Performance Analysis of SVM-Type Per Tone Equalizer Using Blind and Radius Directed Algorithms for OFDM Systems

Babak Haji Bagher Naeeni*
Communication, Ph.D, Electrical Engineering, IRIB University
naeeni@iribu.ac.ir
Hamidreza Amindavar
Communication, Ph.D, Electrical Engineering, Amirkabir University of Technology
hamidami@aut.ac.ir

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Abstract

In this paper, we present Support Vector Machine (SVM)-based blind per tone equalization for OFDM systems. Blind per tone equalization using Constant Modulus Algorithm (CMA) and Multi-Modulus Algorithm (MMA) are used as the comparison benchmark. The SVM-based cost function utilizes a CMA-like error function and the solution is obtained by means of an Iterative Re-Weighted Least Squares Algorithm (IRWLS). Moreover, like CMA, the error function allows to extend the method to multilevel modulations. In this case, a dual mode algorithm is proposed. Dual mode equalization techniques are commonly used in communication systems working with multilevel signals. Practical blind algorithms for multilevel modulation are able to open the eye of the constellation, but they usually exhibit a high residual error. In a dual mode scheme, once the eye is opened by the blind algorithm, the system switches to another algorithm, which is able to obtain a lower residual error under a suitable initial ISI level. Simulation experiments show that the performance of blind per tone equalization using support vector machine has better than blind per tone equalization using CMA and MMA, from viewpoint of average Bit-Error Rate (BER).

Keywords: Constant Modulus Algorithm (CMA); Multi-Modulus Algorithm (MMA); Support Vector Machine (SVM); Orthogonal Frequency Division Multiplexing (OFDM).

1. Introduction

Orthogonal Frequency Division Multiplexing (OFDM) is a robust multi-carrier modulation technology that has been selected for a number of radio standards including Wireless LAN (IEEE 802.11a.g [1], HiperLAN/2[2]), DVB-T[3] and Wireless MAN (IEEE 802.16a [4]).

The first two standards are related to wireless home networking, while DVB-T and wireless MAN are concerned with digital video distribution and broadband wireless access, respectively. Among these, IEEE 802.11a, ERP-OFDM of IEEE 802.11g and HiperLAN/2 are standards for Wireless Local Area Net-works (WLAN) and they have similar physical layers based on the technology of OFDM. OFDM is a multicarrier modulation scheme that partitions a broadband channel into a number of parallel and independent narrowband sub channels. For the sub channels to be independent, the convolution of the signal and the channel must be a circular convolution. It is actually a linear convolution, so it is made to appear circular by adding a cyclic prefix (CP) to the start of each data block, which is obtained by prepending the last samples of each block to the beginning of the block. The conventional OFDM system employs a Guard Interval (GI) and a 1-tap Frequency-domain Equalizer (FEQ) to prevent delay spread distortions.

Provided that the GI is larger than the Channel Impulse Response (CIR), InterSymbol Interference (ISI) can be eliminated. Thus, the effect of delay spread is constrained to the frequency selective fading of the individual subband. This fading can easily be cancelled by the 1-tap FEQ. This scheme used by the conventional OFDM system is simple to implement, but provides low spectral efficiency due to the use of the GI. Moreover its performance is poor, due to the lack of multipath diversity and the energy loss contained within the GI. Also in the case where the CIR is larger than the GI, the system performance is limited by ISI and InterCarrier Interference (ICI). We adopt SVM approach for adaptive blind per tone equalization of OFDM channel. SVM is state-of-

* Corresponding Author

the-art tool for linear and nonlinear input-output knowledge discovery [5]. SVM methodology has been successfully utilized in many signal processing applications, especially, in channel equalization.

Recently, this framework has been used to formulate the blind equalization of constant modulus signals [6-8]. The remainder of this paper is organized as following. In section II, the system model is described. In section III, the blind per tone equalization problem is formulated. Section IV describes the channel model used and the simulation results. Some conclusions are provided in section V.

