BLIND SYMBOL DETECTION FOR MULTIPLE-INPUT MULTIPLE-OUTPUT SYSTEMS VIA PARTICLE FILTERING

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ABSTRACT

A novel blind symbol detection algorithm is proposed for time-selective fading multiple-input-multiple-output (MIMO) systems, whose every channel is described as a second-order autoregressive (AR) model. This algorithm employs the particle filter as the demodulator stage in turbo receivers because the particle filter has the nature characteristics of soft-input soft-output. Moreover, the particle filter has the advantage of parallel computation. Computer simulation results demonstrate the performance of the proposed algorithm.

1. INTRODUCTION

Recently, multiple-input-multiple-output (MIMO) systems received much attention because of its significant boost in performance for high data-rate wireless communications. Its blind symbol detection and equalization also arise in a wide variety of communication and signal processing applications. Among various blind algorithms, what based on the particle filter [1] are very particular for they can be computed in parallel and acted as the channel demodulator in a turbo receiver for their natural soft-input soft-output (SISO) characteristics.

Among the proposed particle filtering algorithm for the wireless communications, [2] applied the particle filter (sequential Monte Carlo, SMC) into the turbo receiver, achieving the good performance. But [2] only considered that the channel was slow-fading, i.e., time-invariant. [3][4] proposed the particle filter in time-selective fading modeled by wavelet bases or the AR model, respectively. Nevertheless, those two methods only considered single-input single-output systems.

In this paper, a novel particle filter is proposed for time-selective MIMO systems, and it acts as a stage in the turbo receiver. Every channel fading is described as a second-order AR model, which can elegantly describe the time-selective fading. Computer simulation results verify and validate the proposed blind symbol detection algorithm.

2. SYSTEM MODEL

Consider an MIMO system with N transmit and M receive antennas. The transmitted symbols are encoded by the vertical Bell Lab's space-time (VBLAST) code scheme. The symbols are assumed to be independent both in time and space, and they belong to a finite alphabet set $\mathcal{B} = \{b_1, \ldots, b_{|B|}\}$. On the m-th receive antenna, the received signal at time t can be written as

$$y_{m,t} = \sum_{n=1}^{N} h_{m,n,t} s_{n,t} + u_{m,t} \tag{1}$$

where $h_{m,n,t}$ is the complex fading coefficient between the m-th receive antenna and the n-th transmit one; $s_{n,t}$ is the transmitted symbol from transmit antenna n at time t; $u_{m,t}$ is the additive white Gaussian noise (AWGN), and $u_{m,t} \sim \mathcal{CN}(0, \sigma_u^2)$.

According to [4], the time-selective channel between the m-th receive antenna and the n-th transmit one can be modeled as a second AR process such that

$$h_{m,n,t} = -\alpha_{1,m,n} h_{m,n,t-1} - \alpha_{2,m,n} h_{m,n,t-1} + v_{m,n,t} \tag{2}$$

where $v_{m,t} \sim \mathcal{CN}(0, \sigma_v^2)$ and $\alpha_{1,m,n}$ and $\alpha_{2,m,n}$ are the known model coefficients which can be determined by fitting the auto correlation function [5]; or by the physical characteristics of the channel [6].

(2) can be rewritten in the matrix-vector form

$$\mathbf{H}_{m,t} = \mathbf{D}\mathbf{H}_{m,t-1} + \mathbf{g}\mathbf{V}_{m,t} \tag{3}$$

where $\mathbf{H}_{m,t} = (h_{m,1,t}, \ldots, h_{m,N,t}, h_{m,1,t-1} \ldots, h_{m,N,t-1})^T$ with size $2N \times 1$; $\mathbf{g} = (\mathbf{I}_{N\times N} \quad \mathbf{0})^T$ with size $2N \times N$; $\mathbf{V}_{m,t} = (v_{m,1,t}, \ldots, v_{m,N,t})^T$ with size $N \times 1$, and

$$\mathbf{D} = \begin{pmatrix} \mathbf{D}_1 & \mathbf{D}_2 \\ \mathbf{0} & \mathbf{I}_{N\times N} \end{pmatrix}$$

with dimensions $2N\times 2N$, $\mathbf{D}_1 = \mathrm{diag}\{-\alpha_{1,m,1}, \ldots, -\alpha_{1,m,N}\}$, and $\mathbf{D}_2 = \mathrm{diag}\{-\alpha_{2,m,1}, \ldots, -\alpha_{2,m,N}\}$.

