CHANNEL ESTIMATION USING PER-SURVIVOR PROCESSING

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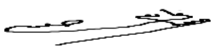
Signature : 

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ABSTRACT

CHANNEL ESTIMATION USING PER-SURVIVOR PROCESSING

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In this thesis per-survivor processing has been used for estimating the coefficients of a frequency selective channel. Two well-known methods, least mean square and recursive least mean square, along with per-survivor processing have been used during channel estimation. To increase the accuracy of the estimated channel coefficients an improved per-survivor processing channel estimation technique has been proposed and from the simulation results it is seen that the proposed technique results in better estimated channel coefficients than the channel coefficients obtained using classical per-survivor approach.

Keywords: Per-Survivor Processing, Channel Estimation, Least Mean Square, Recursive Least Mean Square.

ÖZ

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Bu tez çalışmasında kazanan-patika yöntemi kullanılarak frekans seçici kanal katsayıları en az ortalama kare ve yinelemeli en az ortalama kare yöntemleri kullanılarak hesaplanmıştır. Kazanan patika yöntemi kullanılırken kanal katsayılarının tahmininde en az ortalama ve yinelemeli en az ortalama yöntemleri kullanılmıştır. Hesaplanan kanal katsayılarının doğruluğunu arttırmak için ileri kazanan patika yöntemi önerilmiştir ve benzetim sonuçlarına bakıldığında önerdiğimiz yöntemle elde edilen katsayıların gerçek katsayılarla klasik yöntemle elde edilenlere göre daha yakın olduğu görülmüştür.

Anahtar Kelimeler: Kazanan Patika, Kanal Tahmini, En Az Ortalama Kare, Yinelemeli En Az Ortalama Kare.

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Mother, you are the brightness of my life, to be or not to be an important person in this world I am certain that you will always love me, support me and you will be proud of me. You are the most kind person in this world.

My wife, you were and you are and you will always be the most special person in my life, your support and your love are always making me stronger.

My daughter, I am writing these words now and you are only one and a half years old, I want you to take this passion that I took from your eyes which makes me invincible and I know that one day you will make me proud of you.

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LIST OF ABBREVIATIONS

QoS	Quality of Service
CIR	Channel Impulse Response
MMSE	Minimum Mean Square Error
LMS	Least Mean Square
RMS	Recursive Mean Square
MLSE	Maximum Likelihood Sequence Estimation
RATs	Radio Access Technologies
LTE	Long Term Evaluation
UMTE	Universal Mobile Telecommunication Systems
ISI	Inter-Symbol Interference
MAP	Maximum a Posteriori
LS	Least Square
LMMSE	Linear Minimum Mean Square Error
PSP	Per-Survivor Processing
SNR	Signal to Noise Ratio
BER	Bit-Error Rate
LF	Likelihood Functional
RLS	Recursive Least Squares
AWGN	Additive White Gaussian Noise channel
CV	Classical Viterbi
RSSE	Reduced State Sequence Estimation
DFE	Decision Feedback Equalization
DDFSE	Delayed Decision Feedback Sequence Estimation
WMF	Whitened Matched Filter
VA	Viterbi Algorithm
VS-LMS	Variable Step-Size Least Mean Square
RLMS	Recursive Least Mean Square
BPSK	Binary Phase Shift Keying
FPGA	Field-Programmable Gate Array
DSP	Digital Signal Processing

CHAPTER 1

INTRODUCTION

An Estimate is a quantitative assessment of the potential cost of efforts or the future outcome. Estimation is a process that mostly used to predict the project's cost, size, resources, efforts, or duration. The software market today with increased reliance on external elements and the code to be adapted has led to new types of techniques to estimate. Estimate is a practice that has totally moved from a mere approximations based on the size of the estimates and the functional component to new meaning.

1.1. Channel Estimation

The channel estimation method is quite essential in mobile systems and wireless networks. Whereas, the wireless channel change rapidly with the passage of time, commonly caused by the transmitter and receiver being in motion that influenced by the mobile wireless communication interference. It also happened due to multiple reflections from the surrounding areas, such as hills, buildings and other obstacles. In regards to deliver reliable and speedy data transfer rates, system needs to assess the accurate timely changing network.

The portable radio system is the most important technologies delivered quality of service (QoS) such as voice, video and text data transmission for both movable users and travelers. Information of the instinct reply of propagation channels in mobile wireless estimator help in collecting information which is useful in testing, design and plan a radio transmission system.

The network assessment relied on instructed order of bits which is always distinctive to a particular sender and repeats in each spurt transmission [1]. Channel Estimator for each burst, separately estimate the CIR (channel impulse response) by exploiting transmitted and received bits and also provide knowledge on the CIR to signal sensor. The signal sensor must contain the knowledge of the channel impulse response of the wireless link with already passed sequences. A separate estimator channel can perform this task. At the receiver side demodulation can occur any time, therefore the corrupted modulated signals must pass under the channel estimate by using MMSE, LMS, RMS, MLSE etc. Fig. 1 is showing the channel estimate:

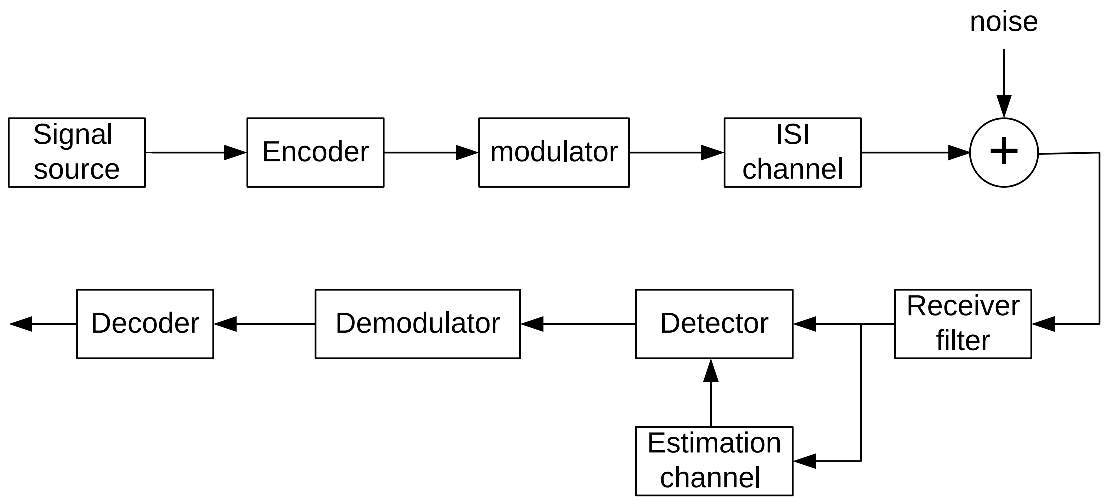

Figure 1: The block diagram of the channel estimator

In order to boost capacity, date bandwidth and optimized packet system that supports various Radio Access Technologies (RATs) advance technologies should be developed. The existing mobile telecommunication networks are known as pre-4G standard, which is actually a part of a new advances long term evolution (LTE) Program. LTE is an improvement to Universal Mobile Telecommunication Systems (UMTS) and a new version of the next generation of mobile telephone.

Radio channels in mobile radio systems usually fade multi-path channels, that cause inter-symbol interference (ISI) in the received signals. To remove that ISI reference, various kind of equalizer can be used. Detection algorithms based on search trellis (such as MLSE or MAP) provide good reception performance, but still they are not much countable. Currently these algorithms are very popular. However, these detectors still require CIR knowledge that contain channel estimation sequence of known bits. Thus, the channel estimator is able to estimate the CIR for each burst separately by exploiting bits transmitted and received.

Digital sources are normally covered by channel coding and secure against channel fading but after a while binary signals modulate and transmit over multi-path fading channel. Noise is also added and combines the received signals. Where there is a multi-path channel, inter-symbol interference (ISI) must be found in the received signal. Therefore a signal sensor/detector such as MLSE or MAP must know about CIR characteristics to make sure that ISI has removed completely. One thing here must be noticed that equalization is also possible with decision feedback, linear, and blind equalizer [2]. After capturing the signal, it decode channel to extract the original message.

Later on the receiver can take advantage of transmitting known bits and received samples correspond to estimate CIR for each separate burst. Least-Squares (LS) or Linear Minimum Mean Squared Error (LMMSE) methods are a few techniques of channel estimation that can be used for the same purpose.

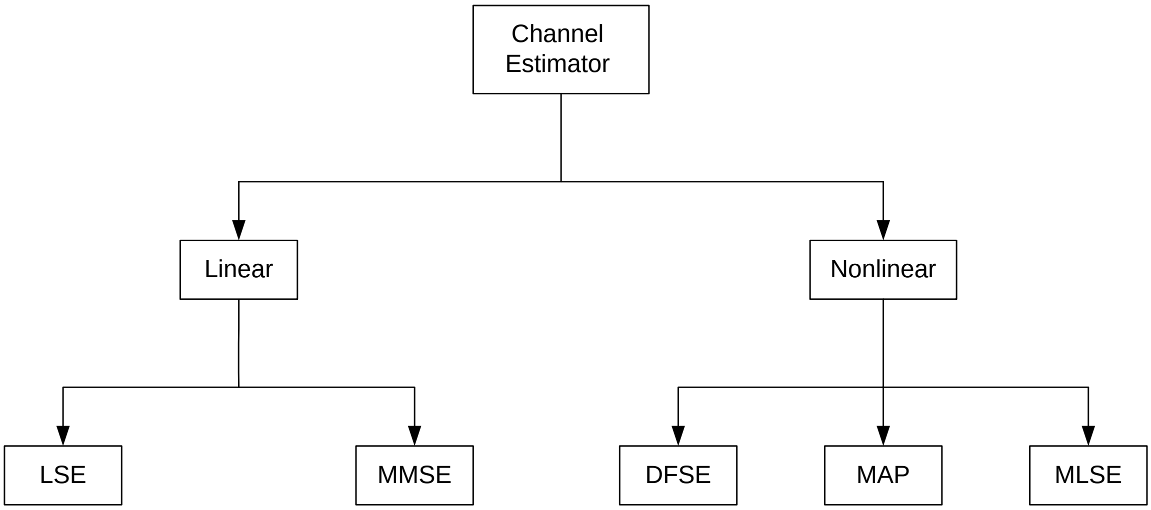

Figure 2: Channel estimator types

1.2. The Problem of Channel Estimation

Radio/wireless channel in a movable networks is a major test as a means of trusted maximum bandwidth communications. When network signals broadcast via the radio channel, they bear different sort of distortion. The recipient gets a lined position of the signals delivered to network users, debilitating factors arbitrary amount of arbitrary delay before. Due to the reflection and incoherent from numerous barriers between sender and receiver, too many duplicates of the similar signals transmitted to the receiver side.

Opposite link asynchronous nature in nature, i.e. the arrival of different signals at the same receiver with different relative time offset [3], with regard to the timing of arbitrary signal in the receiver. Not convert the received signal from the pass band to baseband, and demodulated, digital, and then processed in the basement for detecting and decoding the bits of information. The exposure of a specific user's communicated bits includes the association of the received waveform with a duplicate of the consistent dispersal code at the receiver. Perfect associated requirements a correct approximation of the user's timing offset.

1.3. Training Sequence

When considering the transfer of information through the channel, two most important parts known as sender and receiver complete this transformation process and that are to be trained. This instruction must be delivered before transmitting data and its purpose should be supporting decoding channels, or during both encoding and decoding processes. Usually in fading channels a series of instructions can be delivered gradually either in the beginning of each cohesion period, so that the receiving node can assess the channel properties and later communicate it with preset standards (see, for example, [4], [5], [6],[7]).

Here, the reactions contacts over a period of time less fixed separate DMC memory channel with flawless feedback, any noise and instantaneous (causal) will be studied.

It is assumed that the sender and receiver are completely unaware about the channel matrix Q transmission. However, both nodes are aware that Q relates to a subset Q of organizing exhibitions. By rule, to send training order doesn't need affect the rates can be achieved by a system of communication. You can make the length of the test sequence negligible compared with the Thereafter information order length. Though this is the major purpose of study, and the partitioning between the estimate channel coding data might result in the death as error exponent. Here the work of Feder and Lapidoth would be discuss [8] by which decoding to the families of the World stations are considered without reactions. It shows that global decoders that are optimum in the sense that they accomplish (asymptotically) as well as the highest likelihood decoding tuned to channel more of that transferred by. In actual, show that a mixture of training and decoding sequence designed for the maximum likelihood estimates channel is not optimal.

1.4. Per Survivor Processing (PSP)

Per Survivor Processing (PSP) is a general framework of measurement based on the probability of detective approach, whereas the existence of unidentified values stops the utilization of the old Viterbi approach. The conception is based on the understanding that the PSP-oriented decision estimate unknown parameters that are embedded in the structure of the search algorithm itself. We can say that the PSP doesn't only offers superior performance but also a natural way to address the problem of decoding from first principle which makes it an appropriate vehicle for integrating tasks receiver design.

Various states come across during processes and data must decode in the existence of unknown, possibly time-varying channel parameters. When the predominant signal-to-noise ratio (SNR) is not too huge or is quickly changing then ad hoc approaches for data detection do not work very well. Therefore, more sophisticated solutions are required, in which the loss of earlier well-known methods can be recovered. These solutions of maximum difficulty that perceived practically are actually not feasible. The existing solutions are more demanded due to the improved computational power (speed and memory). Moreover, the traditional arrangement of digital transmitted waveform permits for actual parametric demonstrating, that means the information of a few key waveform parameters serves for replicating the sample waveform of delivered random signal with high accuracy.

Points discussed above are the trend to study more about the channel and utilize that information in detection process. It actually tracks that the structured learned to perform this learning procedure, presentation and examined by its effect on the transmitted Bit-Error Rate (BER) of the driven information, that have a vital role in entire receiver's system efficiency. However reducing the BER in the data analysis procedure is a basic and suitable objective. There are various methodologies for same purpose during existence of all these channel persuaded insufficient issues. Therefore, there is no place for any objection about the best solution, if all the channel data is already recognized. Now the only disorganized thing in observation now is the data and the omnipresent thermal noise.

This issue has been resolve a long time ago, but still there is no any comprehensive solution exist because no one can understand channel completely. Specially in challenging environment it is even more complex due to lack of channel modeling, limited receiving resources, signal collision due to the high traffic of the radio spectrum, and quality of receiving electronic components, etc. Moreover, the extreme profitable wants for more high bandwidth and mobility shows that stations will perform slow and cooperate fewer. Hence, finding the perfect and speedy receiver is even harder. On behalf of this framework, we can say that the present architecture supported by PSP is well developed and it gathered detected data estimation methods that increase receive efficiency. Due to this support receiver can even perform multiple tasks according to user priority and it known as individual task oriented receiver [9].