2. SYSTEM MODEL

In an OFDM system, the incoming serial bit-stream is divided into parallel streams, which are used to QAM-modulate the different tones. After modulation with an inverse fast Fourier transform (IFFT), a cyclic prefix is added to each symbol. If the prefix is longer than the channel impulse response, demodulation can be implemented by means of an FFT, followed by a (complex) 1-tap frequency- domain equalizer (FEQ) per tone to compensate for the channel amplitude and phase effects. If the CP is not as long as the channel delay spread, then inter-channel interference (ICI) and inter-symbol interference (ISI) will be presented, and a channel-shorting (time-domain) equalizer, or TEQ, is needed. The TEQ is chosen such that the convolution of the channel and TEQ has almost all of its energy in a time window no longer than the CP length. TEQ design (for a static environment) has been well explored, notably in [9]-[12]. Mathematically, the received signal vector y is obtained from the transmitted data X via

$$\overbrace{\begin{bmatrix} y_{ks+\nu-T+2} \\ \vdots \\ y_{(k+1)s} \end{bmatrix}}^{y} = \begin{bmatrix} 0_{(1)} & \begin{vmatrix} h & \dots & 0 \\ \ddots & \ddots & \ddots \\ 0 & \dots & h \end{vmatrix} & 0_{(2)} \end{bmatrix}$$

$$\begin{bmatrix} P\,Q_N & 0 & 0 \\ 0 & P\,Q_N & 0 \\ 0 & 0 & P\,Q_N \end{bmatrix} \overbrace{\begin{bmatrix} X_{1:N}^{(k-1)} \\ X_{1:N}^{(k)} \\ X_{1:N}^{(k+1)} \end{bmatrix}}^{X} + \overbrace{\begin{bmatrix} n_{ks+\nu-T+2} \\ \vdots \\ \vdots \\ n_{(k+1)s} \end{bmatrix}}^{n}$$

$$= \mathrm{H}X + n \qquad (1)$$

Where N is the symbol size expressed in samples, k the time index of a symbol, $\mathrm{x_i(k)}$ is a complex sub-symbol for tone i, i = 1, … . , N to be transmitted at symbol period K, $Y_i(k)$ the demodulated output for tone i (after the FFT) and $z_i(k)$ the final output (after frequency - domain equalization). Further, ν denotes the length of the cycle prefix, $s = N + \nu$ the length of a symbol including prefix. $\{h_l, \dots, h_0, \dots, h_{-k}\}$ the channel impulse response in reverse order and n is additive noise or interference. The $\odot$ represents a component wise multiplication. The effective channel H includes the physical channel h, the addition of the cyclic prefix (inserted by p), and the Q_N matrices are N×N IFFT matrices and modulate the input symbols and X contains the symbol of interest as well as the preceding and succeeding symbols. To describe the data model, we consider three successive symbols $X_{1:N}^{(c)}$ to be transmitted at $c = k-1, k, k+1$ respectively. The k th symbol is the symbol of interest; the previous and the next symbol are used to include interferences with neighboring symbols in our model. $0_{(1)}$ and $0_{(2)}$ are zero matrices of size $(N+T-1)\times(N+\nu-T+1-L+\nu)$ and $(N+T-1)\times(N+\nu-T+1-L+\nu)$ respectively. Perfect synchronization at the receiver is assumed in this paper. Van Acker et al. [13] have proposed an alternate equalization structure, called per tone equalization, which accomplishes the same task as the TEQ/FEQ, but with improved performance and comparable complexity. The full details of the per tone structure can be found in [13] briefly, demodulation is accomplished by an FFT of size N which is done by premultiplying y by F_N Per tone equalization of bin i is accomplished by forming a linear combination of the iFFT output and $T-1$ difference terms of the pre-FFT signal, y:

