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A new layered space–time detection algorithm for frequency selective fading multiple-input multiple-output channels based on particle filter*

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In this paper, a new observation equation of non-Gaussian frequency selective fading Bell Labs layered space time (BLAST) architecture system is proposed, which is used for frequency selective fading channels and non-Gaussian noise in an application environment of BLAST system. With othogonal matrix triangularization (QR decomposition) of the channel matrix, the static observation equation of frequency selective fading BLAST system is transformed into a dynamic state space model, and then the particle filter is used for space–time layered detection. Making the full use of the finite alphabet of the digital modulation communication signal, the optimal proposal distribution can be chosen to produce particle and update the weight. Incorporated with current method of reducing error propagation, a new space–time layered detection algorithm is proposed. Simulation result shows the validity of the proposed algorithm.

Keywords: particle filter, multiple-input multiple-output, layered space–time structure, frequency selective fading channels

PACC: 0250, 0260, 0547, 0290

1. Introduction

Information theory shows that the multiple-input multiple-output (MIMO) system has very high channel capacity in a Rayleigh fading environment as compared with single antenna system.[1] In order to use this advantage to increase diversity and coding gain, a series of space–time coding (STC) technique comes out using signal processing and coding theory. Among those STC methods, the Bell Labs layered space time (BLAST) architecture proposed by Foschini[2] is a very promising one, which can achieve a high data rate in broadband wireless communications. Because of its high spectrum efficiency, the BLAST has been introduced into wireless local area networks (WLAN) and other wireless communication standards. The detection algorithm, based on the maximum likelihood (ML) or minimum mean square error (MMSE) criterion, can give optimal detection result for the BLAST system. However, the computation complexity increases exponentially with the number of transmit antennas, which limits its application in the system with a large number of transmit antennas. In order to achieve a compromise between the performance and the computation complexity of the detection algorithm, a new BLAST symbol detection algorithm based on ordered successive interference cancellation (OSIC) was proposed by Golden *et al*[3] which is also called V-BLAST (Vertical-BLAST) and just suitable for the flat fading channels. For the sake of utilizing it in frequency selective (FS) fading MIMO channels, a decision feedback equalizer (DFE) was introduced by Lozano and Papadias[4] to eliminate the intersymbol interference (ISI), which is caused by frequency selective fading. But the performances of V-BLAST and DFE are both limited by error propagation.

In this paper, a new layered space–time detection algorithm for frequency selective fading MIMO channels based on particle filter (PF) is introduced. Because the BLAST system is mainly applicable to an indoor/urban environment with abundant scatters, a noise and channel model corresponding to non-Gaussianity and frequency selectivity of the environment of this kind should be set up first. And then with othogonal matrix triangularization (QR decomposition) of the channel matrix, the new FS-BLAST

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dynamic state space model (DSSM) is built up. Following that, the PF is introduced, and the optimal proposal distribution can be chosen to produce particle and update the weight, which makes the full use of the finite alphabet of the digital modulation communication signals. In order to improve the detection performance, the received signals should be ordered by SNR (signal–noise ratio). And then the PF algorithm is used for layered space–time detection. Finally, simulation and performance analysis of the proposed algorithm are carried out.

In the following, $(\cdot)^{\mathrm{T}}$ and $(\cdot)^{\mathrm{H}}$ are utilized to denote matrix transposition and Hermitian transposition respectively. Also, the operator $\mathrm{vec}(\cdot)$ denotes $\mathrm{vec}([v_1 v_2 \ \ldots \ v_k]) = [v_1^{\mathrm{T}} v_2^{\mathrm{T}} \ \ldots \ v_k^{\mathrm{T}}]^{\mathrm{T}}$.