The basic concept behind the creation of methods group is where PSP is linked up to put on the likelihood-functional (LF) model in the presence of noise over signs. Its been done in order to (a) differentiate among numerous enumerable hypotheses and

(b) assess other helpful limits. The concept of likelihood-based detection and estimation drives probability based outcome, which is totally different from statistic point of view of non-numerical testing or any other learning process such as artificial intelligence or expert-system approach that work on neural network. This approach is most adopted and famous approach for the parametric friendly model communication group. Algorithms involve in these groups can be differentiate through detailed probability based assumptions and externally forcefully applied restraints on the processor structure. Least mean square (LMS), Kalman filter and recursive least squares (RLS) [10] algorithms can be used in PSP decoder, to estimate the channel parameters.

1.5. The AWGN Channel

After the implementation of the transmitter, the next thing that needs to be considered is the modeling of the wireless channel. A wireless channel can be considered as a noisy filter, by which the transmitted signal needs to pass through before reaching to the receiver. Therefore, to simulate a wireless communication system such as the one concerned here, one needs to formulate an appropriate filter which gives an accurate representation of the channel response. This channel modeling can be separated into modeling the AWGN .

The AWGN channel assumes that the noise in the channel is a wide-band noise with constant power spectral density across all frequencies and has a Gaussian amplitude distribution. In a wireless communication system, many noise sources are present, with the most significant being the receiver front end amplifier. As the noise is linearly additive, for all intent and purposes it can be regarded as a single AWGN source which additive corrupts the transmitted signal before it reaches the demodulation in the receiver. Hence, an AWGN channel can be easily modeled in summer which simply adds white Gaussian noise to the receiver input. For simulation purposes, random numbers that model white Gaussian noise are added to the transmitted signal samples.

1.6. Thesis Outline

The study is formed into four chapters. By summarizing, the target of this study is to improve the estimation of the channel coefficient at the receiver side and to achieve values as approximate as possible to the real values by using per-survivor processing. Thus the study is categories as follows: Chapter 1 describes the introduction to the channel estimation by using per-survivor processing generally. Chapter 2 comprises the channel estimation details and per-survivor processing technique with several examples for clarification. Chapter 3 contains the original work and the results of the simulation. And finally Chapter 4 includes the conclusion and future work.

CHAPTER 2

MAXIMUM LIKELIHOOD BASED CHANNEL AND SQUENCE ESTIMATION METHODS

Data detection and channel estimation are the two main issues in the time varying digital communication. The Maximum Likelihood Sequence Estimation (MLSE) [11] provides the best data decoding methods that make sure that the receiver knows the channel parameters correctly. Whenever the existence of unidentified quantities stops the specified usage of the Classical Viterbi (CV) algorithm, Per-Survivor Processing (PSP) provides an effective framework to examine the MLSE algorithms. This rule basically relies on the concept of hidden data estimation approach with integrated framework of the Viterbi system with various programs to useful MLSE and Reduced State Sequence Estimation (RSSE). The channel reduction method that utilized in RSSE has an upfront clarification with relation to the existing rule [19]. Simulation outcome for given algorithms can be applied to certain inter-symbol interference (ISI) channels indicating irrelevant performance deprivation in respect with MLSE.

To reduce the complexity of MLSE algorithm comprise in the IS1 lattice that depends on truncation of the channel impulse feedback and canceled remaining IS1 by choice response Equalization instruments [12]. Many writers have independently present that substantial act enhancement over the direct application of DFE, might found by joint DFE approaches in decoding process. This methodology, firstly mentioned [13] under the framework of immeasurable IS1 channels, that distinguish from conservative DFE. In above scenario the impact of the remaining IS1 canceled, in the counting of each division metric on behalf of the specific survivor order. Moreover currently, numerous writers have projected [14], [15] and protracted the following method [16], [17] by joining it with set segregating rules [18]. The above mention methodology has been denoted as Delayed Decision Feedback Sequence Estimation (DDFSE) [14], and in its advance form RSSE [17].

2.1. Maximum Likelihood Sequence Estimation (MLSE)

The channel state knowledge is usually expected to exist already at the receiver in radio communication systems. Conventionally, a training order is used to analyze the channel estimation. Instead of, the channel can be identifying by utilizing relevant belongings of the passed signals. Though, the computational force need to combined ML result to detect symbol and to estimate channel issue rises proportionally with measurement of the issue. To meaningfully decrease this computational force, combined ML approximation and detection can be formulate as an integer least-squares and present signal-to-noise ratios (SNR) and that issue can be resolved through decoding of known difficulty of experiential methods. In chase of high bandwidth data services has caused in a marvelous quantity of research action in the radio communications community. To get highly reliable transmission, specific consideration has been remunerated to the design of receivers [20], [21]. In system design, one mostly identifies channel information limits at the receiver. These parameters are typically achieved by transmitting a training order, means reducing a segment of the transmission rate. In contrast, in applied system because of fastest variations of channel, minimum resources, training and channel chasing are not feasible. One likely solution is to inversely encode the passing data and to emit the requirement for channel information. One another solution use to compromise the existing belongings of the passing data to learn the channel and one can compromise the passing data relates to a finite alphabet.

The detection of a signal transmitted through a communication channel having memory and additive Gaussian noise has been widely studied for different channel models. Equalization techniques have been used in communication systems to combat the inter-symbol interference (ISI) induced by distributive channels. When the transmitted data sequences can be equip, maximum-likelihood sequence estimation (MLSE) minimizes sequence-error probability and can, hence, be considered as an optimal equalization method. MLSE, implemented using the Viterbi algorithm for known finite channel-impulse response (CIR), is well known [9]. The MLSE algorithm has also been studied for a mobile communication channel that disperses the transmitted signal in both time and frequency domains and whose impulse response is considered as a Gaussian random process [22], [23].

Due to unknown CIR or unknown statistical parameters of the CIR, combined data recognition and channel approximation methods were proposed by combining Viterbi algorithm for data detection with adaptive methods, such as least mean square (MLS), recursive least squares (RLS), and Kalman filtering for estimating the CIR [24], [25] and [26]. However, the inherent decision delay in such procedures causes poor channel tracking in a time-variant environment. The idea of per-survivor processing (PSP) was proposed to combat the decision delay problem, where each survivor path of the trellis diagram in the MLSE structure has its own CIR estimation [27], [28]. Although PSP is a practical way to achieve better performance in a time-variant channel, the nature and degree of optimum of such PSP-based channel estimation procedures, the influence of such estimates on the optimal of the MLSE criterion, and the coupling between estimation, detection, and channel models are not clear.

In following section, we will briefly review the maximum-likelihood sequence estimation (MLSE) for inter-symbol interference (ISI) stations. The model shown in Fig. 3 is communication model that explains a compound sign denoted as M alphabet, which is produced by a source every character retro. The communicating filter, the station, the noise blanching filter (Whitened Matched Filter, WMF) and receiving corresponds are mentioned due to the response of their receiving corresponded [l2].

The process of noise is white, zero-mean, Gaussian and self-determining of the data order, along with the autonomous actual and invented parts of alteration.

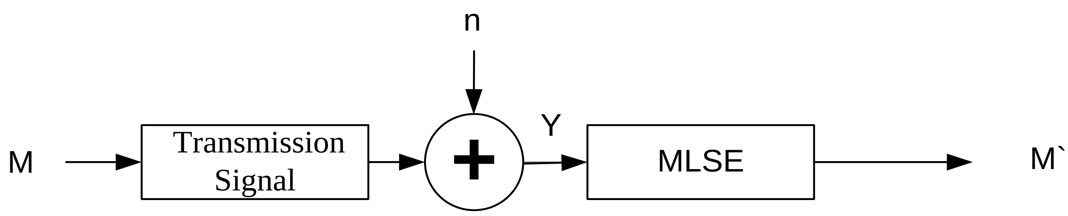

Figure 3: A simple example to system model

The rank of the station (network) is presented very well as the column vector

$$S_t = (m_{t-1}, m_{t-2}, \ldots., m_{t-L})^T \tag{2.1}$$

At the t-th step , the branch metrics are evaluated

$$\lambda_{t+1}(S_t, S_{t+1}) = |y_t - x_t(S_t, S_{t+1})|^2 \tag{2.2}$$

In which,

$$x_t(S_t, S_{t+1}) = \sum_{i=0}^{L} h_i \cdot m_{t-i} \tag{2.3}$$

The signal here known as the noiseless signal components that is linked up with the ranked changes $S_t \rightarrow S_{t+1}$. Then, the metrics $\Gamma_{t+1}(S_{t+1})$ are minimized for all the M^L states according to

$$\Gamma_{t+1}(S_{t+1}) = \min_{S_t}[\Gamma_t(S_t) + \lambda_{t+1}(S_t, S_{t+1})] \tag{2.4}$$

At last, the survivor arranged vectors $P_t(S_t)$ are widen on the conversion that comply Eq. (2.4) according to

$$P_{t+1}(S_{t+1}) = [P_t \mid m_t(S_t, S_{t+1})] \tag{2.5}$$

in which, $m_t(S_t, S_{t+1})$ is the t-th data sign linked up with the measured conversion. The maximum-likelihood sequence estimation (MLSE) algorithm is numerically explained in Example.1, which shows four random data modulated by BPSK that sent over channel which has three nonzero samples.

Example -1

In this example, the data d=(1 1 0 1) is generated randomly and adopted by using BPSK modulation technique to be =(1 1 -1 1). After modulation, by employing 3-tap ISI channel which has three nonzero samples = 0.407, = 0.815 and = 0.407 and applying the following formula, transmission signal can be computed as:

$$x_t \ (S_t \ , S_{t+1}) = \sum_{i=0}^{L} h_i \ . m_{t-i} \quad (2.6)$$

Assume initial state is (-1 -1). Then, the next state will depend on the input sequence by shifting the initial state. Furthermore, this state will be initial state for the next state.

The effect of the input bit which will decide the next state, if the input bit is -1, the next state will be -1-1, if the input bit is 1, that's mean the next state will be 1-1.

Where $m_{t-i}= (1 \ -1 \ -1)^T$ represents a vector which consists of the current state $(-1 \ -1)$ with the current input bit = 1 and h_i is a channel coefficient represented by the vector (h_0, h_1,…., h_{L-1}), since the value of (L=2). Applying Eq. (2.6) as follows

$$x_1 = [0.407 \quad 0.815 \quad 0.407] \begin{bmatrix} 1 \\ -1 \\ -1 \end{bmatrix}$$

Hence $x_1 = -0.815$

In similar way, we can find $x_2 = 0.815$, $x_3 = 0.815$ and $x_4 = -0.001$

Finally, the transmission signal will be x_t=(x_1 x_2 x_3 x_4). The transmission signal is transmitted over Additive White Gaussian Noise channel (AWGN) with mean μ=0 and SNR=20.

The receiver signals are calculated by

$$Y_t = x_t + n \quad (2.7)$$

Now, branch metric can be computed for each branch according to

$$\lambda_{t+1}(S_t , S_{t+1}) = \left| y_t - x_t \ (S_t , S_{t+1}) \right|^2 \tag{2.8}$$

Then, calculating (state metric) Γ_t for each branch according to the following equation

Let $\Gamma_0 = 0$ in initial

$$\Gamma_{t+1}(S_{t+1}) = \min_{S_t}[\Gamma_t(S_t) + \lambda_{t+1}(S_t , S_{t+1})] \tag{2.9}$$

To compute the value of next state metric (Γ_{t+1}), the minimum arrived branch metric which summed with the previous state metric (Γ_{t+1}) is chosen as in Eq. (2.9). This operation is continued until the last bit of the sequence (m_t). Eventually, we have four state metric values and choose the minimum state metric value to detect the survivor path. Thereafter, tracing back is done until the initial state to estimate the sequence. As shown in the following Figure.

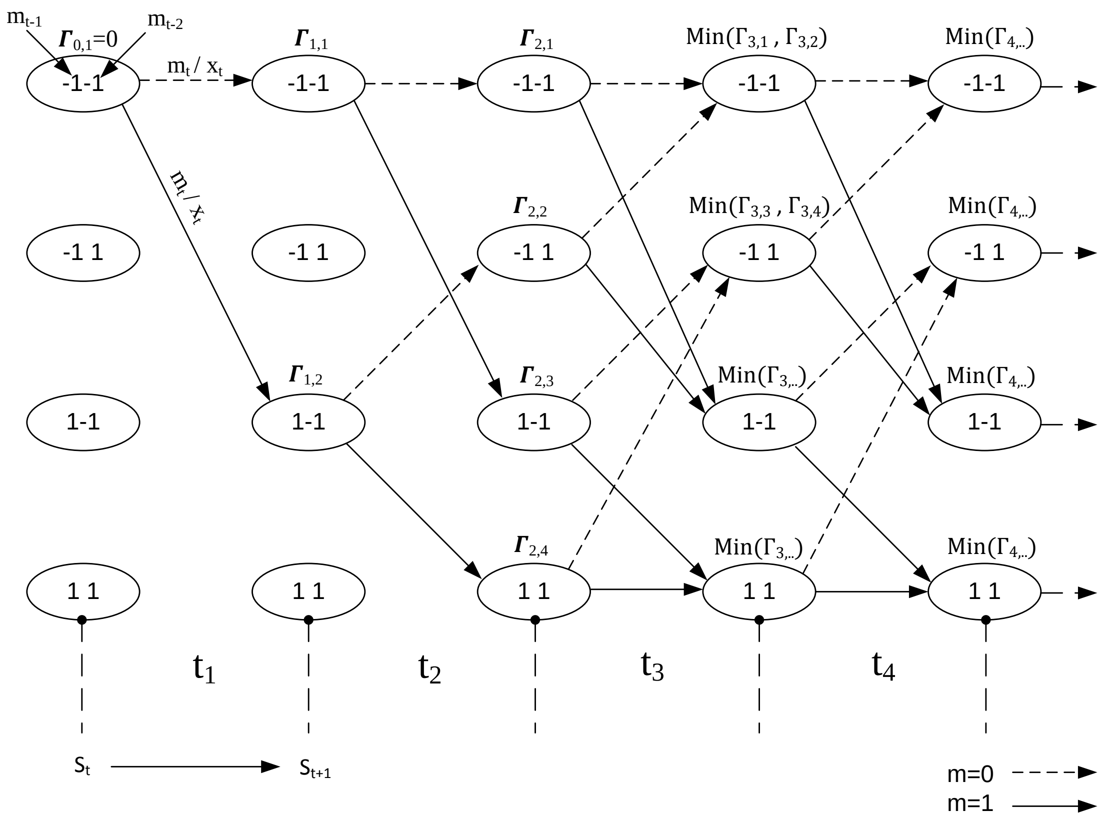

Figure 4: Viterbi MLSE

2.2. The Per-Survivor Processing (PSP)

PSP was started as an approach that delivers Maximum Likelihood Sequence Estimation in an environment where some of the signal constraints are unidentified. The idea behind approach is that diverse approximations of the unidentified parameters are linked with each state in the trellis. The estimations are efficient from one knot in the trellis to the next by using the data related with the trellis edge in data aided parameter approximation. At each knot, only the approximation linked with the winning trail to that knot and the estimate connected with the state from which the winning trail came are used to grow the new estimation to be linked with the state. This harvests a per survivor approximation of the unidentified parameters. Detail explanation of PSP can be found in [27].

