Wireless Channel Blind Identification Using a Generic Adaptive FIR Architecture

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Abstract

In wireless channels there are Non-idealities that cause distortion to the mobile signal such as long distance, multipath and the noise that the channel added to the transmitted signal. This paper utilizes adaptive filtering techniques to solve this channel distortion. Consequently, an adaptive FIR blind identification architecture is developed using four adaptive algorithms to estimate wireless time invariant as well as time varying channels. The four adaptive algorithms are least mean square (LMS), normalized least square (NLMS), recursive least square (RLS) and affine projection algorithm (AFP). The results shows that the RLS outperforms other algorithm in wireless time-invariant channel with least mean square error of (0.0116), and AFA outperforms other algorithms in wireless time-variant channel with least square error of (0.433) and fastest convergence rate. The implications of this wireless channel identification architecture are feasible in detecting next-generation 5G channels and underwater acoustic channel to provide the channel information for further signal processing.

Keywords- least mean square (LMS), normalized least square (NLMS), recursive least square (RLS), affine projection algorithm (AFP), finite impulse response (FIR), wireless channel, adaptive identification architecture, wireless underwater channel, 5G channel.

1. Introduction

Wireless digital communications often require the identification of the channel impulse response that can facilitate channel equalization and maximum likelihood sequence detection [1, 2].

Adaptive wireless channel identification is typically utilized when simpler techniques [3-7] for received sequence detection cannot be used in tele-communication systems. The wireless channel distorts the conformity of the transmitted signals making the decoding of the received information difficult. In such cases where the effects of the channel distortion can be modeled as a linear FIR filter, the transmitted symbols is known as Inter-Symbol Interference (ISI). Thus, an adaptive filter can be developed to model the effects of the channel ISI for purposes of decoding the received information in an optimal manner. Where, the transmitter sends to the receiver a sample sequence *x(n)* that is known to both the transmitter and receiver. The receiver then attempts to model the received signal, *y(n)*, using an adaptive filter whose input is the known transmitted sequence, *x(n)*, and output signal, *d(n)*. After a suitable period of adaptation, the optimal coefficients of the adaptive filter, *h(n)*, are computed and then utilized in a procedure to decode future signals transmitted across this wireless channel. This blind channel identification is achieved by using only the channel output without using a training sequence.

To simulate that, two types of wireless channels, time-invariant and time-variant, are mathematically modelled. Then, generic adaptive wireless channel architecture is designed using adaptive FIR filtering algorithms of least mean square, normalized least mean square, recursive least square and affine projection.

The blind channel identification methods using the second-order cyclostationary statistics were initiated by Tong et al. [8, 9]. Those have attracted research attention [10-13]. The contributions of this paper can be short listed as following;

- Time-invariant channel and time-variant channel are mathematically modeled and adaptively blind identified using four methods.
- Performance indices comparisons of the computer simulated models are presented.

2. Adaptive filtering algorithms

The adaptive wireless channel identification architecture utilized four adaptive algorithms; least mean square (LMS), normalized least square (NLMS), recursive least square (RLS) and affine projection algorithm (AFP).

3. Least Mean Square (LMS)

The LMS algorithm is widely used in deferent application due to low computation complexity, and it is the part of the stochastic gradient algorithms [14]. This algorithm has two input and an output. The inputs are the known signal and the error signal, as the deference between the FIR filter output and the desired signal to be identify. The output signal is the updated filter coefficients.

Definition of the Adaptive LMS Algorithm:

$$h(n) = [h_0(n), h_1(n), h_2(n), \dots, h_M(n)]$$

$$x(n) = [x_0(n), x_1(n), x_2(n), \dots, x_M(n)]$$

Where, h(n) is the filter coefficients at the nth instant.

x(n) is observed signal vector at nth instant.

In this LMS algorithm the Nth order FIR filter coefficients can be adapted according to the following pseudocode form;

Parameters: ***N*** = taps number, ***μ*** = step-size

$$0 < \boldsymbol{\mu} < \frac{2}{\boldsymbol{NS}}$$

S is the maximum value of the input power spectral

Initialization: when the tap-weight vector is known, set $\boldsymbol{h}(0) = \boldsymbol{h}(n)$,

Otherwise, set $\boldsymbol{h}(0) = 0$.

Data: Given ***x(n)*** is the input *M* ×1vector at time *n*

d(n) is the desired response at time step *n.*

Computation:

for n = 1: N; % N = length (x);

y(n) = h(n-1) x^T(n);

e(n) = d(n) – y(n);
h(n) = h(n-1) + μ × e(n) × x(n);
end

Where, **y(n)** is the FIR Filter output by matrix multiplication.

