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Support Vector Machines Regression for MIMO-OFDM Channel Estimation

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ABSTRACT

In this paper, we propose a robust highly selective nonlinear channel estimator for Multiple -Input Multiple-Output (MIMO) Orthogonal Frequency Division Multiplexing (OFDM) system using complex Support Vector Machines Regression (SVR) and applied to Long Term Evolution (LTE) downlink under high mobility conditions .The new method uses the information provided by the pilot signals to estimate the total frequency response of the channel in two phases: learning phase and estimation phase. The estimation algorithm makes use of the reference signals to estimate the total frequency response of the highly selective multipath channel in the presence of non-Gaussian impulse noise interfering with pilot signals. Thus, the algorithm maps trained data into a high dimensional feature space and uses the Structural Risk Minimization (SRM) principle to carry out the regression estimation for the frequency response function of the highly selective channel. The simulations show the effectiveness of the proposed method which has good performance and high precision to track the variations of the fading channels compared to the conventional LS method and it is robust under high mobility conditions.

1. INTRODUCTION

The multiple input multiple output (MIMO) method represents an efficient technique to increase data transmission rate without increasing bandwidth since different data streams are transmitted from each transmit antenna.

In addition, Orthogonal Frequency Division Multiplexing (OFDM) has been effectively used for transmitting high speed data in frequency selective time varying multipath fading channel environments.

The combination of OFDM and MIMO techniques in the same system increases spectral efficiency and improves link reliability without additional transmit power or bandwidth. By implementing the OFDMA access technique in LTE Downlink system, new approaches for time and frequency synchronization, equalisation and channel estimation are needed.

Indeed, the estimated channel frequency response is used to separate the mixed signals received from multiple antennas. An essential aspect is the fact that the performance of the MIMO-OFDM receivers is highly depending on the accuracy of the channel estimator. Thus, as solution to this problem, we are proposing a novel channel tracking technique that relies on a data-aided channel predictor using the the Support Vector Machines Regressor (SVR).

Thus, a proposed SVM robust version for nonlinear channel estimation in MIMO systems with the presence of non-Gaussian impulse noise that is specifically adapted to pilot-aided OFDM structure is presented. In fact, impulses of short duration are unpredictable and contain spectral components on all subchannels which impact the decision of the transmitted symbols on all subcarriers.

The channel estimation algorithm is based on the nonlinear complex support vector machines regression method in order to improve communication efficiency and quality of OFDM systems. The principle of the proposed nonlinear SVR algorithm is to exploit the information provided by the reference signal to estimate the channel frequency response. In highly selective multipath fading channel, where complicated nonlinearities can be present, the estimation precision can be lowed by using linear methods. So, we adapt the nonlinear SVR algorithm which transforms the nonlinear estimation in low dimensional space into the linear estimation in high dimensional space, so it improves the estimation precision.

In this paper, the proposed nonlinear complex SVR technique is applied to LTE downlink highly selective channel using pilot symbols. For the purpose of comparison with conventional LS algorithm, we develop the nonlinear SVR algorithm in terms of the RBF kernel. Simulation section illustrates the advantage of this algorithm over LS algorithm in high mobility environment. The nonlinear complex SVR method shows good results under high mobility conditions due to its improved generalization ability.

The remainder of this paper is organized as follows. Section 2 briefly introduces the OFDM system model. Then, multipath channel model is presented in section 3. Section 4 describes the MIMO-OFDM system. We develop the formulation of the proposed nonlinear complex SVR channel estimation method in section 5. Section 6 presents the simulation results in SISO-OFDM and MIMO-OFDM cases respectively. Finally, in section 7, concludes the paper.

2. OFDM SYSTEM MODEL

The OFDM system model consists firstly of mapping binary data streams into complex symbols by means of QAM modulation. Then data are transmitted in frames by means of serial-to-parallel conversion. Some pilot symbols are inserted into each data frame which is modulated to subcarriers through IDFT. These pilot symbols are inserted for channel estimation purposes. The IDFT is used to transform the data sequence $X(k)$ into time domain signal as follow:

$$x(n) = IDFT_N\{X(k)\} = \sum_{k=0}^{N-1} X(k)\, e^{j\frac{2\pi}{N}kn}, \qquad n = 0, \cdots, N-1 \tag{1}$$

One guard interval is inserted between every two OFDM symbols in order to eliminate inter-symbol interference (ISI). This guard time includes the cyclically extended part of the OFDM symbol in order to preserve orthogonality and eliminate inter-carrier interference (ICI). It is well known that if the channel impulse response has a maximum of L resolvable paths, then the GI must be at least equal to L [1].