PSP is a channel estimation technique which is based on the surviving paths in the VA. In a PSP approach different channel responses are estimated along the surviving trails that are connected with every state in the trellis of the VA simultaneously. Each surviving path maintains and updates its own channel estimate based on the corresponding hypothesized transmitted data sequence [29], and that gain is only used for that surviving path to calculate branch metrics. The existence of individual gains for surviving paths means that each gain estimated is confined within the surviving path, along with its error. Thus unlike conventional MLSE, if one of the gain for a particular surviving path is corrupted with noise or distortion, then the rest of the surviving paths may not be affected, and as decision making is based on the best surviving path, this error would not propagate through the decoding sequence. moreover, as the gain is estimated based on the previous surviving paths, in general, the more reliable the surviving path is the more reliable the channel estimation associated with it is. This therefore increases the reliability in a self-propagating manner (i.e. the better the surviving path, the better the gain, which in turn leads to a more accurate surviving path). Finally, as the gain for each surviving path is calculated based on previous survivors right at the start of the algorithm.

Without feedback from the tentative decision, the delay between receiving and decoding a symbol is significantly reduced. Hence PSP is suitable for fast time varying channels with a great reduction in the effects of error propagation.

Here, we will assume branch metric $\lambda_{t+1}(S_t, S_{t+1})$ is unknown, in the state conversion. The following state might happen during existence of unidentified stations (networks) constraints or while operational with an abridged difficulty lattice. Specifically Eq. (2.2) the experiential signals y_t, or the signals component clear with noise $x_t(S_t, S_{t+1})$, or both of them can work as unknown measures. For example, if the network impulse reply is unknown, the both quantities will be unknown. However, in reality, both the discrete-time equivalent channel and WMF feedback is unidentified. In this scene, of RSSE, except the empirical signal other some doubted affect the silent signal modules because of the existence of remaining ISI are unknown.

With these doubts, it can be assumed that several unidentified amounts may be assessed by utilizing data-aided estimate methods. If data-aided approximations of these amounts are accessible, it can be uses to examine the MLSE methodology Eq. (2.2) and Eq. (5.5). A traditional way for this MLSE estimation is depended on the utilization of initial results for data addition approximation of an unidentified measure, in decision-directed manner.

The above method can be utilized in various acquired knowledge of MLSE (for example, see [l2], [16], and [18]). This approach can also be utilized in early efforts to decrease the various decoding processes by DFE instruments [30]. The disadvantage of this method is the decoding process and its faults in assessment order where various unidentified measure error circulation occur. Moreover, the character of the decrypting order utilized for data-aided measurement relies on large decoding interruption that boost the excellence of the decoding order process but in various steps that results in an undesirable delay in the approximation process [18]. An alternative to the above classical approach is represented by some certain measurement of the unknown values. In following methodology, the order used for data addition estimation of metric branch that corresponds to a specific situation conversion is the classification linked up with the certain path dismissing in the early step. Measurement of MLSE algorithms rely on certain processing in a formal obtained by replacing Eq. (2.2) with

$$\lambda_{t+1}\,(S_t\,,S_{t+1}) = \left|\, \acute{y}_t - \dot{x}_t\;(S_t\,,S_{t+1})\,\right|^2 \tag{2.10}$$

The measurements in above scenario are occupied upon the survivor order dismissing in earlier process. The approach then continues as in Eq. (2.4) and Eq. (2.5). The factor that motivated to follow the approach is to decrease the no of errors that are propagate according to above mentioned traditional approach of decoding process with minimal delay. The driven outcome that shows the basic DDFSE and RSSE can be summarized according to above approach of MLSE in undefined surroundings.

2.3. Applications of Per Survivor Processing

The main concern when designing a PSP-based MLSE receiver is the design of the channel estimation algorithm. The channel estimation is derived from the previous entries of the surviving path. Applications of Per-Survivor Processing (PSP) to adaptive Maximum Likelihood Sequence Estimation (MLSE) and Reduced State Sequence Estimation (RSSE) are investigated in time-varying frequency-selective Rayleigh fading channels, which are typical of digital mobile communication systems. It is shown that the PSP characteristic of providing the channel estimators to the individual survivors with zero-delay, high-quality data-aiding sequences proves essential in a rapidly time-varying environment [31]. In the PSP the least mean square (LMS), recursive least squares (RLS) and Kalman filter [10] algorithms can be used to estimate the channel parameters.

Adaptive algorithms are used to adjust the coefficient of the digital filter, as the error signal Eq. (2.12) is minimized according to some criterion, e.g. the least squares sense. Common algorithms that have found widespread application is the recursive least square (RLS) and the least mean square (LMS)[33]. They gradually reduce the mean square error between the input signal and other reference signal. The main features that approve the use of the LMS algorithm is its low computational complexity, proof of convergence in stationary environment, unbiased convergence in the mean to the Wiener solution, and stable behavior when implemented with finite_ precision arithmetic [32].

2.3.1. Least Mean Square (LMS)

Although the well-known adaptive least mean squares (LMS) algorithm suggests a practical way of estimating unknown channels in any communication system, the associated performance over time-varying channels are known to be far behind that of the optimal Wiener filter especially as the speed of time-variations increases. The main reason behind this degradation is the large eigenvalue spread of the input correlation matrix for fast time-varying channels [33]. This motivates us to explore for a suitable adaptive algorithm as an extension of the conventional LMS algorithm which will be robust to adverse effects of fast fading channel such as the large eigenvalue disparity and hopefully achieve a significantly improved performance yet at a still practical level of complexity as compared to the original algorithm as well as to the optimal Wiener filter.
In the literature, there are several works on the forward-backward signal processing techniques applied to communication problems with a promise of improved overall performance. In [34], a forward-backward LMS (FBLMS) adaptive line enhancer is proposed for stationary systems which make use of the forward and the backward prediction errors jointly to update the weight-vector which eventually achieves a lower level adjustment. This algorithm is further elaborated in [35] which demonstrate the same performance with a less computational burden. In [36], a different approach is preferred in which the adaptations are performed in the forward and the backward directions independently along each of the paths present in the trellis using a per-survivor processing (PSP) based approach [19], [28]. These estimates are then combined using some optimal binding strategies for which the final performance improvement is significant, but unfortunately with an excessively large overall processing complexity.

Adaptive algorithms have a wide variety of application areas due to their self-learning characteristics, computational efficiency and convergence to the optimal non-adaptive solutions. In digital communications, the LMS algorithm is one of the well-known adaptive algorithms that commonly used in numerous applications including equalization and channel estimation.

In this section, only LMS is investigated due to its implementation simplicity. The accuracy and the convergence properties of LMS determine the overall performance of the PSP algorithm. In the time-varying channel, the convergence rate of LMS is governed by the step-size parameter, which determines the tracking ability and convergence rate of the LMS. The conventional PSP was based on fixed step-size LMS. But in a time-varying multi-path and Doppler shift environment, there is no fixed optimized step-size parameter that can estimate the channel well all the time, because the receiver has no knowledge of the terminal speed and other fast changing channel parameter. Without the ability of optimizing the step-size factor, the performance of the PSP will have a significant degradation in dynamic channel conditions. Because of this drawback, the conventional PSP algorithm with fixed step size is impractical. Its performance with optimal step size becomes the high bound for the practical PSP algorithm without optimized step size. The degradation happened due to this inadequate size. To tackle this problem, an adaptive PSP that can speed up the convergence rate and improve the performance of the PSP in time-varying wireless channels without optimizing the step size. This variable step-size approach is applied to each survivor path individually eliminating any dependence between all survivor paths in the original PSP approach. In [37], variable step-size LMS (VS-LMS) algorithms were analyzed and tested in the steady environment which showed its promise of overcoming the slow convergence rate. However, the performance of the VS-LMS algorithms on time-varying channels has not been studied. The proposed adaptive PSP will show that VS-LMS algorithms can also improve the system performance in dynamic environments, due to the high accuracy of the data-aided channel estimation in PSP. The VS-LMS algorithms suffer from another drawback, i.e., the performance is very sensitive to the selection of a parameter representing the step-size updating factor. An optimal has to be determined before applying VS-LMS. Basically, the algorithm transfers the performance dependency on step size into the dependency on step-size updating factor. Letter in this study, we propose a new step-size updating scheme which is independent of any parameters. This new channel estimator can approach the optimum performance of the PSP with optimal step size in highly dynamic channels without any knowledge of the speed and channel conditions. The channel impulse response is expressed by

$$h_t = (h_0, h_1, \ldots., h_{L-1}) \tag{2.11}$$

At the t-th step, for all possible transitions $S_t \rightarrow S_{t+1}$, the following errors are calculated

$$e_t\ (S_t\ , S_{t+1}) = y_t - h_t\ (S_t\ )^{\mathrm{T}}\ S_t \tag{2.12}$$

Here, the vector relies on time now and state dependent. One phase of the Viterbi approach is then achieved and state metrics are computed using

$$\Gamma_{t+1}\ (S_{t+1}) = \min_{S_t}[\ \Gamma_t\ (S_t)\ +\ |\ e_t\ \ (S_t\ , S_{t+1})\ |^2\ ] \tag{2.13}$$

The channel estimates h_t (S_t) are then updated according to the stochastic gradient algorithm

$$h_{t+1}\ (S_{t+1}) = h_t\ (S_t) + ß\ e_t\ (S_t\ , S_{t+1})\ \ S_t \tag{2.14}$$

over those transitions $S_t \rightarrow S_{t+1}$ that satisfy Eq. (2.13). For cooperation between speed of merging and constancy constant ß is chosen. Here it is to be noticed that the linked up with certain path there are a station vector, a metric and a survivor arrangement.

Example - 2

The Least Mean Square (LMS) is approach for channel estimation with per-survivor processing illustrated in this example. At the transmission side, the procedure is identical to the one in example 1. At the receiver side, for all possible transitions $S_t \rightarrow S_{t+1}$, the following errors are calculated for t-th step

$$e_t\ (S_t\ , S_{t+1}) = y_t - h_t\ (S_t\ )^{\mathrm{T}}\ S_t \tag{2.15}$$

The next state metric is calculated by using the value of the computed error in Eq. (2.15) and the value of previous state metric with imposition that the initial value of $\Gamma_0 = 0$ as shown below

$$\Gamma_{t+1}\ (S_{t+1}) = \min_{S_t}[\ \Gamma_t\ (S_t)\ +\ \left|\ e_t\ \ (\ S_t\ ,\ S_{t+1})\ \right|^{2}\ ] \qquad (2.16)$$

The channel estimations (h_t) are then updated according to the following equation

$$h_{t+1}\ (S_{t+1}) = h_t\ (S_t) + ß\ e_t\ (\ S_t\ ,S_{t+1})\ \ S_t \qquad (2.17)$$

The computation of the state metrics is illustrated in the following Figure.

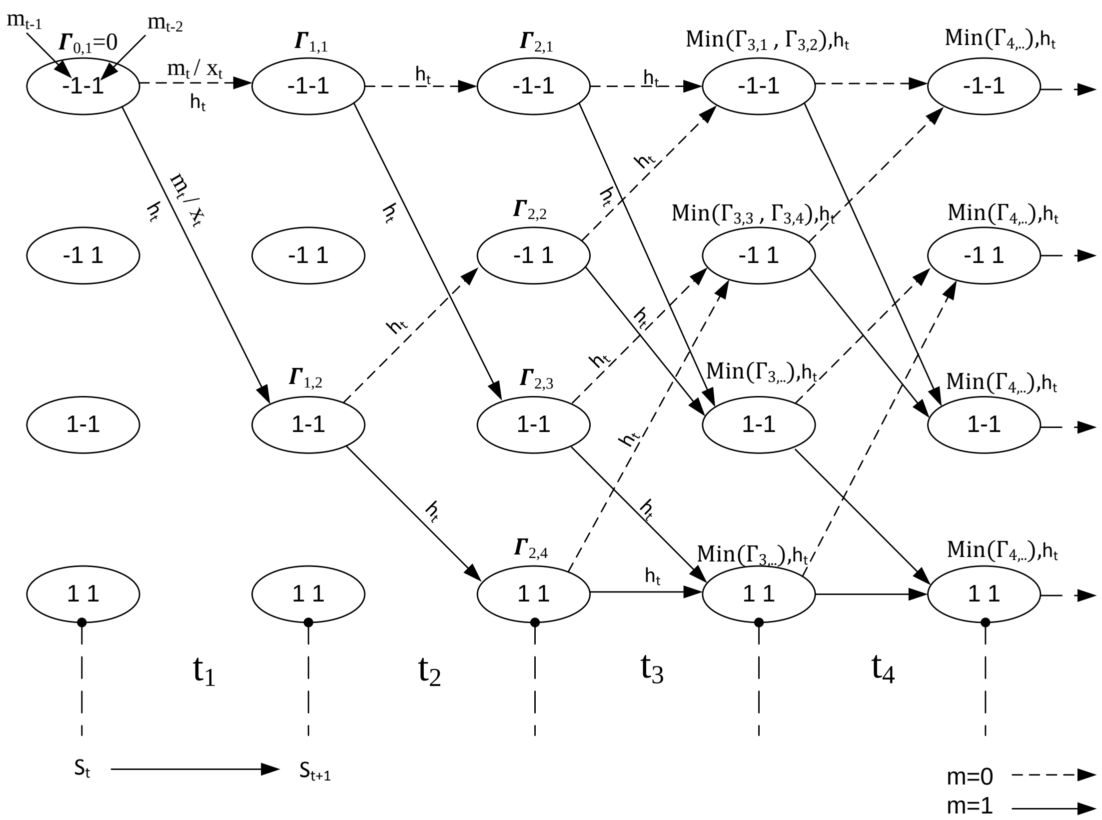

Figure 5: Viterbi MLS

2.3.2. Recursive Least Mean Square (RLMS)

The Recursive least squares (RLS) adaptive filter is an algorithm which recursively finds the filter coefficients that minimize a weighted linear least squares cost function relating to the input signals. This is in contrast to other algorithms such as the least mean squares (LMS) that aim to reduce the mean square error. In the derivation of the RLS, the input signals are considered deterministic, while for the LMS and similar algorithm they are considered stochastic. Compared to most of its competitors, the RLS exhibits extremely fast convergence. However, this benefit comes at the cost of high computational complexity [12]. The RLS algorithm can be used with an adaptive transversal filter to provide faster convergence [38] & smaller steady state error. The RLS algorithm uses the information contained in all the previous input data to estimate the inverse of the auto-correlation matrix of the input vector. It uses this estimate to properly adjust the tap weights of the filter.

