be realized as the outputs of linear digital filters driven by white noise processes, where the filter transfer functions have all-pole, all-zero, and pole-zero realizations for **AR, MA,** and **ARMA** processes, respectively. The digital filters can be implemented as recursive infinite impulse response **(IIR)** filters for **AR** and **ARMA** processes, and as a transversal finite impulse response **(FIR)** filter for an **MA** process. If the stochastic process to be modelled is nonstationary: but quasi-stationary, the digital filter realization is time varying, with time-varying poles and/or zeros.

A. Autoregressive Process

In an auto regressive model of order p, the value $\overline{x_n}$ of the complex stochastic process at time n given as a linear combination of past values and a random input ξ_n, such that

$$\overline{x_n} = -\sum_{k=1}^{p} b_k \overline{x_{n-k}} + \sigma\xi_n \tag{1}$$

Where ξ_n is a complex white noise process with zero mean and unity standard deviation.The system transfer function H(Z),between input and output is represented in terms of model parameters as an all pole function.

$$H(z) = \frac{\sigma}{1+\sum_{k=j}^{p} b_k z^{-k}} \tag{2}$$

The poles of H(Z) are the zeros of the polynomial in the denominator and the number of poles p is referred to as the model order. The discrete power density spectrum is

$$p_m = \frac{\sigma^2 \Delta t}{\left|1+\sum_{k=1}^{p} b_k e^{-j2\Pi mk/M}\right|^2} \tag{3}$$

Where Δt is the sampling interval and p_m is the power at radial frequency.The problem of modeling an arbitrary stochastic process {x,, n = e-, -1, 0, 1, .-} as an AR process reduces to the selection of the model parameters. The manner in which they are selected will depend on a priori information about {x,;. A standard formulation is to select the model parameters such that the linear estimate of the process {x,} at the present time n, given the past p values of the process { X n - k , k = 1: 2, --, p } , is best in a least squares sense. That is, defining the linear estimate of order p as

$$x_n^* = -\sum_{k=1}^{p} \mathrm{b_k x_{n-k}} \tag{4}$$

the parameters are selected such that the estimation error is minimized in a mean square sense

$$\min_{\{a_k\}} E\{\varepsilon_n^2\} = \min_{\{a_k\}} E\{(x_n + \sum_{k=1}^{p} b_k x_{n-k})^2\} \tag{5}$$

This is the digital Wiener optimal one-step prediction filtering problem, and it leads to the specification of the $\{b_k$, $\sigma\}$ as the solution of the normal equations

$$\rho_{in} = -\sum_{k=1}^{p} b_k \rho_{i-k,n} \qquad \text{i=1,2,…….p} \tag{6a}$$

$$\rho_{on} = -\sum_{k=1}^{p} b_k \rho_{kn} + \sigma^2 \tag{6b}$$

where $\rho_{i-k,n}$ is the time-varying autocorrelation function of the nonstationary process.

$$\rho_{i-k,n} \underline{\underline{\Delta}} E\{x_{n-k} x_{n-i}^*\} \tag{7}$$

If the spectrum (which in general is time-varying) of the process is known, then the auto-correlation function can be found by inverse Fourier transformation and the parameters $\{b_k, \sigma\}$ evaluated. If the spectrum is not known, but one has the past p values of the process, as in the above Wiener filtering formulation, then the auto covariance function can be used as a local estimate of the autocorrelation function.

$$\phi_{i-k,n} \triangleq \begin{cases} \sum_{j=n-p-i}^{n-1-k} x_{j-k} x^*_{j-i}, & i<k \\ \sum_{j=n-p-j}^{n-1-i} x_{j-k} x^*_{j-i}, & i>k \end{cases} \quad (8)$$

The auto covariance function can then replace the autocorrelation function in the normal equations. With this replacement ,are known as the Yule-Walker equations and will be referred to in this way in this paper, regardless of whether the auto covariance or autocorrelation functions are used in them. A variety of ways to solve the Yule-Walker equations are available. We will use the Levinson-Durbin approach . Having solved for estimates of the model parameters in this way, one can evaluate the spectral estimate or the linear estimation filter transfer function &z) by using the parameter estimates in expressions (3) and (2), respectively.
The filter will produce a statistical realization of the process {x} when driven by white noise. The spectral estimate is sometimes referred to as the maximum entropy spectral estimate.

