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Support Vector Machines Regression for Channel Estimation in MIMO LTE systems

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Abstract

This paper proposes an efficient scheme to track the time variant channel induced by multipath fading wireless Multiple-Input Multiple-Output Orthogonal Frequency Division Multiplexing (MIMO-OFDM) system in mobility environment with the presence of Gaussian noise. The estimation of the time varying multipath fading channel is performed by using a nonlinear channel estimator based on a complex Multiple Support Vector Machines Regression (M-SVR) which is developed and applied to MIMO Long Term Evolution (LTE) Downlink with Alamouti coding. The obtained results confirm the effectiveness of the proposed technique to track the fading channel compared to the conventional Least Squares (LS), Minimum Mean Squares Error (MMSE) and Decision Feedback methods.

Keywords: *Complex M-SVR, MIMO, OFDM, Alamouti coding and LTE.*

1. Introduction

Multiple-Input Multiple-Output (MIMO) systems have attracted the interest of many researchers because of which have been proposed for increasing reliability of the wireless systems as well as communication capacity. Orthogonal Frequency Division Multiplexing (OFDM) technology avoids channel multipath effect by converting the wideband frequency selective channel into a set of narrow band flat subcarrier. The modulated symbol rate on each subcarrier is lower in comparison to the channel delay spread, thus the intersymbol interference (ISI) can be prevented. Therefore, the combination of MIMO and OFDM approaches (MIMO-OFDM) is an attractive technique for the wireless cellular systems especially over a fading channel.

In MIMO-OFDM systems, channel estimation task is very important to the coherent detection especially in the presence of Gaussian noise. Therefore, many channel estimation techniques have been proposed for MIMO-OFDM systems in the literature. The channel estimation technique used in this paper is based on the M-SVR (Multiple Support Vector Machine Regression) which training sequences are placed in the OFDM symbols to obtain the transmission environment parameters.

Indeed, the principle of the proposed nonlinear complex M-SVR algorithm is to exploit the information provided by the pilot signals to estimate the channel frequency response. Thus, the proposed algorithm is developed in terms of the RBF (Radial Basis Function) kernel and applied to LTE (Long Term Evolution) Downlink multipath fading channel.

Our objective in this work is to implement a MIMO-OFDM semi-blind channel estimator using complex M-SVR. Firstly, the method makes use of the reference symbols to estimate the channel impulse response. Then, the complex M-SVR technique is applied to track the time varying multipath channel for all data symbols.

This paper is organized as follows. We present a related work in section 2. Section 3 briefly introduces the MIMO-OFDM system. In section 4, a semi-blind MIMO-OFDM channel estimator based on the nonlinear complex M-SVR is provided. In section 5, we make some computer simulation results. Finally, section 6 concludes the paper.

2. Related Work

All the use of SVM has already been proposed to solve a variety of signal processing and digital communication problems, such that channel estimation by linear SVM in SISO-OFDM system which is presented in [1].

This study is specifically adapted to a pilot-based OFDM signal in a flat-fading channel and uses the block-type pilot structure. In this type, pilot tones are inserted into all

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subcarriers of pilot symbols with a period in time for channel estimation. This block-type pilot arrangement is suitable for slow fading channels. In fact, [1] consider a packet-based transmission, where each packet consists of a header at the beginning of the packet with a known training sequence or preamble to carry out channel estimation, followed by a certain number of OFDM data symbols. At the preamble, there are a number of OFDM symbols with a fixed number of pilot subcarriers in order to estimate the channel coefficients at pilot positions and then perform interpolation of the channel over all the OFDM symbols in the packet.

However, in time varying channels, block-type pilot arrangement is not efficient and comb-type pilot arrangement is suitable especially in mobility environments.

On the other hand, in [1], the channel's frequency response is estimated over a subset of pilot subcarriers and then interpolated over the remaining (data) subcarriers by using a DFT (Discrete Fourier Transform) based technique with zero padding in the time domain. Therefore, the learning process can be more complex if the size of the pilot symbols is large, so the estimation task becomes slow.

Our contribution focus on the nonlinear M-SVR applied to a MIMO-OFDM system with comb-type pilot structure under mobility conditions. Indeed, we use the indices of pilot positions (as input in training phase) to estimate the channel frequency responses at these pilot positions (as output in training phase), and then channel frequency responses at all subcarriers in each OFDM symbol for each pair of antennas can be obtained by SVM interpolation.