RLS adaptive filters propagate (from one iteration to the next) inverse of the least-squares auto-correlation matrix. However the inverse matrix always updates difference between two matrices, this approach comprehensively known as recursive least-squares (RLS) adaptive filters. The one significant distinction between stochastic gradient adaptive filters and RLS adaptive is that the RLS adaptive filters provide perfect solution of optimized problems at each modification step. The certain order with the major metric corresponds to the desired joint assess of station and arrangement. However, the approach is found by letting

$$x_t\ (S_t\ , S_{t+1}) = h_t\ \ (S_t\ )^T\ \ S_t \tag{2.18}$$

Thus, it is indicated that an assessment of the station impulse response at the t-th step, is shown by a discrete-time complication sum as a scalar product of a time-dependent state-dependent channel vector.

$$h_t\ = (h_0, h_1, \ldots., h_{L-1}) \tag{2.19}$$

a converted data vector

$$\acute{S}_t = \ (m_t\ , m_{t-1}\ , \ldots.\ , m_{t-L}\ )^T \tag{2.20}$$

The maximization of the likelihood function with respect to the channel vector for a given survivor sequence (i.e., the inner maximization). it may be performed by a Recursive Least Square (RLS) algorithm [l2] is given as

$$\max_{\{\mathrm{m_n}\}_{\mathbf{n=0}}^{\boldsymbol{t}}} \quad \max_{\{\mathrm{h_n}\}_{\boldsymbol{n=0}}^{\boldsymbol{L}}} \int (\{y_n\}^{\mathrm{t}}{}_{n=0}\ \big|\ \ \{m_n\}^{t}{}_{n=0}\ , \{h_n\}^{L}{}_{n=0}\ ) \tag{2.21}$$

At the t-th step, $h_{t+1}\ (S_{t+1})$ is estimated by recursively minimizing

$$\xi_{t+1}\ (S_{t+1}) = \sum_{n=0}^{t}\ \omega^{\mathrm{t-n}}\ \big|\ y_n -\ \ - \sum_{i=0}^{L} h_{t+1,i}\ (S_{t+1})\ \ .\ \mathrm{m_{n\text{-}i}}\ \big|^{2} \tag{2.22}$$

in which, the sequence $\{\mathrm{m_n}\}^{\mathrm{t}}{}_{\mathrm{n=0}}$ is associated to the survivor p_{t+1} (S_{t+1}). The weighting factor $0 < \omega < 1$ is introduced to limit the memory of the algorithm to allow for slowly time varying channels. The resulting algorithm is the following. At the t-th step, for all possible transitions $S_t \rightarrow S_{t+1}$ the following error is calculated

$$e_t\ (S_t\ , S_{t+1}) = y_t -\ h_t\ \ (S_t\ )^{\mathrm{T}}\ \acute{\mathrm{S}}_t\ (S_t\ , S_{t+1}) \tag{2.23}$$

After that a step of the Viterbi algorithm processed that referring Eq. (2.13). For each phase and conversion step $S_t \rightarrow S_{t+1}$ that encompass the Kalman gain vectors, the reverse of the correlation matrices, the survivors and the channel impulse replies are updated accordingly.

$$K_{t+1}\ (S_{t+1}) = \frac{p_t\ (S_t)\ \ \acute{\mathrm{S}}_t\ (S_t\ ,S_{t+1})}{\omega + \acute{\mathrm{S}}_t\ (S_t\ ,S_{t+1})\mathrm{T}\ \ p_t\ (S_t)\ \ \ \ \acute{\mathrm{S}}_t\ (S_t\ ,S_{t+1})\mathrm{T}} \tag{2.24}$$

$$p_{t+1}\ (S_{t+1})\ =\ \frac{1}{\omega}\ [\ p_t\ (S_t) -\ K_{t+1}\ (S_{t+1})\ \acute{\mathrm{S}}_t\ (S_t\ ,S_{t+1})\mathrm{T}\ \ p_t\ (S_t)] \tag{2.25}$$

$$h_{t+1}\ (S_{t+1}) = h_t\ (S_t) + K_{t+1}\ (S_{t+1})\quad e_t\ (S_t\ ,S_{t+1}) \tag{2.26}$$

In the further steps the above updated channel vectors are used. Then in the further step of algorithm the above updated station vectors uses. It is been noticed that a survivor order, a station vector, a Kalman gain vector and an assessed of reverse correlation matrix is linked up.

Example - 3

This example explains Recursive Least Mean Square (RLS) algorithm. The process of transmitting signal is similar to Example 1 with a little difference at the receiver side that is computing errors for all possible transitions $\mathrm{S_t} \rightarrow \mathrm{S_{t+1}}$.

$$e_t\ (S_t\ ,S_{t+1})\ =\ y_t -\ \ h_t\ \ (S_t\ )\mathrm{T}\ \ \acute{\mathrm{S}}_t\ (S_t\ ,S_{t+1}) \tag{2.27}$$

subsequently, computing state metric Γ_{t} for each branch in accordance with the following equation.

$$\Gamma_{t+1}\ (S_{t+1})\ =\ \min_{S_t}[\Gamma_t\ (S_t)\ \ +\ \left|e_t\ \ (S_t\ ,S_{t+1})\ \right|2\ ] \tag{2.28}$$

with initial value Γ_0=0.

for each phase and conversion $\mathrm{S_t} \rightarrow \mathrm{S_{t+1}}$ that expand the survivors, the Inverse of the correlation metrics, kalman gain vectors and station impulse responses updates due to

$$K_{t+1}\,(S_{t+1}) = \frac{p_t\ (S_t)\ \ \acute{S}_t\,(S_t, S_{t+1})}{\omega + \acute{S}_t\,(S_t, S_{t+1})\mathrm{T}\ \ p_t\,(S_t)\ \ \ \acute{S}_t\,(S_t, S_{t+1})\mathrm{T}} \tag{2.29}$$

$$p_{t+1}\,(S_{t+1})\ = \frac{1}{\omega}\ [\ p_t\,(S_t) - K_{t+1}\,(S_{t+1})\,\acute{S}_t\,(S_t\,, S_{t+1})\mathrm{T}\ \ p_t\,(S_t)] \tag{2.30}$$

$$h_{t+1}\,(S_{t+1}) = h_t\,(S_t) + K_{t+1}\,(S_{t+1})\quad e_t\,(S_t\,, S_{t+1}) \tag{2.31}$$

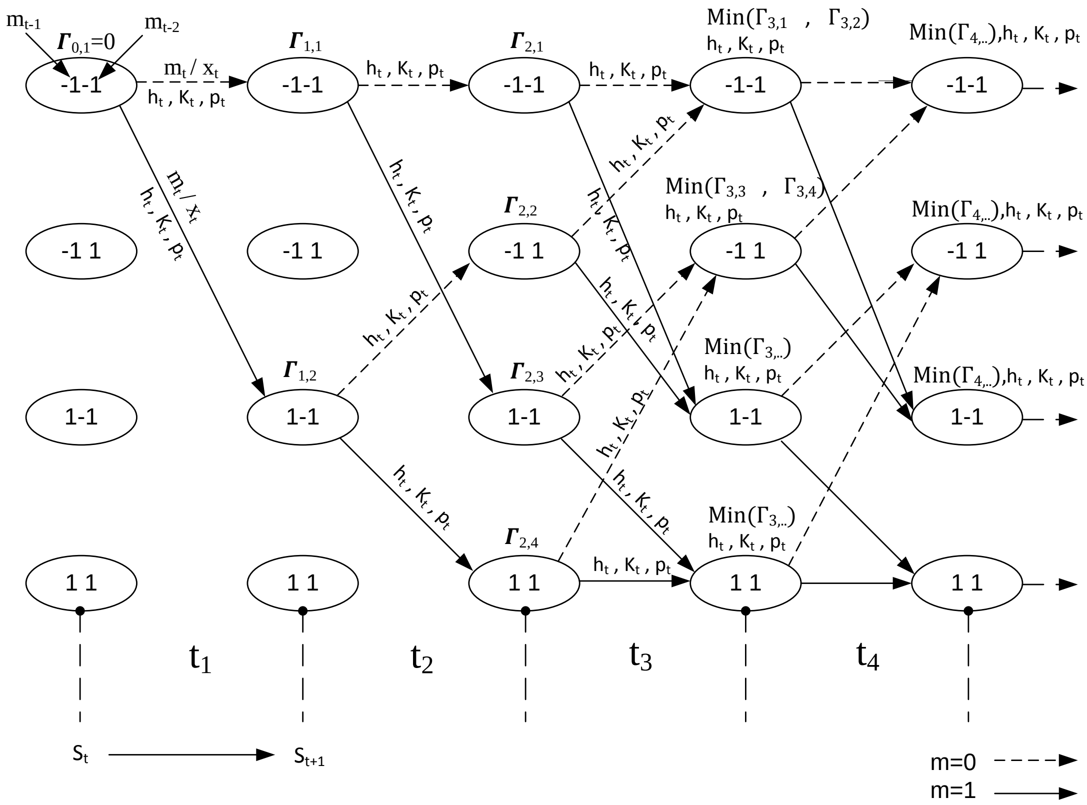

Figure 6: Viterbi RLS

After that the above updated station vectors used in the further process of algorithm. The minimum arrived branch metric which summed with the previous state metric (Γ_t) is chosen as in Eq. (2.28) To determine the value of next state metric (Γ_{t+1}). This procedure is ongoing to the last bit of the sequence. Now, four state metric values are computed, to detect the survivor path and determine the estimation channel coefficient, the minimum state metric value is selected. After that, tracing back is done until the initial state to estimate the sequence.

CHAPTER 3

COMPUTER SIMULATION RESULTS for CHANNEL ESTIMATION

3.1. The Application of The Least Mean Square (LMS)

This chapter proposes the methodology of our work. Our work is performed the channel estimation technique using per-survivor processing which means blind estimation technique. It estimates the channel impulse response (CIR) and sequence at the receiver side. The system is represented in Fig. 7 as shown below

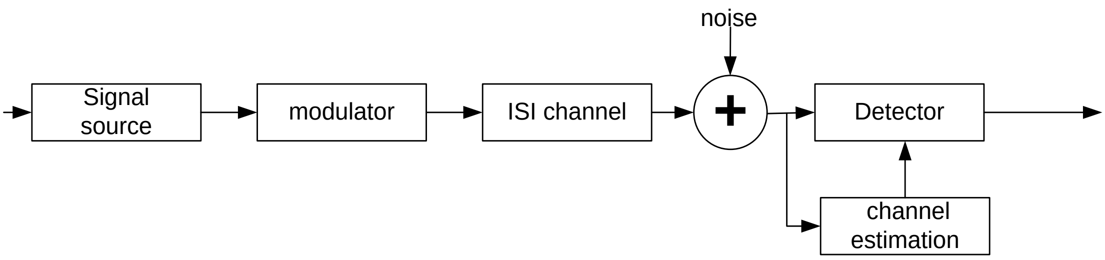

Figure 7: System model

The source generates the data randomly which is represented by

$$A = (a_0, a_1, a_2, \dots \dots \dots., a_t) \tag{3.1}$$

where $a_t \in \{1 , 0\}$.

The data is modulated to binary phase shift keying (BPSK) by M vector

$$M = (m_0, m_1, m_2, \dots \dots \dots., m_t) \tag{3.2}$$

where $m_t \in \{1 , -1\}$.

The transmitted signal is represented by

$$x_t \ (S_t \ , S_{t+1}) = \sum_{i=0}^{L} h_i \, . \acute{S}_{t-i} \tag{3.3}$$

where $\acute{S}_t = (m_{t-1}, m_{t-2}, \ldots., m_{t-L})^T$ exemplifies a vector that consists of the current state (m_{t-1}, m_{t-2}) with the current input bit $= m_t$ and h_i is a channel coefficient represented by the vector (h_0, h_1,…., h_L), since the value of (L=2). After obtaining the transmission signal, sending it over Additive White Gaussian Noise channel (AWGN) with signal to noise ratio.

$$SNR(db) = 10\ log_{10} SNR \tag{3.4}$$

where $SNR = \frac{E_b}{N_o}$ and $\sigma^2 = \frac{N_o}{2}$.

The initial state is equal to (-1 -1). To detect the next state, shifting the initial state with the input sequence bit by bit as explained in Fig. 10.

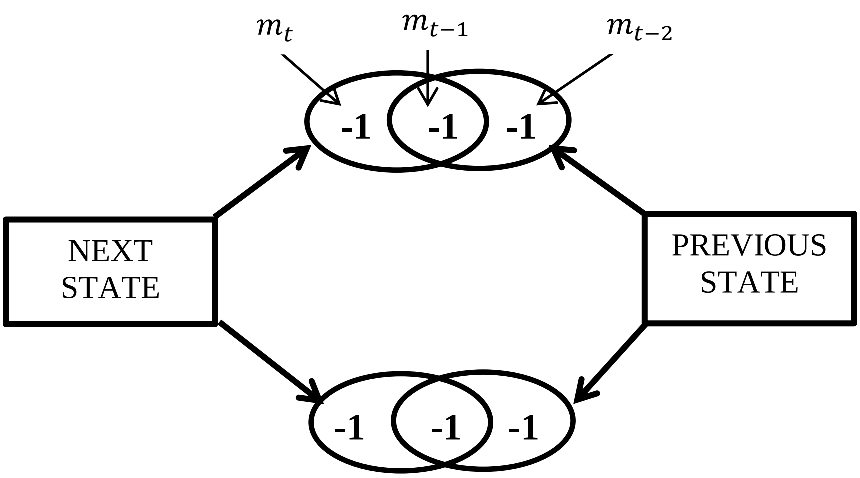

Figure 8: Shift state

The received signal Y can be expressed as follow:

$$Y_t = x_t + \text{n} \tag{3.5}$$

At the receiver side, we use LMS algorithm. At the t-th step, for all potential transitions $S_t \rightarrow S_{t+1}$, the following error is computed considering that the initial channel coefficient (h_i) equals to (0 0 0)

$$e_t\ (S_t\ , S_{t+1}) = y_t - h_t\ \ (S_t\ )^{\mathrm{T}}\ \ S_t \tag{3.6}$$

Now, the vector h is time and state dependent. Then, one step of the Viterbi algorithm is pre-formed to get.

$$\Gamma_{t+1}\,(S_{t+1}) \;=\; \min_{S_t}[\,\Gamma_t\,(S_t) \;+\; \left|e_t\;(S_t\,,S_{t+1})\right|^{2}\,] \tag{3.7}$$

The channel estimates h_t (S_t) are then updated according to stochastic gradient algorithm using.

$$h_{t+1}\,(S_{t+1}) = h_t\,(S_t) + ß\; e_t\;(\,S_t\,,S_{t+1})\;\; S_t \tag{3.8}$$

Forward LMS algorithm ($S_t \rightarrow S_{t+1}$) estimates the forward channel coefficient $\bar{h}_f$ and the sequence. This operation is done by deciding the survivor path from choosing minimum value of the state metric (Γ_t).