Thus, for the OFDM system comprising N subcarriers which occupy a bandwidth B, each OFDM symbol is transmitted in time T and includes a cyclic prefix of duration T_{cp}. Therefore, the duration of each OFDM symbol is $T_u = T - T_{cp}$. Every two adjacent subcarriers are spaced by $\delta f = 1/T_u$. The output signal of the OFDM system is converted into serial signal by parallel to serial converter. A complex white Gaussian noise process $N\ (0, \sigma_w^2)$ with power spectral density $N_0/2$ is added through a frequency selective time varying multipath fading channel.

In a practical environment, impulse noise can be present, and then the channel becomes nonlinear with non Gaussian impulse noise. The impulse noise can significantly influence the performance of the OFDM communication system for many reasons. First, the time of the arrival of an impulse is unpredictable and shapes of the impulses are not known and they vary considerably. Moreover, impulses usually have very high amplitude, and thus high energy, which can be much greater than the energy of the useful signal [2].

The impulse noise is modeled as a Bernoulli-Gaussian process and it was generated with the Bernoulli-Gaussian process function $i(n) = v(n)\lambda(n)$ where $v(n)$ is a random process with Gaussian distribution and power σ_{BG}^2, and where $\lambda(n)$ is a random process with probability [3]

$$P_r(\,\lambda\,(n)\,) = \begin{cases} p & \lambda = 1 \\ 1-p, & \lambda = 0. \end{cases} \tag{2}$$

At the receiver, and after removing guard time, the discrete-time baseband OFDM signal for the system including impulse noise is

$$y(n) = \sum_{k=0}^{N-1} X(k)H(k)e^{j\frac{2\pi}{N}kn} + w(n) + i(n), \qquad n = 0, \cdots, N-1 \tag{3}$$

where $y(n)$ are time domain samples and $H(k) = DFT_N\{h(n)\}$ is the channel's frequency response at the k^{th} frequency. The sum of both terms of the AWGN noise and impulse noise constitute the total noise given by $z(n) = w(n) + i(n)$.

Let Ω_P the subset of N_P pilot subcarriers and ΔP the pilot interval in frequency domain. Over this subset, channel's frequency response can be estimated, and then interpolated over other subcarriers $(N - N_P)$. These remaining subchannels are interpolated by the nonlinear complex SVR algorithm. The OFDM system can be expressed as

$$\begin{aligned} y(n) &= y^P(n) + y^D(n) + z(n) \\ &= \sum_{k\in\{\Omega_P\}} X^P(k)H(k)e^{j\frac{2\pi}{N}kn} + \sum_{k\notin\{\Omega_P\}} X^D(k)H(k)e^{j\frac{2\pi}{N}kn} + z(n) \end{aligned} \quad (4)$$

where $X^P(k)$ and $X^D(k)$ are complex pilot and data symbol respectively, transmitted at the k^{th} subcarrier. Note that, pilot insertion in the subcarriers of every OFDM symbol must satisfy the demand of the sampling theory and uniform distribution [4].

After DFT transformation, $y(n)$ becomes

$$Y(k) = DFT_N\{y(n)\} = \frac{1}{N}\sum_{n=0}^{N-1} y(n)\, e^{-j\frac{2\pi}{N}kn}, \qquad k = 0, \cdots, N-1 \quad (5)$$

Assuming that ISI are eliminated, therefor

$$Y(k) = X(k)H(k) + W(k) + I(k) = X(k)H(k) + e(k), \qquad k = 0, \cdots, N-1 \quad (6)$$

where $e(k)$ represents the sum of the AWGN noise $W(k)$ and impulse noise $I(k)$ in the frequency domain, respectively.

Equation (6) may be presented in matrix notation

$$Y = \boldsymbol{XF}h + W + I = \boldsymbol{X}H + e \quad (7)$$

where

$$\begin{aligned} \boldsymbol{X} &= diag\big(X(0), X(1), \cdots, X(N-1)\big) \\ Y &= [Y(0), \cdots, Y(N-1)]^T \\ W &= [W(0), \cdots, W(N-1)]^T \\ I &= [I(0), \cdots, I(N-1)]^T \\ H &= [H(0), \cdots, H(N-1)]^T \\ e &= [e(0), \cdots, e(N-1)]^T \end{aligned}$$

$$\boldsymbol{F} = \begin{bmatrix} W_N^{00} & \cdots & W_N^{0(N-1)} \\ \vdots & \ddots & \vdots \\ W_N^{(N-1)0} & \cdots & W_N^{(N-1)(N-1)} \end{bmatrix}$$

and $$W_N^{i,k} = \left(\frac{1}{\sqrt{N}}\right) exp^{-j2\pi\left(\frac{ik}{N}\right)}. \quad (8)$$

3. MULTIPATH CHANNEL MODEL

We consider the channel impulse response of the frequency-selective fading channel model which can be written a

$$h(\tau, t) = \sum_{l=0}^{L-1} h_l(t)\, \delta(t - \tau_l) \quad (9)$$

where $h_l(t)$ is the impulse response representing the complex attenuation of the l^{th} path, τ_l is the random delay of the l^{th} path and L is the number of multipath replicas. The specification parameters of an extended vehicular A model (EVA) for downlink LTE system with the excess tap delay and the relative power for each path of the channel are shown in table 1. These parameters are defined by 3GPP standard [5].