3.1 Normalized Least Mean Square (NLMS)

In many application, the input is huge and the LMS algorithm could not adapting the output because of step size. Thus, NLMS is developed to overcome this problem by the normalizing of step size according to input vector energy [15]. The NLMS algorithm can be state in pseudocode form as following;

Parameters: ***N*** = taps number and $\boldsymbol{\mu}$ = adaptation constant

$$0 < \mu < \frac{\mathbf{E}\left[\left|x(n)^2\right|\right]\mathfrak{D}(n)}{\mathbf{E}\left[\left|e(n)^2\right|\right.},$$

Where, $\mathbf{E}\left[\left|e(n)^2\right|\right]$= error signal power,

$\mathbf{E}\left[\left|x(n)^2\right|\right]$ = input signal power,

$\mathfrak{D}(n)$ = mean-square deviation.

Initialization: when the tap-weight vector is known, set $\boldsymbol{h}(0) = \boldsymbol{h}(n)$,

Otherwise, set $\boldsymbol{h}(0) = 0$.

Data: Given: $\boldsymbol{x}(\boldsymbol{n})$ = M×1 tap input vector at time *n*.

d(n) = desired response at time step n.

Computation:

for n = 1: N; % N = length (x);
y(n) = h(n-1) x^T(n); % Filter output by matrix multiplication
e(n) = d(n) – y(n);
$h(n) = h(n-1) + \frac{\mu}{\|x(n)\|^2} \times e(n) \times x(n);$
end

Where $\|x(n)\|^2$ is the squared norm.

3.2 Recursive Least Square (RLS)

This algorithm is useful when the environment is very dynamic and requires speed response [16]. For stationary signals, the RLS filter converges to the same optimal filter coefficients as the Wiener filter. For non-stationary signals, the RLS filter tracks the time diversity of the process [17]. The RLS algorithm can be state in pseudocode form as following;

Parameters: ***N*** = taps number

$\boldsymbol{\mu}$ = forgetting parameter, where, $0 < \mu < 1$,

$\boldsymbol{\alpha}$ = regulation parameter, where $\alpha = \begin{cases} \text{small positive constant for high SNR} \\ \text{large positive constant for low SNR} \end{cases}$

Initialization: set $\boldsymbol{h}(0) = \boldsymbol{0}$

And, $\boldsymbol{R}(0) = \frac{1}{\alpha}\boldsymbol{I}$

Data: Given, $\boldsymbol{x}(\boldsymbol{n})$ = M×1 tap input vector at sample time *n*.

d(n) = desired response at sample time *n*.

Computation:

for n = 1: N; % N = length (x);

y(n) = h^T(n-1) x (n); % Filter output by matrix multiplication

e(n) = d(n) – y(n);

T(n) = R(n-1)x(n);

$$\boldsymbol{l}(\boldsymbol{n}) = \frac{\boldsymbol{T}(\boldsymbol{n})}{\mu + \boldsymbol{x}^{\boldsymbol{T}}(n)\boldsymbol{T}(n)}$$

h^T(n) = h^T(n-1) + l(n) e(n);

$$\boldsymbol{R}(\boldsymbol{n}) = \frac{1}{\mu}\left(\boldsymbol{R}(\boldsymbol{n}-\boldsymbol{1}) - \boldsymbol{l}(\boldsymbol{n})\boldsymbol{x}^{\boldsymbol{T}}(\boldsymbol{n})\boldsymbol{R}(\boldsymbol{n}-\boldsymbol{1})\right)$$

end

Since the adaptive filter coefficients are in the range $0 < h < 1$, thus, time varying can be exploited. Note that the coefficients of the FIR filter stay fixed during the observation period for which the error function is defined [18].

3.3 Affine Projection Algorithm (AFP)

The affine projection algorithm is a multi-dimensional generalization of normalized least mean square (NLMS) adaptive filtering algorithm. Where, each tap FIR filter coefficients vector update of NLMS is viewed as a one dimensional affine projection [19]. Thus, AFP uses the projection order, so this algorithm is extension of NLMS. The AFP algorithm can be state in pseudocode form as following;

Parameters: N=number of taps, μ = adaptation constant and

Initialization: set $\boldsymbol{h}(0) = \boldsymbol{h}(n)$, If the tap-weight vector is known

Otherwise, set $\boldsymbol{h}(0) = 0.$

Data**:** Given ***x(n)*** = *M* ×1 tap-input vector at time step *n*

d(n) = desired response at time step *n*.