3. MIMO-OFDM System

3.1. MIMO-OFDM Model

In a MIMO-OFDM system, the output signal at each receive antenna Rx is a mixed signal consisting of the data streams coming from each transmit antenna Tx. Assuming that the cyclic prefix is longer than the channel response length, the receive signal at the j^{th} Rx antenna can be presented in the frequency domain as follows:

$$R_j[l,k] = \sum_{i=1}^{N_t} H_{i,j}[l,k]\, X_i[l,k] + W_j[l,k],$$
$$j = 1,\cdots,N_r,\ \ 0 \le k \le N-1, \tag{1}$$

Where $H_{i,j}[l,k]$ represents the channel frequency response corresponding to the k^{th} subcarrier at the l^{th} OFDM symbol transmitted between the i^{th} Tx antenna and the j^{th} Rx antenna. Let N, N_t and N_r denote the number of subcarriers, the number of Tx antennas and the number of Rx antennas, respectively. $X_i[l,k]$ denotes the data transmitted from the i^{th} Tx antenna at the l^{th} OFDM symbol on the k^{th} subcarrier. $W_j[l,k]$ is the Additive White Gaussian Noise (AWGN) at the j^{th} receiver antenna, with zero mean and variance σ_w^2 with power spectral density $N_0/_2$, and is assumed to be uncorrelated for different j's, k's and l's.

3.2. Channel Model

We consider the channel impulse response of the mobile wireless time varying multipath fading channel model which can be written as

$$h(\tau,t) = \sum_{q=0}^{L-1} h_q(t)\, \delta(t-\tau_q), \tag{2}$$

where $h_q(t)$ denotes the impulse response representing the complex attenuation of the q^{th} path, τ_q represents the random delay of the q^{th} path and L is the number of multipaths in the channel.

Since the mobile wireless channel is time variant, it is necessary to track the channel response continuously. The next section focus on the nonlinear complex M-SVR applied to a MIMO-OFDM architecture under mobility conditions with comb type pilot structure for multipath channel. The MIMO-OFDM system under consideration requires an estimate of the frequency responses of data subchannels for each OFDM symbol corresponding to each antenna. Therefore, the learning and estimation phases are repeated for all OFDM symbols in order to track the channel variation.

4. Nonlinear Complex M-SVR Estimator

We note first that the index i and j throughout this section denotes the i^{th} and j^{th} antenna at the transmitter and receiver side respectively of the considered MIMO system.

Let the OFDM frame contains Nl OFDM symbols which every symbol includes N subcarriers.

The transmitting pilot symbols for each transmitter antenna i are $\boldsymbol{X}_i^P = diag(X\,(l, m\,\Delta P)), m = 0,1,\cdots,N_P-1$, where l 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 [2].

The proposed channel estimation approach is based on nonlinear complex M-SVR algorithm which has two separate phases: learning phase and estimation phase.

In learning phase, we estimate first the subchannels pilot symbols according to Least Squares criterion to strike $min\ [(Y_j^P - \boldsymbol{X}_i^P\ \boldsymbol{F}h_{i,j})\,(Y_j^P - \boldsymbol{X}_i^P\ \boldsymbol{F}h_{i,j})^H]$ [3], as

$$\widehat{H}_{i,j}^P = \boldsymbol{X}_i^{P^{-1}}\, Y_j^P, \tag{3}$$

where $Y_j^P = Y_j\,(l, m\,\Delta P)$ and $\widehat{H}_{i,j}^P = \widehat{H}_{i,j}\,(l, m\,\Delta P)$ are the received pilot symbols and the estimated frequency responses for the l^{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

$$\widehat{H}_{i,j}(l,k) = f_{i,j}\left(\widehat{H}_{i,j}^P(l, m\,\Delta P)\right), \tag{4}$$

where $k = 0,\cdots,N-1$, and $f_{i,j}(\cdot)$ is the interpolating function, which is determined by the nonlinear complex M-SVR approach.