$$z_i = \bar{v}_i^T \underbrace{\left[\begin{array}{c|c|c} I_{T-1} & 0 & -I_{T-1} \\ \hline 0 & \multicolumn{2}{c}{F_N(i,:)} \end{array}\right]}_{F_i} y \qquad (2)$$

where $\bar{v}_i^T$, F_N an $N \times N$ FFT-matrix and $F_N(i,:)$ the i th row of F_N The linear combiner (not a tapped delay line) $\bar{v}_i$ is the time-reversal of ν_i defined for convenience; and z_i is the equalized data for tone i . The notation on (1) and (2) was introduced in [13], but is repeated here for reference. Determination of the per tone equalizer coefficients has been explored in [13] and [14]. In [13], the optimal coefficients are calculated in a least-squares manner, based on knowledge of the transmission channel, and the signal and noise statistics. In [14], the coefficients are determined in a less computationally-intensive fashion through the use of recursive least-squares (RLS), which requires training through out the adaptation. Imad Barhumi and Marc Moonen have been considered turbo equalization of doubly selective channels in [15].

These approaches are well-suited to a system that has plentiful training and computational power. In this paper, we propose a new method (support vector machine) for determination of the per tone equalizer coefficients and compare its performance with constant modulus algorithm (CMA) from view point of average BER.

In next section, we describe and formulate the multilevel SVM-based blind per tone equalization and CMA-based and MMA-based blind per tone equalization.

3. PROBLEM FORMULATION

3.1 Multilevel SVM-Based Blind Per Tone Equalization

In this section, we describe and formulate the multilevel SVM-based blind per tone equalization and CMA-based and MMA-based blind per tone equalization.

- Blind algorithm

The proposed algorithm [6,7,8] minimizes the following SVM-based cost function for tone i :

$$L_p(\bar{v}_i) = \frac{1}{2}\|\bar{v}_i\|^2 + c\sum_{k=1}^{M} L_\varepsilon(u_i(k)) \quad (3)$$

Where

$$L_\varepsilon(u_i) = \begin{cases} 0, & u_i < \varepsilon \\ u_i^2 - 2u_i\varepsilon + \varepsilon^2, & u_i \geq \varepsilon \end{cases} \quad (4)$$

is a $\boldsymbol{\varepsilon}$-insensitive quadratic loss function modified to guarantee a continuous derivative. Continuity of the derivative is necessary for the numerical stability of the algorithm. We select a suitable penalization term called $u_i(k)$ in order to apply aforementioned cost function for blind equalization. Here, we propose to use $u_i(k) = |e_i(k)|$ with the error term $e_i(k)$ being

$$z_i(k) = \bar{v}_i^{\,T} F_i y(k) \quad (5)$$

and

$$e_i(k) = |z_i(k)|^2 - R_{2,i} = z_i(k) z_i^*(k) - R_{2,i} \quad (6)$$

$R_{2,i}$ is the Godard constant, for tone i and superindex * denotes the complex conjugate. The Godard algorithms [16] adapt the equalizer to minimize the following cost function

$$j_G(\bar{v}_i) = E\left[(|z_i(k)|^p - R_{p,i})^2\right] \quad (7)$$

the ratio $R_{P,i}$ contains the a priori knowledge about the current modulation

$$R_{p,i} = \frac{E[|X_i|^{2p}]}{E[|X_i|^p]} \quad (8)$$

CMA is the Godard algorithm for $p = 2$. The proposed method introduces a penalty term inspired by the CMA cost function. For optimality reasons, IRWLS is used. This procedure has been successfully applied to solve SVM's [17] and it has recently proven to converge to the SVM solution [18]. A first order Taylor series expansion of $L_\varepsilon(u_i)$ is used to obtain the cost function that produces the IRWLS algorithm

$$L'_p(\bar{v}_i) = \frac{1}{2}\|\bar{v}_i\|^2 + C\left[\sum_{k=1}^{M} L_\varepsilon(u_i(j,k)) + \left.\frac{dL_\varepsilon(u_i)}{du_i}\right|_{u_i(j,k)} [u_i(k) - u_i(j,k)]\right] \quad (9)$$

where $u_i(j,k) = |e_i(j,k)|$ and $e_i(j,k) = \left|\bar{v}_j^T(j,k) F_i y(k)\right|$ - $R_{2,i}$ error term after the $j-th$ iteration. Then, a quadratic approximation is constructed as following.