Table 1. Extended Vehicular A model (EVA) [5].

Excess tap delay [ns]	Relative power [dB]
0	0.0
30	-1.5
150	-1.4
310	-3.6
370	-0.6
710	-9.1
1090	-7.0
1730	-12.0
2510	-16.9

4. MIMO-OFDM SYSTEM

Figure 1 shows a MIMO-OFDM system model corresponding to Alamouti STBC scheme with two transmit and two receive antennas. The modulation block is used to modulate the original binary symbol using the complex constellation. MIMO encoders are needed to increase the spatial diversity since multiple antennas are used at the transmitter and receiver. MIMO systems can be implemented in different ways to obtain either a capacity gain or a diversity gain to combat signal fading.

The OFDM modulation method consists of transmitting a block of data symbols in parallel on channel subcarriers. An OFDM modulator can be easily and powerfully implemented using the Inverse Discrete Fourier Transform (IDFT) on a block of data symbols. Each block of IDFT coefficients is preceded by a cyclic prefix (CP) with length equal at least to the channel delay spread to prevent inter-symbol interference (ISI). Usually, a pilot sequence insertion is used in the channel estimator to predict a channel frequency response at the receiver side to equalize for the channel impairments and thus to estimate the transmitted signal.

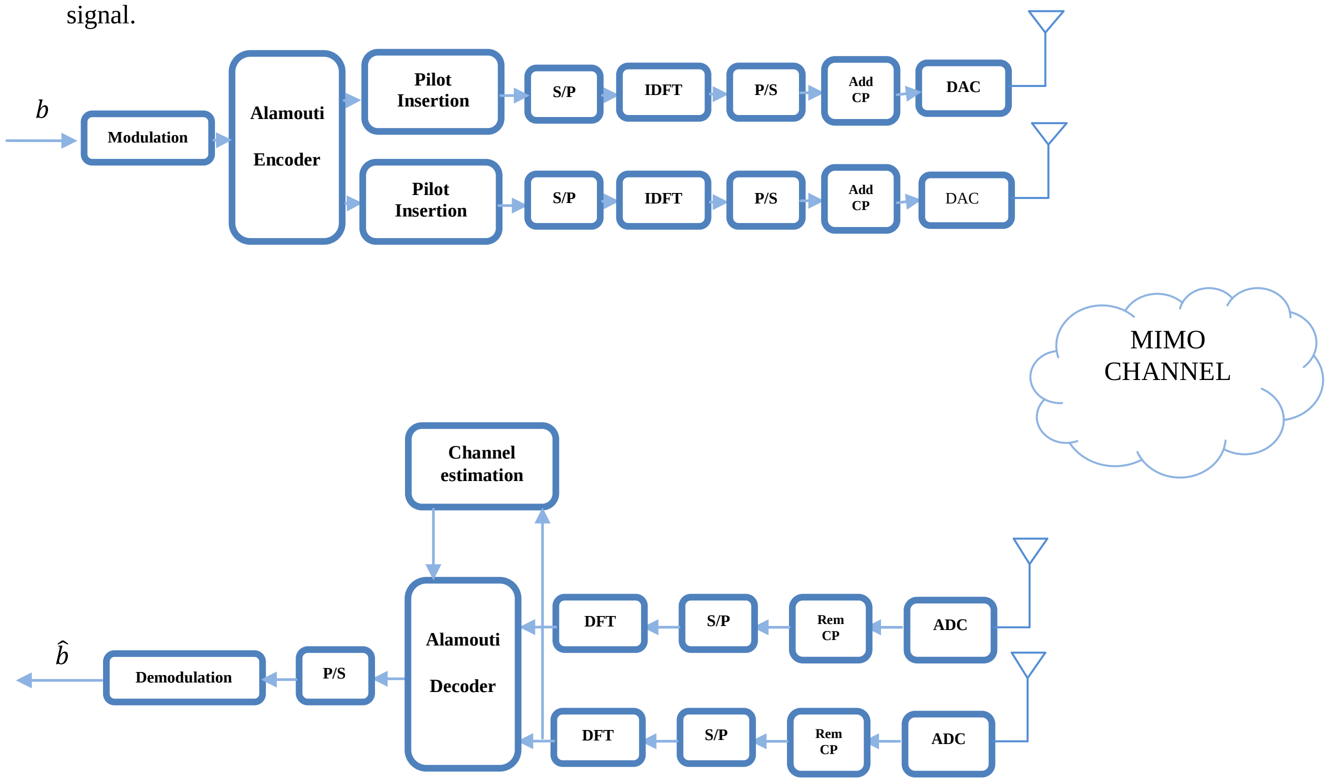


Figure 1. MIMO-OFDM System model

5. SUPPORT VECTOR MACHINES REGRESSION ESTIMATOR

Let the OFDM frame contains Ns OFDM symbols which every symbol includes N subcarriers. The transmitting pilot symbols are $\boldsymbol{X}^P = diag(X\,(s, m\,\Delta P)), m = 0,1,\cdots, N_P - 1$, where s and m are labels in time domain and frequency domain respectively, and ΔP is the pilot interval in frequency domain. Pilot insertion in the subcarriers of every OFDM symbol must satisfy the demand of sampling theory and uniform distribution [5].