Also, (1) can be rewritten as

$$y_{m,t} = \mathbf{s}_t \mathbf{g}^T \mathbf{H}_{m,t} + u_{m,t} \tag{4}$$

* Partially supported by the National Natural Science Foundation (No. 60272071) and the Research Fund for Doctoral Program of Higher Education (No. 20020698024) of China.

where $\mathbf{s}_t = (s_{1,t}, \ldots, s_{N,t})$ with dimensions $1 \times N$ represents the transmitted symbols at time t.

3. PARTICLE FILTERING

3.1. General framework

A general framework for the particle filter is briefly explained as follows: Consider a dynamic system described as the following state-space form

$$\begin{aligned} \text{state equation:} \quad & \mathbf{z}_t = f_t(\mathbf{z}_{t-1}, \mathbf{v}_t) \\ \text{observation equation:} \quad & \mathbf{y}_t = g_t(\mathbf{z}_t, \mathbf{u}_t) \end{aligned} \tag{5}$$

where $\mathbf{z}_t$, $\mathbf{y}_t$, $\mathbf{u}_t$, and $\mathbf{v}_t$ are the state variable, the observation, the state noise and the observation noise at time t, respectively. Now let $\mathbf{Z}_t = (\mathbf{z}_0, \ldots, \mathbf{z}_t)$ and $\mathbf{Y}_t = (\mathbf{y}_0, \ldots, \mathbf{y}_t)$. Our object is to estimate $\mathbf{Z}_t$ sequentially from the observation $\mathbf{Y}_t$. Based on the Bayes theorem, the *a posteriori* probability density function (PDF) $p(\mathbf{z}_t|\mathbf{Y}_t)$ is the key entity of the optimal solution. However, this PDF may be difficult to obtain and the followed calculation could be intractably complex. To solve it, the true *a posteriori* PDF can be approximated as discrete weighted values. According to [7], we have

$$P(\mathbf{Z}_t|\mathbf{Y}_t) \approx \sum_{j=1}^{J} w_k^{(j)} \delta(\mathbf{Z}_t - \mathbf{Z}_t^{(j)}) \tag{6}$$

where $\{\mathbf{Z}_t^{(j)}, w_t^{(j)}\}$ is a random measure of the *a posteriori* PDF $p(\mathbf{Z}_t|\mathbf{Y}_t)$, $\{\mathbf{Z}_t^{(j)}\}$ is a set of support points, $w_t^{(j)}$ are the samples of $p(\mathbf{Z}_t|\mathbf{Y}_t)$, and chosen according to the principle of *importance sampling* and normalized such that $\sum_j w_t^{(j)} = 1$.

However, direct sampling from $p(\mathbf{Z}_t|\mathbf{Y}_t)$ is often not available because this distribution is usually difficult to obtain. To circumvent this, we can substitute the *a posteriori* PDF by a new proposal density $q(\mathbf{Z}_t|\mathbf{Y}_t)$ to make samples generated easily. $q(\cdot)$ is also called *importance density*. Then, the new weights can be calculated as

$$w_k^{(j)} \propto \frac{p(\mathbf{Z}_t^{(j)}|\mathbf{Y}_t)}{q(\mathbf{Z}_t^{(j)}|\mathbf{Y}_t)}$$

After using the suitable importance density, the particle filtering can be implemented sequentially [7]. Generally, the particle filter can be illustrated as follows.

Suppose that at time $t-1$, we have obtained J sets of properly weights samples $\mathbf{Z}_{t-1}^{(j)}$ and their associated weights $w_{t-1}^{(j)}$. When the new observation $\mathbf{y}_t$ arrives, the update of the sample sets from $t-1$ to t is as follows.

For $j = 1, \ldots, J$

. Draw a sample $\mathbf{Z}_t^{(j)}$ from the importance density $q(\mathbf{z}_t|\mathbf{Z}_{t-1}^{(j)}, \mathbf{Y}_t)$ and set $\mathbf{Z}_t^{(j)} = \{\mathbf{Z}_{t-1}^{(j)}, \mathbf{z}_t^{(j)}\}$.