In mobility environments, where the fading channels present complicated nonlinearities, linear approaches cannot achieve high estimation precision. Therefore, we adapt here a nonlinear complex M-SVR method since SVM is superior in solving nonlinear, small samples and high dimensional pattern recognition [2]. Thus, we map the input vectors to a higher dimensional feature space $\mathcal{H}$ (possibly infinity) by means of nonlinear transformation $\boldsymbol{\varphi}$. So, the regularization term is referred to the regression vector in the Reproducing Kernel Hilbert Space (RKHS). The following regression function is then

$$\widehat{H}_{i,j}(m\,\Delta P) = \boldsymbol{w}_{i,j}^{\boldsymbol{H}}\boldsymbol{\varphi}_{i,j}(m\,\Delta P) + b_{i,j} + e_{i,j}^{m}, \quad m = 0,\cdots,N_P-1 \qquad (5)$$

where $\boldsymbol{w}_{i,j}$ is the weight vector, $b_{i,j}$ is the bias term and residuals $\{e_{i,j}^{m}\}$ 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 given by [5]

$$\mathcal{L}^{\varepsilon}\left(e_{i,j}^{m}\right) = \begin{cases} 0, & \left|e_{i,j}^{m}\right| \le \varepsilon \\ \dfrac{1}{2\gamma}\left(\left|e_{i,j}^{m}\right| - \varepsilon\right)^2, & \varepsilon \le \left|e_{i,j}^{m}\right| \le e_C \\ C\left(\left|e_{i,j}^{m}\right| - \varepsilon\right) - \dfrac{1}{2}\gamma C^2, & e_C \le \left|e_{i,j}^{m}\right|, \end{cases} \qquad (6)$$

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 $\mathcal{L}^{\varepsilon}\left(e_{i,j}^{m}\right) = \mathcal{L}^{\varepsilon}\left(\mathcal{R}\left(e_{i,j}^{m}\right)\right) + \mathcal{L}^{\varepsilon}\left(\Im\left(e_{i,j}^{m}\right)\right)$ since $\{e_{i,j}^{m}\}$ are complex, where $\mathcal{R}(\cdot)$ and $\Im(\cdot)$ represent real and imaginary parts, respectively.

Now, we can state the primal problem as minimizing

$$\frac{1}{2}\left\|\boldsymbol{w}_{i,j}\right\|^2 + \frac{1}{2\gamma}\sum_{m\in I_1}(\xi_{i,j}^{m} + \xi_{i,j}^{m\,*})^2 + C\sum_{m\in I_2}(\xi_{i,j}^{m} + \xi_{i,j}^{m\,*}) + \frac{1}{2\gamma}\sum_{m\in I_3}(\zeta_{i,j}^{m} + \zeta_{i,j}^{m\,*})^2 + C\sum_{m\in I_4}(\zeta_{i,j}^{m} + \zeta_{i,j}^{m\,*}) - \frac{1}{2}\sum_{m\in I_2,I_4}\gamma C^2 \qquad (7)$$

constrained to

$$\mathcal{R}\left(\widehat{H}_{i,j}(m\,\Delta P) - \boldsymbol{w}_{i,j}^{\boldsymbol{H}}\boldsymbol{\varphi}_{i,j}(m\,\Delta P) - b_{i,j}\right) \le \varepsilon + \xi_{i,j}^{m}$$
$$\Im\left(\widehat{H}_{i,j}(m\,\Delta P) - \boldsymbol{w}_{i,j}^{\boldsymbol{H}}\boldsymbol{\varphi}_{i,j}(m\,\Delta P) - b_{i,j}\right) \le \varepsilon + \zeta_{i,j}^{m}$$
$$\mathcal{R}\left(-\widehat{H}_{i,j}(m\,\Delta P) + \boldsymbol{w}_{i,j}^{\boldsymbol{H}}\boldsymbol{\varphi}_{i,j}(m\,\Delta P) + b_{i,j}\right) \le \varepsilon + \xi_{i,j}^{m\,*}$$
$$\Im\left(-\widehat{H}_{i,j}(m\,\Delta P) + \boldsymbol{w}_{i,j}^{\boldsymbol{H}}\boldsymbol{\varphi}_{i,j}(m\,\Delta P) + b_{i,j}\right) \le \varepsilon + \zeta_{i,j}^{m\,*}$$
$$\xi_{i,j}^{m\,(*)}, \zeta_{i,j}^{m\,(*)} \ge 0, \qquad (8)$$

for $m = 0,\cdots,N_P-1$, where $\xi_{i,j}^{m}$ and $\xi_{i,j}^{m\,*}$ are slack variables which stand for positive and negative errors in the real part, respectively. $\zeta_{i,j}^{m}$ and $\zeta_{i,j}^{m\,*}$ 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 (7) subject to constraints in (8), into the optimization of the dual functional, we must first introduce the constraints into the primal functional to obtain the primal-dual functional.