The proposed channel estimation technique is based on nonlinear complex SVR algorithm which has two separate phases: learning phase and estimation phase. In learning phase, we estimate first the subchannels pilot symbols according to LS criterion to strike $min\ [(Y^P - \boldsymbol{X}^P\boldsymbol{F}h)\,(Y^P - \boldsymbol{X}^P\boldsymbol{F}h)^H]$ [9], as

$$\widehat{H}^P = \boldsymbol{X}^{P\ -1}\, Y^P \tag{15}$$

where $Y^P = Y\,(s, m\,\Delta P)$ and $\widehat{H}^P = \widehat{H}\,(s, m\,\Delta P)$ are the received pilot symbols and the estimated frequency responses for the s^{th} OFDM symbol at pilot positions $m\,\Delta P$, respectively.

Then, in the estimation phase and by the interpolation mechanism, frequency responses of data subchannels can be determined. Therefore, frequency responses of all the OFDM subcarriers are

$$\widehat{H}\,(s, q\,) = f\left(\widehat{H}^P(s, m\,\Delta P)\right) \tag{16}$$

where $q = 0,\cdots, N-1$, and $f(\cdot)$ is the interpolating function, which is determined by the nonlinear complex SVR approach.

Linear approaches cannot achieve high estimation precision in high mobility environments where the fading channels present very complicated nonlinearities. Therefore, we adapt here a nonlinear complex SVR method since SVM is superior in solving nonlinear, small samples and high dimensional pattern recognition [5]. Thus, we map the input vectors to a higher dimensional feature space $\mathcal{H}$ (possibly infinity) by means of nonlinear transformation $\boldsymbol{\varphi}(\cdot)$. So, the regularization term is referred to the regression vector in the RKHS. The following regression function is then

$$\widehat{H}(m\,\Delta P) = \boldsymbol{w}^{\boldsymbol{T}}\boldsymbol{\varphi}(m\,\Delta P) + b + e_m, \qquad m = 0,\cdots, N_P - 1 \tag{17}$$

where $\boldsymbol{w}$ is the weight vector, b is the bias term well and residuals $\{e_m\}$ account for the effect of both approximation errors and noise. In the SVM framework, the optimality criterion is a regularized and constrained version of the regularized Least Squares criterion. In general, SVM algorithms minimize a regularized cost function of the residuals, usually the Vapnik's $\varepsilon - insensitivity$ cost function [4].

To improve the performance of the estimation algorithm, a robust cost function is introduced which is ε -Huber robust cost function [10], given by

$$\mathcal{L}^{\varepsilon}(e_m) = \begin{cases} 0, & |e_m| \le \varepsilon \\ \dfrac{1}{2\gamma}(|e_m| - \varepsilon)^2, & \varepsilon \le |e_m| \le e_C \\ C(|e_m| - \varepsilon) - \dfrac{1}{2}\gamma C^2, & e_C \le |e_m| \end{cases} \tag{18}$$

where $e_C = \varepsilon + \gamma C$, ε is the insensitive parameter which is positive scalar that represents the insensitivity to a low noise level, parameters γ and C control essentially the trade-off between the regularization and the losses, and represent the relevance of the residuals that are in the linear or in the quadratic cost zone, respectively. The cost function is linear for errors above e_C, and quadratic for errors between ε and e_C. Note that, errors lower than ε are ignored in the $\varepsilon - insensitivite$ zone. The quadratic cost zone uses the $L_2 - norm$ of errors, which is appropriate for Gaussian noise, and the linear cost zone limits the effect of sub-Gaussian noise [1]. Therefore, the ε -Huber robust cost function can be adapted to different types of noise.