. Calculate the importance weight by

$$\tilde{w}_t^{(j)} = w_{t-1}^{(j)} \frac{p(\mathbf{Z}_t^{(j)}|\mathbf{Y}_t)}{p(\mathbf{Z}_t^{(j)}|\mathbf{Y}_t) q(\mathbf{z}_t|\mathbf{Z}_{t-1}^{(j)}, \mathbf{Y}_t)}$$

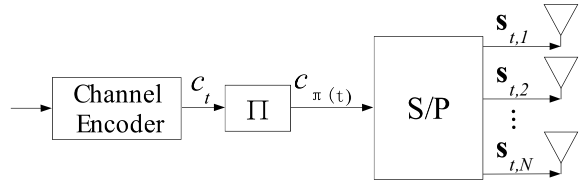

Fig. 1 Transmitter

. Normalize the weight $w_t^{(j)} = \tilde{w}_t^{(j)} / \sum_{j=1}^{J} \tilde{w}_t^{(j)}$.

The choice of the important density is *really* important. From [7] we know, the bad choice will lead to the degeneracy phenomenon [7], i.e., all the weights but one of the particles are near zero after a few iterations, implying that it costs a large computational effort to update particles whose contribution to the *a posteriori* PDF $p(\mathbf{z}_t|\mathbf{Y}_t)$ is almost zero. On the contrary, good choice can minimize the variance of the weights. And then, more effective samples are generated and the better estimation is achieved.

According to [4][7], the optimal importance density is the *a posteriori* importance density, defined as $q(\mathbf{z}_t|\mathbf{Z}_{t-1}^{(j)}, \mathbf{Y}_t) \triangleq p(\mathbf{z}_t|\mathbf{Z}_{t-1}^{(j)}, \mathbf{Y}_t)$. Nevertheless, the direct use of the optimal importance density is impossible except two cases [7]: 1) $\mathbf{z}_t$ is a member of finite set, or 2) $p(\mathbf{z}_t|\mathbf{Z}_{t-1}^{(j)}, \mathbf{Y}_t)$ is Gaussian. Luckily, all the two conditions are satisfied in our problem. Therefore, the *a posteriori* importance density is our choice. And the associated importance weights are calculated as

$$w_t^{(j)} \propto w_{t-1}^{(j)} p(\mathbf{Z}_t|\mathbf{Y}_{t-1}^{(j)}, \mathbf{Z}_{t-1}) \tag{7}$$

3.2. Application in our scheme

Consider the MIMO system described in section 2. Denote $\mathbf{S}_t \triangleq \{\mathbf{s}_0, \ldots, \mathbf{s}_t\}$ and $\mathbf{Y}_t \triangleq \{\mathbf{y}_0, \ldots, \mathbf{y}_t\}$, where $\mathbf{y}_t = (y_{1,t}, \ldots, y_{M,t})$ is the whole received signal vector at time t, and $\mathbf{Y}_{m,t} \triangleq \{y_{m,0}, \ldots, y_{m,t}\}$. According to (3)(4), the state variable here is $\mathbf{s}_t$, and the importance density is chosen as the *a posteriori* importance density

$$q(\mathbf{s}_t^{(j)}|\mathbf{S}_t^{(j-1)}, \mathbf{Y}_t) \triangleq p(\mathbf{s}_t^{(j)}|\mathbf{S}_t^{(j-1)}, \mathbf{Y}_t) \tag{8}$$

where $\mathbf{s}_t^{(j)}$ is a sample drawn by the particle filter at time t.

And we have

$$\begin{aligned} p(\mathbf{s}_t^{(j)} = \mathbf{b}_i|\mathbf{S}_t^{(j-1)}, \mathbf{Y}_t) &\propto p(\mathbf{y}_t|\mathbf{S}_{t-1}^{(j)}, \mathbf{Y}_{t-1}, \mathbf{s}_t = \mathbf{b}_i) \\ &= \prod_{m=1}^{M} p(y_{m,t}|\mathbf{S}_{t-1}^{(j)}, \mathbf{s}_t = \mathbf{b}_i, \mathbf{Y}_{m,t-1}) p(\mathbf{s}_t = \mathbf{b}_i|\mathbf{S}_{t-1}^{(j)}, \mathbf{Y}_{t-1}) \\ &\triangleq a_{t,i}^{(j)} \end{aligned} \tag{9}$$

where $\mathbf{b}_i \in \mathcal{B}^N$.