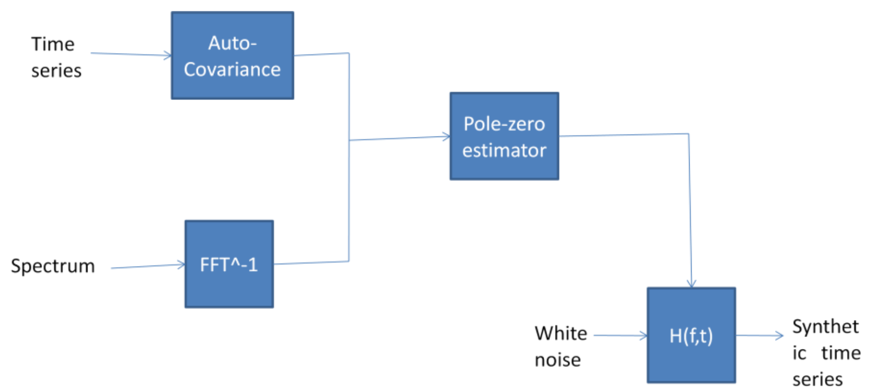

Fig-1. Linear Spectral Prediction Approach To Modeling Stochastic Quasi-Stationary Coherent Time Series.

The Levinson-Durbin algorithm is utilized to solve the Yule-Walker equations to obtain the optimal set of non stationary poles, or more precisely, the optimal set of non stationary filter coefficients for each beam.

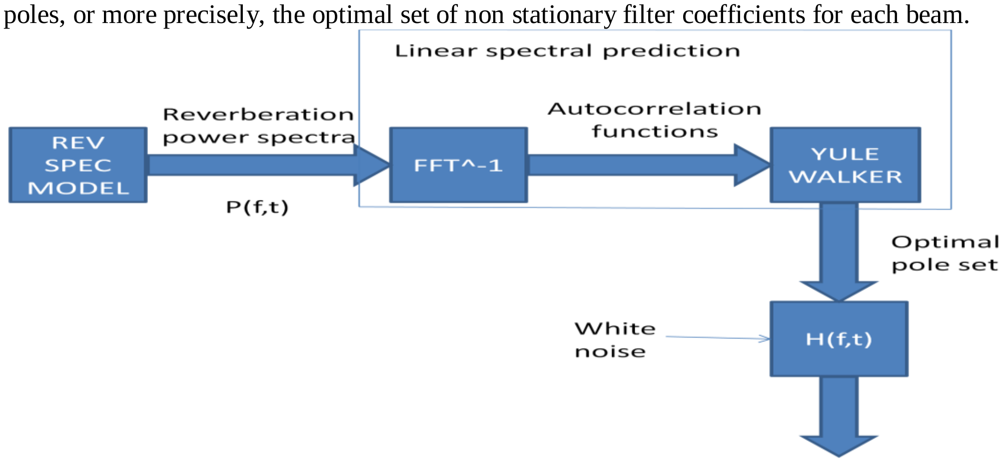

Fig-2. Processing Flow Of Reverberation Simulation Model.

The generation of coherent reverberation which is correlated between beams and overlapping spectra is illustrated in Fig.3 ,where Ha, Hb, .-, Hn,, represent transfer functions of the linear filters associated with beams, a, b, ...,n, respectively.

