Journal of Zhejiang University SCIENCE A
ISSN 1009-3095 (Print); ISSN 1862-1775 (Online)
www.zju.edu.cn/jzus; www.springerlink.com
E-mail: jzus@zju.edu.cn

Blind receiver for OFDM systems via sequential Monte Carlo in factor graphs*

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Received Feb. 23, 2006; revision accepted Aug. 24, 2006

Abstract: Estimation and detection algorithms for orthogonal frequency division multiplexing (OFDM) systems can be developed based on the sum-product algorithms, which operate by message passing in factor graphs. In this paper, we apply the sampling method (Monte Carlo) to factor graphs, and then the integrals in the sum-product algorithm can be approximated by sums, which results in complexity reduction. The blind receiver for OFDM systems can be derived via Sequential Monte Carlo (SMC) in factor graphs, the previous SMC blind receiver can be regarded as the special case of the sum-product algorithms using sampling methods. The previous SMC blind receiver for OFDM systems needs generating samples of the channel vector assuming the channel has an *a priori* Gaussian distribution. In the newly-built blind receiver, we generate samples of the virtual-pilots instead of the channel vector, with channel vector which can be easily computed based on virtual-pilots. As the size of the virtual-pilots space is much smaller than the channel vector space, only small number of samples are necessary, with the blind detection being much simpler. Furthermore, only one pilot tone is needed to resolve phase ambiguity and differential encoding is not used anymore. Finally, the results of computer simulations demonstrate that the proposal can perform well while providing significant complexity reduction.

Key words: Orthogonal frequency division multiplexing (OFDM), Factor graphs, Sequential Monte Carlo (SMC), Blind receiver, Virtual-pilot
doi:10.1631/jzus.2007.A0001 **Document code:** A **CLC number:** TN92

INTRODUCTION

Orthogonal frequency division multiplexing (OFDM) is generally known as an effective technique for high data rates and has been adopted by standards such as Digital Audio and Video Broadcasting (DAB and DVB) (ETSI, 1994; 1997). OFDM is robust against frequency selectivity of a multipath channel and the single-tap equalization can be used to detect the transmitted symbols if frequency-selective fading channels are known. Although, the use of pilot tones is the most robust way to estimate the channel parameters and detect the symbols, in order to conserve bandwidth, blind OFDM detection techniques have been proposed (Muquet and de Courville, 1999; Cai and Akansu, 2000; Cui and Tellambura, 2006), which use the special properties of the OFDM systems, such as cyclostationarity, cyclic prefix (CP), virtual subcarriers, and finite alphabets, and those blind detectors need averaging over many OFDM blocks. Blind detection requiring fewer OFDM blocks have also been proposed (Huang *et al*., 2006), while it is still computationally complex. The approaches based on Sequential Monte Carlo (SMC) can be computed in parallel and the data symbols can be detected over one OFDM block (Yang and Wang, 2002; Lu and Wang, 2001), so SMC blind detection can be attractive for wireless communications (Guo and Wang, 2003; Yu

* Project supported by the National Hi-Tech Research and Development Program (863) of China (No. 2003AA123310) and the National Natural Science Foundation of China (No. 60332030)

et al., 2006).

It is known that unified receiver can be developed based on sum-product algorithms operating in factor graphs (Worthen and Stark, 2001; Loeliger, 2004). In this paper, we develop an improved blind detection via the sum-product algorithm and Monte Carlo approximation, with the previous SMC blind detection (Yang and Wang, 2002) being regarded as the special case of the proposal. Under the state-space framework, the channels are high dimensional continuous variables, and thus quite large number of samples are needed in order to promise the accuracy of Monte Carlo approximation. We draw the initial samples of virtual-pilots instead of drawing the initial samples of the channel vector directly, which results in significant complexity reduction. To resolve the phase ambiguity, only one pilot tone is required and the differential encoding is not necessary anymore. The simulation results show that the proposal can provide performance improvement while reducing computational complexity.

