

# Implementation of a Composite Hybrid LMS/RLS Adaptive Deconvolution System for Seismic Oil Prospecting (With MATLAB)

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**Abstract**— A composite adaptive deconvolution system that integrates a proposed hybrid Least Mean Square(LMS) and Recursive Least Squares (RLS) adaptive filtering algorithm with existing LMS, RLS, Normalised LMS,etc., algorithms for deconvolution of seismic sequences is proposed. The composite model accepts input as reflections detected from an oil well. The system then removes echoes and reverberations using system's identification principles before subjecting the emergent sequence (primary and secondary reflections) to adaptive deconvolution using a choice algorithm among multiple algorithms stacked for that purpose. The output sequence (the estimated primary reflections), the error sequence as well as the filter coefficient numbers/values are then graphically displayed for visual appraisal. The proposed system is implemented with MATLAB and it has a graphical user interface that shifts the choice of the algorithm for deconvolution to the user. Convergence is tested by comparing the output of each adaptive deconvolution algorithm with the standardized Albert Wiener's signal deconvolution output. Results obtained by testing the system with data sourced from The Mathworks Inc. shows that the hybrid LMS/RLS algorithm converges faster to the Wiener's coefficients at lower offset and higher iteration values compared to the other algorithms.

**Keywords**— seismic, reflection, deconvolution, algorithm, exploration, prospecting, least-squares, adaptive, filtering

## 1. INTRODUCTION

Oil prospecting or exploration can be achieved by various methods ranging from the pre-historic use of hunches or heuristics (rule of thumb) to the conventional use of core samples (coring), the magnetometer (Magnetic Method), the gravimeter (Gravity Method), soil chemical analysis (Chemical Method), natural and induced electrical currents (Electrical Method), Radioactivity (Radioactive Method), Well Logging, use of Seismographs or seismometers (Seismic

Method), etc. Of all these oil exploration methods, the seismic method which uses seismographs, geophones (for onshore exploration) and Hydrophones (for offshore exploration) is the method often used for exploration in most developed and developing countries[2][5].

Oil prospecting, both in onshore and offshore environments comprises of very complex processes some of which involve heavy instrumentation, microscopic and visible organic and inorganic matter evaluation, sound/shock wave generation and detection of reflected signals, etc. To a geologist, geophysicist, or seismologist, the sound made by a particular substratum (an area under survey for oil deposits) is directly or indirectly related to the properties of that substratum, viz. the chemical composition of the underlying rocks, the geophysical processes that characterize the area in terms of denudation, rock formation, weathering, solidification, volcanicity, etc [15].

It is therefore of common practice to try and study the kind of sound or vibration that the layers of the earth will give when an acoustic signal generator is used to generate a wave that propagates down the layers of the earth crust. Hence dynamites or other modern signal generators are used to generate a train of pulses into the earth or water and geophones (seismic wave detectors) or other signal detectors are planted on some remote places on the same plane to detect the kind of vibration, reverberation, travel speed, soil properties, etc. that emerges from the excitation sequence.

In this research, we formulate statistical procedures for modeling the response of the earth crust to an excitation sequence (signal) both on the bare ground or marshy fields/shallow waters (Onshore) and in the sea or deep water (Offshore). The modeled procedures are then implemented in Matlab for seismic sequence enhancement by least squares Error (LSE), least mean square (LMS), and hybrid LSE/LMS methodologies.

## 2.0 ENVIRONMENTAL GEOLOGY OF AN OIL FIELD (ONSHORE/OFFSHORE)

### 2.1 A Schematic of an Oil Field

An open field or ground which has little or no surface water is said to be an onshore environment [10]. Such an environment can be geographically stratified into different layers as shown in “fig.2.1,” below.

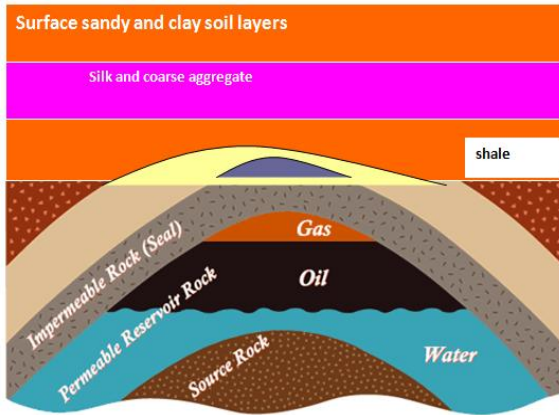


Fig. 2.1 A cross section of the earth surface showing the layers of the earth and an oil reservoir in an onshore scenario (Adapted from [11]).

In order to collect seismic data, shock waves are sent into the ground and signal detecting devices are used to measure how long it takes for the subsurface rocks to reflect these waves back to the surface [11]. The shock waves used today are generated by pounding the earth surface with giant vibrator trucks (see “fig 3.2”). This is preferred to the erstwhile use of explosives and dynamites which may cause other environmental hazards. When these shock waves travel into the earth, boundaries between the rocks reflect part of these waves back while some percentage of the wave energy goes downward. The reflected waves and their arrival times are then detected and recorded by listening devices known as geophones.

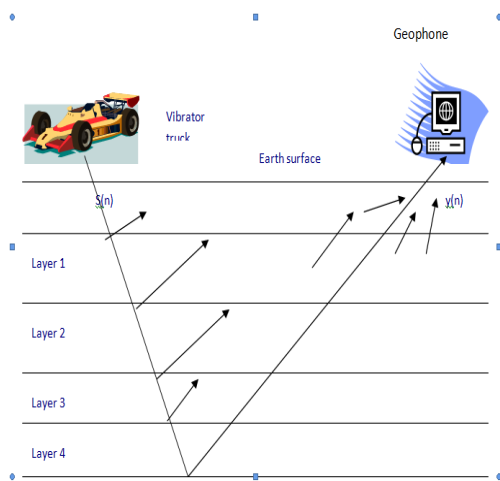


Fig.2.2: shock waves propagation in an onshore environment

The geophysicist or geologist then collects the data in the geophone for computer processing. The computer uses the

inbuilt digital filters to process the geophone’s raw data and converts it to seismic lines [11].

### 3.0 MODELS/ALGORITHM FORMULATION

Simple mathematical modeling reveals that “y(n),” the received signal, can be modeled in terms of “s(n),” the excitation signal, and the boundary delays “d<sub>i</sub>” as

$$y(n) = \sum_{i=1}^N a_i s(n - d_i) \tag{3.1}$$

Where {a<sub>i</sub>} are the coefficients of reflection at the interfaces between the various layers of the earth and {d<sub>i</sub>} denotes the corresponding set of propagation delays. Moreover, N is a finite integer and refers to the total number of coefficients counting from 1. i.e. n=1,2,3,..., N [2][3].

It must be noted that the propagation delay is a function of the time t taken for the excitation wave s(n) to travel to the reflector, get reflected and then be received at the geophone as y(n). This time is modeled as

$$t = 2D/v \tag{3.2}$$

Where D is the depth of the medium (distance from top to the reflector) and v is the signal velocity in the rocks.

Hence “d<sub>i</sub>,” defined as

$$d_i = \tau - t \tag{3.3}$$

are the propagation delays, τ is the actual time taken for a signal to travel from the source to the reflector and then back to the geophone and t is the ideal time that a signal with wave velocity v is supposed to travel to and fro the depth in the absence of propagation delays between rock boundaries. Moreover, the delay is used to estimate the reflectivity of water coefficients and these reflectivity coefficients are of great importance in the deconvolution of the received signal [7].

In practice, the number ‘N’ of reflection coefficients is usually large hence the quality and wave content of y(n) depends largely on the properties of the layers of the rocks that reflect s(n). Moreover, seismic analysis and evaluation over time reveals that y(n) is a convolution (a complex mixture) of the excitation signal s(n) and the sequence u(n) which characterizes the medium or layers of the earth[2][3][4].

This u(n) is modeled as

$$u(n) = \sum_{i=1}^L a_i \eta(n - d_i) \tag{3.4}$$

where {a<sub>i</sub>} and {d<sub>i</sub>} are as defined above, but the delayed transient “η” is the main factor that the geophysicist is out to analyze, while i=1, 2, ..., L, for any finite integer L.

To achieve this, we try to isolate the component u(n) from the received signal y(n) by means of deconvolution (the inverse operation that separates convolved signals) of the convolved sequence(s) below:

$$y(n) = s(n) * u(n) \tag{3.5}$$

While in the offshore scenario, a third sequence ‘r(n)’ is convolved with u(n) such that

$$y(n) = s(n) * u(n) * r(n) \tag{3.6}$$

Hence the basic onshore model for least squares error treatment is “(3.5),” or

$$y(n) = s(n) * \left\{ \sum_{i=1}^L a_i \eta(n - d_i) \right\} \quad (3.7)$$

Note: ALG shall be used as an acronym for ‘Algorithm’ in the formulations below.

### 3.1 Algorithm Formulation for Model Optimization

#### ALG.1: Onshore Model Optimization Procedure by Conventional Least Squares

Given the model in “(3.5)” or “(3.7)” above, we will adopt the least squares optimization criterion in designing a least squares error inverse filter for deconvolving  $s(n)$  from  $u(n)$  so that  $u(n)$  can be studied in isolation. To do this, the following statistical assumptions are invaluable [3][4][5].

