© 2016 IJEDR | Volume 4, Issue 4 | ISSN: 2321-9939

Comparative Study of Channel Estimation Techniques

[1]Gauri S. Godbole, [2]Shailaja Gaikwad
[1]ME Student, [2]Assistant Professor

[1]Electronics Department,
[1]Terna Engineering College, Navi Mumbai, Maharashtra, India

***Abstract*—The objective of this work is to enhance the knowledge about channel estimation and to compare the existing channel estimation techniques . Normally the received signal is corrupted by the channel i.e. Multipath, ISI. The estimation of a time-varying multipath fading channel is a difficult task for the receiver. In this work following estimation algorithms are studied viz. LMS, RLS, MMSE, LS, EV, Capon method.**

***Key Words*— LMS, RLS, MMSE, LS, EV, Capon method.**

I. INTRODUCTION

A channel is a medium, which transfer data or information from transmitter to receiver. Channel estimation technique give receiver an indication about the channel conditions and hence will the decision in detecting the transmitted information. The feature of any physical medium is that , the transmitted signal is corrupted in various way by frequency and phase distortion, inter symbol interference, thermal noise etc. and the receiver receives corrupted signal. Estimation means prediction, detection or approx. calculation, characterizing the effect of the physical channel on the input sequence. We can say a channel is well estimated when its error minimization criteria is satisfied.

Channel estimation algorithm explains the behavior of the channel and allows the receiver to approximate the impulse response of the channel. The error can be minimized by equalization technique. It helps to produce a channel to ideal channel when voice, data and video can pass through the channel. .

In a practical wireless communication system, channel knowledge is never known a priori, so blind and semi-blind assumptions are used or a pilot symbols are used that is known for the receiver. However, in a spectral efficient wireless communication system, it's always desirable to limit the number of transmitted pilot symbols. That's why blind and semi-blind techniques are more favorable and desired and have been studied extensively.

In this paper we will Compare three methods for Channel estimation problems based in semi-blind approach for MU-MIMO systems; Least square method LS, CAPON method and the Eigenvector method. Performance comparison is based on the Minimum mean square error (MMSE). Further we will compare LMS, RLS, MMSE algorithms with respect to fading channel conditions.

II. CHANNEL ESTIMATION TECHNIQUES

A. LMS (Least mean square) ALGORITHM

- LMS algorithm uses the estimates of the gradient vector from the available data.
- LMS incorporates an iterative procedure that makes successive corrections to the weight vector in the direction of the negative of the gradient vector which leads to the minimum mean square error.
- Compared to other algorithms LMS algorithm is relatively simple.
  Input: A random process x(n);

  FIR filter of weights: (w0, w1, …wN-1);

  Filter output: $Y(n) = w^T x(n)$;

  Error signal: $e(n) = d(n) – y(n)$

  Where d(n) is desired output.

  From the method of steepest descent, weight vector equation is given by:

$W(n) = W(n) + ½ \mu[-\nabla(E\{e^2(n)\})]$

Where 'µ' is the step-size parameter and controls the convergenve characteristics of the LMS algorithm.

B. RLS (Recursive Least Square) Algorithm

- RLS adaptive filter is an algorithm which recursively finds the filter coefficients that minimize a weighted linear least squares cost function relating to the inputs signal.
- This is in contrast to other algorithm such as the LMS algorithm that aim to reduce mean square error.
- The RLS algorithm for a p-th order RLS filter can be summarized as,
  Parameters:
  p = Filter order;
  λ = Forgetting factor;
  δ = Value of initialize P(0)
  Initialization :$w_n = 0$
  $P(0) = \delta^{-1}I$ Where I is the (p+1)-by-(p+1) identity matrix
  Computation: For n =0,1,2…
  Then the weight update can be given by the following equation:

  $w(n) = w(n-1) + \alpha(n)\, g(n)$

  Where,
  $\alpha(n) = d(n) - w(n-1)^T x(n)$
  $g(n) = p(n-1)z(n)\{\lambda + x^T(n)P(n-1)x(n)\}^{-1}$