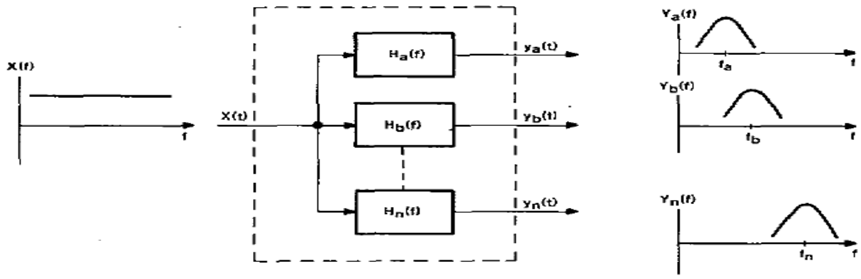

Fig-3. Parallel Structure Of Coherent Multiple-Beam Time Series Filter

III. REVERBERATION SPECTRUM MODELING

The generation of a time series based on the existance of a spectrum was discussed. Here, an approach to generating the expected spectrum for sonar reverberation as a function of pertinent sonar system parameters and environmental conditions is presented. The approach is a numerical evaluation scheme based on a spatial grid approach of Ackerman for a general formulation of reverberation developed by Faure, Ol'shevskii and Middleton. This leads to the computation of surface, volume, and/or bottom reverberation spectra and Dower levels as functions of:
a) transmit signal waveform and power level,
b) spreading and absorption propagation losses,
c) backscattering strength,
d) transmit and receive beam patterns,
e) sonar platform-ocean geometry, and
f) sonar and scatter motion.
Although the formulation can be extended to relax some of the following , intrinsic assumptions include:
a) primary scattering only,
b) iso-sound-speed ocean,
c) direct propagation path,
d) narrow-band transmit signals,
e) back scattering is from a large number of randomly distributed weak discrete scatters,
f) radial velocity distribution of scatters is spatially uniform.

In order to make the analysis tractable we make the following assumptions:
a) reverberation is a zero-mean random process;
b) many scatterers simultaneously contribute to the reverberation producing a Gaussian signal (i.e., central limit theorem);
c) the transmitted signal and resultant reverberation are narrow Band (i.e., the signal bandwidth is a small fraction of the carrier frequency);
d) the sonar transmitter and receiver are colocated;
e)scatterer radial velocities are independent and identically distributed Gaussian random variables for all volume and boundary scattering elements;
f)scatterer cross sections are independent of spatial position;and
g) reverberation can be considered stationary over short intervals of time (i.e., quasi-stationarity

A. Faure, Olshevskii And Middleton Formulation:
The power density spectrum $P_f(f,r)$ of the reverberation envelope at the receiver input from scatters at range r and frequency f, letting * designate the convolution operations given by

$$P_f(f,r) = \sigma^2(r) Y_f(f,r) * \left|S_{Tf}(f)\right|^2 * D_f(f) \qquad (9)$$

Where
$\sigma^2(r)$ = Total reverberation power from scatters at range *r*,

$Y_f(f,r)$ = Sonar motion envelope (power density) spectrum resulting from sonar motion and stationary (non moving) scatters at range r,

$$\int_{-\infty}^{\infty} Y_f(f,r)df = 1 \qquad (10)$$

$|S_{Tf}(f)|$ = Transmit signal envelope (energy density) Spectrum,

$$\int_{-\infty}^{\infty} |S_{Tf}(f)|^2 df = 1 \qquad (11)$$

$D_f(f)$ = Scatter motion spectrum resulting from random motion of the scatters.. Since it is a probability function.

$$\int_{-\infty}^{\infty} D_f(f)df = 1 \qquad (12)$$

The terms σ^2, Y_f and D_f depends on whether the reverberation is from volume, surface or bottom scatters.
The reverberation power levels are given by

$$\sigma_v^2(r) = \frac{p_0^2 cTs_v 10^{-2\alpha r}}{2r^2} \int_{\theta B}^{\theta S}\int_0^{\Pi} b_{TR}(\theta,\psi)d\psi d\theta \qquad (13)$$

$$\sigma_S^2(r) = \frac{p_0^2 cTs_S 10^{-2\alpha r}}{2r^3} \int_0^{\Pi} b_{TR}(\theta_S,\psi)\cos\theta_S d\psi \qquad (14)$$