Then, by making zero the primal-dual functional gradient with respect to $\varpi_{i,j}$, we obtain an optimal solution for the weights

$$\boldsymbol{w}_{i,j} = \sum_{m=0}^{N_P-1}\psi_{i,j}^{m}\,\boldsymbol{\varphi}_{i,j}(m\,\Delta P) = \sum_{m=0}^{N_P-1}\psi_{i,j}^{m}\,\boldsymbol{\varphi}_{i,j}(P_m), \qquad (9)$$

where $\psi_{i,j}^{m} = (\alpha_{\mathcal{R},m,i,j} - \alpha_{\mathcal{R},m,i,j}^{*}) + j(\alpha_{I,m,i,j} - \alpha_{I,m,i,j}^{*}$ with $\alpha_{\mathcal{R},m,i,j}, \alpha_{\mathcal{R},m,i,j}^{*}, \alpha_{I,m,i,j}, \alpha_{I,m,i,j}^{*}$ are the Lagrange multipliers 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

$$\boldsymbol{G_{i,j}}(u,v) = <\boldsymbol{\varphi_{i,j}}(P_u), \boldsymbol{\varphi_{i,j}}(P_v)> = K_{i,j}(P_u,P_v), \qquad (10)$$

where $K_{i,j}(P_u,P_v)$ 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 $\boldsymbol{w}_{i,j}$ into the primal dual functional and grouping terms. Therefore, the dual problem consists of maximizing

$$-\frac{1}{2}\boldsymbol{\psi_{i,j}^{H}}\left(\boldsymbol{G_{i,j}} + \gamma\boldsymbol{I}\right)\boldsymbol{\psi_{i,j}} + \mathcal{R}\left(\boldsymbol{\psi_{i,j}^{H}}Y_j^p\right) - \left(\boldsymbol{\alpha_{\mathcal{R},i,j}} + \boldsymbol{\alpha_{\mathcal{R},i,j}^{*}} + \boldsymbol{\alpha_{I,i,j}} + \boldsymbol{\alpha_{I,i,j}^{*}}\right)\boldsymbol{1}\mathcal{E} \qquad (11)$$

constrained to

$$0 \le \alpha_{\mathcal{R},m,i,j}, \alpha_{\mathcal{R},m,i,j}^{*}, \alpha_{I,m,i,j}, \alpha_{I,m,i,j}^{*} \le C, \qquad (12)$$

where $\boldsymbol{\psi_{i,j}} = [\psi_{i,j}^{0},\cdots,\psi_{i,j}^{N_P-1}]^T$; $\mathbf{I}$ and $\mathbf{1}$ are the identity matrix and the all-ones column vector, respectively; $\boldsymbol{\alpha_{\mathcal{R},i,j}}$ is the vector which contains the corresponding dual variables, with the other subsets being similarly represented. The weight vector can be obtained by optimizing (11) with respect to $\alpha_{\mathcal{R},m,i,j}, \alpha_{\mathcal{R},m,i,j}^{*}, \alpha_{I,m,i,j}, \alpha_{I,m,i,j}^{*}$ and then substituting into (9).

Therefore, and after training phase, frequency responses at all subcarriers in each OFDM symbol for each pair of antenna (*i,j*) can be obtained by SVM interpolation

$$\widehat{H}_{i,j}(k) = \sum_{m=0}^{N_P-1} \psi_{i,j}^{m} K_{i,j}(P_m, k) + b_{i,j} \quad (13)$$

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].

5. Computer Simulations

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 presented in table 1. These parameters are defined by 3GPP standard [6].

Table 1. Extended Vehicular A model (EVA) [6].

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

.

In order to demonstrate the effectiveness of our proposed technique and evaluate the performance in the presence of AWGN noise under mobility condition, we used a varied range of signal-to-noise ratio (SNR). The SNR is given by [4]

$$SNR_{dB} = 10log_{10}\left(\frac{E\left\{\left|IDFT(R_j[l,k]) - IDFT(W_j[l,k])\right|^2\right\}}{\sigma_w^2}\right). \quad (22)$$

The complex M-SVR algorithm parameters are set as: $C = 100,\ \gamma = 10^{-5}, \mathcal{E} = .001$.