C. MMSE (Minimum Mean Square Estimator)

- In MMSE we search a function F [where $F$and H is related as in such that $\boldsymbol{H}$ is on average is close to the true channel realization $\boldsymbol{H}$as possible.

$$\hat{H} = F(\boldsymbol{Y})$$

- In other words, we try to minimize the mean square error of H for a given realization of Y. the mean square error is given in following equation and the argument to minimize it is given in

$$E_{H,}[\,\|\boldsymbol{H} - \hat{H}\|^2]$$

- The main advantage of the MMSE is that it tries to find the best tradeoff between the contribution of the mean squared norm of bias and the variance of the estimator based on the fact that it exploits the knowledge of about the channel and noise covariance matrices.

D. LS (Least square)

- The LS square method can be used to estimate the channel vectors $\{\ \}^p{}_{p=}1$. Consider as the number of training symbols (Training Blocks).
- With n = 1, 2, … Jt we have:

$$\overline{y(n)} = \sum_{p=1}^{p} \bar{\bar{A}}\left(\overline{Sp(n)}\right)hp + \overline{ZZ}(n)$$

Where $\overline{Sp(n)}$ and $\overline{ZZ}(n)$ is a vectorized signal and noise components respectively.

E. CAPON

- CAPON method was suggested for channel estimation for MU-MIMO system. When applied to MU-MIMO channel estimation problems the Capon linear receiver can be considered as a sort of spatio–temporal filter. The Capon "spectrum" is defined below and it defined as the output of the corresponding Capon receiver:

$$P_C^K(h) = \frac{1}{a_K^T(h)R^{-1}a_K(h)}$$

Where $\boldsymbol{R}$ is the data covariance matrix and (·) is a linear operator in the normalized channel vector

$h = {h_p}/{||h_p||}$ for the K = 1, …,2K the number of receivers to be used in parallel to estimate the symbols vector.

- To estimate the normalized channel vector as the P values that minimize $Q_c(h)$ given in following equation based on fact that the channel vectors are linearly independent.

$$Q_c(h) = h^T \left(\sum_{K=1}^{2K} \Phi_K^T R^{-1} \Phi_K \right) h$$

- Based on above equation the channel vectors are expected to belong the subspace spanned by minor eignvectors of the matrix given in folloeingequation , or more accurately on the eignvectorscrossponding to the p smallest eigenvalues of this matrix.

$$\Psi := \sum_{K=1}^{2K} \Phi_K^T R^{-1} \Phi_K$$

F. EV (Eigenvector Method)

- The Eigenvector method (EV) is a common used method for spectral estimation problems. It's closely related to the MUSIC algorithm.
- Its estimates the Noise subspace from the peaks of the Eigen spectrum (MUSIC Spectrum)(4.18), the only difference here is the definition or the method used to obtain the null space.
- For the RRQR case we developed the problem based on the MUSIC spectrum and obtained the Null space by multiplying the smallest Eigen vectors (that corresponds to the smallest Eigen values of the covariance Matrix) and their conjugates.
- In the EV case we multiple by the Eigen values that has been already obtained during the extraction of the Eigen vectors from the covariance matrix.
- We can define the Eigen values for the noise-subspace as $\boldsymbol{w}$ with size $1 \times (2MT - 2KP)$ and the EV space can be written as :

$$P_{EV} = \frac{1}{tr\{A^T(h_p) E w E^T A(h_p)\}}$$

The same procedure applies in the derivation of matrix $\boldsymbol{\Omega}$ and then to estimate the channel vector $\hat{h}_p$.