#### 3.1.1 Assumptions

- We assume that the sequence  $u(n)$  that characterizes the medium is made up of a collection of uncorrelated reflections. Hence  $u(n)$ , just like white noise will have an autocorrelation sequence given by

$$\gamma(l) = \begin{cases} C_u, & l=0 \\ 0, & l \neq 0 \end{cases} \quad (3.8)$$

Where  $C_u$  is an arbitrary constant equal to the expectation, “ $E_u$ ” of  $u$ .

- Assume also that the sequence  $s(n)$ , the input train of pulses, is made up of highly correlated impulses (waveforms) such that successive samples of  $s(n)$  do not vary much from one another. This means that  $s(n)$  can be estimated from past samples of  $s(n)$ , viz.  $s(n-1)$ ,  $s(n-2)$ ,  $s(n-3)$ , ... . Hence we can comfortably form a weighted linear combination of the past  $L$  sample of  $s(n)$ , a process called linear prediction.
- However, since geophysical evidence over time proves that the excitation sequence  $s(n)$  (which is unmeasured a priori) is the domineering component of the convolution in “3.5,” [4][13][8] then it becomes very reasonable to also predict  $s(n)$  based on past samples of  $y(n)$  (which were actually received at the geophone), viz.  $y(n-1)$ ,  $y(n-2)$ ,  $y(n-3)$ , ... ,  $y(n-L)$ . i.e.

$$\hat{s}(n) = \sum_{i=1}^L \alpha_i y(n-i) \quad (3.9)$$

The error due to the estimation of  $s(n)$  with  $\hat{s}(n)$  is denoted by  $e(n)$  and is given by

$$e(n) = s(n) - \hat{s}(n) \quad (3.10)$$

which we seek to minimize by least square means. This procedure is captured in the block diagram of “fig.3.3,” below where  $y(n)$  is as defined in “3.5” above.

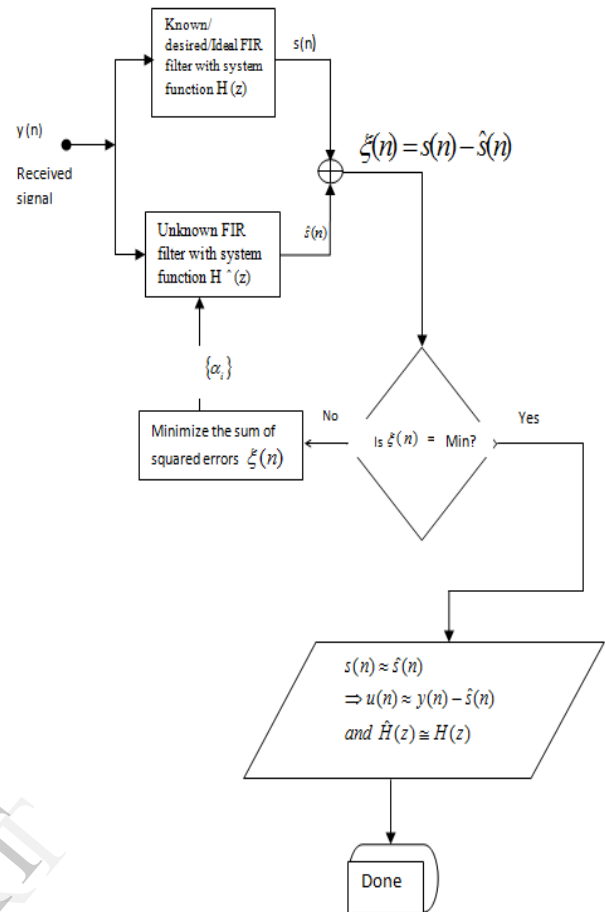


Fig. 3.3: Finite Impulse Response (FIR) inverse filter model for isolation of the unwanted component  $\hat{s}(n)$  from  $u(n)$ .

Where  $H(z)$  is the ideal impulse response of the desired filter and  $\hat{H}(z)$  is the estimated impulse response of the designed digital filter

To continue the minimization process, let

$$\xi(n) = \sum_{n=0}^{\infty} e^2(n) \quad (3.11)$$

denote the sum of squared errors. Then

$$\xi(n) = \sum_{n=0}^{\infty} \left\{ s(n) - \sum_{i=0}^L \alpha_i y(n-i) \right\}^2 \quad (3.12)$$

, Where the substitution in “3.6” was used and  $\{\alpha_i\}$  are filter coefficients.

Now, differentiating  $\xi(n)$  partially with respect to each of the filter coefficients  $\{\alpha_i\}$  and equating the result to zero (for orthogonality),

$$\frac{\partial}{\partial \alpha_i} \{ \xi(n) \} = \frac{\partial}{\partial \alpha_i} \left[ \sum_{n=0}^{\infty} \left\{ s(n) - \sum_{i=0}^L \alpha_i y(n-i) \right\}^2 \right] = 0$$

$$\begin{aligned} &\Rightarrow \sum_{i=0}^L \alpha_i \sum_{n=0}^{\infty} s(n)s(n-m) \\ &= \sum_{n=0}^{\infty} s(n)s(n-m) \end{aligned} \quad (3.13)$$

$$\text{i.e. } \sum_{i=0}^L \alpha_i \gamma_{yy} = r_{sy}(n) \quad ; \quad (3.14)$$

$$m = 0, 1, 2, 3, 4, \dots, L$$

Where  $\gamma_{yy}(m)$  is the autocorrelation of the sequence  $y(n)$  defined as:

$$\gamma_{yy}(m) = \sum_{n=0}^{\infty} y(n)y(n-m) \quad (3.15)$$

and  $r_{sy}(m)$  is the cross correlation between the desired output sequence  $s(n)$  and the input sequence  $y(n)$ , defined as

$$r_{sy}(m) = \sum_{n=0}^{\infty} s(n)y(n-m) \quad (3.16)$$

The convolution sum “3.14” is the set of Yule Walker equations, also called normal equations, [2] which have been solved some decades ago [8][5] with varying degrees of complexity.

Expressing the set “3.14” in matrix form, we have

$$\begin{bmatrix} \gamma_{yy}(0) & \gamma_{yy}(1) & \cdots & \gamma_{yy}(L) \\ \gamma_{yy}(1) & \gamma_{yy}(0) & \cdots & \gamma_{yy}(L-1) \\ \vdots & \vdots & \ddots & \vdots \\ \gamma_{yy}(L) & \gamma_{yy}(L-1) & \cdots & \gamma_{yy}(0) \end{bmatrix} \begin{bmatrix} \alpha_0 \\ \alpha_1 \\ \vdots \\ \alpha_L \end{bmatrix} = \begin{bmatrix} r_{sy}(0) \\ r_{sy}(1) \\ \vdots \\ r_{sy}(L) \end{bmatrix} \quad (3.17)$$

Or in vector form as:

$$\gamma_{yy} \alpha = r_{sy} \quad (3.18)$$

Notice that the formulation “3.18” is still the same as “3.14,” the familiar Yule Walker or normal equations whose solution yields the least squares optimized filter coefficients  $\{\alpha_i\}$ .

Moreover, if the optimized least squares filter  $\hat{H}(z)$  with impulse response  $\hat{s}(n)$  is to be the approximate inverse filter needed, then the desired response must be

$$s(n) = \hat{s}(n) \quad (3.19)$$

Hence the cross correlation between  $s(n)$  and  $y(n)$  reduces to

$$r_{sy}(m) = \begin{cases} y(0), & m = 0 \\ 0, & \text{otherwise.} \end{cases} \quad (3.20)$$

Thus equation 3.17 reduces to

$$\begin{bmatrix} \gamma_{yy}(0) & \gamma_{yy}(1) & \cdots & \gamma_{yy}(L) \\ \gamma_{yy}(1) & \gamma_{yy}(0) & \cdots & \gamma_{yy}(L-1) \\ \vdots & \vdots & \ddots & \vdots \\ \gamma_{yy}(L) & \gamma_{yy}(L-1) & \cdots & \gamma_{yy}(0) \end{bmatrix} \begin{bmatrix} \alpha_0 \\ \alpha_1 \\ \vdots \\ \alpha_L \end{bmatrix} = \begin{bmatrix} y(0) \\ 0 \\ \vdots \\ 0 \end{bmatrix} \quad (3.21)$$

Or the in vector form as

$$\gamma_{yy} \alpha = C \quad (3.22)$$

Where  $\alpha$  is the vector of filter coefficients and  $C = \{y(0), 0, \dots, 0\}'$ .

Notice that  $\gamma_{yy}$  is still Toeplitz as it is both symmetric and has equal elements along both diagonals, making it readily invertible. Moreover, the vector product “3.22” is a Toeplitz combination of the Toeplitz matrix  $\gamma_{yy}$  and the column vector  $\alpha$ . Since all Toeplitz matrices are invertible, “3.21” can readily be solved by Gaussian Elimination, Levinson and Durbin Algorithms as well as by computer programming means.

In the Gaussian method, our target is to invert the matrix  $\gamma_{yy}$  such that

$$\gamma_{yy}^{-1} \cdot \gamma_{yy} \cdot \alpha = \gamma_{yy}^{-1} \cdot C \quad (3.23)$$

$$\text{i.e. } I \alpha = \gamma_{yy}^{-1} C \quad (3.24)$$

$$\text{or } \alpha = \gamma_{yy}^{-1} C \quad (3.25)$$

where  $I$  is the identity matrix.