Computation:

for n = 1: N;

y(n) = x^T(n) h(n-1); % Filter output by matrix multiplication

e(n) = d(n) – y(n);

$$\boldsymbol{h}(\boldsymbol{n}) = \boldsymbol{h}(\boldsymbol{n}-\boldsymbol{1}) + \mu \times \boldsymbol{x}^{\boldsymbol{T}}(\boldsymbol{n})\left(\boldsymbol{x}(\boldsymbol{n})\boldsymbol{x}^{\boldsymbol{T}}(\boldsymbol{n})\right)^{-1}\boldsymbol{e}(\boldsymbol{n})\,;$$

end

The desired update equation of h(n) for the affine projection adaptive filter is uniquely determined by the data matrix ***x(n)*** and the error vector, ***e(n)***, by acting on the old weight vector, ***h(n-1)***, to produce the updated weight vector ***h(n)***.

4. Wireless Channel Mathematical Model

A wireless communication system is transmitting information through wireless channels. A mathematical model is constructed to reflect the most important characteristics of the transmission channel. This mathematical model is the prelude of the channel's simulation using Matlab tool.

4.1 Time-Invariant Channel

The time invariant channel may represent transmission medium for a stationary receiver in one location, So that the impulse response, *h(n)*, of this channel can be written as below:

$$h(\tau) = a_1\delta(\tau-\tau_1)e^{j\theta_1} + a_2\delta(\tau-\tau_2)e^{j\theta_2} \ldots + a_N\delta(t-\tau_N) * e^{j\theta_N} \quad 1$$

Which can be expressed in closed form as;

$$h(\tau) = \sum_{k}^{L} a_k\delta(\tau-\tau_k)\, e^{j\theta_k} \quad 2$$

Where, L : number of path, a, θ, τ : path loss, phase and delay respectively. From above we note that the time parameter eliminated because the channel is not changing in time, moreover the channel have different delays and attenuations and phase shift the Fig. 1 relates these parameter (attenuation, path delay and phase) in one diagram.

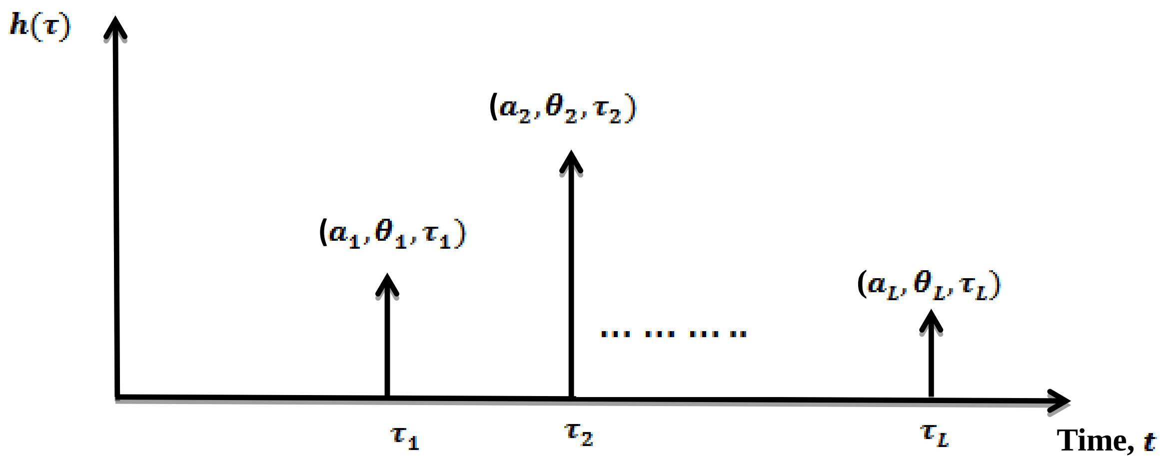

Fig.1 General Impulse response of a time-invariant channel

The channel output signal is the convolution formula plus the white Gaussian noise, *w(n)* ;

$$y(n) = \sum_{k=1}^{L} h(n)x(n-k) + w(n) \qquad 3$$

4.2 Time-Variant Channel

Physical channels that have multipath phenomena such as ionospheric channel, the transmitted signal could show the effect by time-variant linear filter with varying impulse response $h(t,\tau)$ [20]

$$h(t,\tau) = \sum_{n}^{N} a_n(t)\, e^{-j\theta_n(t)}\, \delta(\tau - \tau_n(t)) \qquad 4$$