In backward LMS algorithm ($S_t \rightarrow S_{t+1}$) , it is similar to forward LMS algorithm with a little bit difference that starts from the last bit as initial bit and updates the backward channel coefficient $\bar{h}_b$ down to m_0. Finally, we got the values of the channel estimation from determining the survivor path.

Bidirectional LMS algorithm [40] is the average of forward $\bar{h}_f$ and backward $\bar{h}_b$ channel coefficients as in Eq. (3.9). Where we compute the channel coefficient for forward and backward algorithms.

$$\bar{h}_{av} = \frac{\bar{h}_f + \bar{h}_b}{2} \tag{3.9}$$

The error square of channel impulse response is

$$Av \;=\; (h_0 \;-\; \bar{h}_0\,)2 \;+\; (h_1 \;-\; \bar{h}_1\,)2 \;+\; (h_2 \;-\; \bar{h}_2\,)2 \tag{3.10}$$

Where h is the channel coefficient in the transmission and $\bar{h}$ is the estimated channel coefficient.

3.2. The Simulation Results

The simulation result of classical least mean square (LMS) with the calculation of forward, backward and bidirectional algorithms [39] are shown in Fig. 9.

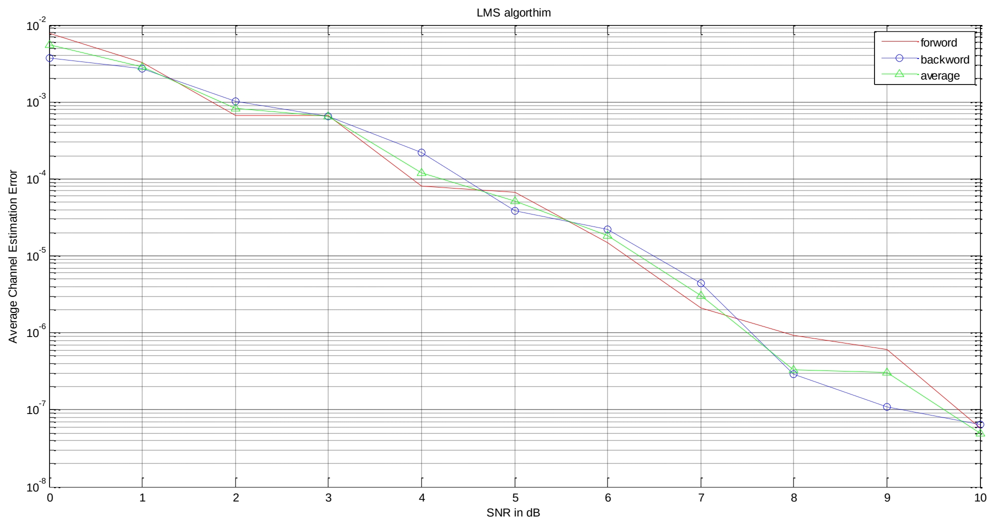

Figure 9: Forward, Backward and Bidirectional LMS

Fig. 10 shows an algorithm which is similar to classical forward (LMS) algorithm with a little bit deference that this algorithm uses iterations. In the first iteration, estimate the sequence and the channel coefficients. After that, use those channel coefficients as initial channel coefficients for the next iteration. Apply mathematical computations on estimated sequence only and estimate channel coefficients again. Repeat this operation for a sufficient number of iterations.

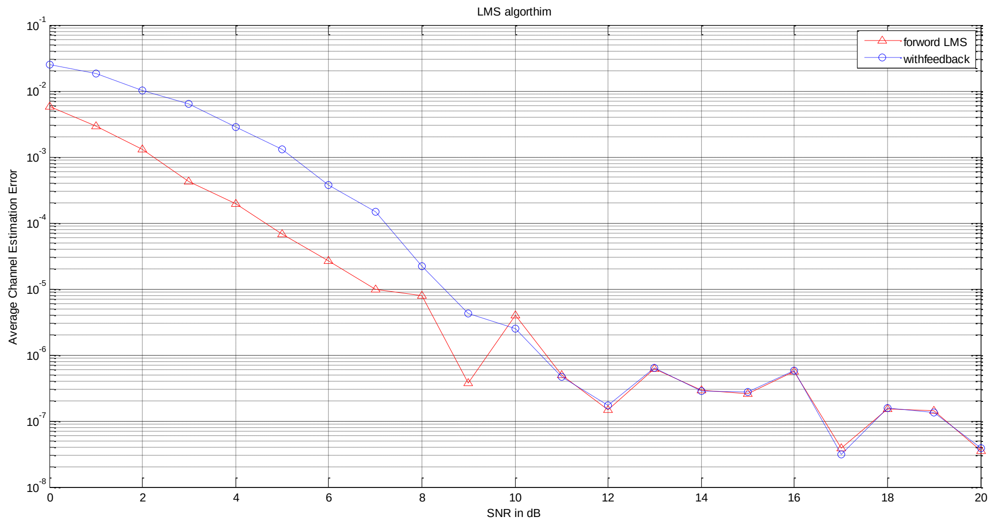

Figure 10: LMS with feedback

At another trying to improve the estimation of channel coefficients with average method of the estimated coefficient.

a) Channel coefficient = (h_{path1} + h_{path2} + h_{path3}+ h_{path4}) / 4.

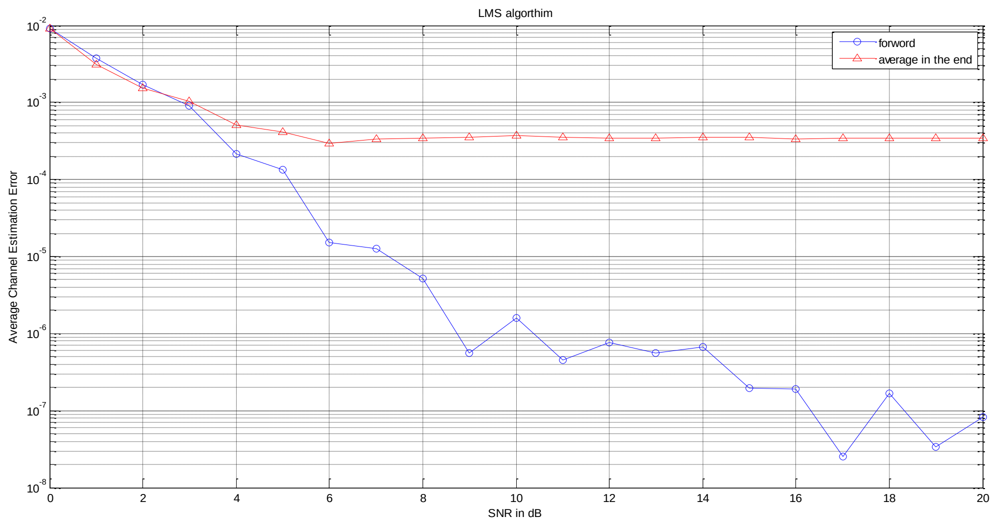

Figure 11: Average of all estimated coefficient

b) Channel coefficient = average of the best two survivor paths.

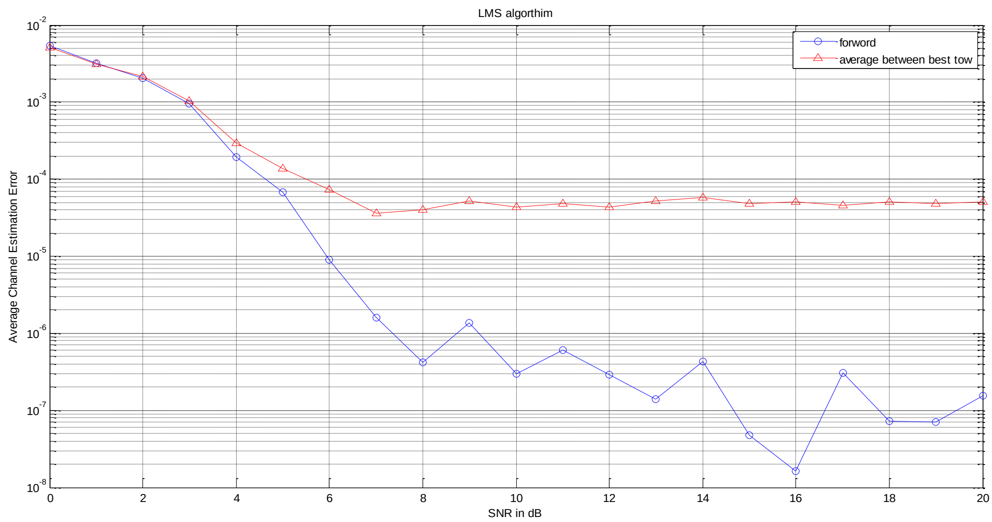

Figure 12: Average between the best two

c) Channel coefficient = 0.4 * *h* (the best channel coefficient) + 0.3 * *h* (the second best channel coefficient) + 0.2 * *h* (the third best channel coefficient) + 0.1 * *h* (the best fourth channel coefficient).

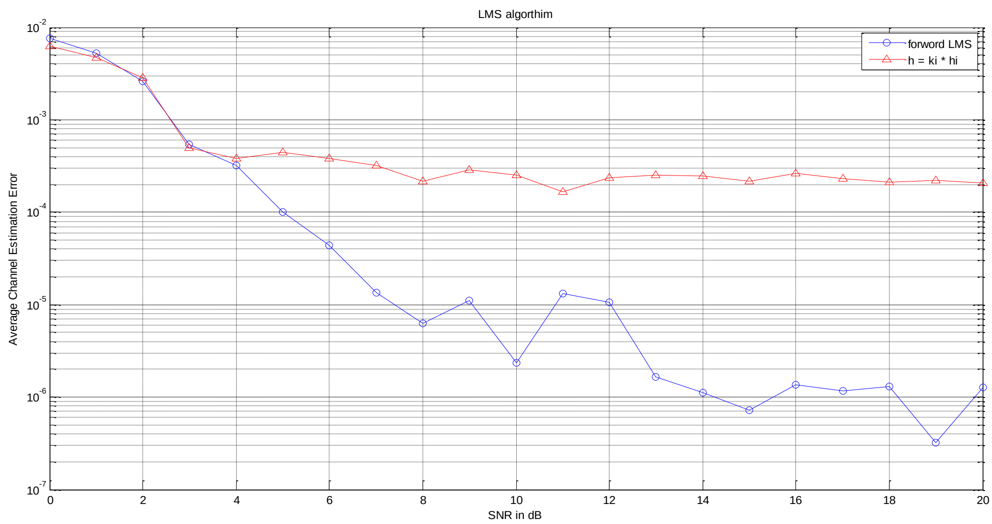

Figure 13: Channel coefficient by ratios

At other hand Channel coefficient = 0.5 * h (the best channel coefficient) + 0.3 * h (the second best channel coefficient) + 0.1 * h (the third best channel coefficient) + 0.1 * h (the best fourth channel coefficient).

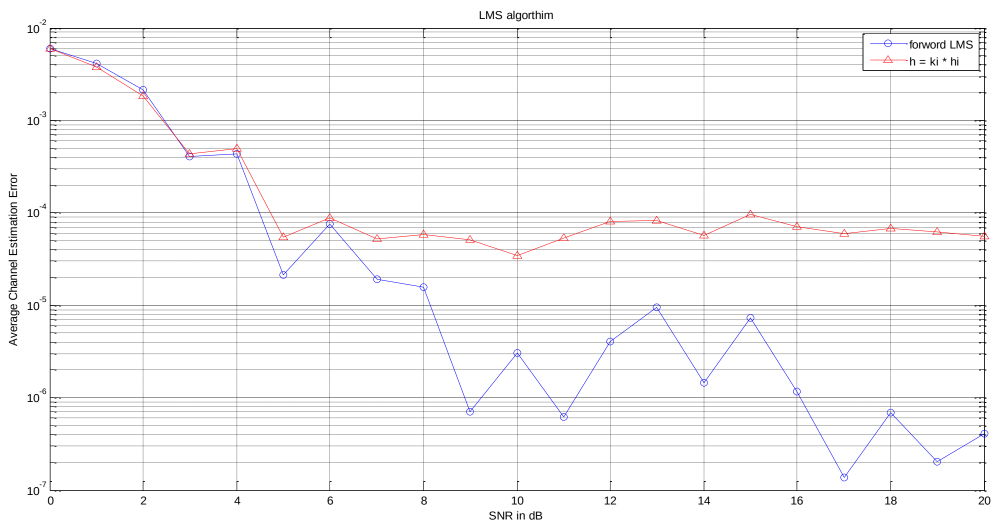

Figure 14: Channel coefficient by other ratios

As mentioned before, the survivor path is taken and the other path is neglected at each state. In this algorithm, we used the neglected path to employ it by multiply it by the Z factor and denoted the result as a correction term. This correction term is added to the updating channel estimation or subtracted from it. As we mentioned before.