$\sigma_B^2(r)$ = same as $\sigma_S^2(r)$, except s_B and θ_B replace s_S and θ_S respectively. (15)

Where

p_0^2 = transmit source mean square pressure,
C = speed of sound in water (m/s)
T = time duration of transmit signal (s),
r = range from mono static sonar to center of set of discrete scatterers (m),
α = absorption loss ,
s_v, s_B, s_S = volume (m-3), surface (m-') bottom (m-2) backscattering strength, respectively,
$b_{TR}(\theta,\psi)$ = transmit-receive product power beampattern.
ψ = azimuthal angle (rad),
θ = elevation angle (rad),
θ_S = sin^-1 (z/r) = elevation angle to surface at range *r* and sonar depth *z* (rad),
θ_B =sin^-1(zb-z/r) = elevation angle to bottom, at range *r* and sonar vertical distance above bottom of *(zB - Z)* (rad).

The transmit-receive beam pattern is further defined by

$$b_{TR}(\theta,\psi) = [b_T(\theta,\psi)+b_T(\theta,-\psi)].[b_R(\theta,\psi)+b_R(\theta,-\psi)] \qquad (16)$$

Where

$b_T(\theta,\psi)$ = transmit power beam pattern
$b_R(\theta,\psi)$ = receive power beam pattern

The surface backscattering strength can be represented as a function of surface grazing angle w i nd speed, and frequency (f) through models such as the Chapman-Harris model

$$S_S = 10\log s_S$$
$$= 3.3\beta\log(\theta_S/30) - 42.4\log\beta + 2.6$$
$$\beta = 158(vf^{0.33})^{-0.58} \qquad (18)$$

The bottom backscattering strength can be represented as

$$S_B = 10\log s_B$$
$$= 10\log(\sin^2\theta_B) - 27. \qquad (19)$$

The sonar motion envelope spectrum for volume, surface, and bottom reverberation, for a sonar moving at constant speed *v0* and constant direction are given by

$$Y_{vf}(f,r) = F\left\{\frac{\int_{\theta B}^{\theta S}\int_0^{\Pi} b_{TR}(\theta,\psi)\exp(\frac{j4\Pi\upsilon_0 T}{\lambda})d\psi d\theta}{\int_{\theta B}^{\theta S}\int_0^{\Pi} b_{TR}(\theta,\psi)d\psi d\theta}\right\} \qquad (20)$$

$$Y_{sf}(f,r) = F\left\{\frac{\int_0^{\Pi} b_{TR}(\theta_S,\psi)\exp(\frac{j4\Pi v_0 T}{\lambda}\cos\theta\cos\psi)\cos\theta_b d\Psi d\theta}{\int_0^{\Pi} b_{TR}(\theta_S,\psi)\cos\theta_S d\Psi}\right\} \qquad (21)$$

$Y_{Bf}(f,r)$ =same as $Y_{sf}(f,r)$ except θ_S replace θ_b. (22)

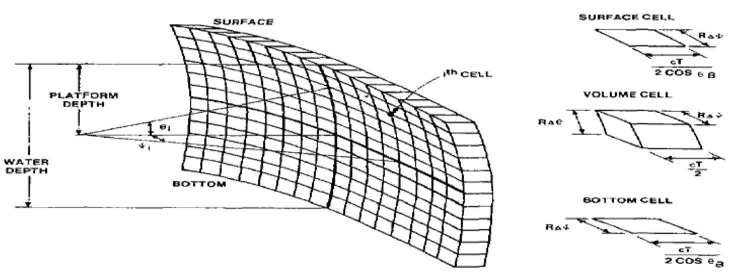

Fig- 4. Spatial Division Of Reverberation Field.