Where, h = channel impulse response, a, θ and τ = path loss, phase, delay respectively.
The effect of time delay, attenuation and phase shift on the invariant channel, that have ten paths, are investigated. Assume that the receiver moving towards the transmitter in velocity at 300 km/second, moreover, constant angle of arrival is equal to zero to be the maximum Doppler shift:

$$f_d = f * \frac{v}{c} * \cos(\theta) \qquad 5$$

Where, f_d = Doppler frequency, V= velocity of receiver, C=speed of light and θ =angle of arrival. The received signal can be written by the equation:

$$y(n) = \sum_{k=1}^{L} h(k,n)x(n-k) + \mathrm{w(n)} \qquad 6$$

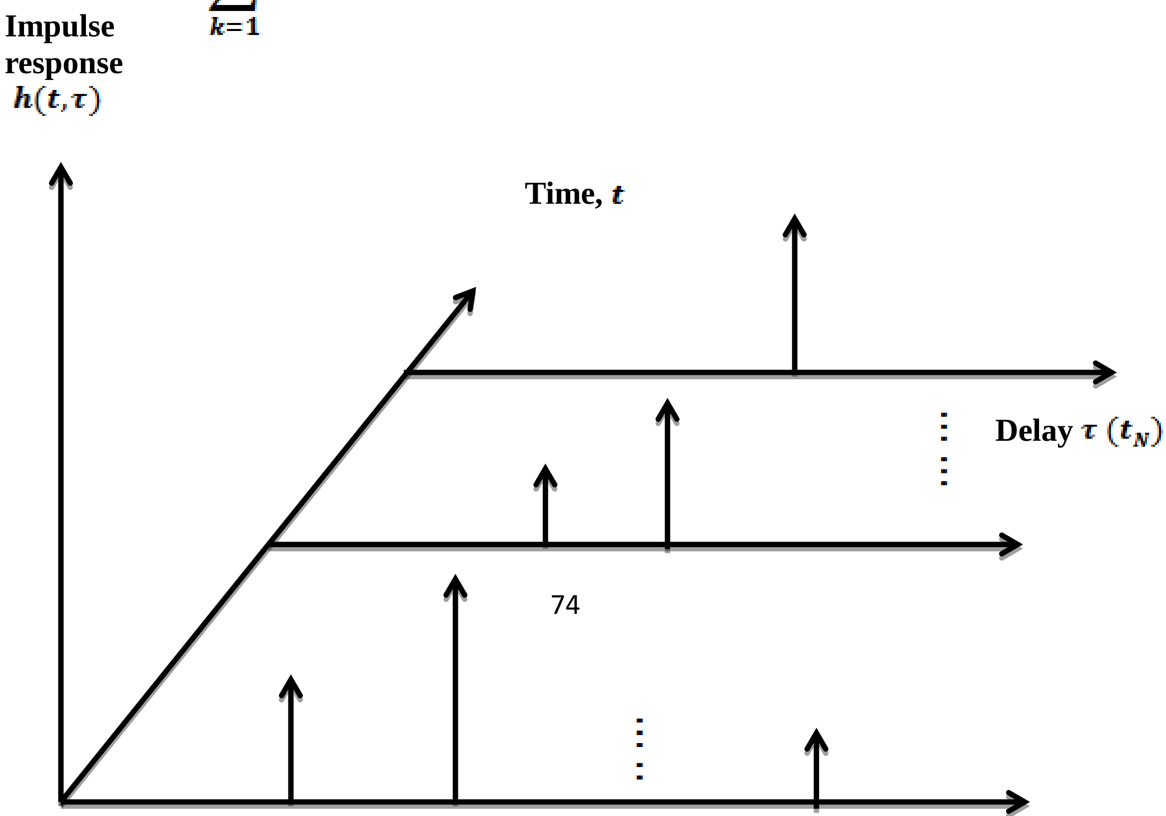

Fig. 2 A linear time-variant channel [21]

The input signal, for both models, is

τ_1 τ_2 τ_2 τ_3 τ_N

$$x(t) = Re\left\{ e^{j2\pi f_c t} \right\} \quad 7$$

$$x(t) = Re\{\cos 2\pi f_c t\} - Im\{sin2\pi f_c t\} \quad 8$$

Take into account whole transmitted and received signals in real domain the reason that the modulators are designed to utilize the oscillators that produce a real sinusoidal (to complex exponentials),

$$x(t) = Re\{cos2\pi f_c t\} \quad 9$$

5. Results and Discussions

Computation complexity, mean square error and convergence time are the performance indices of these four adaptive algorithms (LMS, NLMS, RLS and AFP). The Computation Complexity describes the amount of arithmetic operations per iteration and the necessary number of iterations to achieve a desired performance level. The mean square error is the quadratic function of the error, e(n),

$$MSE = E[|e(n)|^2] \quad 10$$

The third performance index is convergence rate which represents the number of iterations required for the algorithm to converge to its steady state mean square error.