3.2.1. The Addition of The Compensating Term

1) $h_{t+1}\,(S_{t+1}) = h_t\,(S_t) + ß\, e_t\,(\,S_t\,, S_{t+1})\;\; S_t$ (3.11)

After that, Channel coefficient = $h_{t+1}\,(S_{t+1}) + Z * \bar{h}_{\,t+1}\,(S_{t+1})$

a) Z = 0.001

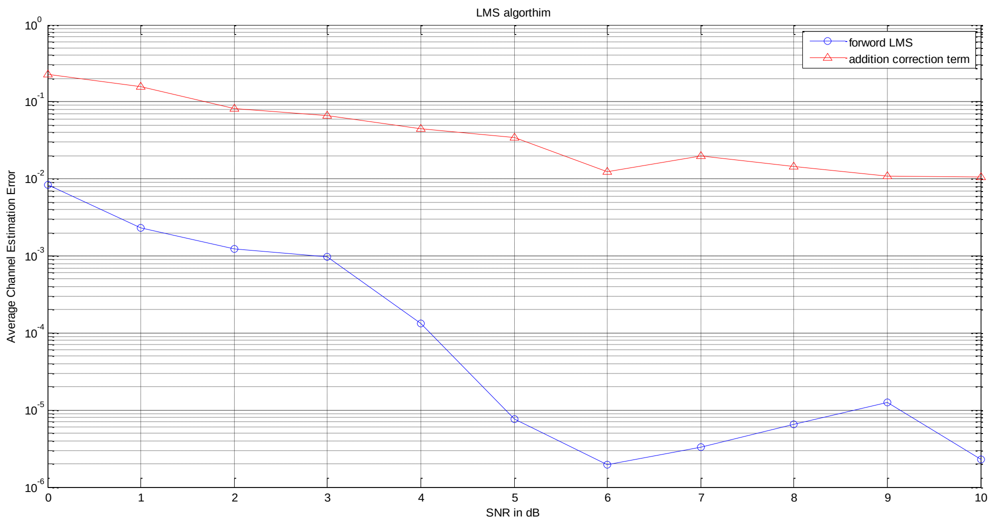

Figure 15: Simulation results with addition of correction term (Z=0.001)

b) Z = 0.0001

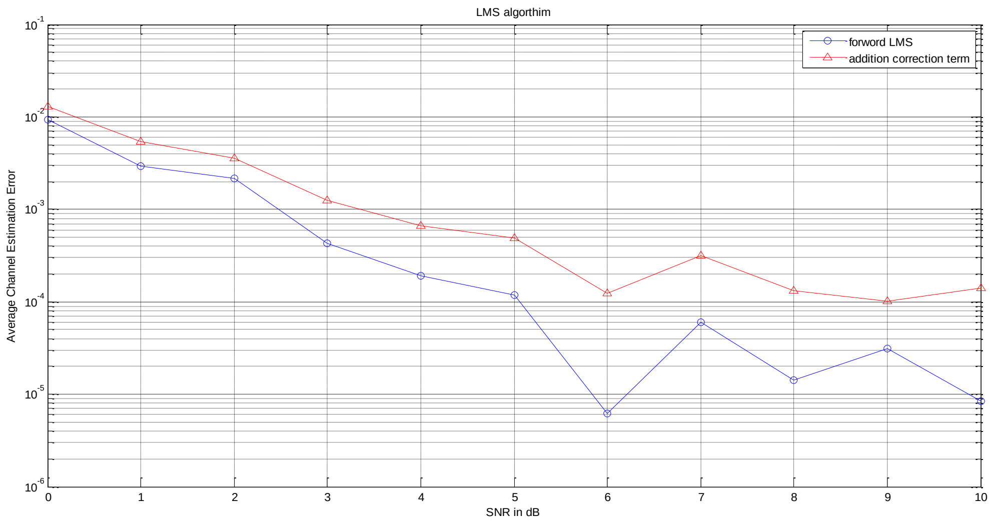

Figure 16: Simulation results with addition of correction term (Z=0.0001)

c) Z = 0.00001

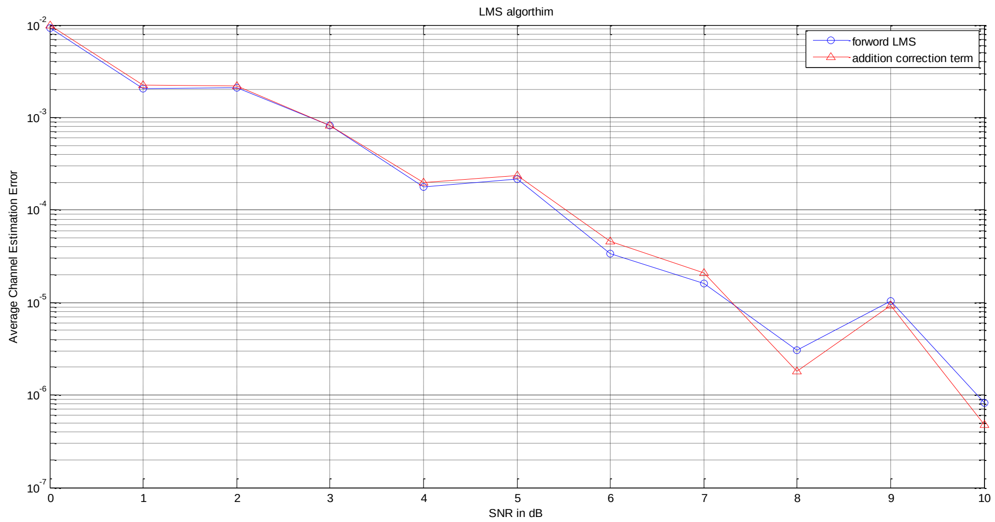

Figure 17: Simulation results with addition of correction term (Z=0.00001)

d) Z = $\sigma^3 * 0.01$

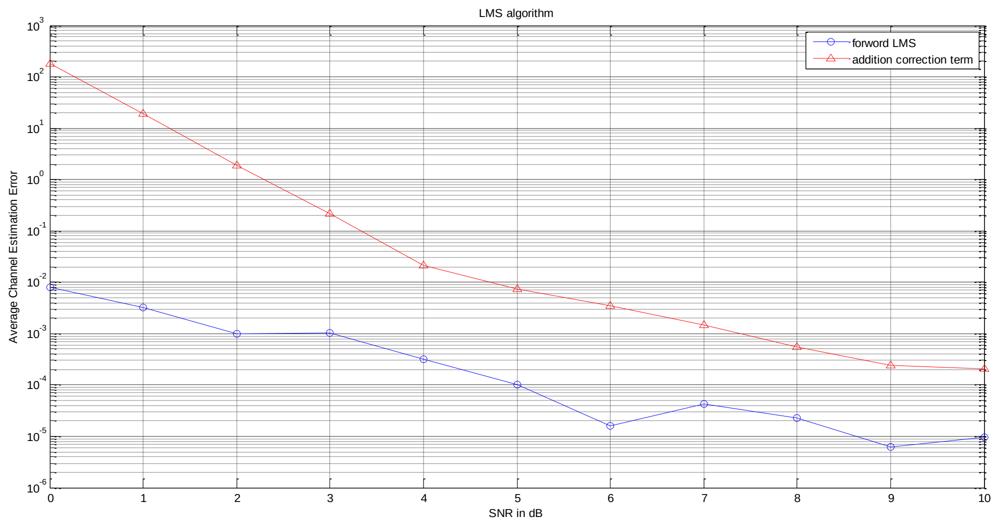

Figure 18: Simulation results with addition of correction term (Z = $\sigma^3 *$ 0.01)

e) Z = $\sigma^4 * 0.01$

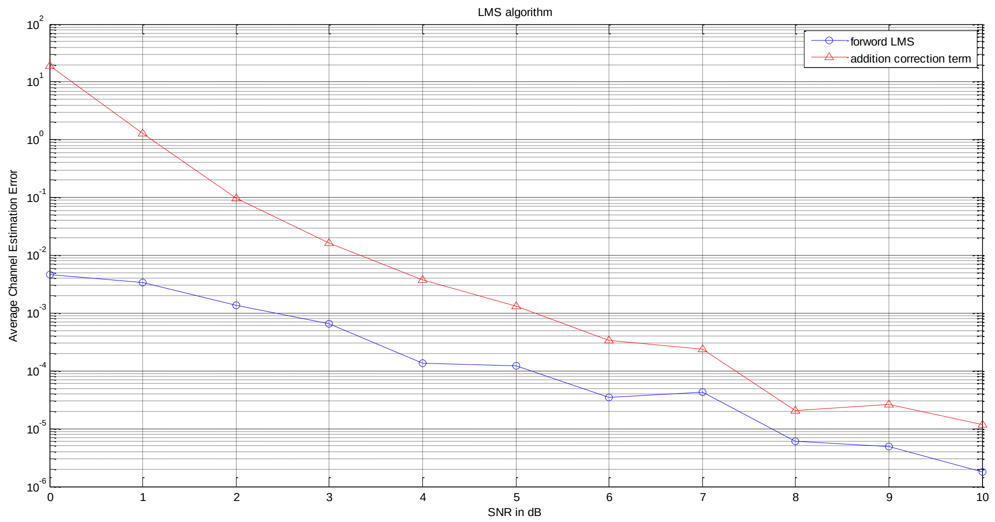

Figure 19: Simulation results with addition of correction term (Z = $\sigma^4 *$ 0.01)

2) $h_{t+1}\ (S_{t+1}) = h_t\ (S_t) +$ ß $e_t\ (\ S_t\ , S_{t+1})\ \ S_t$ (3.12)

After that, Channel coefficient = (1-Z) * $h_{t+1}\ (S_{t+1})$ + Z * $\bar{h}_{\ t+1}\ (S_{t+1})$

a) Z = 0.01

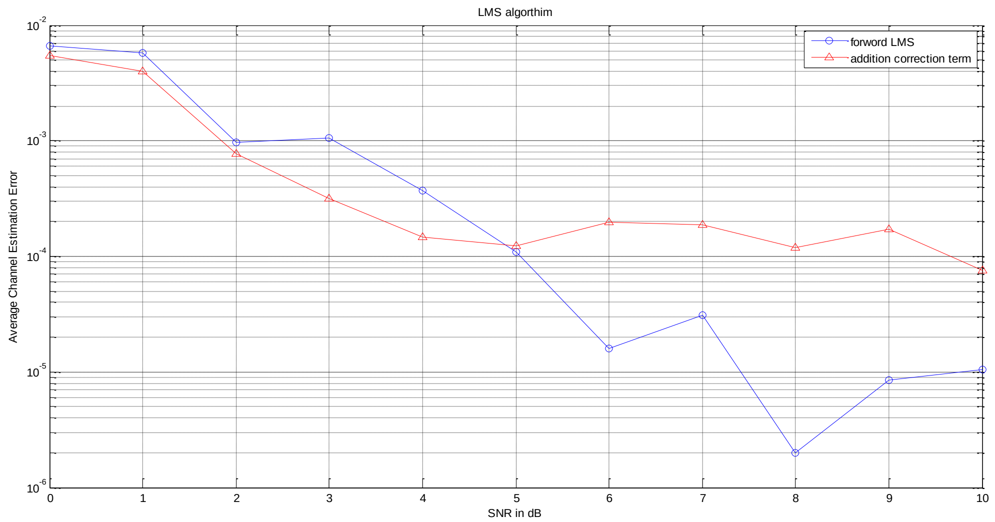

Figure 20: Simulation results with addition of correction term (Z = 0.01) on both sides

b) Z = 0.001

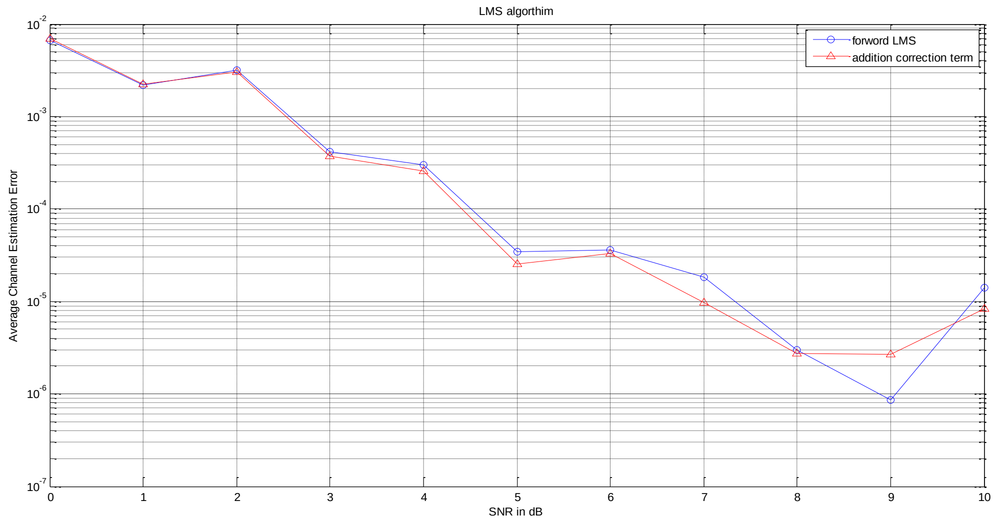

Figure 21: Simulation results with addition of correction term (Z = 0.001) on both sides

c) Z = 0.0001

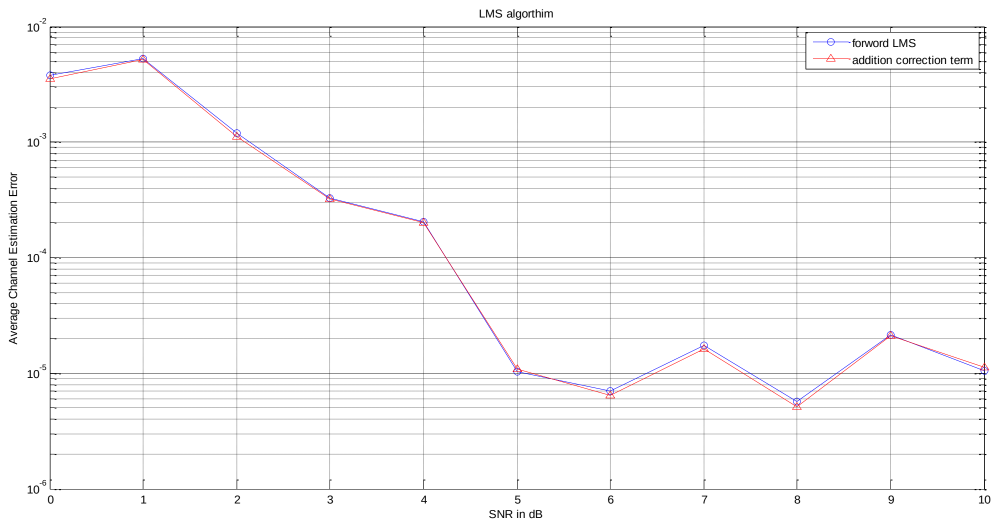

Figure 22: Simulation results with addition of correction term (Z = 0.0001) on both sides