2. FS-BLAST system model and detection method

2.1. FS-BLAST channel and non-Gaussian measurement noise model

The frequency selective fading BLAST system is shown in Fig.1. At the transmitter, data are divided into M sub-data flows, which are coded, mapped, and parallel transmitted by M transmit antennas, while signals are received using N parallel antennas ($N \geq M$). The received signals are sampled at a symbol rate and, therefore, the receiver structure is symbol-spaced. It is assumed that the channel is stationary over each burst of data, although it changes from burst to burst. Perfect channel estimation at the receiver is further assumed. If the number of taps in the channel response is L, the sampled channel response from transmitter m to receiver n, including transmit and receive filters, is denoted by

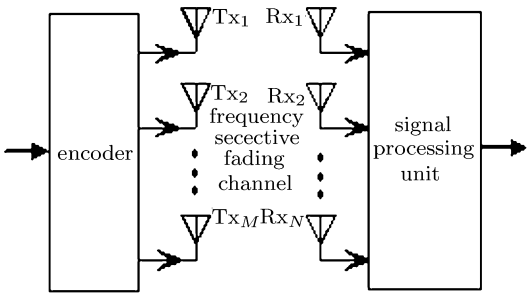


Fig.1. FS-BLAST system diagram.

$$\boldsymbol{h}_{nm} = [h_{nm}(1) \quad h_{nm}(2) \quad \ldots \quad h_{nm}(L)]^{\mathrm{T}}. \tag{1}$$

BLAST is mainly suitable for high data rate wireless communication in an indoor/urban environment, and the measurement noise in these environments is not Gaussian noise. In this paper, measurement noise distribution in FS-BLAST channel is modelled as the Middleton class A noise model, which has been used extensively to model the impulsive noise commonly generated in an indoor/urban wireless environment.[5] The probability density function (pdf) of this model is given by

$$n(t) \sim (1-\varepsilon)N(0, \kappa\zeta^2) + \varepsilon N(0, \zeta^2), \tag{2}$$

where $0 \leq \varepsilon \leq 1$, $N(0, \ \kappa\zeta^2)$ represents the ambient background noise, while $N(0, \zeta^2)$ represents an impulsive component with probability ε. By varying the parameters ε and κ, the total variance of noise can be fixed as $\sigma^2 = (1-\varepsilon)\kappa\zeta^2 + \varepsilon\zeta^2$.

We can assemble the $\boldsymbol{h}_{nm}$ vectors into M separate matrices of size $N \times L$ as follows:

$$\boldsymbol{H}_m = \left[\boldsymbol{h}_{1m}^{\mathrm{T}} \quad \boldsymbol{h}_{2m}^{\mathrm{T}} \quad \ldots \quad \boldsymbol{h}_{Nm}^{\mathrm{T}}\right]^{\mathrm{T}}, \quad m = 1, 2, \ \ldots, \ M. \tag{3}$$

If the sequence of L symbols transmitted by the mth antenna from time slot $k-L+1$ to k denoted by

$$\boldsymbol{s}_m(k : k-L+1) = [s_m(k) \quad s_m(k-1) \quad \ldots \quad s_m(k-L+1)]^{\mathrm{T}}, \quad m = 1, 2, \ \ldots, \ M, \tag{4}$$

then all the data transmitted by M transmit antennas from time slot $k-L+1$ to k can be written as the following vector:

$$\boldsymbol{S}(k : k-L+1) = \mathrm{vec}([\boldsymbol{s}_1(k : k-L+1) \quad \boldsymbol{s}_2(k : k-L+1) \quad \ldots \quad \boldsymbol{s}_M(k : k-L+1)]). \tag{5}$$

Therefore, the $N \times 1$ received vector $y(k)$ at time k can be expressed as

$$\boldsymbol{y}(k) = [\boldsymbol{H}_1 \quad \boldsymbol{H}_2 \quad \ldots \quad \boldsymbol{H}_{\mathrm{M}}]\boldsymbol{S}(k : k-L+1) + \boldsymbol{n}(k), \tag{6}$$

where $[\boldsymbol{H}_1 \ \boldsymbol{H}_2 \ \ldots \ \boldsymbol{H}_M]$ is an $N \times LM$ matrix, as usual $LM > N$. For the later derivation, a column full-rank matrix is designed. Let $\boldsymbol{y}(k+r:k)$ denote the column vector of received signals from time k to $k+r$ as follows:

$$\boldsymbol{y}(k+r:k) = \mathrm{vec}([y(k+r) \ \ y(k+r-1) \ \ \ldots \ \ y(k)]) + \boldsymbol{n}(k+r:k). \tag{7}$$