Then, the importance weight can be calculated as

$$\begin{aligned} w_t^{(j)} &\propto w_{t-1}^{(j)} p(\mathbf{Y}_t|\mathbf{S}_{t-1}^{(j)}, \mathbf{Y}_{t-1}) \\ &= w_{t-1}^{(j)} \sum_{\mathbf{b}_i \in \mathcal{B}^N} p(\mathbf{y}_t|\mathbf{S}_{t-1}^{(j)}, \mathbf{Y}_{t-1}, \mathbf{s}_t = \mathbf{b}_i) \\ &= w_{t-1}^{(j)} \sum_{\mathbf{b}_i \in \mathcal{B}^N} a_{t,i}^{(j)} \end{aligned} \tag{10}$$

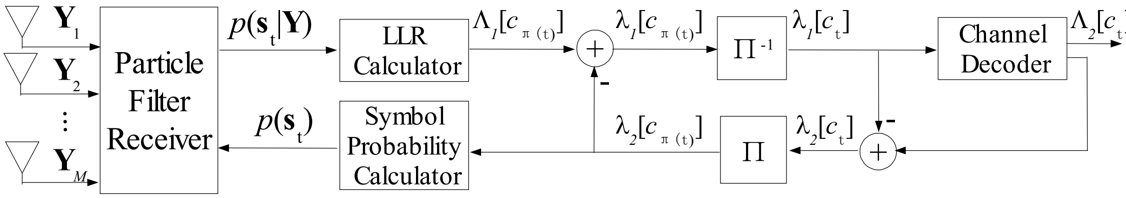

Fig. 2 Turbo receiver of RSC codes

Both (9) and (10) require computing $p(y_{m,t}|\mathbf{S}_{t-1}^{(j)}, \mathbf{s}_t = \mathbf{b}_i, \mathbf{Y}_{m,t-1})$, which is the likelihood function after marginalizing out $\mathbf{H}_{m,t}$, and can be obtained from the predictive procedure of the Kalman filter as

$$p(y_{m,t}|\mathbf{S}_{t-1}^{(j)}, \mathbf{s}_t = \mathbf{b}_i, \mathbf{Y}_{m,t-1}) \sim \mathcal{N}(\mu_t^{(j)}, \Sigma_t^{(j)})$$

where

$$\begin{aligned} \mu_t^{(j)} &= \mathbf{s}_t \mathbf{g}^T \mathbf{D} \mu_{t-1}^{(j)} \\ \Sigma_t^{(j)} &= \mathbf{s}_t \mathbf{g}^T \Xi_t^{(j)} \mathbf{g} \mathbf{s}_t^T + \sigma_u^2 \end{aligned}$$

where $\Xi_t^{(j)}$ is the covariance of the channel matrix $\mathbf{H}_{m,t}^{(j)}$.

Also, $\mathbf{H}_{m,t}^{(j)}$ denotes the sample of the m-th channel matrix at time t, which can be calculated by the Kalman filter

$$\mathbf{H}_{m,t}^{(j)} = \mathbf{D}\mathbf{H}_{m,t}^{(j-1)} + \mathbf{K}_t^{(j)}(y_{m,t} - \mu_t^{(j)}) \quad (11)$$

$$\mathbf{K}_t^{(j)} = \Xi_t^{(j)} \mathbf{g}(\mathbf{s}_t^{(j)})^T / \Sigma_t^{(j)} \quad {}_{(2N\times 1)}(12)$$

$$\mathbf{P}_t^{(j)} = (\mathbf{I} - \mathbf{K}_t^{(j)} \mathbf{s}_t^{(j)} \mathbf{g}^T) \Xi_t^{(j)} \quad {}_{(2N\times 2N)}(13)$$

$$\Xi_t^{(j)} = \mathbf{D}\mathbf{P}_{t-1}^{(j)} \mathbf{D}^H + \mathbf{g}\mathbf{g}^T \sigma_v^2 \quad {}_{(2N\times 2N)}(14)$$

Finally, the *a posteriori* probability of the transmitted symbols at time t can be calculated by

$$p(\mathbf{s}_t = \mathbf{b}_i|\mathbf{Y}_t) = \sum_{j=1}^{J} p(\mathbf{s}_n^{(j)} = \mathbf{b}_i) w_t^{(j)} \quad (15)$$

Then, the proposed blind particle filtering symbol detector is summarized as:

(1) Initialization: Set the initial channel matrix, whose every element is complex Gaussian distribution with mean zero and variance 1. All importance weights are set to $w_{-1}^{(j)} = 1, j = 1, \ldots, J$.