d) $Z = \sigma * 0.01$

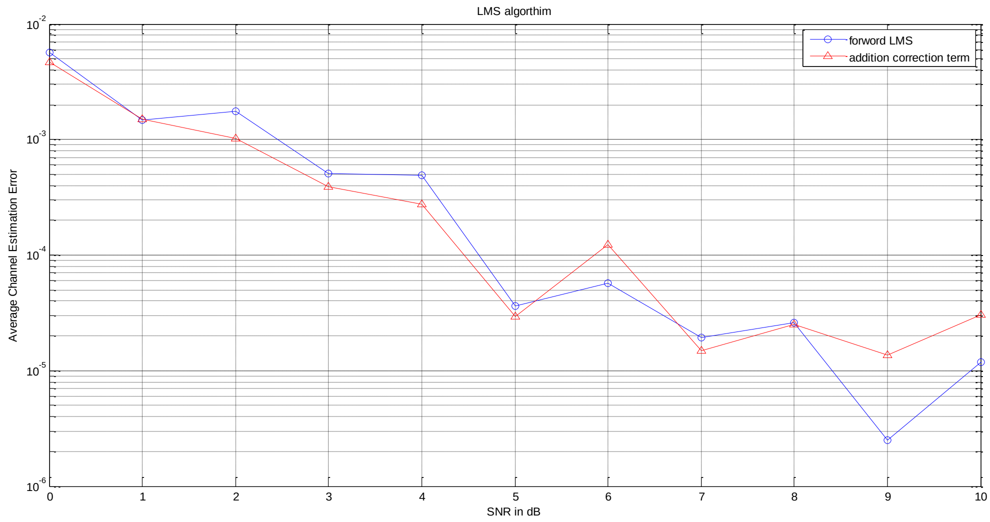

Figure 23: Simulation results with addition of correction term ($Z = \sigma * 0.01$) on both sides

e) $Z = \sigma^2 * 0.01$

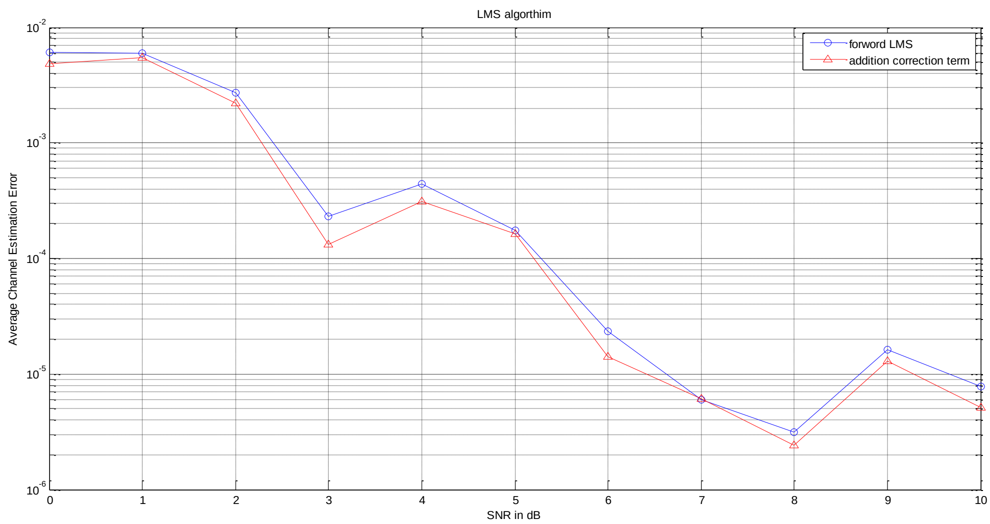

Figure 24: Simulation results with addition of correction term ($Z = \sigma^2 * 0.01$) on both sides

f) $Z = \sigma^3 * 0.01$

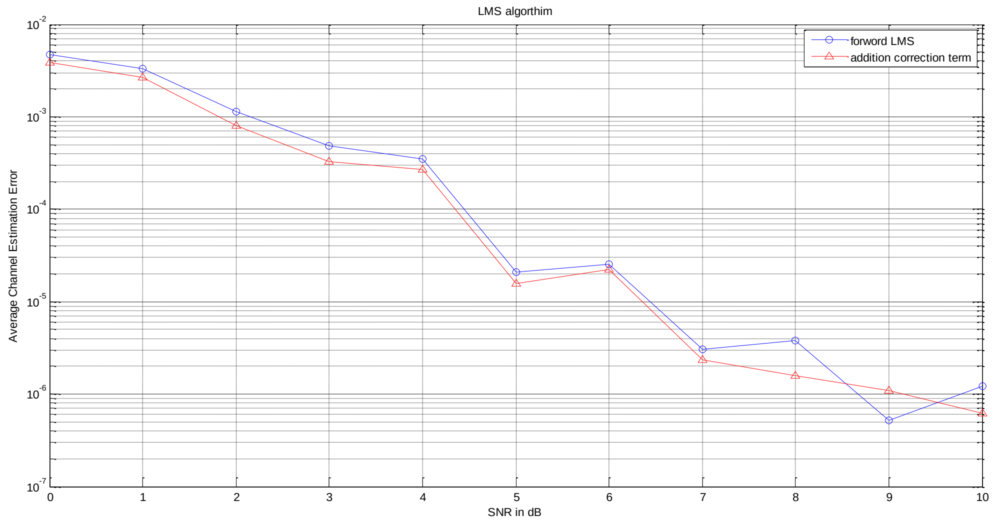

Figure 25: Simulation results with addition of correction term ($Z = \sigma^3 * 0.01$) on both sides

g) $Z = \sigma^4 * 0.01$

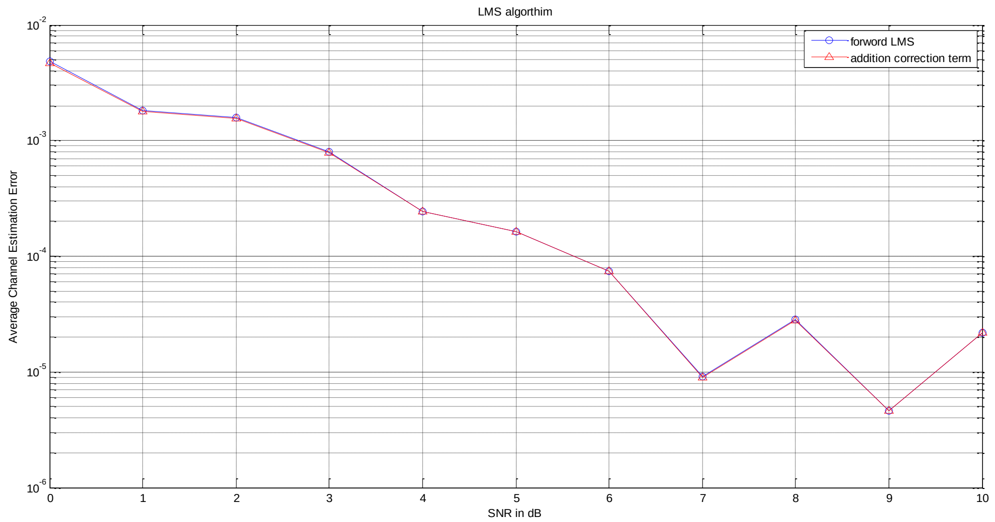

Figure 26: Simulation results with addition of correction term ($Z = \sigma^4 * 0.01$) on both sides

3.2.2. The Subtraction of The Compensating Term

1) $h_{t+1}\ (S_{t+1}) = h_t\ (S_t) + ß\ e_t\ (\ S_t\ , S_{t+1})\ \ S_t$ (3.13)

After that, Channel coefficient = $h_{t+1}\ (S_{t+1})$ - Z * $\bar{h}\ _{t+1}\ (S_{t+1})$

a) Z = 0.001

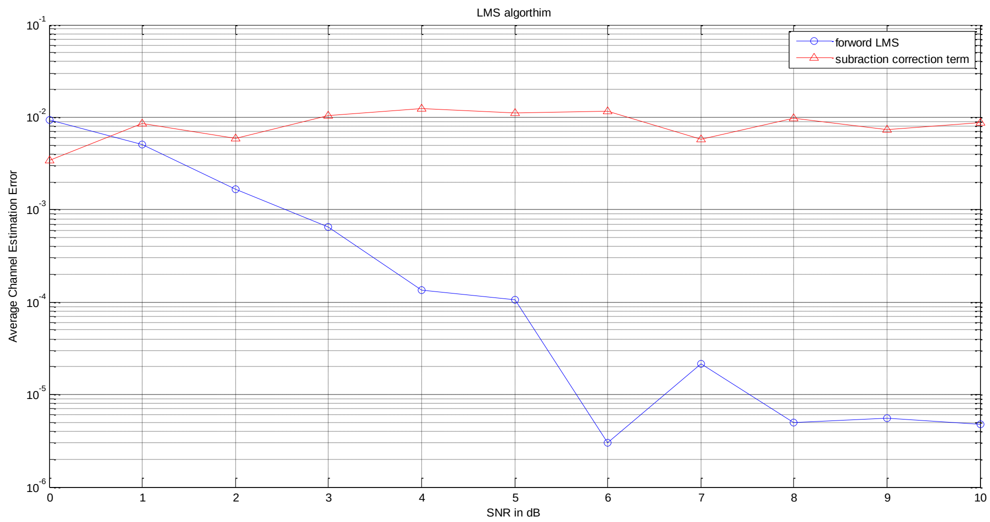

Figure 27: Simulation results with subtraction of correction term (Z = 0.001)

b) Z = 0.0001

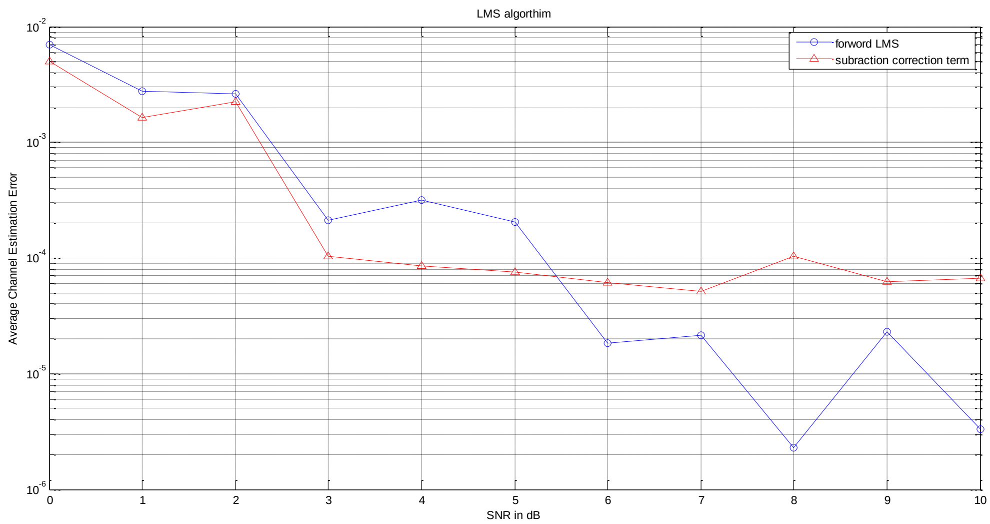

Figure 28: Simulation results with subtraction of correction term (Z = 0.0001)

c) Z = 0.00001

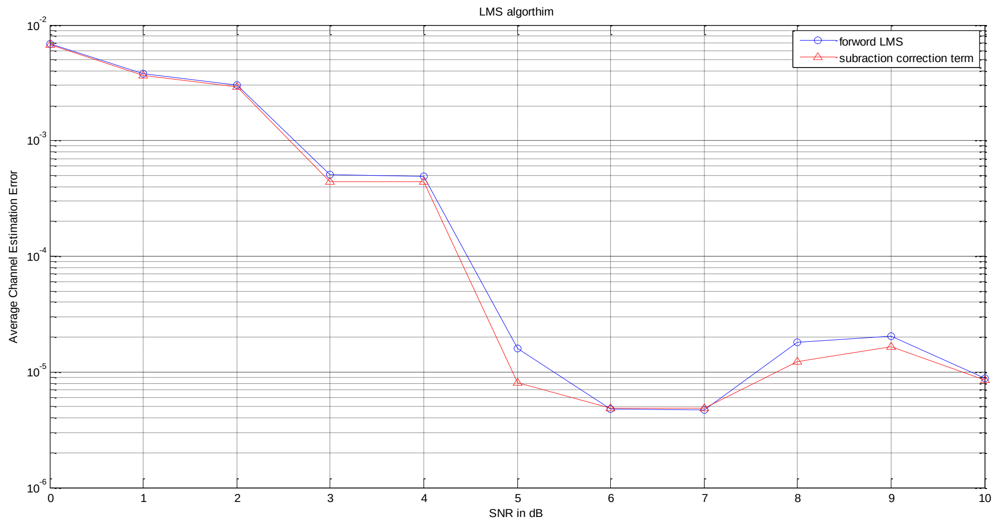

Figure 29: Simulation results with subtraction of correction term (Z = 0.00001)

d) Z = $\sigma^3 * 0.001$

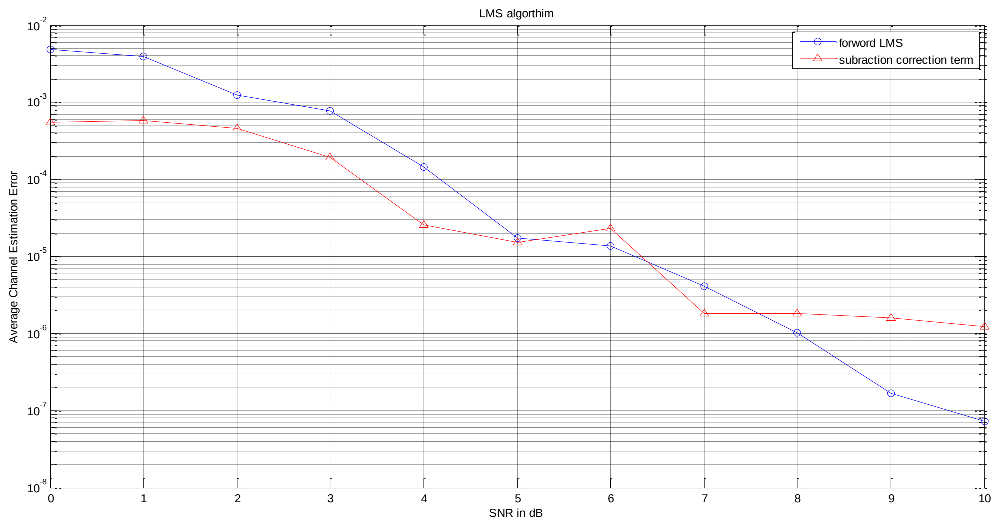

Figure 30: Simulation results with subtraction of correction term (Z =$\sigma^3 * 0.01$)