Therefore, the system model can be expressed as

$$\boldsymbol{y}(k+r:k) = \begin{bmatrix} \boldsymbol{H}_1 00 & \cdots & 0\boldsymbol{H}_2 00 & \cdots & 0 & \cdots & \boldsymbol{H}_M 00 & \cdots & 0 \\ 0\boldsymbol{H}_1 00 & \cdots & 0\boldsymbol{H}_2 00 & \cdots & 0 & \cdots & \boldsymbol{H}_M 0 & \cdots & 0 \\ \vdots & & \ddots & & & & \vdots & & \\ 00 & \cdots & 0\boldsymbol{H}_1 00 & \cdots & 0\boldsymbol{H}_2 00 & \cdots & 0 & \cdots & \boldsymbol{H}_M \end{bmatrix} \begin{bmatrix} \boldsymbol{s}_1(k+r:k-L+1) \\ \vdots \\ \boldsymbol{s}_M(k+r:k-L+1) \end{bmatrix} + \boldsymbol{n}_{N(r+1)\times 1},$$

which can be simplified into

$$\boldsymbol{y} = \boldsymbol{H}\boldsymbol{S} + \boldsymbol{n}, \tag{8}$$

where received signal $\boldsymbol{y}$ from time k to $k+r$ is an $N(r+1)$-dimensional column vector; transmit signal $\boldsymbol{S}$ from time k to $k+r$ is an $M(L+r)$-dimensional column vector; $\boldsymbol{H}$ is an $N(r+1) \times M(L+r)$ matrix; measurement noise $\boldsymbol{n}$ from time k to $k+r$ is an $N(r+1)$-dimensional column vector, the pdf of its entries is given by the expression (2).

2.2. FS-BLAST detection algorithm

To solve the problem of the layered space–time detection in frequency selective fading MIMO channel, Lozano and Papadias[4] introduced a modified V-BLAST algorithm for frequency selective Rayleigh fading channel, which is also called FS-V-BLAST algorithm. Figure 2 shows the main framework of FS-V-BLAST detector, which is concatenated by M sub-detectors and detects the M sub-data flows in descending order of SNR. Each detector consists of multi-input single-output decision feedback equalizer (MISO-DFE) and interference canceller (IC).

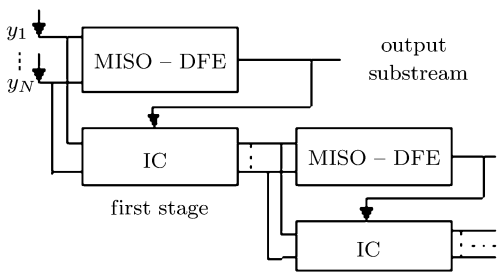


Fig.2. FS-V-BLAST detection scheme.

The DFE in every stage consists of K_f taps feedforward filter and K_b taps feedback filter. In fact, Ginis and Cioffi[6] have proved that the detector based on decision feedback (DF) principle for V-BLAST is equivalent to the generalized decision feedback equalizer (GDFE). In the following, we consider the FS-BLAST detection method from the aspect of DFE.

In an FS-BLAST receiver, the channel matrix is decomposed according to the Gram–Schmidt QR decomposition as[7]

$$\boldsymbol{H} = (\boldsymbol{Q} \ \ \bar{\boldsymbol{Q}}) \begin{pmatrix} \boldsymbol{R} \\ \boldsymbol{0} \end{pmatrix}, \tag{9}$$

where $\boldsymbol{Q}$ and $\bar{\boldsymbol{Q}}$ are $N(r+1) \times M(L+r)$ and $N(r+1) \times (N(r+1) - M(L+r))$ unitary matrices, $\boldsymbol{R}$ is an $M(L+r) \times M(L+r)$ lower triangular matrix, and $\boldsymbol{0}$ is an $(N(r+1) - M(L+r)) \times M(L+r)$ matrix with all entries equal to 0. And then we left multiply $\boldsymbol{Q}^\mathrm{H}$ on each side of Eq.(8) and obtain