$$L''_p(\bar{v}_i) = \frac{1}{2}\|\bar{v}_i\|^2 + C\left[\sum_{k=1}^{M} L_\varepsilon(u_i(j,k)) + \left.\frac{dL_\varepsilon(u_i)}{du_i}\right|_{u_i(j,k)} \frac{(u_i(k))^2 - (u_i(j,k))^2}{2u_i(j,k)}\right]$$

$$= \frac{1}{2}\|\bar{v}_i\|^2 + \frac{1}{2}\left[\sum_{k=1}^{M} \alpha_i(k)|e_i(k)|^2 + CTE\right] \quad (10)$$

CTE represents constant terms that do not depend on

$\bar{v}_i$, and the weights $a_i(k)$ are

$$\alpha_i(k) = \frac{C}{u_i(j,k)} \left.\frac{dL_\varepsilon(u_i)}{du_i}\right|_{u_i(j,k)} \quad (11)$$

$$= \begin{cases} 0, & u_i(j,k) < \varepsilon \\ \frac{2C(u_i(j,k)-\varepsilon)}{u_i(j,k)}, & u_i(j,k) \geq \varepsilon \end{cases} \quad (12)$$

$L''_P(\bar{v}_i)$ is a quadratic functional for $L_P(\bar{v}_i)$ in (3) that presents the same value $L''_P(\bar{v}_i(j)) = L_P(\bar{v}_i(j))$ and gradient for $\nabla_{\bar{v}_i} L''_P(\bar{v}_i(j)) = \nabla_{\bar{v}_i} L_P(\bar{v}_i(j))$ for $\bar{v}_i = \bar{v}_i(j)$. Therefore, we can define $\bar{p}_i(j) = \bar{v}_i(s) - \bar{v}_i(j)$ as a descending direction for $L_P(\bar{v}_i)$, where $\bar{v}_i(s)$ is the least square solution to (10), and we can use it to construct a line search method [19], $i.e.$ $\bar{v}_i(j+1) = \bar{v}_i(j) + \eta_i(j)\ p_i(j)$. The value to $\eta_i(j)$ can be computed using a backtracking line search [18], in which $\eta_i(j)$ is initially set to 1 and if $L_P(\bar{v}_i(j+1)) \geq L_P(\bar{v}_i(j))$, it is iteratively reduced until a strict decrease in the functional in (3) is observed. To obtain the solution to $L''_P(\bar{v}_i)$, its gradient is set to zero

$$\nabla_{\bar{v}_i} L''_p(\bar{v}_i) = \bar{v}_i + 2\sum_{k=1}^{M} \alpha_i(k)\left(|\lambda_i|^2 - R_{2,i}\right)\xi_i = 0 \quad (13)$$

where $\lambda_i = \bar{v}_i^T F_i y(k)$ and $\xi_{i=}\bar{v}_i^T F_i y(k) F_i^* y^*(k)$. Equation (13) is a nonlinear function of $\bar{v}_i$. In order to circumvent this nonlinearity, the per tone equalizer output $z_i(k)$ is considered fixed, which leads to

$$\nabla_{\bar{v}_i} L_p''(\bar{v}_i) = \bar{v}_i + 2\sum_{k=1}^{M} \alpha_i(k)(\beta_i - R_{2,i})\xi_i = 0 \quad (14)$$

where $\beta_{i=}\bar{v}_i^T F_i y(k) z_i^*(k)$ and $\zeta_{i=} z_i(k) F_i^* y^*(k)$, (14) can be expressed in matrix form as