The results depend on the adaptation algorithm that has optimum computation complexity, less mean square error, and the fast convergence rate. The simulation result consists of tables and curves representing the performance characteristics of time-invariant and time-variant channels. AFP has a projection order of (5) and (2) in time-invariant and time- variant channel respectively.

5.1 Time-Invariant Channel results

The time invariant channel is mathematically modelled in equations (1), (2) and (3). This channel model can be identified using adaptive filtering architecture for wireless time-invariant channel as depicted in Fig. 3. The input signal samples are injected in the adaptive FIR model as well as in the unknown time-invariant channel. The unknown coefficients of the channel are adjusted to approach the FIR filter coefficients after a certain number of iterations.

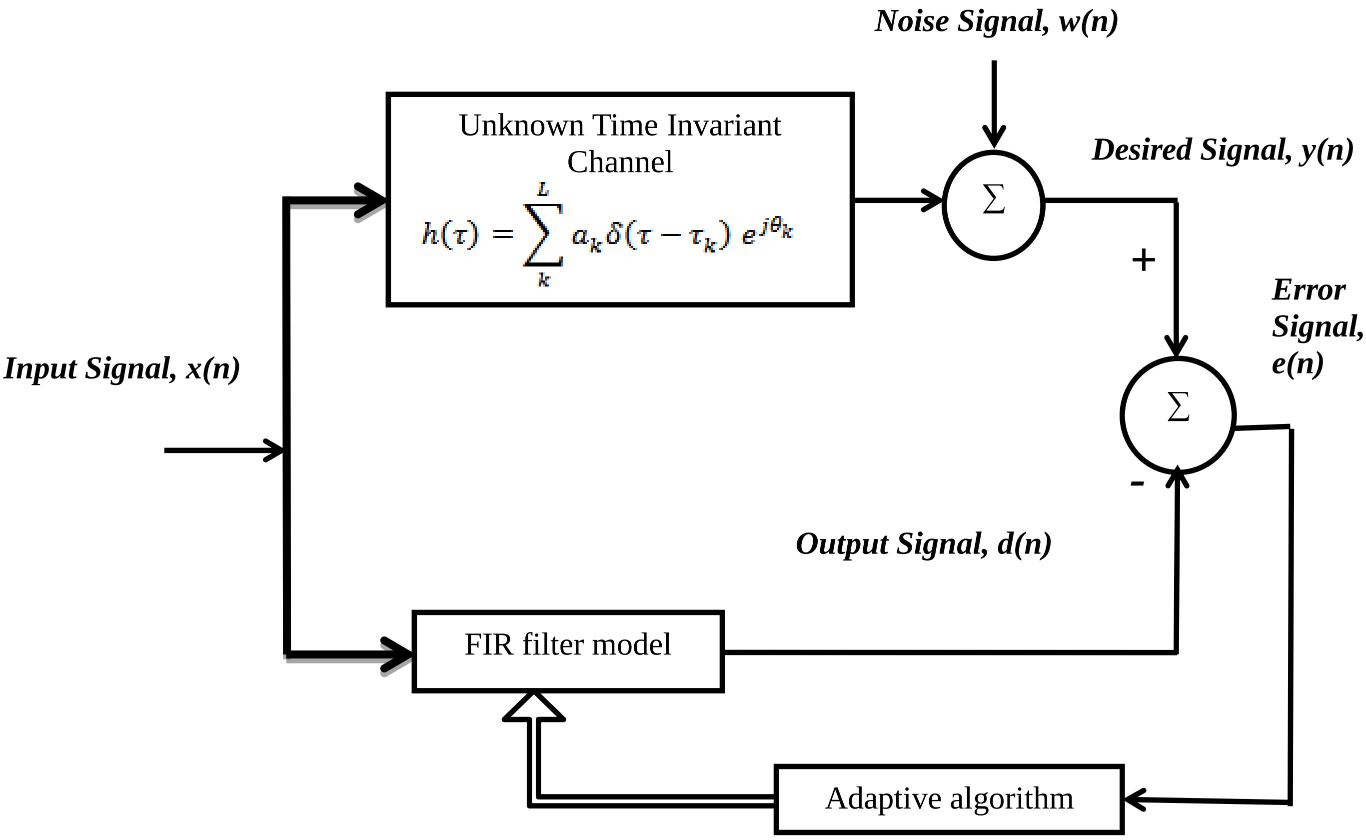

Fig. 3 Adaptive filtering architecture for wireless time- invariant channel

The impulse response of the channel with ten different paths is as shown in Fig. 4 below.