$$\bar{\boldsymbol{y}} = \boldsymbol{Q}^\mathrm{H}\boldsymbol{y} = \boldsymbol{R}\boldsymbol{S} + \bar{\boldsymbol{n}} \tag{10}$$

or

$$\bar{y}_m = r_{m1}s_1 + r_{m2}s_2 + \ \cdots \ + r_{mm}s_m + \bar{n}_m, \tag{11}$$

where $\bar{y}_m$, r_{ij}, and s_i are the mth, ijth and ith entry of the vector $\bar{\boldsymbol{y}}$, matrix $\boldsymbol{R}$ and vector $\boldsymbol{S}$, respectively, and $\bar{\boldsymbol{n}}$ is still an independent identically distributed (i.i.d.) random vector with the pdf given by the expression (2). From Eq.(10), a DF scheme can be readily carried out according to[7,8]

$$\hat{s}_1 = Q\left(\frac{\bar{y}_1}{r_{11}}\right),$$

$$\hat{s}_m = Q\left(\left(\bar{y}_m - \sum_{i=1}^{m-1} r_{mi}s_i\right) \Big/ r_{mm}\right),\ m = 2, 3, \ldots.$$

The implementation using DF principle is computationally more efficient, but its performance is limited by error propagation. A prevalent approach to reducing this effect is to reorder the data streams according to their SNRs, and then the data streams are detected in descending order of their SNRs. It should be noted, however, that reordering can only decrease the effect of error propagation but not eliminate it.

We approach the problem from a Bayesian perspective, in which the detecting of the transmit sequence $\boldsymbol{S}$ from the observation signal $\boldsymbol{y}$ polluted by noise is equivalent to the resolving of the marginalized posterior distribution (MPD) of each transmit symbol s_m, and make the soft decision using marginalized minimum mean square error (MMMSE) principle. According to MMMSE, the decision statistic for s_m is expressed as

$$z_m = E[s_m|\boldsymbol{y}] = \sum_{s\in A} s_m p(\boldsymbol{s}|\boldsymbol{y}), \tag{12}$$

where $A = \{a_1, a_2, \ \ldots \ a_K\}$ is the alphabet set of the constellation in use and $p(\boldsymbol{s}|\boldsymbol{y})$ is the full posterior distribution. A final decision on s_m can be obtained by mapping z_m to the nearest constellation point in A.[7]

MMMSE decision criterion can eliminate the error propagation and obtain the optimal solution, but its complexity is the same as that of ML receiver since K^{ML} terms must be evaluated on the posterior distribution, which makes the MMMSE method prohibitive for practical use. In the following section, PF detection algorithm based on MMMSE for FS-BLAST systems is deduced.

3. PF detection algorithm in FS-BLAST systems

3.1. Monte Carlo sampling

Monte Carlo (MC) sampling is a powerful method of approximating desired distribution and calculating high-dimensional integral.[9−14] It has been intensively studied by the statistics community in the past decade and has aroused great interest of researchers in the area of statistical signal processing and communications in recent years.[15−17] Using MC to obtain the MMMSE estimation (12), random sample $\left\{\boldsymbol{s}^{(j)}\right\}_{j=1}^{J}$ based on posterior distribution $p(\boldsymbol{s}|\boldsymbol{y})$ is required, where J denotes the size of the sample. Hence, the expression (12) can be approximated to

$$z_m \approx \frac{1}{J}\sum_{j=1}^{J} s_m^{(j)}. \tag{13}$$

Along with the increase of J, the expression (13) converges to z_m gained by true posterior distribution $p(s_m|\boldsymbol{y})$. About the detection problem of FS-BLAST, the expression (13) is feasible, since the sample size J is much less than K^{ML}.[7]