We simulate the MIMO-OFDM Downlink LTE system with parameters presented in table 2 with Alamouti coding.

The nonlinear complex M-SVR estimate a number of OFDM symbols in the range of 140 symbols per receive antenna, corresponding to one radio frame LTE. Note that, the LTE radio frame duration is 10 ms [7], which is divided into 10 subframes. Each subframe is further divided into two slots, each of 0.5 ms duration.

Note that, in the LTE system, when two or more transmitter antennas are applied, the pilot symbols are transmitted orthogonally in space. Indeed, this orthogonality in space is obtained by letting all other antennas be silent in the resource element in which one antenna transmits a pilot symbol [8].

Table 2. Parameters of simulations [7], [9] and [10].

Parameters	Specifications
Constellation	16-QAM
Mobile Speed (Km/h)	30
T_s (μs)	72
f_c (GHz)	2.15
δf (KHz)	15
B (MHz)	5
Size of DFT/IDFT	512
Number of paths	9

For the purpose of evaluation the performance of the nonlinear complex M-SVR algorithm under mobility conditions, we consider a scenario for Downlink LTE system with Alamouti coding for a mobile speed equal to 30 Km/h.

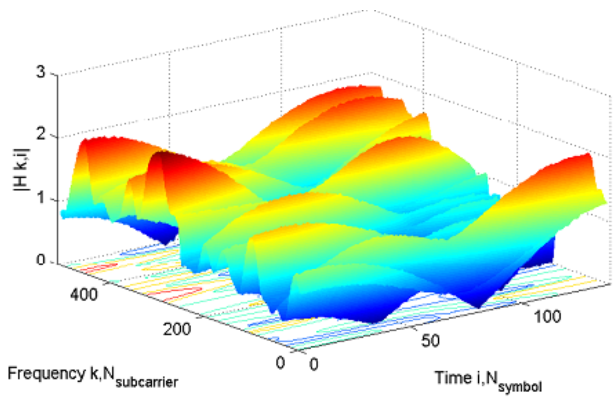

Fig. 1. Variations in time and in frequency of the channel frequency response for mobile speed = 30 Km/h.

Fig. 1 presents the variation in time and in frequency of the channel frequency response for $H_{11}[l,k]$ which is simulated at the given multipath channel parameters.

Fig. 2 presents the $H_{11}[l,k]$ channel response tracked by the proposed M-SVR method at SNR = 30 dB.

Indeed, Fig. 2 shows that the nonlinear channel response in their real and imaginary parts is well tracked by the proposed complex M-SVR technique under mobility conditions.

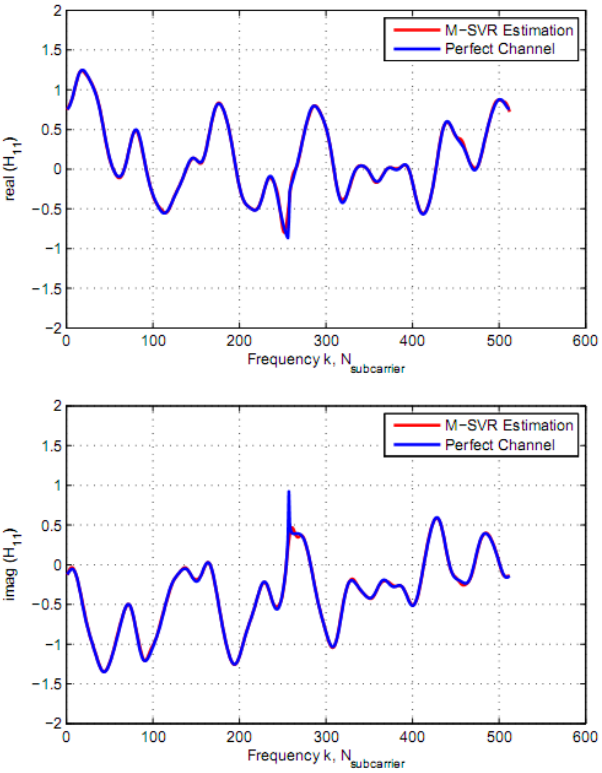

Fig. 2. An example of the proposed channel tracking and the time variant channel frequency response $H_{11}[l,k]$ simulated at SNR = 30 dB for mobile speed 30 Km/h.