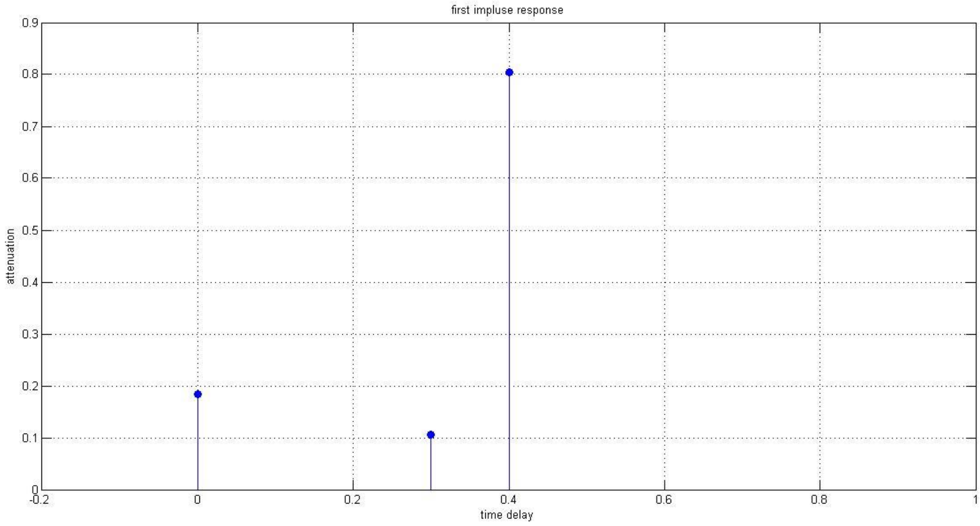

Fig. 4 The impulse response of a time invariant channel

The performance indices are summarized in Table 1. An observation of the RSL algorithm outperforms the other adaptive algorithms in identifying the wireless time-invariant channel.

Table 1 Performance Comparison of wireless time –invariant channel identification architecture's Adaptive Algorithms, where N (=10) is filter order using (100) iteration

Adaptive Algorithm	Computation complexity	Mean Square Error
LMS	$2N+2$	0.0214
NLMS	$3N+1$	0.0169
RLS	$4N^2$	0.0116
AFP	$2N^3$	0.0158

The computational complexity of the four is further illustrated in the curve of Fig 5.

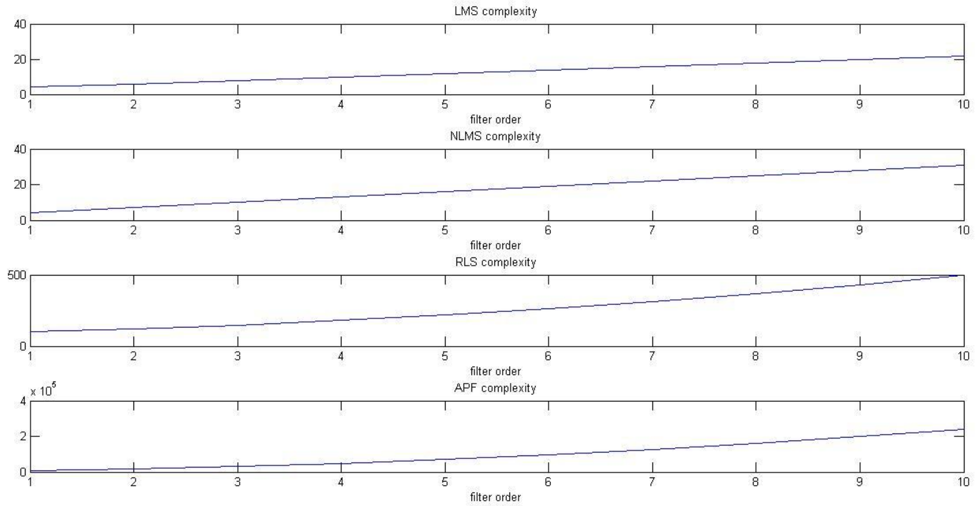

Fig. 5 Computation complexity curve plotted against the adaptive algorithms.

Filter coefficients adapted to the channel coefficients with step-size = 0.04 for the LMS, and step-size = 1 for AFP and NLMS, and the RLS forgetting factor = 0.99 with the following mean square error of Fig. 6.