Let $\mathcal{L}^{\varepsilon}(e_m) = \mathcal{L}^{\varepsilon}(\mathcal{R}(e_m)) + \mathcal{L}^{\varepsilon}(\mathfrak{I}(e_m))$ since $\{e_m\}$ are complex, where $\mathcal{R}(\cdot)$ and $\mathfrak{I}(\cdot)$ represent real and imaginary parts, respectively. Now, we can state the primal problem as

$$min\ \frac{1}{2}\ \|\boldsymbol{w}\|^2 + \frac{1}{2\gamma}\sum_{m\in I_1}(\xi_m+\xi_m^*)^2 + C\sum_{m\in I_2}(\xi_m+\xi_m^*) + \frac{1}{2\gamma}\sum_{m\in I_3}(\zeta_m+\zeta_m^*)^2 + C\sum_{m\in I_4}(\zeta_m+\zeta_m^*)$$
$$-\frac{1}{2}\sum_{m\in I_2,I_4}\gamma C^2 \tag{19}$$

constrained to

$$\mathcal{R}\big(\widehat{H}(m\,\Delta P) - \boldsymbol{w^T}\boldsymbol{\varphi}(m\,\Delta P) - b\big) \le \varepsilon + \xi_m$$

$$\mathfrak{I}\big(\widehat{H}(m\,\Delta P) - \boldsymbol{w^T}\boldsymbol{\varphi}(m\,\Delta P) - b\big) \le \varepsilon + \zeta_m$$

$$\mathcal{R}(-\widehat{H}(m\,\Delta P) + \boldsymbol{w^T}\boldsymbol{\varphi}(m\,\Delta P) + b) \le \varepsilon + \xi_m^*$$

$$\mathfrak{I}(-\widehat{H}(m\,\Delta P) + \boldsymbol{w^T}\boldsymbol{\varphi}(m\,\Delta P) + b) \le \varepsilon + \zeta_m^*$$

$$\xi_m^{(*)}, \zeta_m^{(*)} \ge 0 \tag{20}$$

for $m = 0, \cdots, N_P - 1$, where ξ_m and ξ_m^* are slack variables which stand for positive and negative errors in the real part, respectively. ζ_m and ζ_m^* are the errors for the imaginary parts.
I_1, I_2, I_3 and I_4 are the set of samples for which:
I_1 : real part of the residuals are in the quadratic zone;
I_2 : real part of the residuals are in the linear zone;
I_3 : imaginary part of the residuals are in the quadratic zone;
I_4 : imaginary part of the residuals are in the linear zone.

To transform the minimization of the primal functional (19) subject to constraints in (20), into the optimization of the dual functional, we must first introduce the constraints into the primal functional.

Then, by making zero the primal-dual functional gradient with respect to ϖ_i, we obtain an optimal solution for the weights

$$\boldsymbol{w} = \sum_{m=0}^{N_P-1}\psi_m\,\boldsymbol{\varphi}(m\,\Delta P) = \sum_{m=0}^{N_P-1}\psi_m\,\boldsymbol{\varphi}(P_m) \tag{21}$$

where $\psi_m = (\alpha_{\mathcal{R},m} - \alpha_{\mathcal{R},m}^*) + j(\alpha_{I,m} - \alpha_{I,m}^*)$ with $\alpha_{\mathcal{R},m}, \alpha_{\mathcal{R},m}^*, \alpha_{I,m}, \alpha_{I,m}^*$ are the Lagrange multipliers (or dual variables) for real and imaginary part of the residuals and $P_m = (m\,\Delta P)$, $m = 0, \cdots, N_P - 1$ are the pilot positions.

Let the Gram matrix defined by

$$\boldsymbol{G}(u,v) = <\boldsymbol{\varphi}(P_u), \boldsymbol{\varphi}(P_v)> = K(P_u, P_v) \tag{22}$$

where $K(P_u, P_v)$ is a Mercer's kernel which represent the RBF kernel matrix which allows obviating the explicit knowledge of the nonlinear mapping $\boldsymbol{\varphi}(\cdot)$. A compact form of the functional problem can be stated in matrix format by placing optimal solution $\boldsymbol{w}$ into the primal dual functional and grouping terms. Then, the dual problem consists of

$$max\ -\frac{1}{2}\boldsymbol{\psi}^H(\boldsymbol{G}+\gamma\boldsymbol{I})\boldsymbol{\psi} + \mathcal{R}(\boldsymbol{\psi^H}Y^P) - (\boldsymbol{\alpha_{\mathcal{R}}} + \boldsymbol{\alpha_{\mathcal{R}}^*} + \boldsymbol{\alpha_I} + \boldsymbol{\alpha_I^*})\boldsymbol{1}\mathcal{E} \tag{23}$$

constrained to

$$0 \le \alpha_{\mathcal{R},m}, \alpha_{\mathcal{R},m}^*, \alpha_{I,m}, \alpha_{I,m}^* \le C \tag{24}$$

where $\boldsymbol{\psi} = [\psi_0, \cdots, \psi_{N_P-1}]^T$; **I** and **1** are the identity matrix and the all-ones column vector, respectively; $\boldsymbol{\alpha_{\mathcal{R}}}$ is the vector which contains the corresponding dual variables, with the other subsets being similarly represented. The weight vector can be obtained by optimizing (23) with respect to $\alpha_{\mathcal{R},m}, \alpha^*_{\mathcal{R},m}, \alpha_{I,m}, \alpha^*_{I,m}$ and then substituting into (21).