$$[2X_i^H D_{\alpha,i} D_{|z|^2,i} X_i + I]\bar{v}_i = 2R_{2,i} X_i^H D_{\alpha,i} Z_i \quad (15)$$

where $X_i^T = [F_i y(1), F_i y(2), \ldots, F_i y(M)]$, $D_{\alpha,i}$ is a diagonal matrix with diagonal elements $a_i(k)$ and $D_{|z|^2,i}$ is another diagonal matrix with diagonal elements $|z_i(k)|^2$ and $z_i^T = [z_i(1), z_i(2), \ldots, z_i(M)]$ for k=*1,2,…,M*, I is the identity matrix, and H denotes the Hermitian operator.

Implementation Details: With respect to parameters C and $\boldsymbol{\varepsilon}$, although further research is necessary to determine their optimal values, but the algorithm is not very sensitive to its choice. Typically, values of $C = 10$ and $\boldsymbol{\varepsilon}$ =0.01 produce suitable results under a wide range of channels and signal to noise ratios.

Consideration: $e_i(j,k)$ denotes the error for tone i after *j-th* iteration for $k = 1,2,\ldots,M$. In $e_i(j,k)$ =$|\bar{v}_i^T(j) F_i y(k|^2$-$R_{2,i}$ for tone i, $(i = 1,2,\ldots,N)$, amounts of $y(k)$, $(k = 1,2,\ldots,M)$ are constant for each of iterations, $(j = 1,2,\ldots,J)$ and for one realization of channel and amounts of $y(k)$ change with changing the tap coefficients of the channel (another realization of channel). For example: for tone i, after computing $\bar{v}_i^T(1)$ in 1-th iteration, we have $e_i(1,1) = |\bar{v}_j^T(1) F_i y(1)| - R_{2,i}$, $e_i(1,2) = |\bar{v}_j^T(1) F_i y(2)|$-$R_{2,i}$,…., $e_i(1,M) = |\bar{v}_j^T(1) F_i y(M)|$-$R_{2,i}$. amounts of $y(k)$ for $k = 1,2,\ldots,M$are constant for other iterations until complete convergence and change with changing the tap coefficients of the channel and this method repeats for one thousand realization of channel.

Finally, the IRWLS procedure is summarized in the following steps:

1. Initialization: initialize $\bar{v}_i(1)$, obtain $z_i(k)$ by (5), $e_i(k)$ by (6), calculate $u_i(k) = e_i(k)$ and compute $a_i(k)$ from (11). Set $j = 1$.
2. Compute $\bar{v}_i(s)$ by solving (15) and set $\eta_i(j) = 1$.
3. Set $\bar{v}_i(j+1)$=$\bar{v}_i(j) + \eta_i(j)[\bar{v}_i(s) - \bar{v}_i(j)]$. If $L_P(\bar{v}_i(j+1)) < L_P(\bar{v}_i(j))$ go to step 5.
4. Set $\eta_i(j)$=$\boldsymbol{\rho}\,\eta_i(j)$ with $0<\rho<1$ and go to step 3.
5. Recompute $e_i(k), u_i(k)$ and $a_i(k)$, set $j = j + 1$ and go to step 2 until convergence.

Radius directed algorithm: The radius directed algorithm is formulated by replacing $R_{2,i}$ in the blind algorithm by the radius $R_{m,i}(k)$, which is defined as
$R_{m,i}(k) = min_{R_{m,i}}(\left||z_i(k)|^2 - R_{m,i}\right|)$

here, $R_{m,i}(k)$, are the different values of $|X_i|^2$ in the underlying signal constellation. For instance, for a 16-QAM with levels $\pm 3, \pm 1$ in both the phase and quadrature components, $R_{m,i} = 2,10,18$. With this simple modification, the error term to be penalized is

$$e_i(k) = |z_i(k)|^2 - R_{m,i}(k) \quad (16)$$

and the matrix system to obtain the solution $\bar{v}_i(s)$ becomes

$$[2X_i^H D_{\alpha,i} D_{|z|^2,i} X_i + I]\bar{v}_i = 2X_i^H D_{\alpha,i} D_{R,i} Z_i \quad (17)$$