e) Z = $\sigma^{4} * 0.001$

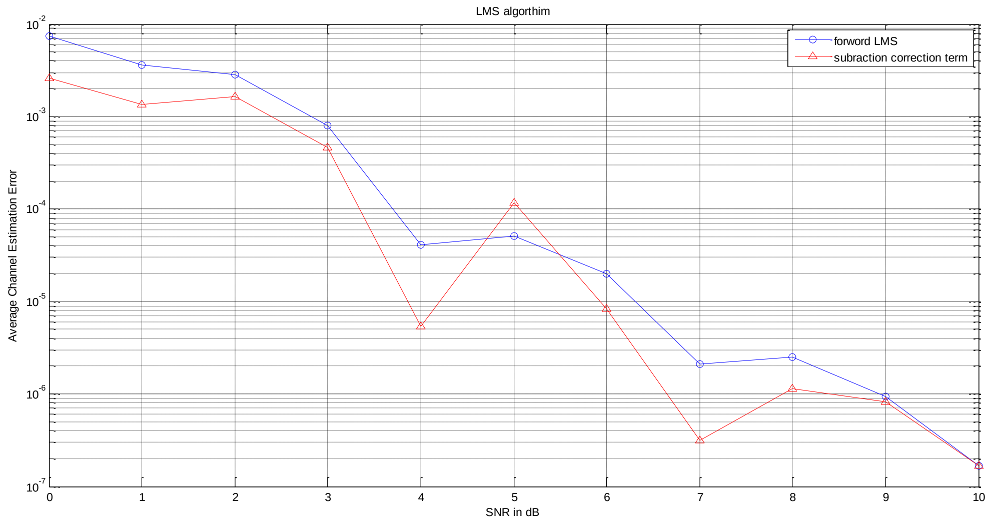

Figure 31: Simulation results with subtraction of correction term (Z =σ^{4} * 0.01)

f) SNR= 0 to 5 where Z = $\sigma^{3} * 0.001$

And SNR=6 to 10 where Z = $\sigma^{4} * 0.001$

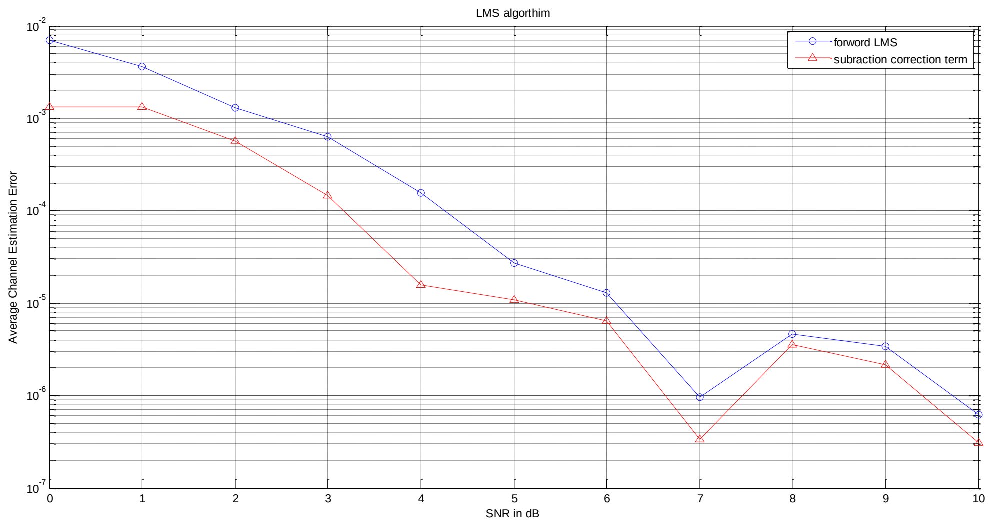

Figure 32: Simulation results with subtraction of correction term (Z =σ^{3} * 0.01 and σ^{4} * 0.01)

2) $h_{t+1}\,(S_{t+1}) = h_t\,(S_t) + ß\, e_t\,(S_t\,, S_{t+1})\; S_t$ (3.14)

After that, Channel coefficient = (1-Z) * $h_{t+1}\,(S_{t+1})$ - Z * $\bar{h}_{\,t+1}\,(S_{t+1})$

a) Z = 0.001

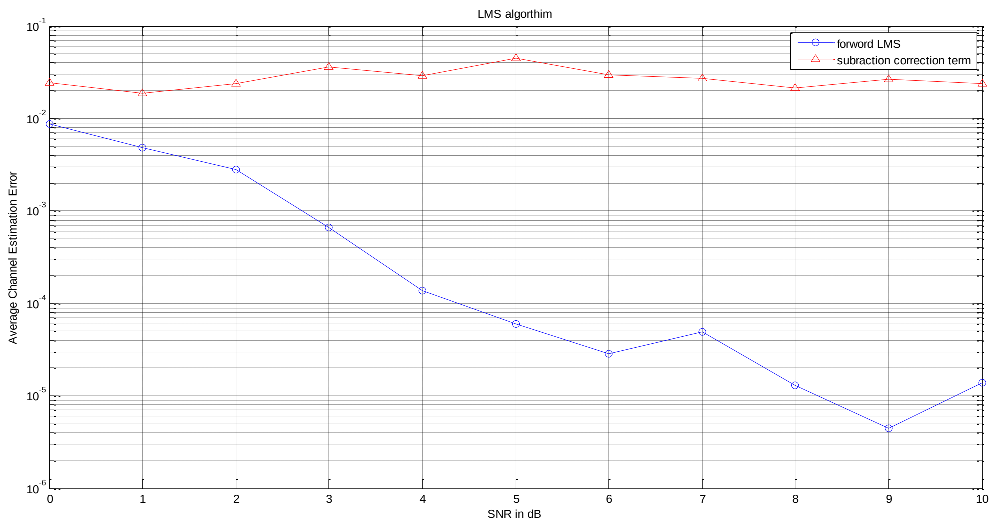

Figure 33: Simulation results with subtraction of correction term (Z = 0.001) on both sides

b) Z = 0.0001

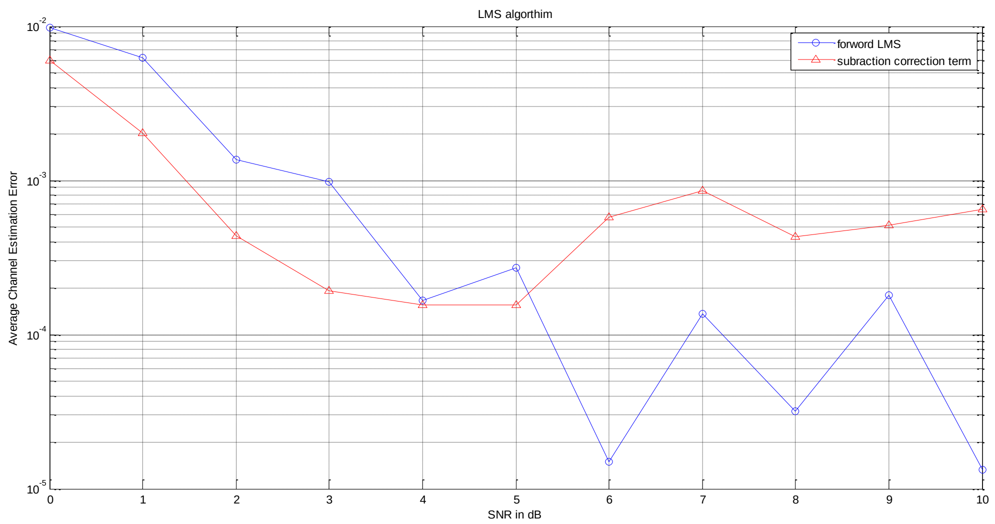

Figure 34: Simulation results with subtraction of correction term (Z = 0.0001) on both sides

c) Z = σ^3 * 0.001

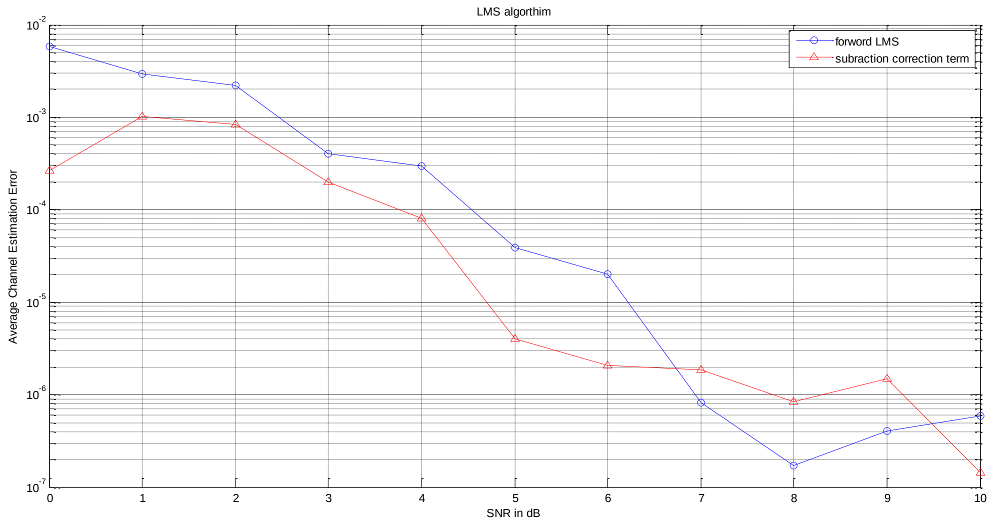

Figure 35: Simulation results with subtraction of correction term (Z =σ^3 * 0.001) on both sides

d) Z = σ^4 * 0.001

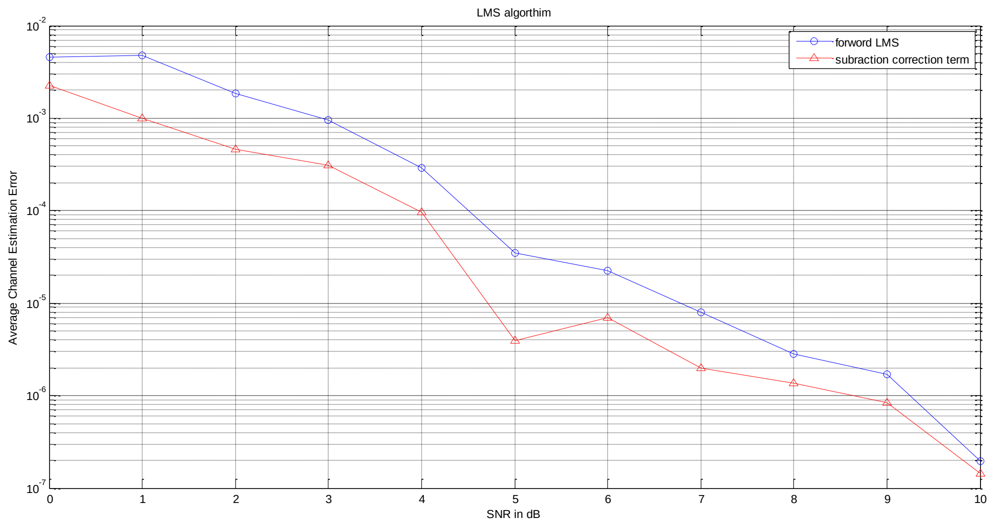

Figure 36: Simulation results with subtraction of correction term (Z =σ^4 * 0.001) on both sides

From the simulation results above, we found a lot of method to improve the estimation of the channel impales response (CIR). From those results, we noticed that some of the methods are affective at low signal to noise ratio but they are ineffective at high signal to noise ratio as shown in Fig. 20, Fig. 23, Fig. 25, Fig. 28, Fig. 30, Fig. 34 and Fig. 35 . Another method for estimating the channel coefficient is taking the average of all survivor paths, average of the best two paths or taking the incommensurate ratios of the paths. Also, addition or subtraction a constant as a correction term. All of these methods have worse estimation than classical LMS algorithm as shown in Fig. 10, Fig. 11, Fig. 12, Fig. 13, Fig. 14, Fig. 15, Fig. 16, Fig. 17, Fig. 18, Fig. 19, Fig. 21, Fig. 22, Fig. 24, Fig. 26, Fig. 27, Fig. 29, Fig. 31 and Fig. 33. Finally, the best results are gotten from the method of addition and subtraction a constant which is multiplied by the variance of the AWGN as in Fig. 32 and Fig. 36.

CHAPTER 4

CONCLUSION

The aim of this thesis is to estimate the value of the channel impulse response (CIR) closer to the real value. A class of algorithms for MLSE have been used, based on the principle of performing signal processing operations, needed for the estimation of unknown parameters, in a per-survivor method. Introduced by several authors for state complexity decrease in Inter-symbol Interference environment, DDFSE and RSSE make use of this principle. A number of algorithms have been used that apply the per-survivor processing PSP to estimate the sequence and the Channel Impulse Response (CIR) as Least Mean Square (LMS) and Recursive Least Square (LS). By using LMS in the presence of the unknown quantity channel parameter to estimate the channel impulse response.

The receiver design was carried out in a simulated environment developed in MATLAB. Through the use of a simulated environment, and disregarding some practical parts of the design like symbol synchronization, an efficient receiver design was developed, with most of the effort going into developing the signal processing algorithm for the receiver.

By applying LMS over AWGN channel we got the value of channel impulse response (CIR). A part is added to (or subtracted from) the equation of updating channel estimation as a correction term to improve CIR values. The correction term has two fractions, the first one is the neglected path which assumed that it has information, the second one is the variance of the noise AWGN channel. By multiplying these tow fractions, better estimation values for the CIR are achieved. From the results that we obtained, we conclude that the neglected path has information and it is possible to benefit from it to estimate the channel impulse response.

4.1. Suggestions for Future Research

As seen throughout the thesis, there are a number of observations which suggest that further improvements could be achieved that could not be implemented due to time and resource constraints. In Recursive Least Square algorithm, correction terms can be used to achieve better estimation values for the channel impulse response. Hence, the neglected paths can be used as correction terms to update channel estimation. Moreover, hardware implementation of the suggested structure can be applied by using FPGA or DSP boards.

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APPENDICES A

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M.Sc.	Çankaya Univ., Electronic and Communication Engineering	2014
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2011- Present	Karbala TV	S.N.G. Engineer
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FOREIN LANGUAGES

English, Arabic, beginner Turkish

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Books, Swimming.