The power density spectrum Pf(f, ***r)*** of the reverberation envelope given by (9) is evaluated numerically dividing space into a set of cells, as illustrated in Fig. 6. The ocean is divided into spherical shells which represent the portion of the ocean that is ensonified by the signal wavefront at particular instants of time after transmission (and corresponding ranges).

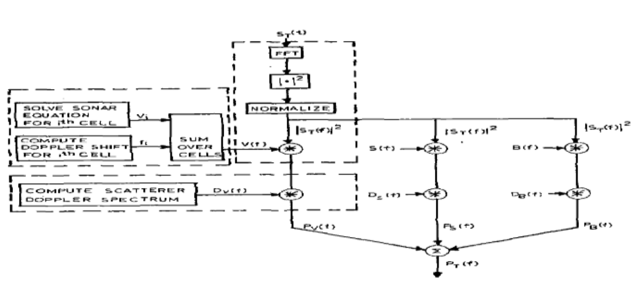

Fig- 5. Reverberation Spectrum Model

IV. DETECTION OF ECHO SIGNAL IN REVERBERATION BACKGROUND

Reverberation is caused by seabed, sea surface and the inhomogeneity of the granule in the seawater. As anoise, reverberation can influence the detection performance of target echo and cause some serious problems to active sonar . Due to the fact that reverberation and target echo are correlative and their spectrums are close, how to restrain reverberation is a problem necessary to be solved for active sonar. Inorder to restrain the reverberation signal we are using pre whiten method here.

A. Pre-whiten method

The principle of this method is that an AR model is established from reverberation and then a whiten filter is designed using the power spectrum of this model. Reverberation data is considered as Gaussian color noise. And the spectrum transformations between adjacent data segments are not obvious. The rationality of this hypothesis has been verified. The performance of this method is nicer even echo-toreverberation ratio is comparative low. On the premise of this hypothesis, a method using all-pole pre-whiten filters is proposed based on AR model at first. Then ,based on this model ,order partition algorithim is brought forward in detail.

The AR model of reverberation data is shown in equation $r(n) = -\sum_{i=1}^{p} a_i r(n-i) + w(n)$

(23)

where w(n) is a Gaussian white noise with an average of 0, {a1, a2, …, ap} are estimated using the adjacent segment data. And its power spectrum is shown in equation (2).

$$s(w) = \frac{\sigma^2}{\left|1+\sum_{i=1}^{p} a_i e^{-jwt}\right|} \qquad (24)$$

When the parameters ai of this AR model have been estimated, the system function of pre-whiten filter is as follows:

$$H(z) = \frac{1}{1+\sum_{i=1}^{p} a_i z^{-i}} \qquad (25)$$

Output data y(n) is obtained by data x(n) passing the above system function

$$y(n) = x(n) * z^{-1}[H(z)] \qquad (26)$$

B. Order Partition Pre-Whiten Algorithm

Order partition pre-whitens algorithm means that the sampled reverberation data is processed according to time order.

Firstly, reverberation data is partitioned into several segments. Supposing that the echo signal s(n) is included in the signal x(n) which is received by hydrophone during the observation time T. The pulse width of s(n) is T_P . Data x(n) is partitioned into several segments and the width of each segment is

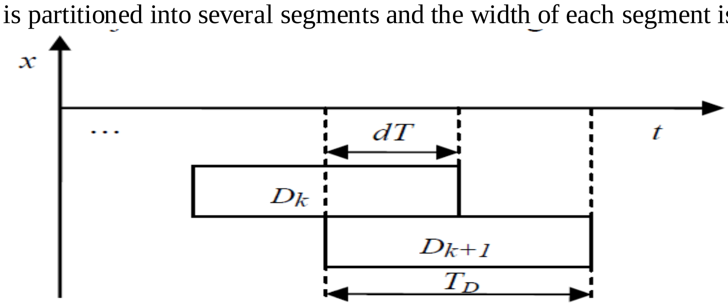

Fig 6. Sketch Map Of Data Partition

Firstly, reverberation data is partitioned into several segments. Supposing that the echo signal s(n) is included in the signal x(n) which is received by hydrophone during the observation time T. The pulse width of s(n) is T_P . Data x(n) is partitioned into several segments and the width of each segment is T_D as manifested in Fig.1, where dT denotes offset between the adjacent kth and k+1th data segments.The following conditions should be satisfied when partitioning the data into several segments:

(1) The width of each data segment should be equivalent to the usable signal s(n) in order to satisfy the requirement of local stationarity.