### 3.1.2 Computational complexity

The use of Gaussian elimination to solve a system of  $L$  equations for  $L$  unknowns requires  $L(L+1) / 2$  divisions,  $(2L^3 + 3L^2 - 5L)/6$  multiplications, and  $(2L^3 + 3L^2 - 5L)/6$  subtractions, for a total of approximately  $2L^3 / 3$  operations. This means that it has a complexity of order  $L^3$  or  $O(L^3)$ . [9]

This algorithm can be used on a computer for systems with thousands of equations and unknowns. However, the cost becomes prohibitive for systems with millions of equations. These large systems are generally solved using iterative methods. Specific methods exist for systems whose coefficients follow a regular pattern [16]. Both the Levinson and Durbin Algorithms exploit recursion and iteration to solve the Yule-walker's equation with the key advantage that the computational complexity is reduced to order  $L^2$  [9].

In this research, however, our objective is to achieve a further reduction in computational complexity, irrespective of the size of  $L$ , by using computer programming logic (Matlab) to write a program that

- Hides the computational complexity occasioned by the numerous equations encountered in this model development or at least reduce the order further;

- Attempt to capture the entire offshore and onshore modeling processes in software for petroleum exploration.

**ALG. 2: THE PROPOSED ADAPTIVE LEAST SQUARES RECURSIVE FILTER (ALSRDF)**

In order to effectively handle the problem of estimating the least squares coefficients as in “3.14” and “3.18,” the following algorithm is formulated.

Generally, the least squares solution gave rise to a formulation of the form [8]:

$$\gamma_{yy} \alpha = r_{sy} \tag{3.27}$$

This research seeks for ways to reduce the computation time by exploiting recursion as follows:

Consider the input sequence  $s(n)$ , the desired sequence  $u(n)$  and the coefficients of the digital filter for update  $\alpha(n)$  configured into an adaptive filter as

$u(n), s(n), \alpha(n) = [\alpha_0(n), \alpha_1(n), \dots, \alpha_{L-1}(n)]$ , where  $L$ = filter length. The estimate of the desired signal can be modeled as the output of the filter as:

$$\hat{u}(n) = \alpha^T(n) s(n) \tag{3.28}$$

Where  $\hat{u}(n)$  is an estimate of the desired signal  $u(n)$  (the signal that characterizes the earth content). See “fig 3.4,” below for a typical transversal filter flow diagram.

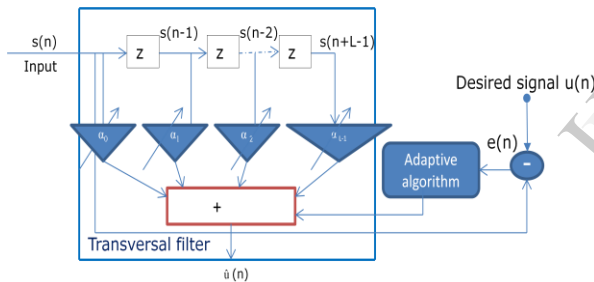


Fig.3.4: Configuration of a RLS Adaptive filter

Where  $\hat{u}(n)$  is an estimate of the desired signal  $u(n)$ .

But the filter error is given by

$$e(n) = u(n) - \hat{u}(n) = u(n) - \alpha^T(n) s(n) \tag{3.29}$$

Minimization of the mean squared error means taking expectation of the squared errors. That is,

$$E(e^2(n)) = E\{[u(n) - \alpha^T(n) s(n)]^2\} \\ = \gamma_{uu} - 2\alpha^T(n) \gamma_{us}(n) + \alpha^T(n) R_{uu}(n) \tag{3.30}$$

But we prefer the minimization of least squares error, which means

$$\phi = \partial \frac{\sum e^2(n)}{\partial n} = 0 \text{ (for orthogonality)} \tag{3.31}$$

Recall that

$$\alpha = R_{uu}^{-1} \gamma_{us} \tag{3.32}$$

Where  $R_{uu}$  is the autocorrelation matrix of the output signal and  $r_{us}$  is the cross correlation between  $u(n)$  and  $s(n)$ [1].

Also,  $u(n) = [u(n), u(n-1), \dots, u(n-L)]^T$ . Hence, the vector product of “3.32” can be expressed in recursive form as

$$R_{uu}(n) = R_{uu}(n-1) + y(n)y^T(n) \tag{3.33}$$

Using an exponentially decaying process, we have

$$R_{uu}(n) = \phi R_{uu}(n-1) + y(n)y^T(n) \tag{3.34}$$

Hence the recursive realization of the time-update formulae is given in inverse matrix form as

$$R_{uu}^{-1}(n) = \Psi R_{uu}^{-1}(n-1) + \text{update}(n) \tag{3.35}$$

**ALG.3: The Proposed Hybrid LSE/LMS Algorithm**

**Step 1: Least Squares Problem formulation**

Consider a finite set of observations  $\{s(n)\}$  and  $\{u(n)\}$ , where  $\{u(n)\}$  is the set of all past samples from  $n = 0$  to now. We define three deterministic cost functions as:

$$1. \quad \zeta_{LSE}(c) = \sum_{k=0}^n |e[k]|^2 \tag{3.36}$$

, where  $e(k) = s(k) - u(k)$  (3.37)

$$2. \quad \zeta_{LMS}(c) = E\{e[n]^2\} \tag{3.38}$$

And in terms of weighted least squares error (WLSE) as:

$$3. \quad \zeta_{WLSE}(c, n) = \sum_{k=n-M+1}^n \phi^{n-k} |e[k]|^2 \tag{3.39}$$

The problems 1, 2 and 3 can essentially be given the following optimal solutions as modeled in 4, 5 and 6 below, respectively.

$$4. \quad C_{LSE} = \arg \min_c \zeta_{LSE}(c) \tag{3.40}$$

Which essentially means: find those filter coefficients that minimize the cost function in problem 1.

$$5. \quad C_{LMS} = \arg \zeta_{LMS}(c) \tag{3.41}$$

Which similarly means: find those filter coefficients that minimize the cost function in problem 2, and

$$6. \quad C[n] = \arg \min_c \zeta_{LSE}(c, n), \text{ where the function}$$

$$\zeta(c, n) = \sum_{k=n-L+1}^n \phi^{n-k} |e[k]|^2$$

is such that  $\phi$  is the forgetting factor and  $\phi [0 < \phi \leq 1]$

**Step 2: Hybrid Model Formulation**

We now formulate a hybrid optimum solution

$$C_{LMS, WLSE} = \arg \zeta_{LMS, WLSE}(c) \tag{3.42}$$

such that “3.42” combines the Least Mean Square and Weighted Least Squares optimization advantages, where the cost function associated with “3.42” is formulated as

$$\zeta_{LMS,LSE}(c,n) = E[\zeta(c,n)] = E\left[\sum_{k=n-L+1}^n \phi^{n-k} |e[k]|^2\right] \quad (3.43)$$

Notice that the LMS strategy takes expectation of  $|e(k)|^2$  ordinarily, while the WLSE takes the sum of the expression  $|e(k)|^2$ , weighted by an exponential weighting factor  $\phi^{n-k}$ ,  $[0 < \phi \leq 1]$

Now, since  $s(n)$  and  $u(n)$  are assumed jointly stationary and stochastic zero mean processes, [6] we specify

i. the autocorrelation function  $r_{ss}(k) = E[s(n)s(n-k)] \quad (3.44)$

ii. the autocorrelation matrix  $R_{ss} = E\{s[n]s^T[n]\} \quad (3.45)$

And the corresponding cross correlation matrix as

iii.  $\rho_{su} = E\{u(n)s(n)\} \quad (3.46)$

Assume that  $u[n]$  is the output of a linear FIR filter to the input  $s[n]$ . Then

$$u[n] = h^T s[n] \quad (3.47)$$

and  $\dim(h) = \dim(c) \quad (3.48)$

Note: Reference [6] gives more details from a similar process.

The desired signal  $u(n)$  can be modeled using Systems Identification principles [6] as

$$u[n] = h^H s[n] + v[n] \quad (3.49)$$

Where “fig. 3.5,” below, shows  $v[n]$  as noise superimposed on the input signal and ‘h’ is the impulse response of the system to be identified and  $v(n)$  is additive noise.

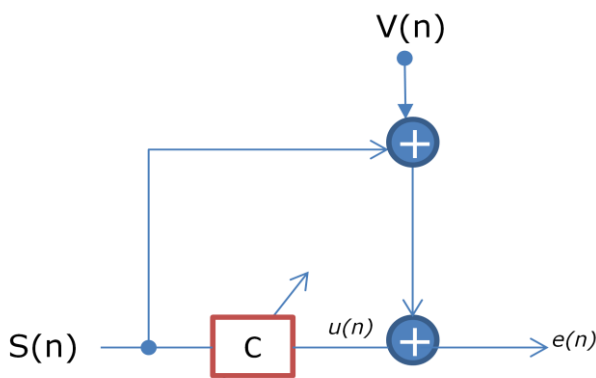


Fig.3.5: Systems Identification problem in a noisy environment

Then from “3.43”, the hybrid cost function

$$\zeta_{MSE,LSE}(c,n) = E[\zeta(c,n)] = E\left[\sum_{k=n-L+1}^n \phi^{n-k} |e[k]|^2\right]$$

can be manipulated such that

$$\zeta_{MSE,LSE}(c,n) = E\left[\sum_{k=n-L+1}^n \phi^{n-k} |e[k]|^2\right] = E[\mu[n]^2] - 2\rho^H c + c^H R_{uu} c \quad (3.50)$$

Where the forgetting factor is set to the default,  $\phi = 1$ .