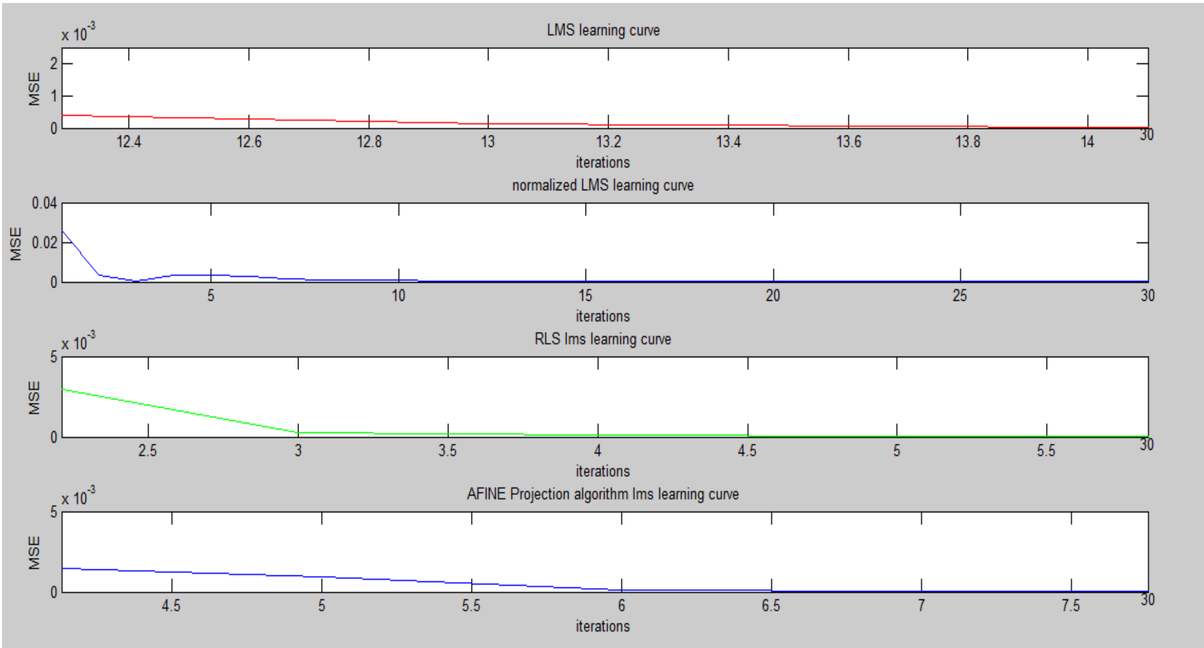

Fig. 6 learning curve of the four adaptive algorithms, iteration=100, filter order=10

5.2 <u>Time-Variant Channel Simulation</u>

The adaptive identification architecture, depicted in Fig. 7, is emulating the mathematically model of the time-variant channel as in (4), (5) and (6).