Therefore, and after learning phase, frequency responses at all subcarriers in each OFDM symbol can be obtained by SVR interpolation

$$\hat{H}(k) = \sum_{m=0}^{N_P-1} \psi_m K(P_m, k) + b \tag{25}$$

for $k = 1, \cdots, N$. Note that, the obtained subset of dual multipliers which are nonzero will provide with a sparse solution. As usual in the SVM framework, the free parameter of the kernel and the free parameters of the cost function have to be fixed by some a priori knowledge of the problem, or by using some validation set of observations [4].

6. SIMULATION RESULTS

6.1. SISO CASE

In order to demonstrate the effectiveness of our proposed technique and evaluate the performance, two objective criteria, the signal-to-noise ratio (SNR) and signal-to-impulse ratio (SIR) are used. The SNR and SIR are given by [3]

$$SNR_{dB} = 10log_{10}\left(\frac{E\{|y(n) - w(n) - i(n)|^2\}}{\sigma_w^2}\right) \tag{22}$$

and

$$SIR_{dB} = 10log_{10}\left(\frac{E\{|y(n) - w(n) - i(n)|^2\}}{\sigma_{BG}^2}\right) \tag{23}$$

Then, we simulate the SISO-OFDM downlink LTE system with parameters presented in table 2. The nonlinear complex SVR estimate a number of OFDM symbols in the range of 140 symbols, corresponding to one radio frame LTE. Note that, the LTE radio frame duration is 10 ms [9], which is divided into 10 subframes. Each subframe is further divided into two slots, each of 0.5 ms duration.

For the purpose of evaluation the performance of the nonlinear complex SVR algorithm under high mobility conditions, we consider a scenario for downlink LTE system for a mobile speed equal to 120 Km/h. Accordingly, we take into account the impulse noise with $p = .05$ which was added to the reference signals with different rates of SIR.

Figure 2 presents the variations in time and in frequency of the channel frequency response for the considered scenario.

Table 2. Parameters of simulations [9], [10] and [11].

Parameters	Specifications
Constellation	16-QAM
Mobile Speed (Km/h)	120
T_s (µs)	72
f_c (GHz)	2.15
δf (KHz)	15
B (MHz)	5
Size of DFT/IDFT	512
Number of paths	9

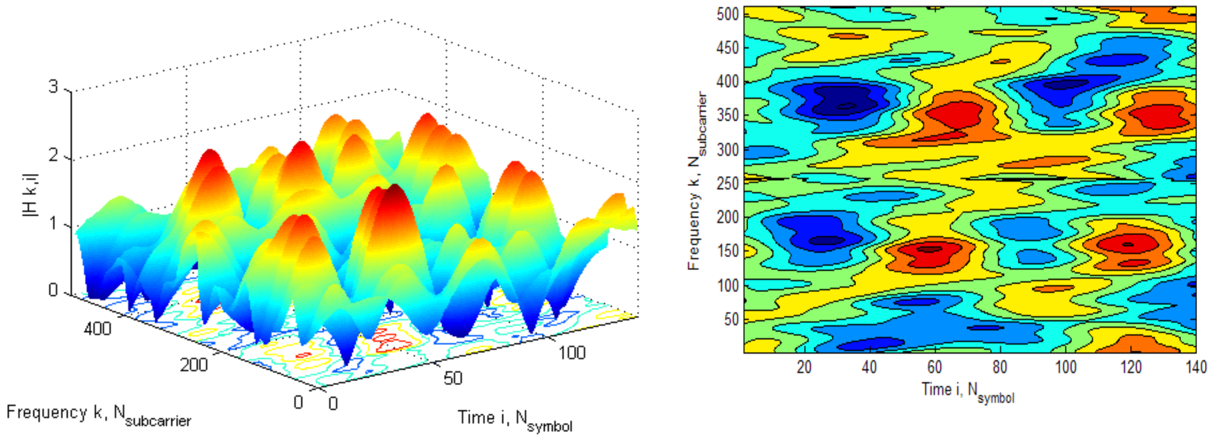
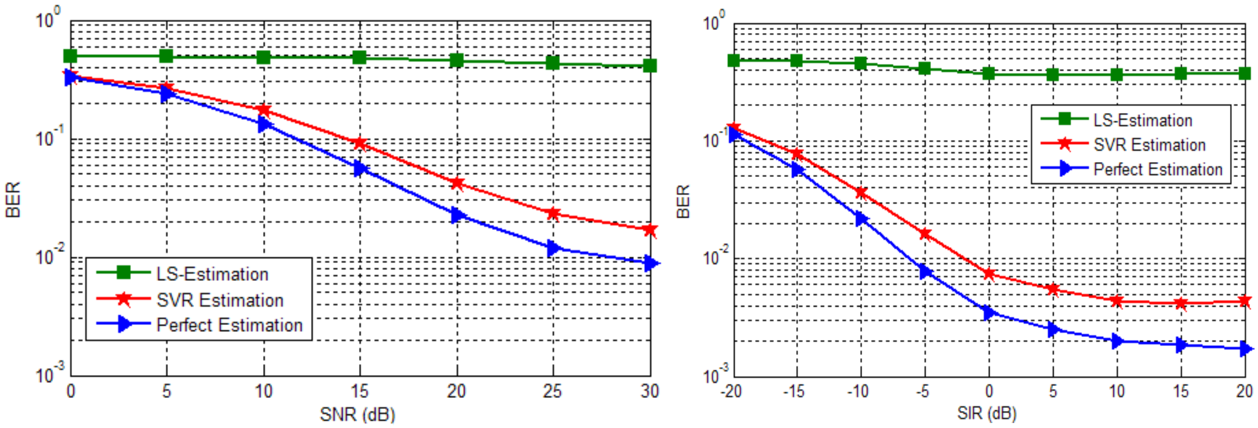