One difficulty associated with the MC method is the direct sampling from posterior distribution $p(\boldsymbol{s}|\boldsymbol{y})$. Therefore, lots of sampling methods are introduced. One of the most common sampling methods is importance sampling algorithm. In implementing the importance sampling, one first draws samples $\left\{\boldsymbol{s}^{(j)}\right\}_{j=1}^{J}$ from a proposal distribution $\pi(\boldsymbol{s}|\boldsymbol{y})$, which must be easy of sampling. Then, the weights of the samples are calculated by

$$w^{(j)} = \frac{p\left(\boldsymbol{s}^{(j)}|\boldsymbol{y}\right)}{\pi\left(\boldsymbol{s}^{(j)}|\boldsymbol{y}\right)} \forall j, \tag{14}$$

and normalized as $\bar{w}^{(j)} = w^{(j)} / \sum_{j=1}^{J} w^{(j)}$. It should be noted that this normalization process eliminates the necessity of knowing the normalizing constants of $p(\boldsymbol{s}|\boldsymbol{y})$ and $\pi(\boldsymbol{s}|\boldsymbol{y})$ in computing the weights (14). These samples and weights approximate $p(s_m|\boldsymbol{y})$, and using them, z_m in the expression (12) can be estimated by

$$z_m \approx \sum_{j=1}^{J} \bar{w}^{(j)} s_m^{(j)}. \tag{15}$$

The effectiveness of importance sampling is affected by the choice of proposal distribution. In general, the more similar to $p(\boldsymbol{s}|\boldsymbol{y})$ the $\pi(\boldsymbol{s}|\boldsymbol{y})$ is, the less the samples are needed to achieve the same performance.[18]

3.2. PF detection algorithm in FS-BLAST systems

PF is a sequential Monte Carlo (SMC) method, which is usually realized using sequential importance sampling. The PF is basically applied to resolving the dynamic system described by the DSSM. Recently, it has also been used as an alternative importance sampling method for static systems.[19] In the following, the detection for FS-BLAST system is resolved according to Refs.[7] and [8].

The FS-BLAST system described in Eq.(10) is essentially a static system. If $\boldsymbol{s}$ is considered to be a vector of static state variables and $\bar{y}_1 \ \ldots \ \bar{y}_m$ that are the output of feedforward filter considered to be the space update, then the recursive relation between $\bar{\boldsymbol{y}}$ and $\boldsymbol{s}$ can be regarded as a dynamic system. Therefore, the decision of s_m is equivalent to resolving the posterior distribution $p(s_m|\bar{\boldsymbol{y}}_{1:m})$. According to the Markovian property of DSSM, $p(s_m|\bar{\boldsymbol{y}}_{1:m})$ can be calculated recursively as follows:

$$\begin{aligned} p(\boldsymbol{s}_{1:m}|\bar{\boldsymbol{y}}_{1:m}) &= \frac{p(\bar{y}_m|\boldsymbol{s}_{1:m-1},\bar{\boldsymbol{y}}_{1:m-1})p(\boldsymbol{s}_{1:m}|\bar{\boldsymbol{y}}_{1:m-1})}{p(\bar{y}_m|\bar{\boldsymbol{y}}_{1:m-1})} \\ &\propto p(\bar{y}_m|\boldsymbol{s}_{1:m})p(s_m)p(\boldsymbol{s}_{1:m-1}|\bar{\boldsymbol{y}}_{1:m-1}). \end{aligned} \tag{16}$$

The formula (16) is obtained by using $p(s_m|\boldsymbol{s}_{1:m-1},\bar{\boldsymbol{y}}_{1:m-1}) = p(s_m)$, i.e. s_m is independent of data from other antennas and previous observations. Recursively calculating the posterior distribution $p(\boldsymbol{s}|\bar{\boldsymbol{y}})$ needs recursively importance sampling, hence the proposal distribution can be chosen as

$$\pi(\boldsymbol{s}_{1:m}|\bar{\boldsymbol{y}}_{1:m}) = p(s_m|\boldsymbol{s}_{1:m-1},\bar{\boldsymbol{y}}_{1:m})\pi(\boldsymbol{s}_{1:m-1}|\bar{\boldsymbol{y}}_{1:m-1}). \tag{17}$$