$D_{R,i}(i)$, is a diagonal matrix with diagonal elements $R_{m,i}(k)$. The corresponding IRWLS algorithm is the same one summarized in blind algorithm with the following differences:

- Step 1: Since this algorithm is used as the second step of a dual mode algorithm, $\bar{v}_i(1)$ is the value of $\bar{v}_i$ provided by the blind algorithm.
- Steps 1 and 5: $e_i(k)$ is evaluated by (17), instead of (6).
- Step 2: $\bar{v}_i(s)$ is obtained by solving (18), instead of (15).

3.2 CMA-based blind adaptive per tone equalization

The constant modulus algorithm is a popular alternative in decision-directed algorithms. A detailed review of its convergence behaviour in single-carrier systems can be found in [20]. CMA attempts to minimize the dispersion of the equalized symbols by performing a stochastic gradient descent of

$$J_{CM,i} = E[(|z_i(k)|^2 - \gamma_i)^2] \quad (18)$$

for each bin i, where $z_i(k)$ is the per tone equalizer output and $\gamma_{i=E[|X_i|^4]/E[|X_i|^2]}$. The resulting algorithm; i.e., CMA-based blind adaptive per tone equalization, for $i = 1,\ldots,N$ and $k = 1,2,3,\ldots$, is

$$z_i(k) = \bar{v}_i^T(k) F_i y(k)$$
$$\bar{v}_i(k+1) = \bar{v}_i(k) - \mu z_i(k)(|z_i(k)|^2 - \gamma_i) F_i^* y^*(k) \quad (19)$$

C. MMA-based blind adaptive per tone equalization

Oh and chin [21], and Yang et al. [22] proposed a modified CMA called the multimodulus algorithm (MMA), whose cost function is

$$\mathcal{J}_{MMA,i} = \mathcal{J}_{R,i} + \mathcal{J}_{I,i} + E\left[\left(z_{R,i}^2(k) - \gamma_{R,i}\right)^2\right] + E\left[\left(z_{I,i}^2(k) - \gamma_{I,i}\right)^2\right] \qquad (20)$$

for each bin i, where $z_{R,i}(k)$ and $z_{I,i}(k)$ are the real and imaginary parts of the per tone equalizer output, respectively; $\gamma_{R,i}$ and $\gamma_{I,i}$ are given by

$$\gamma_{R,i} = \frac{E[X_{R,i}^4]}{E[X_{R,i}^2]} \quad and \quad \gamma_{I,i} = \frac{E[X_{I,i}^4]}{E[X_{I,i}^2]} \qquad (21)$$

in which $X_{R,i}(k)$ and $X_{I,i}(k)$ denote the real and imaginary parts of X_i respectively. Decomposing the cost function of MMA into the real and imaginary parts, thus allows both the modulus and the phase of the per tone equalizer output to be considered; therefore, joint blind per tone equalization and carrier-phase recovery may be simultaneously accomplished, eliminating the need for a rotator to perform separate constellation-phase recovery in steady-state operation. The resulting algorithm; i.e., MMA-based blind adaptive per tone equalization, for $i = 1, \dots, N$ and $k = 1, 2, 3, \dots$, is

$$z_i(k) = \overline{v}_i^T(k) F_i y(k)$$
$$\overline{v}_i(k+1) = \overline{v}_i(k) - \mu e_i(k) F_i^* y^*(k) \qquad (22)$$

where $e_i(k) = e_{R,i}(k) + j e_{I,i}(k)$, in which $e_{R,i}(k) = z_{R,i}(k)(z^2{}_{R,i}(k) - \gamma_{R,i})$ and $e_{I,i}(k) = z_{I,i}(k)(z^2{}_{I,i}(k) - \gamma_{I,i})$.