(2) To ensure that the echo signal s(n) is fully included in one segment, the width of s(n) should be smaller than each data segment. The following inequation should be satisfied:

$$T_D > T_P \qquad (27)$$

(3) To ensure that the echo signal s(n) is situated in the next adjacent data segment when s(n) is not completely included in a certain segment, following inequation should be satisfied:

$$dT \leqq T_D - T_P \qquad (28)$$

According to the actual situation, the width of each data segment is double of the usable signal and the data overlapping rate is ½.

$$T_D = 2T_P \qquad (29)$$

$$dT = 1/2(T_D) \qquad (30)$$

Secondly, the AR model of the kth data segment is established. In the method, the system function of the prewhiten filter which is based on the kth data segment for the k+1th data segment is as follows:

$$H_k(z) = \frac{1}{1+\sum_{i=1}^{pk} a_{k,i} z^{-i}} \qquad (31)$$

Lastly, the output data $y_{k+1}(n)$ is obtained by passing data $x_{k+1}(n)$ through above system function:

$$y_{k+1}(n) = x_{k+1}(n) * z^{-1}[H_k(z)] \qquad (32)$$

The flow chart of order partition pre-whiten algorithm is shown in below figure.

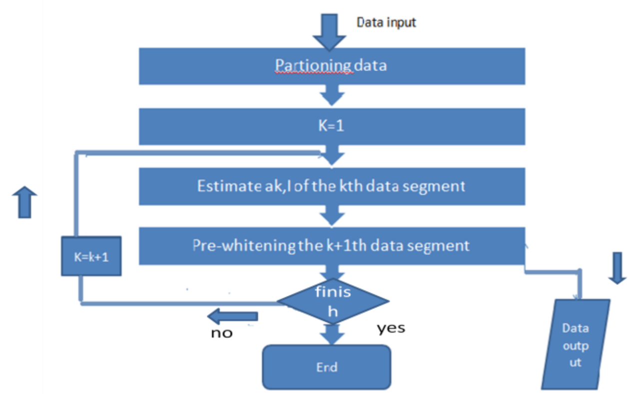

Fig 7:Flow Chart Of Order Partition Pre-Whiten Algorithm

V. SIMULATIONS AND RESULTS

The reverberation power spectrum using faure,olshevskii, and middeleton formulation is obtained and the tccording to the block diagram and the time series using autoregressive model is obtained.