III. Comparative study and analysis

- The performance of LMS & RLS algorithm with respect to channels is studied & compared.
- The received signal is equalized faster if RLS is used as channel estimation algorithm compared to LMS.
- The RLS algorithm generates less error than LMS.
- This is due to fact that standard deviation of RLS is less compared to LMS.
- Further we have studied comparison between MMSE, LS, Capon and EV method.
- The Capon method gives a better performance compared to the LS method.
- It's essential to mention that the number of the training symbols used in the simulation is very small, yet the results are very good for fair SNR values (10 to 15 dB).
- The performance is better as the training symbol numbers increase.
- In all the cases Eigen Value method & the Capon method are showing a comparable performance.
- At high SNR values the Eigen value and Capon almost perform the same, and this is expected since subspace estimation methods.
- The reciprocity principle assumes that the forward and reverse channels are identical given that the time, frequency and antenna locations are the same. The former method can't be used with frequency duplex schemes.

IV. Conclusion and future work

Channel estimation problems are of vital importance to the telecommunication literature; it gives the receiver side a full knowledge of the channel state and hence helps in detecting the transmitted information precisely. Among the available approaches, we have explored three methods for Semi-blind approach, and we have introduced a common method used in Spectral estimation; the Eigenvector (EV) method to the channel estimation problem for MU-MIMO systems.
This paper presents a comparison between LMS & RLS algorithms and further compares three common methods for MU-MIMO semi-blind channel estimation and the EV method.

- From the comparison between LMS & RLS algorithm we can see that RLS algorithm generates less error than LMS and AWGN channel produces smallest amount of error value.

- The error value increases for changing from AWGN to Rician fading channel and Rician fading channel to Rayleigh method.
- On the other hand mathematical computation is simple and straight forward for LMS compared to RLS and hence implementation of LMS algorithm is easier.
- In further comparison in this paper we studied that The EV method showed a comparable performance in terms of the MMSE with the CAPON method and an improved performance when compared to the least Square (LS) method.
- The Eigenvector method depends on the extraction of the Noise-subspace that corresponds to the Null space extracted
- from the received data covariance matrix.
- When compared to the MUSIC search algorithms the EV includes the use of the Eigen values corresponding to the smallest Eigen vectors of the data covariance matrix in the extraction of the null space.
- This thesis has explored techniques used for semi-blind channel estimation for Flat-block fading, a future work can be done to explore and suggest techniques to the Fast Selective channels case.
- Another work can be done on the signal sub-space side rather than the noise-subspace side that has been explored in this paper.
- A common methods used with the signal subspace in the spectral estimation can be used in channel estimation problems like Blackmann-Tukey, Minimum Variance and Autoregressive methods.

REFERENCE

[1] Tirthankar Paul, PriyabratabKarmarkar, SauravDhar,"Comparative study ofchannel estimation algorithms under different channel scenario", International journal of computer application(0975-8887), vol. 34. No. 7, November 2011.

[2] Mohammad NaserFawwazKhasawneh,"Comparison study for Multi- user MIMO channel estimation techniques",August 2009, Jordan University of science and Technology.

[3] Wei,L., Dong, J., Ye, F. and Yang,S.(2009),"Research on a new kind of Rake-MKFA receiver based on DS-UWB system",5th International Conference on wireless communications, Networking and MobileComputing. 24-26 Sept.2009. WiCom '9; doi:10.1109/WICOM.2009.5305739.

[4] Shetty k. k., "Least mean square algorithm", http://etd.lib.fsu.edu/thesis/available/etd-04092004-143712/unrestricted/ch_6lms.pdf.

[5] Kai Yu, and Bjorn Ottersten, Models for MIMO propagation channels: a review,John Wiley & sons. Ltd.2002.

[6] S. M. Kay, fundamentals of statistical signal processing: estimation theory, Vol.1, Prentice Hall PTR, 1993.

[7] Togla M. Duman and Ali Ghrayeb, Coding for MIMO Communication System, John wiley and Sons, Ltd,2007.

[8] GeogrgeTsoulos, MIMO Systems Technology for wireless Communications, Taylor and Francis Group, LLC, 2006.

[9] Anton A. Huurdeman, The Worldwide history of Telecommunications, John wiley and sons, Inc,1996.

[10] Monson H, Hayes, Statistical Digital Signal Processing and Modeling, John Eileyand sons, Inc, 1996.