The following steps are cycled at the t-th recursion ($t = 0, \ldots, T$), For $j = 1, \ldots, J$

(2) For $n = 1, \ldots, N$ and every $\mathbf{b}_i \in \mathcal{B}^N$, compute $a_{t,i}^{(j)}$ and draw a sample $\mathbf{s}_t^{(j)}$ from $\mathcal{B}^N$ according to (9).

(3) Compute the importance weight $w_t^{(j)}$ according to (10).

(4) For $m = 1, \ldots, M$, update the *a posteriori* mean and covariance of $\mathbf{H}_{m,t}^{(j)}$ according to (11)-(14).

(5) Compute the *a posteriori* probability of $\mathbf{s}_t$ according to (15).

4. TURBO RECEIVER

As shown previously, the particle filter not only employs the *a priori* symbol probability $p(\mathbf{s}_t = \mathbf{b}_i|\mathbf{S}_{t-1}^{(j)}, \mathbf{Y}_{t-1})$, but outputs the *a posteriori* symbol probability $p(\mathbf{s}_t = \mathbf{b}_i|\mathbf{Y}_t)$ as well. Then it can perfectly act as the demodulator stage in the turbo receiver because of its nature of SISO. Furthermore, it makes the turbo receiver not need the channel information any more, which is very useful when the channel is fast-fading.

The detail of the transmitter and turbo receiver is illustrated in Fig. 1 and 2. The turbo receiver includes two stages: a particle filter and a channel decoder which are separated by a deinterleaver and an interleaver.

In this paper, two codes are employed to demonstrate the validity and effectivenss of the proposed algorithm. The two codes are the recursive system convolution (RSC) code and the low density parity check (LDPC) code, respectively, To the RSC code, an MAP channel decoding algorithm is exploited. Let $\Lambda_1[c_{\pi(t)}]$ and $\Lambda_2[c(t)]$ be the output *a posteriori* log-likelihood ratio (LLR) of the particle filter and channel decoder, respectively. $\Lambda_1[c_{\pi(t)}]$ is defined and calculated as [2]

$$\begin{aligned} \Lambda_1[c_{\pi(t)}] &\triangleq \log \frac{p(c_{\pi(t)} = 1|\mathbf{Y})}{p(c_{\pi(t)} = 0|\mathbf{Y})} \\ &= \underbrace{\log \frac{p(\mathbf{Y}|c_{\pi(t)} = 1)}{p(\mathbf{Y}|c_{\pi(t)} = 0)}}_{\lambda_1[c_{\pi(t)}]} + \underbrace{\log \frac{p(c_{\pi(t)} = 1)}{p(c_{\pi(t)} = 0)}}_{\lambda_2[c_{\pi(t)}]} \end{aligned} \quad (16)$$

where $\lambda_2[c_{\pi(t)}]$ is the *a priori* LLR, calculated by the channel decoder in the previous iteration; $\lambda_1[c_{\pi(t)}]$ is the *extrinsic* information outputted by the particle filter. And then it deinterleaved and fed back to the channel decoder as the *a priori* information.

Also, the output *a posteriori* LLR of the channel decoder is given by

$$\Lambda_2[c_t] \triangleq \log \frac{p(c_t = 1|\lambda_1[b_l])}{p(c_t = 0|\lambda_1[b_l])} = \lambda_2[b_i] + \lambda_1[b_i] \quad (17)$$

where the *extrinsic* information $\lambda_2[b_i]$ outputted by the channel decoder is fed to the particle filter as the *a priori* information, and the *a priori* probability need by the particle filter is given by

$$p(\mathbf{s}_t = \mathbf{b}_i) = \prod_{n=1}^{N} p(s_{t,n} = b_i) \quad (18)$$

where $p(s_{t,n} = 1) = 0.5 * (1 + \tanh(0.5 * \lambda_2[s_{t,n}]))$.

At the last iteration, the LLRs are made hard decision before output.

The receiver of the LDPC code is similar to the above one, but much simpler. Because the LDPC decoder can input and output the probability of the transmitted symbols directly, the LLR calculator and symbol probability calculator can be fully omitted.