The associated importance weight for the jth sample is then calculated as[7]

$$\begin{aligned} w_m^{(j)} &= \frac{p\left(\boldsymbol{s}_{1:m}^{(j)}|\bar{\boldsymbol{y}}_{1:m}\right)}{\pi\left(\boldsymbol{s}_{1:m}^{(j)}|\bar{\boldsymbol{y}}_{1:m}\right)} \\ &\propto p(\bar{y}_m|\boldsymbol{s}_{1:m-1}^{(j)},\bar{\boldsymbol{y}}_{1:m-1})w_{m-1}^{(j)} \\ &\propto u_m^{(j)}w_{m-1}^{(j)}, \end{aligned} \tag{18}$$

where $u_m^{(j)}$ is called the incremental weight. The proposal distribution given by the expression (17) is usually called optimal proposal distribution in the PF literature because it produces weights with minimal variance conditional on $\boldsymbol{s}_{1:m-1}^{(j)}$ and $\bar{\boldsymbol{y}}_{1:m}$.[20] From the expressions (17) and (18), it is clear that the samples and weights can be obtained recursively based on those acquired at step $m-1$, and this recursive implementation of importance sampling is known as SIS. In the jargon of PF, $s_m^{(j)}$ and $\boldsymbol{s}_{1:m}^{(j)}$ are named particle and trajectory, respectively.

The above implementation procedure of PF requires drawing samples from proposal distribution $p\left(s_m|\boldsymbol{s}_{1:m-1}^{(j)},\bar{\boldsymbol{y}}_{1:m}\right)$ and calculating the weight increment $u_m^{(j)}$. The two requirements amount to the calculation of the likelihood function for each symbol in symbol space, which is easily obtained as

$$\lambda_k^{(j)} = p\left(\bar{y}_m\middle|s_m = a_k, \boldsymbol{s}_{1:m-1}^{(j)}\right), \tag{19}$$

where the distribution of $\left(\bar{y}_m - r_{m,m}a_k - \sum_{i=1}^{m-1} r_{m,i}s_i^{(j)}\right)$ is given by the expression (2). Then, a sample a_k from proposal distribution $p\left(s_m|\boldsymbol{s}_{1:m-1}^{(j)},\bar{\boldsymbol{y}}_{1:m}\right)$ is drawn with a probability of $\lambda_k/\sum_{i=1}^{k}\lambda_i$.[7] The weight increment can be readily obtained as

$$u_m^{(j)} = \sum_{s_k\in A} p\left(\bar{y}_m\middle|s_m,\boldsymbol{s}_{1:m-1}^{(j)}\right)p(s_m) = \frac{1}{K}\sum_{k=1}^{K}\lambda_k^{(j)}. \tag{20}$$

Using the above formulae to obtain the trajectories $\left\{\boldsymbol{s}_{1:m}^{(j)}\right\}_{j=1}^{J}$ and their weights $\left\{w_m^{(j)}\right\}_{j=1}^{J}$ of step m, the desired posterior distribution $p(\boldsymbol{s}|\bar{\boldsymbol{y}})$ (equal to $p(\boldsymbol{s}|\boldsymbol{y})$) can be fitted by weighted samples. Finally, the decision can be made using these weighted samples according to the MMSE. It is worth stressing that the weighted samples are essentially probability masses that represent the posterior distribution. Hence, they can be used for resolving other problems related to posterior distribution. For example, we can compute the maximum a posteriori (MAP) estimate by choosing the trajectory with the largest cumulative weight.[8]

An important issue of PF is in need of resampling. In the process of PF, the initialized J samples can cover the objective space, while the corresponding weights represent the objective distribution effectively. But after several iterations, most of the particles have no effect on the whole estimate because their weights are close to zero. Therefore, resampling is required to replace the negligible weight particles by those from the high-density area of the desired posterior distribution. The use of resampling can move the mass of the samples closer to the true state and therefore yields a more effective representation of the distribution than the generic importance sampling. Nonetheless, excessive use of resampling may increase computation complexity and impoverish the sample diversity. It means that the particle with large weight might be chosen many times, and there would be a large number of repeated particles in the sampling result. Then the diversity of particles might be lost. There are lots of resampling methods, and the system resampling,[21] which has the minimum sampling variance, is chosen in this paper. To reduce the number of resampling, we use the effective number of samples to decide whether to utilize the resampling or not. The effective number of samples at step m can be approximated as $N_{\text{eff}} = 1/\sum_j\left(w_n^{(j)}\right)^2$ using its sample weight. Re-

sampling is carried out only if $N_{\text{eff}} < N_{\text{th}}$, where the N_{th} is defined as a threshold.