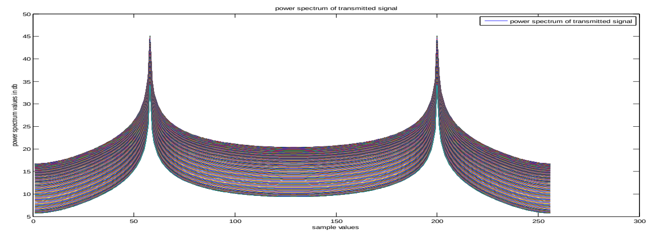

Fig-8 Transmitted Signal Power Spectrum

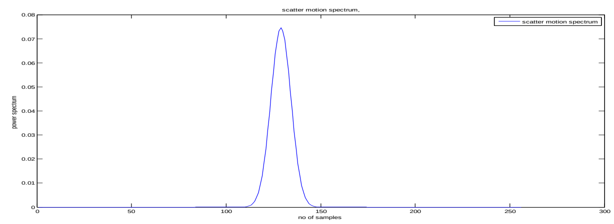

Fig-9. Scattering Motion Spectrum

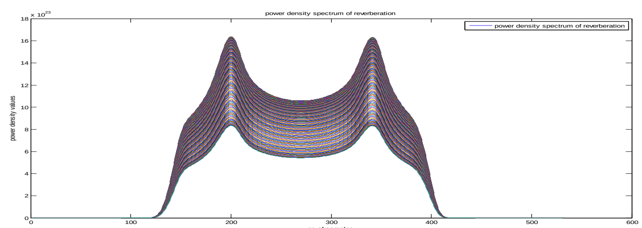

Fig-10. Power Density Spectrum Of Reverberation

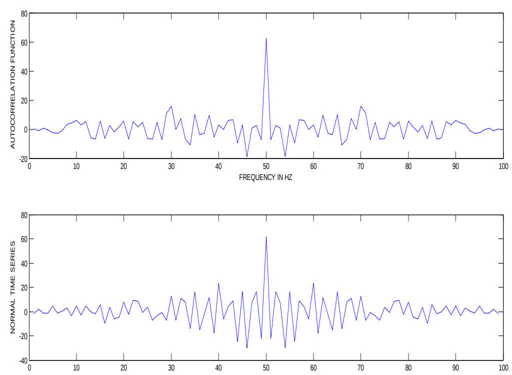

Fig-11. Time Series from autocorrelation function

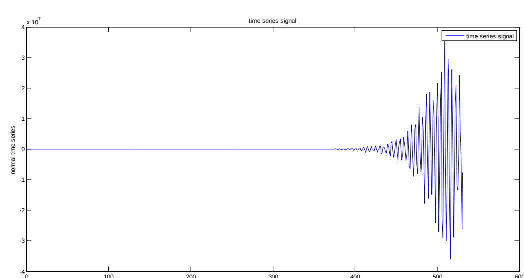

Fig-12. Time Series from the reverberation spectra

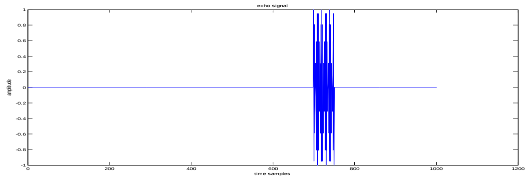

Fig 13: Echo Signal

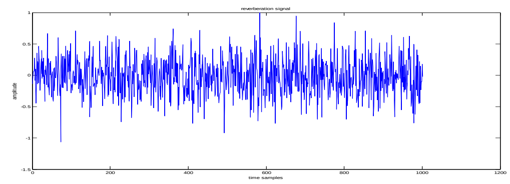

Fig 14:ReverberationSignal

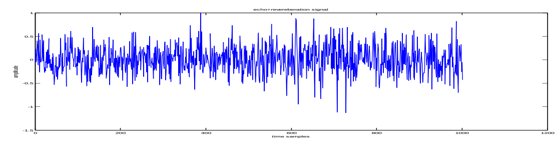

Fig 15 : Echo+Reverberation Signal

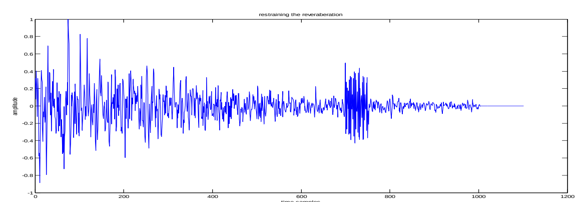

Fig 16: Restraining The Reverberation Signal

II. CONCLUSION

This paper describes the approach to the numerical generation of reverberation time series and echo detection algorithm. on the premise of local stationary of reverberation, a method using all pole partition pre whiten filters which is based on AR model is proposed. The simulation results indicate that this method is effective even in the background of low echo to reverberation ratio of input. Moreover, the order partition algorithm is the better approach for detecting the echo signal in reverberation background.

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