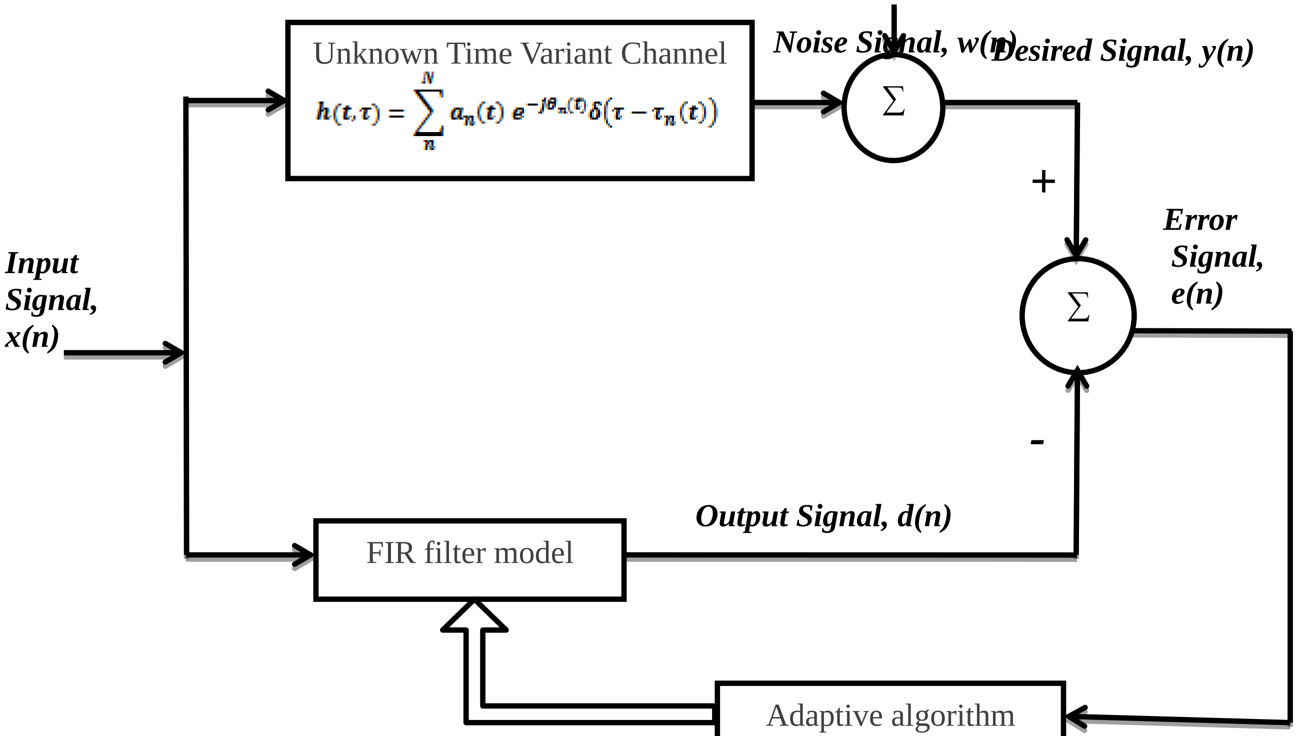

Fig. 7 Wireless Time-variant channel identification architecture

The input signal is sampled in the adaptive FIR model as well as in the unknown time-invariant channel. Then, the unknown coefficients of the channel are adjusted to approach the FIR filter coefficients after a certain number of iterations.

Table 2 Performance Comparison of wireless time –invariant channel identification architecture's Adaptive Algorithms, where N (=10) is filter order using (100) iteration.

Adaptive Algorithm	Computation complexity	Mean Square Error
LMS	*2N+2*	3.1481
NLMS	*3N+1*	0.7979
RLS	$4N^2$	0.0454
AFP	$2N^3$	0.0433

Filter coefficients adapted to the channel coefficients with step-size = 0.04 for the LMS, and step-size = 1 for AFP and NLMS, and the RLS forgetting factor = 0.99 with the following mean square error of Fig. 8.

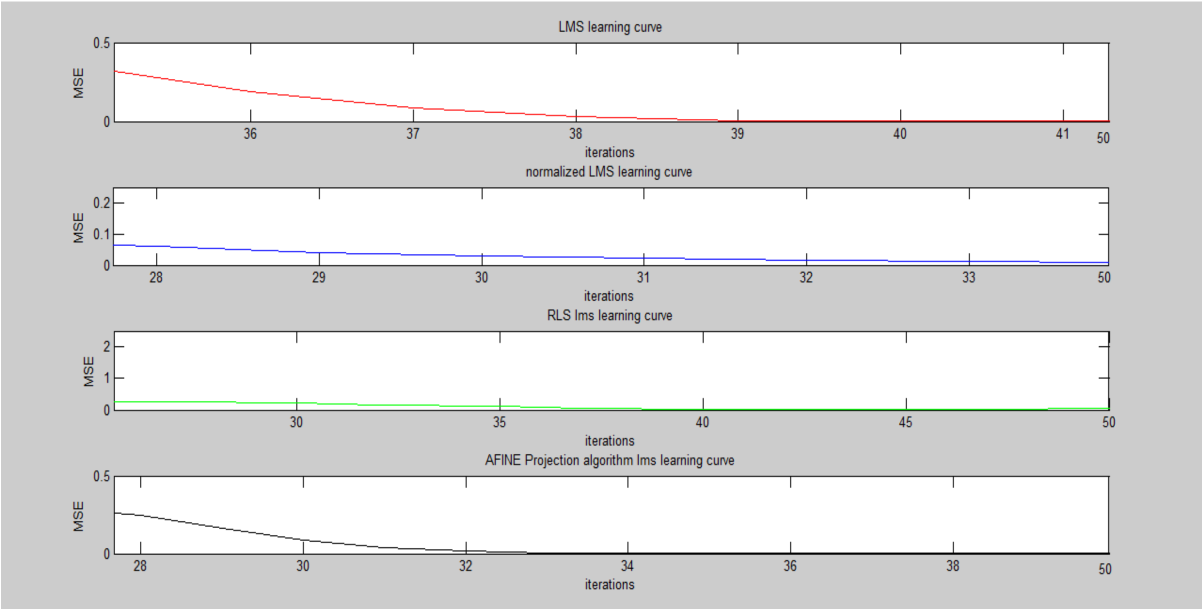

Fig. 8 learning curve for time varying channel filter order = 10, number of iteration =100.

6. Conclusion

This paper is presented a comparative performance evaluation of four adaptive blind identification methods of wireless channel. This investigation is efficiently developed through computer simulation of wireless channel mathematical model for the least square error and convergence rate for both time invariant and variant channels.

Improving the current state of adaptive algorithmic aspect of wireless channel, to go upward the next-generation 5G channel model, a novel breakthrough emerging techniques are needed to be innovated. A golden ratio-inspired approach that structured over the emerging Union Dipole Theory [22] may be one of the potential future solutions.

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