4. Channel model and simulation results

A multipath fading channel in [23] with $L = J-1)L_1 + L_2$ taps is used based on the following impulse response model

$$h(l) = \sum_{j=0}^{J-1} e^{-\beta_1 j} \sum_{m=jL_1}^{j L_1 + L_2 - 1} \alpha_m e^{-\beta_2(m - jL_1)} \delta(l-m) \quad (23)$$

where a_m is a zero mean complex, circularly symmetric, Gaussian random process such that $E[a_m a_j^*] = \delta(m-j,$ β_1 and β_2 are exponential decay factors. In simulations, $J = 3, L_1 = L_2 = 7$ for L=21 and $J = 4, L_1 = L_2 = 6$ for $L = 24, = 0$, and $\beta_1 = 0$ $\beta_{2=}0.25$ are chosen. The CIR intervals are $L = 21$ and $L = 24$ which are longer than the CP interval and the additive Gaussian noise, $n(k)$, is a white process. One thousand independent realizations of $h\,(l)$ based on (23) have been used in simulations for a 16-QAM and 64-QAM OFDM systems with $N = 64$ subcarriers and a CP interval $\upsilon = 16$ Number of taps for per tone equalization is $T = \nu + 1$. A burst of 2500 OFDM symbols is assumed to be transmitted ($M = 2500$). Hence the CIR is assumed constant for each burst. Each data point in the simulation results (Figures1, 2 and 3) is obtained by averaging over 1000 such bursts. Without loss of generality, 16-QAM and 64-QAM mapping for all sub channels has been employed and all sub channels are used.

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5. Conclusion

In this paper, we proposed a new blind OFDM channel equalization method based on SVM for multilevel signals. In order to determine the equalizer coefficients, we used the difference of the per tone equalizer output and the $R_{2,i}$ parameter of the CMA algorithm. Our simulations showed that the average BER for per tone equalization using blind-SVM was better than per tone equalization using CMA and MMA for 16-QAM.

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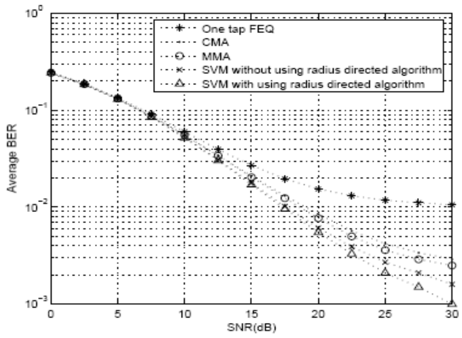

Fig.1 The average bit-error rate as a function of SNR, CIR interval is L=21, 16-QAM

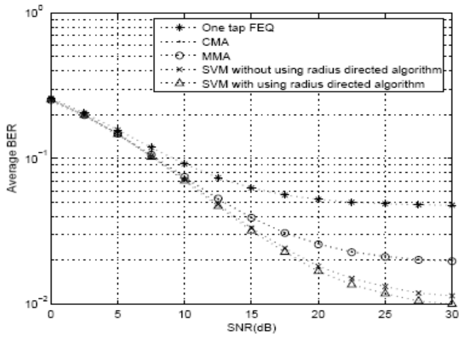

Fig.2 The average bit-error rate as a function of SNR, CIR interval is L=24, 16-QAM

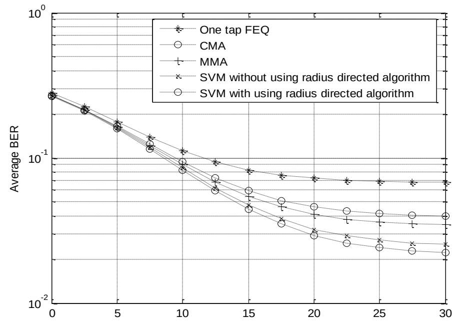

Fig.3 The average bit-error rate as a function of SNR, CIR interval is L=21,64-QAM