Figure 2. Variations in time and in frequency of the channel frequency response for a mobile speed at 120 Km/h.

Figure 3.a shows the performance of the LS and nonlinear complex SVR algorithms as a function of SNR in the presence of additive Gaussian noise and impulse noise for SIR = -5 dB with $p = .05$., while figure 3.b shows the performance of the LS and nonlinear complex SVR algorithms as a function of SIR for SNR =30 dB and $p = .05$.

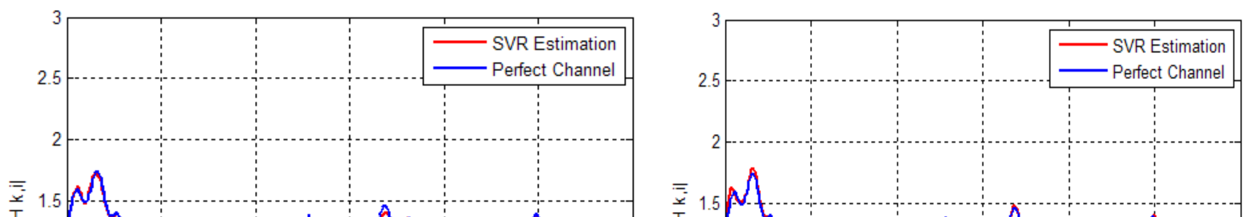
A poor performance is noticeably exhibited by LS and better performance is observed with nonlinear complex SVR.



a) b)

Figure 3. a) BER as a function of SNR for SIR=-5 dB with $p = .05$ and b) BER as a function of SIR for SNR=30 dB with $p = .05$ for a mobile speed at 120 Km/h.

An example of the proposed channel tracking and the nonlinear time variant channel frequency response simulated at the given multipath channel parametersis presented in figure 4. Blue line is the channel response tracked by the the proposed method at a) SNR=30 dB and SIR=-5 dB and b) SNR=30 dB and SIR=-10 dB. Fig.4 shows that the nonlinear channel response is well tracked by the proposed method.



a) b)

Figure 4. An example of the proposed channel tracking and the nonlinear time variant channel frequency response simulated at a) SNR=30 dB and SIR=-5dB b) SNR=30dB and SIR=10 dB.

6.1. MIMO CASE

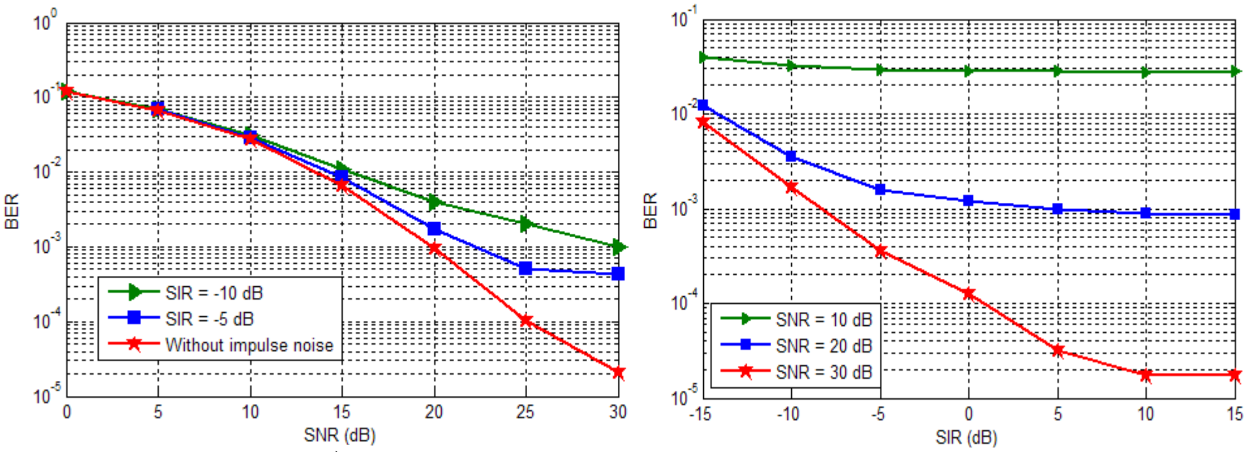
LTE MIMO-OFDM Downlink system with parameters shown in table 2 with Alamouti coding is simulated. Also, these parameters are based on Downlink LTE system and the number of transmit and receive antennas. The performance of the proposed estimator is evaluated with the variation of the number of transmit and receive antenna.