SIGNAL MODEL

The discrete-time baseband equivalent model of OFDM systems is considered. In an OFDM system, the information bit stream $\{b_i\}$ is encoded and then the resulting code bit stream is interleaved. After interleaving, the interleaved code bit stream $\{c_{m,j}\}$ is then passed to a modulator, which maps each J-dimensional binary bit vector $[c_{m,1},c_{m,2},\ldots,c_{m,J}]^{\mathrm{T}}$ to a complex symbol X_m from the 2^J-ary symbol alphabet $\mathcal{S}=\{\alpha_i|i=1,\ldots,2^J\}$. The symbol stream $\{X_m\}$ is partitioned into blocks, with each block consisting of N symbols which can be expressed as an $N\times1$ column vector

$$\boldsymbol{X}=[X_0,X_1,\ldots,X_{N-1}]^{\mathrm{T}}. \tag{1}$$

After taking inverse discrete Fourier transform (IDFT) of the vector $\boldsymbol{X}$, the sampled signal in the time domain can be expressed as

$$\boldsymbol{x}=\boldsymbol{Q}^{\mathrm{H}}\boldsymbol{X}, \tag{2}$$

where H denotes conjugate transpose, $\boldsymbol{Q}$ is the standard N-dimensional DFT matrix with

$$Q(l,k)=\frac{1}{\sqrt{N}}\mathrm{e}^{-\mathrm{j}(2\pi lk)/N},\ 0\le l,k<N. \tag{3}$$

Assume that the cyclic prefix (CP) of length equal to channel memory is inserted in each OFDM block to eliminate interblock interference (IBI), and then over an OFDM block duration, the received signal vector can be written as

$$\boldsymbol{y}=\boldsymbol{H}\boldsymbol{x}+\boldsymbol{z}=\boldsymbol{H}\boldsymbol{Q}^{\mathrm{H}}\boldsymbol{X}+\boldsymbol{z}, \tag{4}$$

where $\boldsymbol{y}, \boldsymbol{x}, \boldsymbol{z}\in\mathbb{C}^N$, $\boldsymbol{H}\in\mathbb{C}^{N\times N}$ and $\boldsymbol{z}$ is the Gaussian noise vector with variance σ_n^2, and the (p,q)th component of the channel matrix $\boldsymbol{H}$ can be written as

$$H(p,q)=\begin{cases}h_{p-q}, & 0\le p-q<L,\\ h_{p-q+N}, & p-q+N<L,\\ 0, & \text{otherwise},\end{cases} \tag{5}$$

where $\boldsymbol{h}=[h_1,\ldots,h_{L-1}]^{\mathrm{T}}$ represents the sampled channel impulse response and L is the maximum channel delay. It can be seen that the channel matrix $\boldsymbol{H}$ is a circular matrix.

Output of the DFT operation at the receiver for an OFDM block can be written as

$$\boldsymbol{Y}=\boldsymbol{Q}\boldsymbol{y}=\boldsymbol{Q}\boldsymbol{H}\boldsymbol{Q}^{\mathrm{H}}\boldsymbol{X}+\boldsymbol{Z}=\boldsymbol{G}\boldsymbol{X}+\boldsymbol{Z}, \tag{6}$$

where $\boldsymbol{Y}$, $\boldsymbol{X}$ and $\boldsymbol{Z}$ are the DFTs of $\boldsymbol{y}$, $\boldsymbol{x}$ and $\boldsymbol{z}$, respectively. We can write $\boldsymbol{Y}$ as

$$\boldsymbol{Y}=[Y_0,Y_1,\ldots,Y_{N-1}]^{\mathrm{T}}\in\mathbb{C}^{N\times1}, \tag{7}$$

and we can regard $\boldsymbol{G}$ as the channel matrix in frequency domain. As $\boldsymbol{H}$ is a circular matrix, $\boldsymbol{G}$ becomes a diagonal matrix, and then the received signal at the kth subcarrier can be written as

$$Y_k=Q(k,k)X_k+Z_k=\boldsymbol{Q}'(k,:)\boldsymbol{h}X_k+Z_k, \tag{8}$$

where

$$Q(k,k)=\sum_{l=0}^{L-1}h(l)\mathrm{e}^{-\mathrm{j}(2\pi kl)/N}, \tag{9}$$

$\boldsymbol{Q}'$ is a matrix constructed from the first L columns of matrix $\boldsymbol{Q}$ multiplied by a factor $\sqrt{N}$, and $\boldsymbol{Q}'(k,:)$ denotes the kth row of matrix $\boldsymbol{Q}'$.