5. SIMULATIONS

Extensive computer simulations have been conducted to demonstrate the effectiveness of the proposed symbol detector. In simulations, the differential binary phase shift keying (DBPSK) is exploited to overcome the phase ambiguous [4]. The coefficients of the AR model are $-\alpha_{1,m,n} = -1.989710$, $-\alpha_{2,m,n} = 0.989745$, ($m = 1, \ldots, M; n = 1, \ldots, N$), reflecting a VBLAST system of the Doppler spread of 2.12KHz and data rate of 512K bps. σ_v^2 is chosen to make the AR process have a unit power, and the signal to noise ratio (SNR) is calculated as $10\log(N/\sigma_u^2)$. 50 particles are drawn at every filter step. The resampling procedure occurs when $\frac{1}{J}\sum_{j=1}^{J}(w_t^{(j)}/\bar{w}_t - 1)^2 > 9$, where $\bar{w}_t$ is the mean of $w_t^{(j)}$.

Both code rates are 1/2, and both block size of code bits are 512 while that of information bits are 256. The RSC code is a length-5 convolution code with generators (23,35) in octal notation, while the LDPC code is constructed according to the Mackey-Neal rule [8] with column weight $t = 3$. The S-random [9] interleaver ($S = 11$) is used for two codec schemes.

The performance of the proposed detector is evaluated with the bit error rate (BER). Fig. 3 and 4 show the performance of the RSC code and the LDPC code when the number of transmit and receive antennas are $(N, M) = (2, 2)$, $(2, 3)$, $(3, 2)$, respectively. The maximum iteration times is 5 for RSC codes and 15 for LDPC codes. Obviously, the BER decreases when the SNR increases. Moreover, the performance of the TURBO-BLAST decoder [10], requiring the accurate channel state information (CSI), is also shown in Fig. 3 and 4. From simulations, we observe that the performance of the proposed algorithm is close to that in Ref. [10] when the number of transmit and receive antennas are the same. In additon, Fig. 3 and 4 show that the performance of the RSC code is better than that of the LDPC one. However, the computation burden of LDPC code is much less than that of the RSC one.

Furthermore, the proposed detector can achieve good performance even with fewer receive antennas than transmit ones. Clearly, the major limitation of the conventional VBLAST detector can be eliminated.

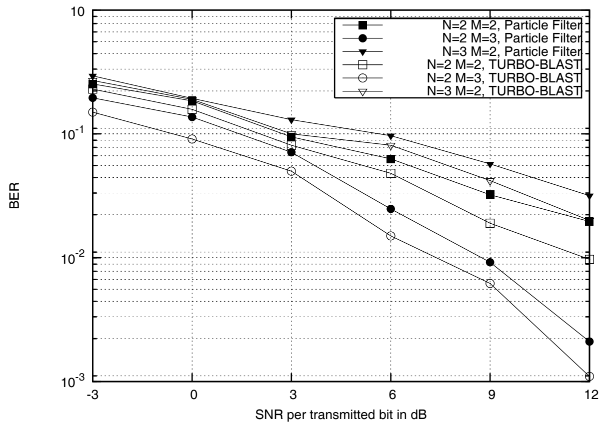

Fig. 3 Performance of the RSC code

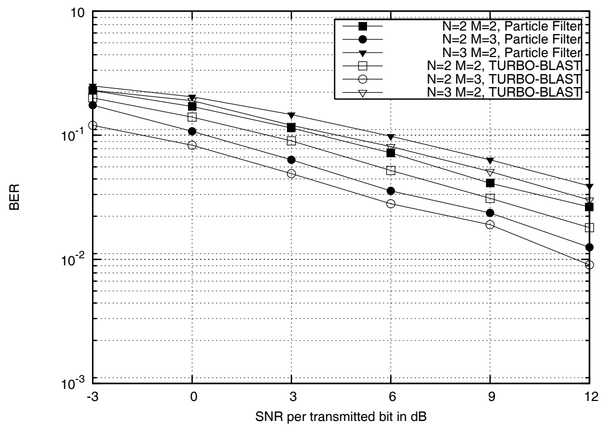

Fig. 4 Performance of the LDPC code

6. CONCLUSIONS

In this paper, a blind symbol detector based on the particle filtering and the iterative decoding is proposed for the VBLAST coded MIMO systems. By exploiting the particle filtering, we can make the turbo receiver be a blind detector. Simulation results show that not only its performance is close to the nonblind algorithm, but also it can be applied with fewer receive antennas than transmit ones.

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