Moreover, the gradient of the cost function with respect to the coefficient vector ‘c’, according to [6], is given as

$$\Delta_c \zeta_{MSE,LSE}(c) = 2(R_{uu} c - \rho) \quad (3.51)$$

Notice that instead of inverting the autocorrelation matrix  $R_{uu}$  as we did before, the Gradient Search Method avoids the computational complexity associated with matrix inversion by use of iteration to update the coefficient vector  $[c(n)]$ . This results in the coefficient update rule,

$$c[n] = c[n-1] + \mu(\rho - R_{uu} c[n-1]) \quad (3.52)$$

Where  $\mu$  is a step size parameter [6] and the negative gradient is the term

$$\rho - R_{uu} c(n-1) = -\Delta_c \zeta_{MSE,WLSE}(c) \Big|_{c=c(n-1)} \quad (3.53)$$

### 3.2 PERFORMANCE COMPARISON BY SIMULATION

The following algorithm is used to compare the performance of these algorithms:

#### 3.2.1 Algorithm for Comparison of Adaptive Filtering Algorithmic performances

- Step 1: Create the Signals for Adaptation;
- Step 2: Generate a noisy signal;
- Step 3: Corrupt the Desired Signal by adding the Noisy Signal;
- Step 4: Create a reference signal that is highly correlated with the signal in step 2 above [14].
- Step 5: Construct adaptive filters based on proposed algorithms, viz:

- i. Adaptive Least Mean Square (ALMS) and Normalized Adaptive Least Mean Square (NALMS);
- ii. Conventional Recursive Least squares (CRLS) and Adaptive Recursive Least Squares (ARLS);
- iii. Improved ARLS;
- iv. Hybrid LMS/RLS.

Step 6: Graphically display their output sinusoids for comparison and performance evaluation with respect to the ideal ALBERT WIENER’S STANDARDIZED OUTPUT.

Step 7: Investigate convergence using algorithmic learning curves.

Step 8: End.

3.3 PROPOSED DECONVOLUTION SYSTEM'S ARCHITECTURE

The following block diagram gives a schematic for deconvolving seismic sequences.

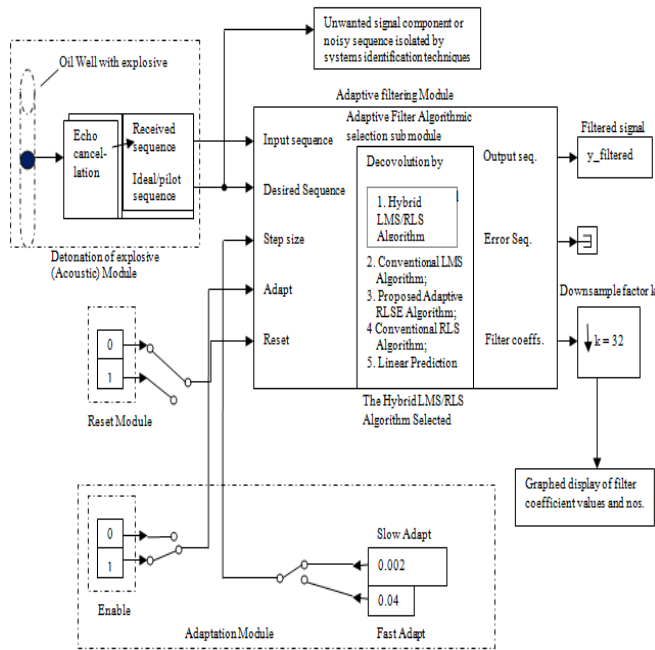


Fig. 3.6 Architecture of the proposed composite adaptive deconvolution system.

In effect, the proposed system accepts input as reflected sequences due to an explosion from an oil well, compares it with a pilot sequence and processes both sequences with a down-sample factor 'k = 32' leaving the choice of algorithm (from at least 5 different algorithms) and adaptation step size selection to the user.

4.0 SYSTEM'S IMPLEMENTATION/SIMULATION WITH MATLAB

In this section, the implementation of An Adaptive Least Squares Digital Filter model for Oil Processing both in Offshore and Onshore environments is considered. This system's realization strategy is summarized below:

4.1 WHY MATLAB FOR IMPLEMENTATION

The programming Language employed for the implementation of the system is Matlab 7.9. The reasons that informed the use of Matlab in the implementation of Adaptive Least Square Digital Filters include the ease for functions and data plotting, an inherent numerical computing environment, easy database design, manipulations and query processing, inbuilt Graphical User Interface(GUI), synergy with C, C++, JAVA, FORTRAN, SIMULINK, etc.

4.1.1 Graphical User Interface (GUI)

This serves as a link between the intended users and the intricacies of the software and hardware components of the system. The GUI hides from the end users the complex communication between the designed/implemented system's software and the computer's hardware making it possible for an end user who is grossly uninformed on the workings of the machine hardware to place a query in plain language and get an instant or near instant feedback.

4.1.2 System Requirements:

1. The software used is MATLAB<sup>(R)</sup> – The language of technical computing, version 7.9.0.529 (R2009b) 32 – bit (win 32), August 12, 2009, License number: 161051
2. Windows operating system (preferably windows 2000 and latter variants).
3. Platform and system's requirements: Windows 32 bit, Windows 64-bit, Mac OSA 64 bit and Linux 64-bit are supported.

4.2 IMPLEMENTATION OF THE PROPOSED COMPOSITE MODEL (IN MATLAB)

4.2.1 DATABASE FOR THE PROPOSED SIMULATION

The modeled algorithms in section 3 are meant to be implemented with Matlab R2009b with the aim of assisting in the deconvolution of highly convolved seismic traces or sequences. Most of the areas in the Northern Nigeria like the Kukawa Axis of the Borno Basins, the Chad basin, and the Bida Basins do not have available exploration data for open source use. Hence equivalent terrains were sort after using Google earth and other prospecting tools. In this respect, therefore, the data for this simulation is sourced from the Mathworks Inc., USA. They are tabulated in table 4.1 and 4.2(see appendices) and are repeatedly referred to during the coding process.

Data set.1:

Table 4.1: Parametric datasets for simulating adaptive filtering algorithms

Data records	Iterations(L)	No. of Filter order (L)	Step size (mu)	Block length (n)	Input to adaptive filter (x)
1	100	2	0.001	1	Randn(1,100)
2	200	4	0.002	2	Randn(1,200)
3	300	6	0.003	3	Randn(1,300)
4	400	8	0.004	4	Randn(1,400)
5	500	10	0.005	5	Randn(1,500)

Data records	No. of Iterations(L)	Filter order (L)	Step size ( $\mu$ )	Block length (n)	Input to adaptive filter (x)
6	600	13	0.006	6	Randn(1,600)
7	700	14	0.007	7	Randn(1,700)
8	800	16	0.008	8	Randn(1,800)
9	900	18	0.009	9	Randn(1,900)
10	1000	20	0.010	10	Randn(1,1000)
11	1100	22	0.011	11	Randn(1,1100)
12	1200	24	0.012	12	Randn(1,1200)
13	1300	26	0.013	13	Randn(1,1300)
14	1400	28	0.014	14	Randn(1,1400)
15	1500	30	0.015	15	Randn(1,1500)
16	1600	32	0.016	16	Randn(1,1600)
17	1700	34	0.017	17	Randn(1,1700)
18	1800	36	0.018	18	Randn(1,1800)
19	1900	38	0.019	19	Randn(1,1900)
20	2000	40	0.020	20	Randn(1,2000)
21	2200	42	0.040	21	Randn(1,2200)
22	2400	44	0.080	22	Randn(1,2400)
23	2600	46	0.120	23	Randn(1,2600)
24	2800	48	0.160	24	Randn(1,2800)
25	3000	50	0.200	25	Randn(1,3000)

#### 4.2.2 Algorithmic Simulation by Matlab R2009b

This study proposed a hybrid LMS/RLS Adaptive filtering algorithm, an Adaptive RLSE algorithm and an improved LSE algorithm. However, owing to the desire to model a composite deconvolution system for onshore and offshore seismic sequence deconvolution, other extant algorithms like the

Conventional Least Mean Square (CLMS), Normalized LMS, etc will all be put together by matlab coding.