As has been pointed out, the advantage of PF over the DF principle is its ability to reduce and even prevent error propagation. Approximated by PF detector, the solution of MMMSE approaches the true solution with the increase of the sample size J. Because that the solution of MMMSE is based on MPD that is independent of the decision on symbol from other antennas, the MMMSE decision on the symbol of interest is immune to decision errors on other symbols. Consequently, the PF can be very effective in reducing and eventually preventing error propagation. However, when the sample size is limited, there would appear error propagation to a certain degree. There are several methods to solve this problem: augmenting the sample size, choosing an appropriate proposal distribution and resampling algorithm, and incorporating the reducing error propagation algorithm.

4. Simulation results and performance analysis

In order to estimate the performance of the proposed PF detector, simulation is carried out in the following aspects: the performance comparison among the FS-BLAST based on PF, the FS-V-BLAST and the ML detection algorithm; the impact of different particle numbers on the performance of PF detector; the improvement by using the ordering of the detection performance compared with no ordering; the effect of Gaussian and non-Gaussian noise models on detection performance, etc. Let the number of symbol-spaced taps in the channel response be 6, the fading coefficient of Rayleigh fading channel $\boldsymbol{H}$ be 0.5, and the quasi-static channel matrix $\boldsymbol{H}$ be constant in the data block with its length of 256, where the relation between the blocks is treated as i.i.d. The system with Quadrature Phase Shift Keying (QPSK) modulation has $M = 4$ transmit antennas and $N = 6$ receive antennas, and the length of observation data for constructing matrix $\boldsymbol{H}$ is $r = 16$. The measurement noise is produced using the model given by the expression (2), where the coefficients ε and κ that represent the non-Gaussianity are modifiable. But the total variance σ^2 of noise is invariant, and the modification of SNR is achieved through the change of transmit power. All the following symbol error rate (SER) performance curves are obtained by performing the MC simulation 1000 times.

First of all, the simulation for the impact of noise model on detection performance is carried out. Let $\zeta^2 = 1.2$ in the expression (2). When the probabilities ε of impulsive noise components is 0.1, 0.2 or 0.3, the corresponding κ values should be 0.81, 0.79 or 0.76 to make the total noise variance $\sigma^2 = 1$, respectively. Based on the previous three groups of ε and κ, the measurement noises are produced by the expression (2), and three groups of received data are produced by the expression (8). Whereafter, the layered space–time detection is processed according to the proposed algorithm, using the practical distribution of noise and the Gaussian distribution that has the same mean and variance (equivalent to standard normal distribution). The 'SER–SNR' curves of detection result are shown in Fig.3.

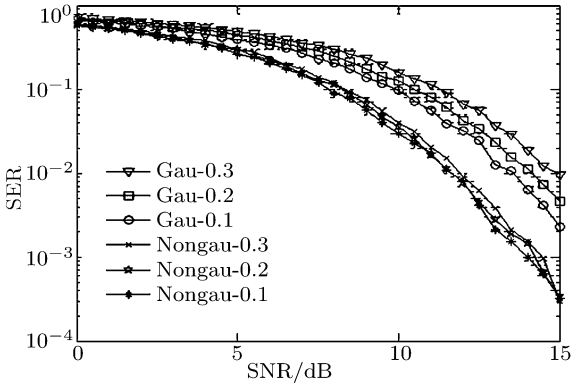


Fig.3. The SER–SNR curves of proposed detection algorithm using Gaussian and non-Gaussian noise models.