Figure 5.a shows the variations of BER as a function of SNR without and with impulse noise for SIR=-5 and -10 dB with $p = .05$ for two transmit antennas $(Nt = 2)$ and one receive antenna $(Nr = 1)$. Figure 5.b shows the variations of BER as a function of SIR in the presence of additive Gaussian noise for SNR=10, 20 and 30 dB with $p = .05$ for two transmit antennas and one receive antenna.

We can remark that BER decrease and good performances are obtained when SNR and SIR increase.

Figure 6.a presents the performance of the nonlinear complex SVR estimator for the Alamouti MIMO-OFDM system with $(Nt = 2)$ and $(Nr = 2)$ as a function of SNR in the presence of impulse noise interfering with pilot signals for a mobile speed at 120 Km/h for SIR = -10 and -5 dB with $p = .05$. In addition, figure 6.b shows the performance of the nonlinear complex SVR estimator for the Alamouti MIMO-OFDM system with $(Nt = 2)$ and $(Nr = 2)$ as a function of SIR in the presence of additive Gaussian noise for SNR = 10, 20 and 30 dB with $p = .05$.

Good performance is realised when the number of transmit and receive antennas increases which increases transmit and receive diversity.



a) b)

Figure 5. a) BER as a function of SNR and b) BER as a function of SIR for $(Nt = 2)$ and $(Nr = 1)$ with $p = .05$ for a mobile speed at 120 Km/h.

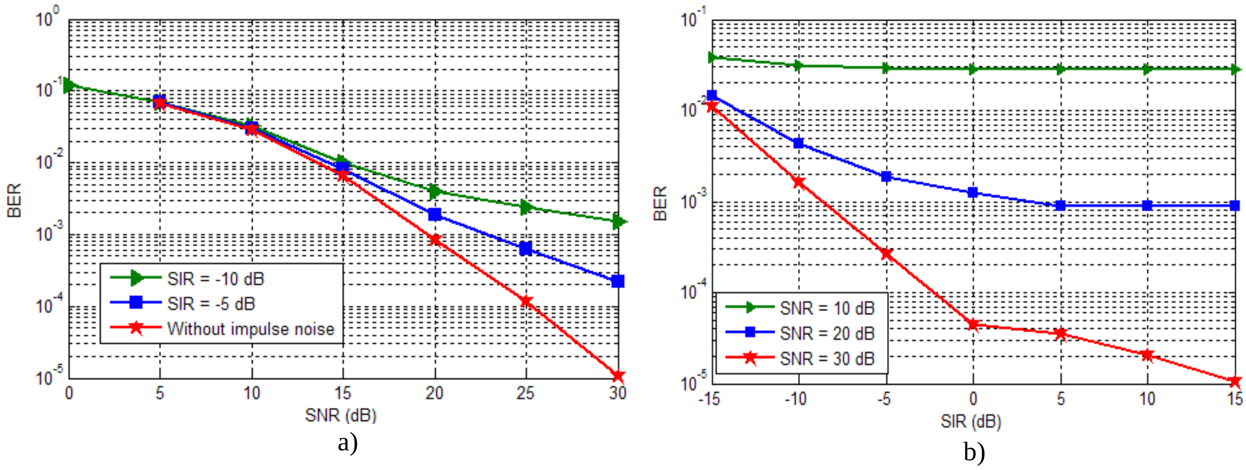


Figure 6. a) BER as a function of SNR and b) BER as a function of SIR for $(Nt = 2)$ and $(Nr = 2)$ with $p = .05$ for a mobile speed at 120 Km/h.

7. CONCLUSION

In this paper, a new nonlinear complex SVR based channel estimation technique for a highly selective multipath fading downlink MIMO-OFDM LTE system with Alamouti coding under high mobility conditions in the presence of non-Gaussian impulse noise interfering with OFDM reference symbols is presented. The proposed channel estimation method is based on learning process that uses training sequence to estimate the channel variations. Our formulation is based on nonlinear complex SVR specifically developed for pilot-based OFDM systems with MIMO architecture. Simulations have confirmed the capabilities of the proposed nonlinear complex SVR in the presence of Gaussian and impulse noise interfering with the pilot symbols for a high mobile speed when compared to LS standard method. The proposal takes into account the temporal-spectral relationship of the OFDM signal combined with the Alamouti scheme for highly selective channels. The Gram matrix using RBF kernel lead to a significant benefit for tracking channel variations in OFDM systems especially in those scenarios in which impulse noise and deep fading are presents.

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