#### 4.2.3 Graphical user Interface:

The user interface of the implemented seismic oil exploration system is presented below

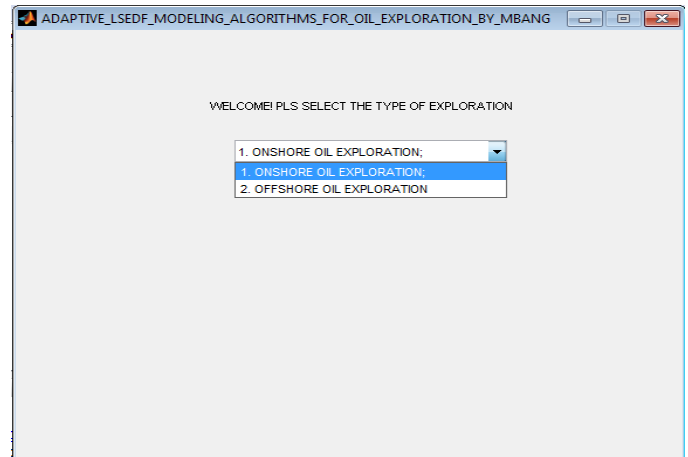


Fig. 4.1: Graphical User Interface for the proposed composite seismic deconvolution system.

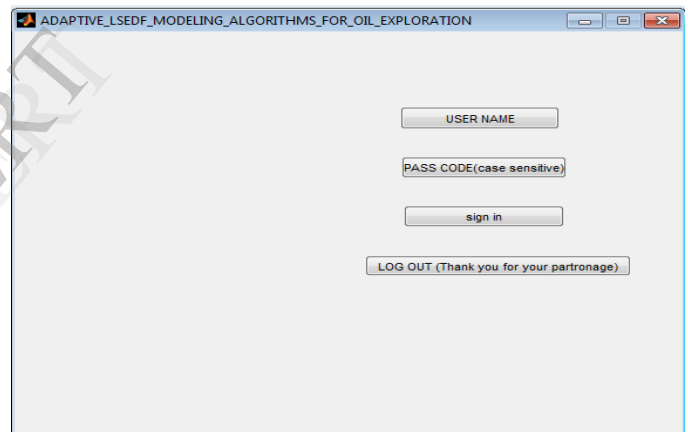


Fig. 4.2: Log on screen/user authentication interface.

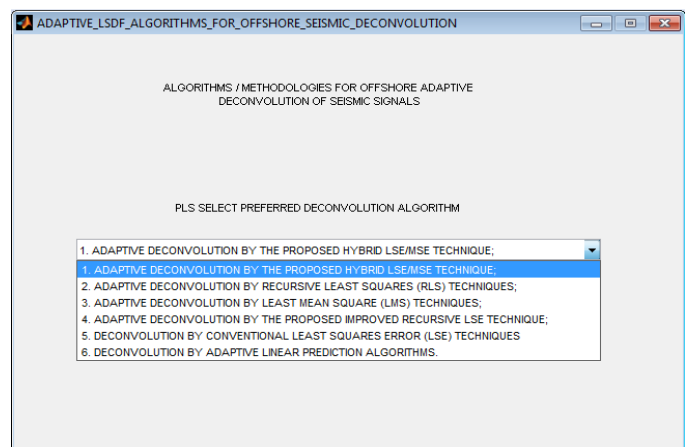


Fig.4.3: Interactive Algorithm selection screen.



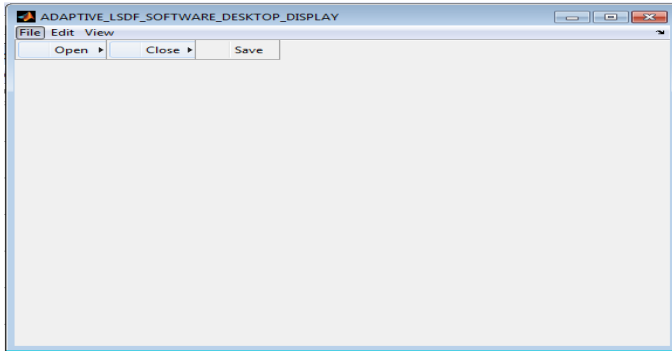


Fig. 4.4: Desktop Display screen

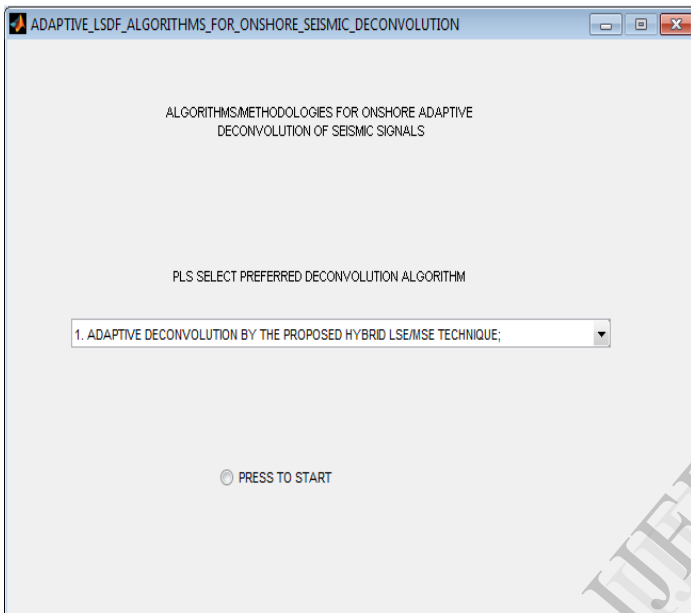


Fig. 4.5: Logon screen after choice algorithm has been selected.

### 4.3 Algorithmic Outputs

1. Application of the Hybrid LMS/LSE algorithm on data records.

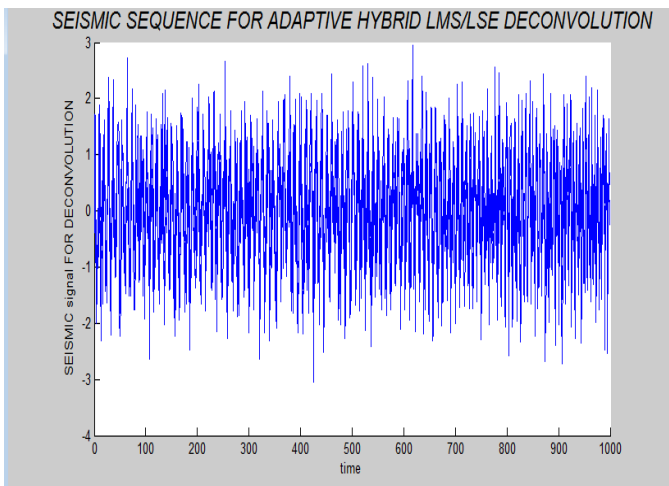


Fig. 4.6: Matlab plot of record 10 from Data set 1

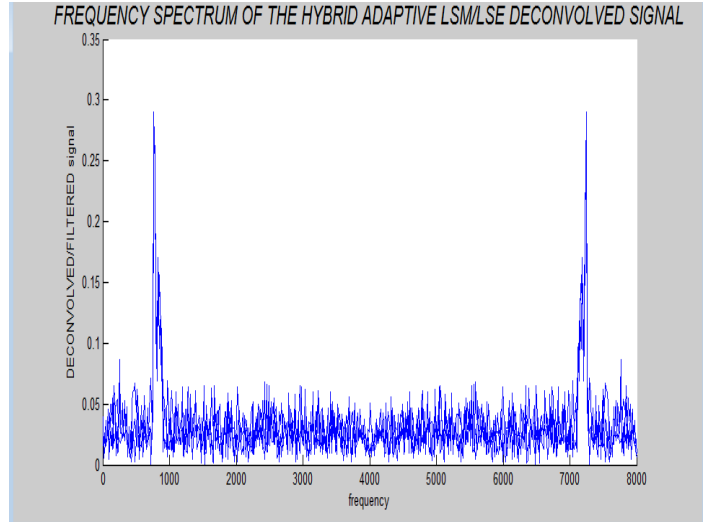


Fig. 4.7: Application of the Hybrid LMS/LSE algorithm to record 10 of Data Set 1 (for 8000 iterations).

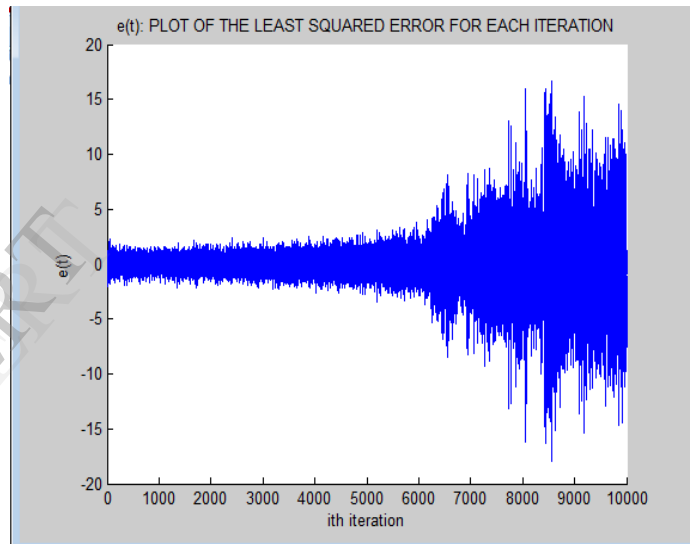


Fig. 4.8: plot of the LSE resulting from the operation on record 10 of Data set 1 using the hybrid for an explosive number of iterations (10,000).