The number of particles used in simulation is 150. In the figure, 'Gau' and 'Nongau' denote the Gaussian and non-Gaussian noise models, respectively. And '0.1', '0.2', '0.3' denote the probabilities ε of impulsive noise appearing during the noise measurement. As shown in Fig.3, the performance of the non-Gaussian noise detection algorithm is much better than that of the Gaussian noise detection algorithm. The performance of non-Gaussian noise detection algorithm does not vary much when ε has different values. However, the performance of the detection algorithm under the Gaussian noise model becomes worse when ε becomes larger. This is because that if ε is larger, the probability of impulsive noise becomes greater, and the non-Gaussianity of measurement noise is more prominent. Then the error of simulating the measurement noise using Gaussian distribution is larger, too. The PF is very capable of processing the non-Gaussian signal, while the measurement noise in an indoor/urban en-

vironment, which is suitable for the BLAST system, is non-Gaussian. Therefore, the algorithm proposed in this paper is very practical.

As shown in Fig.4, the performances of non-Gaussian layered space–time detection algorithm based on the PF with $\varepsilon = 0.1$ and different particle numbers are compared with those of FS-V-BLAST method and ML detection method. In Fig.4, the 'PF'

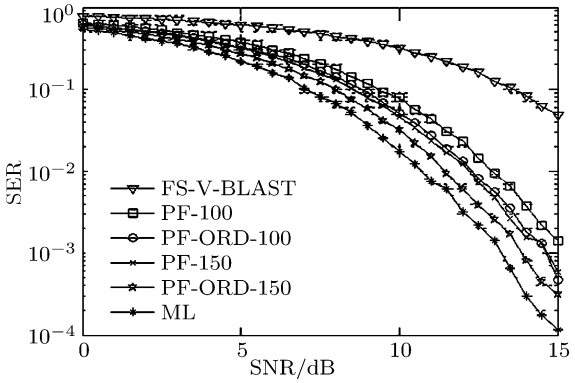


Fig.4. The SER–SNR curves of several kinds of detection algorithms.

denotes particle filter, the 'ORD' represents the introduced ordering, '100' and '150' refer to the particle numbers. The SER performance of the proposed detection algorithm is better than that of FS-V-BLAST method as shown in Fig.4 especially with high SNR. The reason is that when the SNR is high, the imperfect interference cancellation is the main cause that affects the performance of layered space–time detection. The PF detector based on MMMSE solves the MPD problem to realize the layered space–time detection, which can theoretically eliminate the interference between antennas. This is similar to the ML detection algorithm. However, since the QR decomposition reduces the degree of freedom of the elements on the diagonal of the triangular matrix,[22] the layered space–time detection algorithm based on PF is a little bit worse than the ML detection method in SER performance. The computation complexity of algorithm proposed in this paper is $O(KMLJ)$, and the computation complexity of ML detection method is $O(K^{ML})$. As to the frequency selective fading BLAST communication system, the value of K cannot be 1, which should be 2 at least, normally 4 or 8, and the product of ML is relatively large (usually larger than 12, at least 6). The value of J is determined by the choice of proposal distribution. Usually, the better the proposal distribution is chosen, the less the particles are needed. Normally, the J does not exceed 500. Therefore, the K^{ML} is far larger than $KMLJ$, which means that the computation complexity of the algorithm proposed in this paper is much less than that of ML algorithm. For example, in this paper $K = M = 4$, $L = 6$, even if when $J = 150$, the $K^{ML} = 4^{24} = 281474976710656$ is far larger than $KMLJ = 4 \times 4 \times 6 \times 150 = 14400$. The introduction of ordering and the increase in particle number can both improve the detection performance and reduce the SER, but the computation complexity would increase correspondingly.

5. Conclusions

In this paper, the layered space–time detection problem of frequency selective fading MIMO channel in a non-Gaussian noise environment is studied. Since the existing methods have the problems of error propagation, regarding the non-Gaussian noise as Gaussian noise, the layered space–time detection algorithm for frequency selective fading MIMO channel based on PF is proposed, which is launched on by constructing the channel matrix and measurement noise model. And in that process, the DSSM is formed by QR decomposition. Theoretical analysis and computer simulation show that the proposed algorithm has advantages of processing the non-Gaussian noise, eliminating the error propagation, reducing the SER，etc. Its SER performance is close to that of ML detection algorithm. The computation complexity of the proposed algorithm is less than that of ML method, but it still requires the real-time detection of broadband BLAST system. Therefore, reducing the computation complexity and improving the detection speed of the proposed algorithm will be subjects of our future researches.

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