Fig. 3 shows the performance of LS, MMSE, Decision Feedback and M-SVR estimation techniques with Alamouti coding for $(N_t = 2,\ N_r = 1)$ in the presence of AWGN noise for a mobile speed at 30 Km/h. A poor performance is noticeably exhibited by LS for all noise levels, and good performance is observed with complex M-SVR which outperforms also MMSE and Decision Feedback.

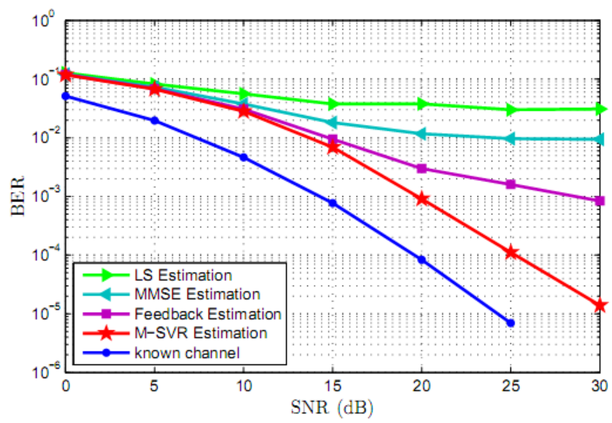

Fig. 3. BER as a function of SNR for a MIMO system with Alamouti (2×1) encoding scheme for a mobile speed at 30 Km/h.

Fig. 4 presents a comparison between LS, MMSE, Decision Feedback and complex M-SVR techniques for Alamouti coding with $(N_t = 2,\ N_r = 2)$. Fig. 4 confirms the results obtained in Fig. 3 for (2×1) Alamouti coding and shows that LS, MMSE and Decision Feedback suffer from a high BER, however, complex M-SVR performs better than other estimators in mobility condition for all SNR levels.

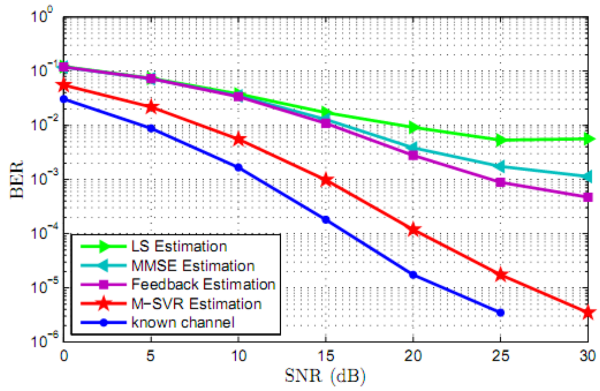

Fig. 4. BER performance of M-SVR with Alamouti (2×2) encoding scheme for a mobile speed at 30 Km/h.

Regarding the complexity of these estimators, LS is the least complex estimator because it contains only one matrix inversion operation. However, the Decision Feedback estimator contains two operations of matrix inversion and two operations of matrix multiplication, and the MMSE estimator suffers from high complexity, especially if matrix inversions are needed each time the data change. On the other hand, the M-SVR estimator uses quadratic programming (*quadprog* function in Optimization MATLAB Toolbox) with the functions *Buffer* and *kron* for fast computation of kernel matrix using the Kronecker product, and thus the algorithm becomes faster.

5. Conclusion

This paper describes a semi-blind MIMO-OFDM channel estimation algorithm based on the M-SVR method to compensate and estimate channel effect for the MIMO-OFDM communication system. Indeed, this paper adopts the nonlinear complex M-SVR based channel estimator for a Downlink MIMO-LTE system with (2×1) and (2×2) Alamouti coding in the presence of AWGN noise interfering with OFDM pilot symbols in mobility environment.

Our formulation is based on nonlinear complex M-SVR specifically developed for comb type pilot arrangement-based MIMO-OFDM system. The proposed method is based on training process that uses learning sequence to estimate the channel variations. Therefore, pilot symbols are inserted into different subcarriers at different antennas in order to increase the convergence rate and the estimation accuracy. Through experimentation, results have confirmed the capabilities of the proposed nonlinear complex M-SVR MIMO-OFDM estimator in the presence of Gaussian noise interfering with the pilot symbols when compared to LS, MMSE and Decision Feedback with Alamouti coding. The proposal takes into account the temporal-spectral relationship of the OFDM signal which is used in the SVM framework for a time varying multipath fading wireless mobile channel.

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