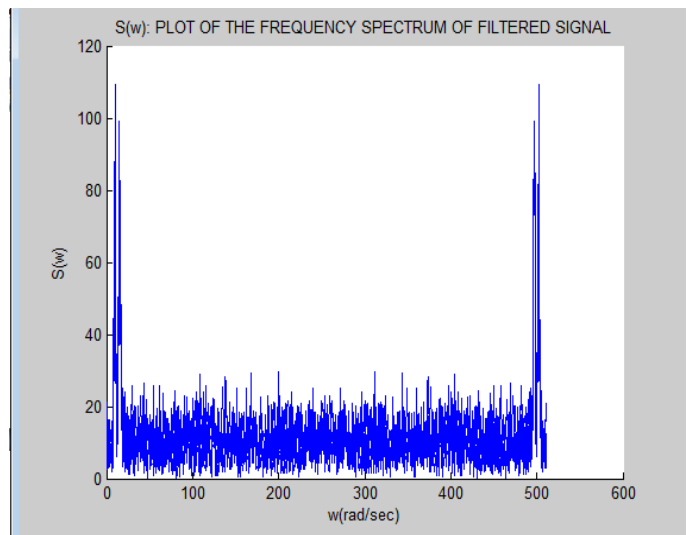


Fig.4.9a: Frequency spectrum of enhanced signal

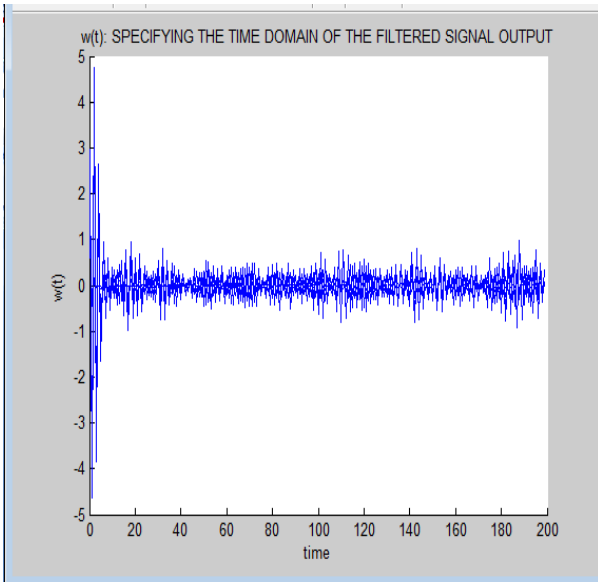


Fig. 4.9b: Time spectrum of hybrid enhanced signal

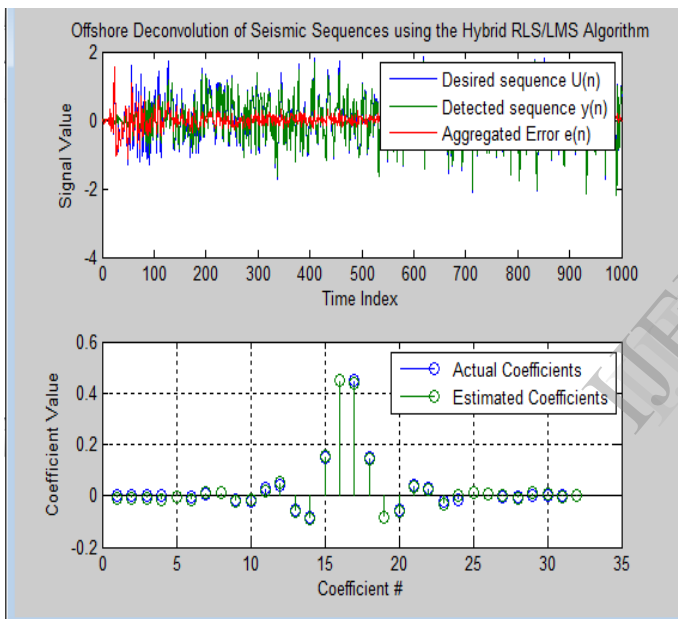


Fig.4.10: Offshore Deconvolution of record 28 of Data set 2 (i.e. depths are >200m above sea level) using the hybrid.

1. Application of the Conventional LMS algorithm on data records.

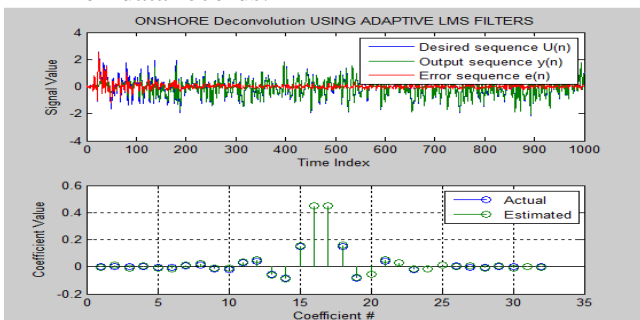


Fig. 4.11a: Deconvolution of record 10 of data set 2

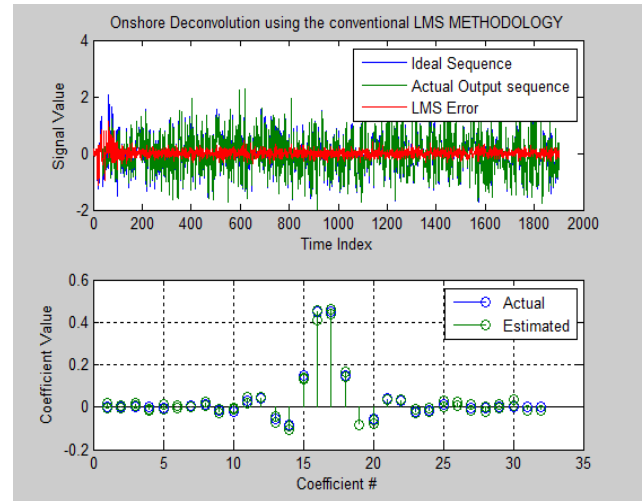


Fig.4.11b: Deconvolution of record 19 of data set 1 in a simulated onshore environment (i.e on land or marshy fields/shallow waters).

2. Application of the Improved (Adaptive) Recursive Least Squares Algorithm to seismic data records:

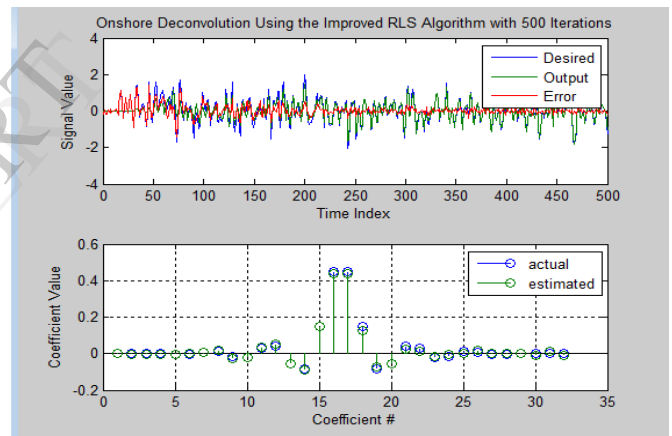


Fig. 4.12: Onshore deconvolution of record no.18 of data set 2.

4. Application of Predictive Deconvolution techniques on data records

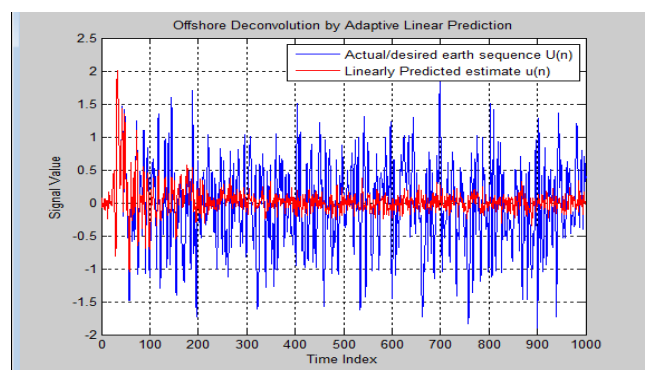


Fig. 4.13: Predictive deconvolution of record 18 of data set 2.

### 5. Graphical Comparison of Algorithmic Outputs

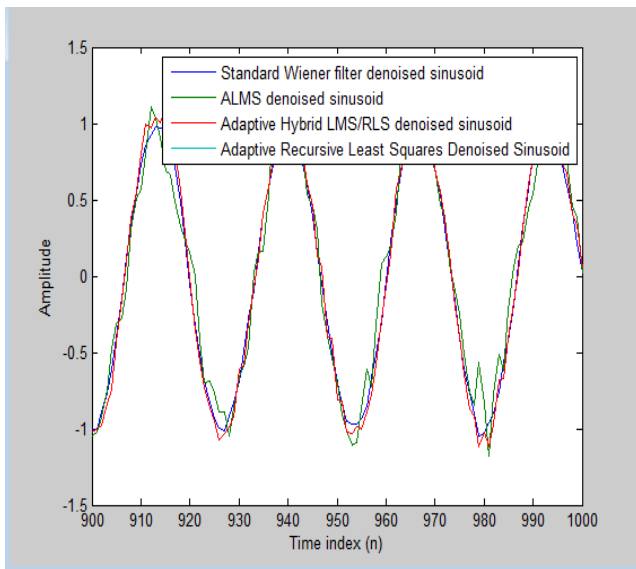


Fig. 4.14: Use of record 10 of data set 1 for algorithmic comparison

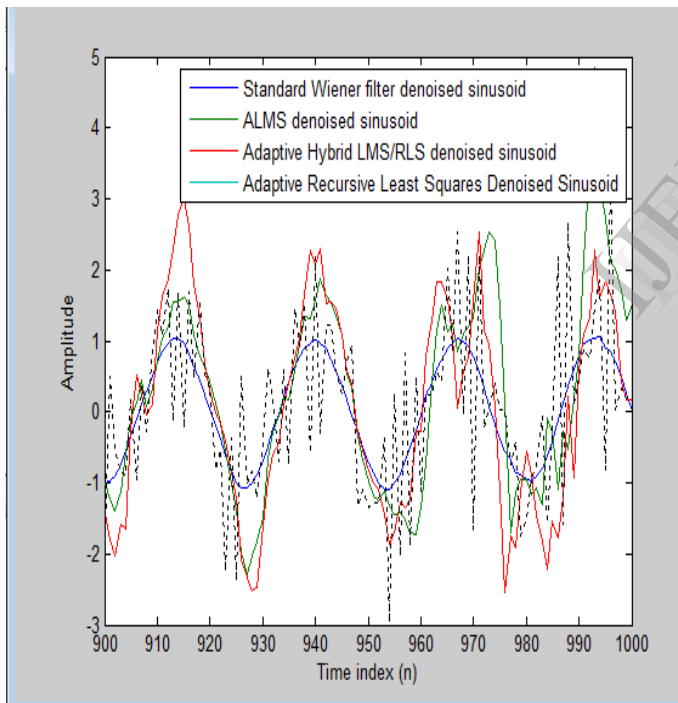


Fig. 4.15: Comparison of the ALMS, Adaptive Hybrid LMS/RLS and the ARLS algorithmic outputs with the standard Wiener filter output (based on effects on the sinusoid of record 18 of data set 2).

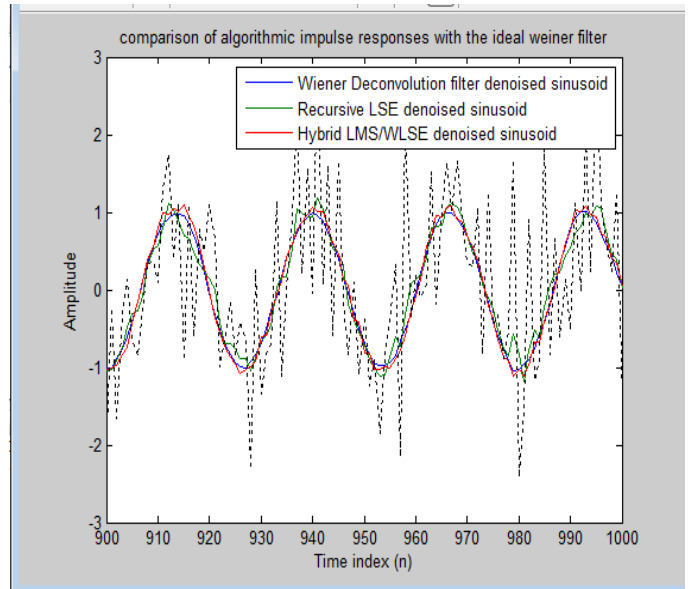


Fig. 4.16: Comparison of the ARLS, the Adaptive Hybrid LMS/RLS and the standard Wiener Deconvolution filter's output (based on effects on the sinusoid of record 18 of data set 2).

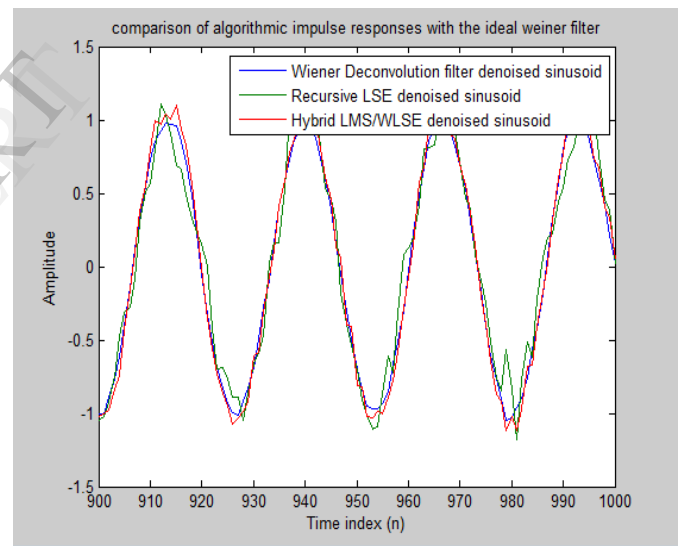


Fig.4.17: Comparison of the Conventional RLS algorithm, the Adaptive Hybrid LMS/RLS and the standard Wiener Deconvolution filter's output ( based on effects on the sinusoid of record 18 of data set 2).

## 6. GRAPHICAL INVESTIGATION OF ALGORITHMIC CONVERGENCE USING LEARNING CURVES WITH RESPECT TO THE MSE OF EACH ALGORITHM

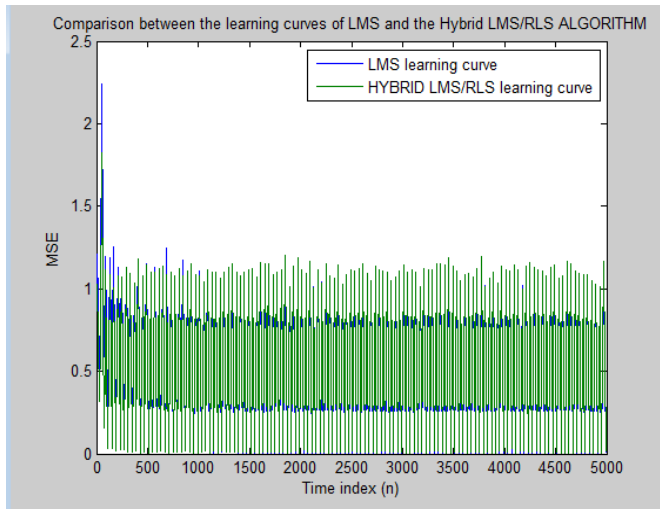


Fig. 4.18: Comparison between the LMS's and the Hybrid LMS/RLS Algorithmic learning curves based on record no.40 of data set 2, adapted to double the maximum sample number.

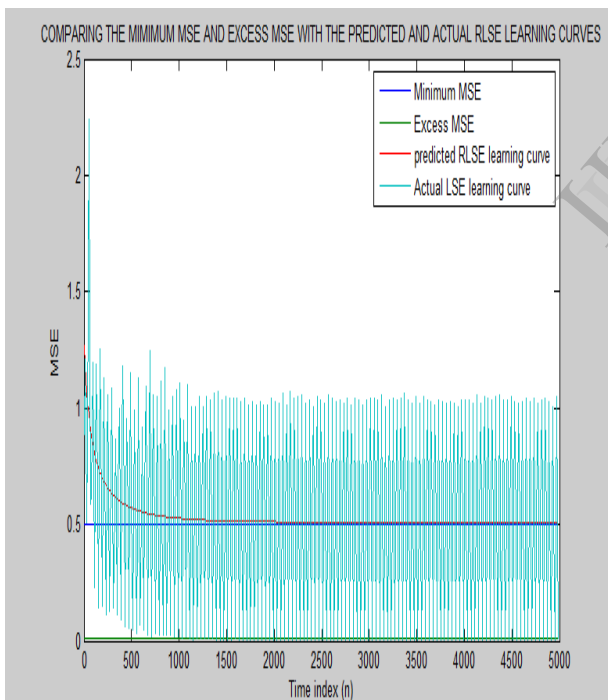


Fig. 4.19: Comparison of the RLSE and the conventional LSE algorithmic outputs using their mean square errors and learning curves for record 40 of data set 2..

### 4.4 Deductions:

Algorithmic outputs based on “data set 1” in chapter 4 and “data set 2,” in the appendices were presented graphically in terms of learning curves and wavelets. This choice was informed by the very fact that the tabulation of each point on

all those graph plots will definitely consume more space and be cumbersome to understand by a layman.

## 5.0 CONCLUSION/RECOMMENDATIONS

### 5.1 CONCLUSION

The Least squares criterion and its application to the modeling of least squares digital filters is most unique and offers several performance prospects. This research evolved a hybrid adaptive least squares error (LSE) / Least Mean Square Error Model and its' accompanying algorithm for handling signal deconvolution in both offshore and onshore exploration terrains. The research also developed a composite model composed of the combination of all the algorithms proposed with some extant algorithms. The model makes for ease in the deconvolution of seismic traces by choice algorithms taking advantage of the easy-to-use graphical user interface designed with Matlab for the composite seismic sequence deconvolution system proposed. This system equally makes for the comparison of algorithmic efficiencies by the plotting of their learning curves and tests for convergence with respect to the standardized Albert Werner's filter coefficients.

The designed and implemented composite seismic data deconvolution system was simulated by the help of data sets obtained from The Mathworks Inc., USA and Marine Geosciences Data Systems(MGDS), Canada. Results are displayed graphically for a visual impact.

### 5.2 CONTRIBUTIONS OF THE RESEARCH TO KNOWLEDGE

The research has been able to

- study the existing Least Mean Squares (LMS) and Recursive Least Squares adaptive filtering models and develop a hybrid LMS / RLS model; and
- provide a hybrid LMS and RLS Adaptive filtering algorithm and thus pioneer the concatenation of these two digital filter coefficients' adaptation techniques thereby combining their respective advantages for improved signal analysis for oil prospecting.
- develop a composite block model that combines the proposed hybrid LMS/RLS algorithm with existing adaptive filtering algorithms to make for a multi-algorithm based software for seismic deconvolution in both offshore and onshore scenarios.

### 5.3 Recommendations/Future Research

Further research on the design and implementation of adaptive filters should be sponsored to ensure that most tools like fuzzy logic, genetic programming, etc are incorporated for better results while putting to use state of the art seismic tools and equipment in a standardized computer laboratory.

Appendices:

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Data set 2:

Table: 4.2: Data for System's Simulation.

SIGNAL PROCESSING DATA PARAMETERS									
Records	No of samples	Desired sinusoid(waveform)	Filter Length	Step size	Autoregressive coeff.	Moving average	Sample realizations	Decimation factor	Reflectivity sequence
	n	S(n)	L	$\mu$	ar	ma	nr	M	v
1	(1:10)	sin(0.01*pi*n)	1	0.001	[1,1/2]	[1,-0.8,0.4,-0.2]	1	5	0.8*randn(10,1)
2	(1:20)	sin(0.05*pi*n)	4	0.002	[1,1/4]	[1,-0.6,0.2,-0.4]	1	5	0.6*randn(20,1)
3	(1:30)	sin(0.10*pi*n)	7	0.003	[1,1/8]	[0.25,0.25,-0.25,-0.25]	3	5	0.25*randn(30,1)
4	(1:40)	sin(0.15*pi*n)	10	0.004	[2,1/2]	[0.2,-0.4,0.4,-0.2]	6	5	0.4*randn(40,1)
5	(1:50)	sin(0.20*pi*n)	13	0.005	[2,1/4]	[1,-0.125,0.125,-1]	10	5	0.125*randn(50,1)
6	(1:60)	sin(0.25*pi*n)	16	0.006	[2,1/8]	[1,-0.8,0.4,-0.2]	15	10	0.8*randn(60,1)
7	(1:70)	sin(0.30*pi*n)	19	0.007	[1,1/2]	[1,-0.6,0.2,-0.4]	21	10	0.6*randn(70,1)
8	(1:80)	sin(0.35*pi*n)	22	0.008	[1,1/4]	[1,-0.8,0.4,-0.2]	28	10	0.25*randn(80,1)
9	(1:90)	sin(0.40*pi*n)	25	0.009	[1,1/8]	[1,-0.6,0.2,-0.4]	36	10	0.4*randn(90,1)
10	(1:100)	sin(0.45*pi*n)	28	0.01	[2,1/2]	[0.25,-0.25,0.25,-0.25]	45	10	0.125*randn(100,1)
11	(1:110)	sin(0.50*pi*n)	31	0.011	[2,1/4]	[0.2,-0.4,0.4,-0.2]	75	15	0.8*randn(110,1)
12	(1:120)	sin(0.55*pi*n)	34	0.012	[2,1/8]	[1,-0.125,0.125,-1]	110	15	0.6*randn(120,1)
13	(1:125)	sin(0.60*pi*n)	37	0.013	[1,1/2]	[1,-0.8,0.4,-0.2]	150	15	0.25*randn(125,1)
14	(1:130)	sin(0.65*pi*n)	40	0.014	[1,1/4]	[1,-0.6,0.2,-0.4]	195	15	0.4*randn(130,1)
15	(1:135)	sin(0.70*pi*n)	43	0.015	[1,1/8]	[1,-0.8,0.4,-0.2]	240	15	0.125*randn(135,1)
16	(1:140)	sin(0.75*pi*n)	46	0.016	[2,1/2]	[1,-0.6,0.2,-0.4]	300	20	0.8*randn(140,1)
17	(1:145)	sin(0.80*pi*n)	49	0.017	[2,1/4]	[0.25,-0.25,0.25,-0.25]	360	20	0.6*randn(145,1)
18	(1:150)	sin(0.85*pi*n)	52	0.018	[2,1/8]	[0.2,-0.4,0.4,-0.2]	420	20	0.25*randn(150,1)
19	(1:155)	sin(0.90*pi*n)	55	0.019	[1,1/2]	[1,-0.125,0.125,-1]	495	20	0.4*randn(155,1)
20	(1:160)	sin(0.95*pi*n)	58	0.02	[1,1/2]	[1,-0.8,0.4,-0.2]	570	20	0.125*randn(160,1)
21	(1:160)	sin(1.0*pi*n)	61	0.021	[1,1/4]	[1,-0.6,0.2,-0.4]	650	20	0.8*randn(165,1)
22	(1:160)	sin(0.01*pi*n)	64	0.022	[1,1/8]	[1,-0.8,0.4,-0.2]	700	5	0.6*randn(170,1)
23	(1:160)	sin(0.05*pi*n)	67	0.023	[2,1/2]	[1,-0.6,0.2,-0.4]	800	5	0.25*randn(175,1)

SIGNAL PROCESSING DATA PARAMETERS									
Records	No of samples	Desired sinusoid(waveform)	Filter Length	Step size	Autoregressive coeff.	Moving average	Sample realizations	Decimation factor	Reflectivity sequence
	n	s	L	$\mu$	ar	ma	nr	M	v
24	(1:600)	$\sin(0.010*\pi*n)$	70	0.024	[2,1/4]	[0.25,-0.25,0.25,-0.25]	8	5	$0.4*\text{randn}(800,1)$
25	(1:600)	$\sin(0.015*\pi*n)$	73	0.025	[2,1/8]	[0.2,-0.4,0.4,-0.2]	13	5	$0.125*\text{randn}(850,1)$
26	(1:600)	$\sin(0.020*\pi*n)$	76	0.026	[1,1/2]	[1,-0.125,0.125,-1]	18	5	$0.8*\text{randn}(900,1)$
27	(1:600)	$\sin(0.025*\pi*n)$	79	0.027	[1,1/4]	[1,-0.8,0.4,-0.2]	24	10	$0.6*\text{randn}(950,1)$
28	(1:600)	$\sin(0.030*\pi*n)$	82	0.028	[1,1/8]	[1,-0.6,0.2,-0.4]	30	10	$0.25*\text{randn}(1000,1)$
29	(1:600)	$\sin(0.035*\pi*n)$	85	0.029	[2,1/2]	[1,-0.8,0.4,-0.2]	39	10	$0.4*\text{randn}(1100,1)$
30	(1:600)	$\sin(0.040*\pi*n)$	88	0.03	[2,1/4]	[1,-0.6,0.2,-0.4]	48	10	$0.125*\text{randn}(1200,1)$
31	(1:600)	$\sin(0.045*\pi*n)$	91	0.031	[2,1/8]	[0.25,-0.25,0.25,-0.25]	59	10	$0.8*\text{randn}(1300,1)$
32	(1:600)	$\sin(0.050*\pi*n)$	94	0.032	[1,1/2]	[0.2,-0.4,0.4,-0.2]	70	15	$0.6*\text{randn}(1400,1)$
33	(1:600)	$\sin(0.055*\pi*n)$	97	0.033	[1,1/4]	[1,-0.125,0.125,-1]	83	15	$0.25*\text{randn}(1500,1)$
34	(1:600)	$\sin(0.060*\pi*n)$	100	0.034	[1,1/8]	[1,-0.8,0.4,-0.2]	96	15	$0.4*\text{randn}(1600,1)$
35	(1:600)	$\sin(0.065*\pi*n)$	103	0.035	[2,1/2]	[1,-0.6,0.2,-0.4]	111	15	$0.125*\text{randn}(1700,1)$
36	(1:600)	$\sin(0.070*\pi*n)$	106	0.036	[2,1/4]	[1,-0.8,0.4,-0.2]	126	15	$0.8*\text{randn}(1800,1)$
37	(1:600)	$\sin(0.075*\pi*n)$	109	0	[2,1/8]	[1,-0.6,0.2,-0.4]	143	20	$0.6*\text{randn}(1900,1)$
38	(1:600)	$\sin(0.080*\pi*n)$	112	0	[1,1/2]	[0.25,-0.25,0.25,-0.25]	160	20	$0.25*\text{randn}(2000,1)$
39	(1:600)	$\sin(0.085*\pi*n)$	115	0	[1,1/2]	[0.2,-0.4,0.4,-0.2]	192	20	$0.4*\text{randn}(2250,1)$
40	(1:600)	$\sin(0.090*\pi*n)$	118	0	[1,1/4]	[1,-0.125,0.125,-1]	225	20	$0.125*\text{randn}(2500,1)$
41	(1:600)	$\sin(0.095*\pi*n)$	121	0	[1,1/8]	[1,-0.8,0.4,-0.2]	261	20	$0.8*\text{randn}(2750,1)$
42	(1:600)	$\sin(0.100*\pi*n)$	124	0	[2,1/2]	[1,-0.6,0.2,-0.4]	300	5	$0.6*\text{randn}(3000,1)$

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