In fact, we can rewrite Eq.(6) as

$$\boldsymbol{Y} = \boldsymbol{X}'\boldsymbol{G}' + \boldsymbol{Z} = \boldsymbol{X}'\boldsymbol{Q}'\boldsymbol{h} + \boldsymbol{Z} = \boldsymbol{B}\boldsymbol{h} + \boldsymbol{Z}, \tag{10}$$

where $\boldsymbol{X}'$ is a diagonal matrix having $\boldsymbol{X}$ as its main diagonal.

SEQUENTIAL MONTE CARLO IN FACTOR GRAPHS

Consider a communication system. Let $x_{0:n}=\{x_0,x_1,\ldots,x_n\}$ and $y_{0:n}=\{y_0,y_1,\ldots,y_n\}$ denote respectively the unobserved transmitted signals and the observed received signals up to the time n. Assume the communication system is a dynamic system modeled in state-space form

$$x_n = \Psi(x_{n-1}, u_n),\ \ y_n = \Omega(x_n, v_n), \tag{11}$$

where u_n and v_n are independent noise.

For the dynamic system described in Eq.(11), the *a posterior* probability function $p(x_{0:n}|y_{0:n})$ can be factored as (Punskaya *et al*., 2002)

$$\begin{aligned} p(x_{0:n} \mid y_{0:n}) &\propto p(x_{0:n})p(y_{0:n} \mid x_{0:n}) \\ &= p(x_0)\prod_{i=0}^{n} p(y_i \mid x_i)p(x_i \mid x_{i-1}), \end{aligned} \tag{12}$$

where $\propto$ denotes equality up to a scale factor. This factorization can be represented by the factor graph shown in Fig.1a and Fig.1b.

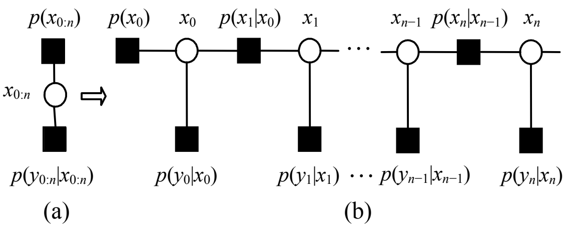

Fig.1 Factor graphs for communication systems

The receiver for the communication system must deal with the problem of computing the Minimum Mean Square Estimate (MMSE) of $x_{0:n}$, which is

$$\hat{x}_{0:n} = \int x_{0:n} p(x_{0:n} \mid y_{0:n}) \mathrm{d}x_{0:n}. \tag{13}$$

The important sampling method can be used to approximate this intractable integral (Yang and Wang, 2002; Liu and Chen, 1998; Punskaya, 2003). Assume the samples $\{x_{0:n}^{(j)}\}_{j=1}^{M}$ are drawn from the trial distribution $q(x_{0:n}|y_{0:n})$ instead of the distribution $p(x_{0:n}|y_{0:n})$, then the MMSE estimate of $x_{0:n}$ can be rewritten as

$$\left.\begin{aligned} &\hat{x}_{0:n} = \sum_{j=1}^{M} x_{0:n}^{(j)} \tilde{w}_n^{(j)}, \\ &\hat{p}(x_{0:n} \mid y_{0:n}) = \sum_{j=1}^{M} \tilde{w}_n^{(j)} \delta(x_{0:n} - x_{0:n}^{(j)}), \\ &w_n^{(j)} = \frac{p(x_{0:n}^{(j)} \mid y_{0:n})}{q(x_{0:n}^{(j)} \mid y_{0:n})} \propto \frac{p(y_{0:n} \mid x_{0:n}^{(j)}) p(x_{0:n}^{(j)})}{q(x_{0:n}^{(j)} \mid y_{0:n})}, \\ &\tilde{w}_n^{(j)} = w_n^{(j)} \Big/ \sum_{i=1}^{M} w_n^{(i)}, \end{aligned}\right\} \tag{14}$$

where $\delta(\cdot)$ denotes Dirac (Kronecker) delta function and $w_n^{(j)}$ are so-called importance weight whose recursive expression can be written as (Yang and Wang, 2002)

$$w_n^{(j)} \propto w_{n-1}^{(j)} \cdot \frac{p(y_n \mid x_n^{(j)}) p(x_n^{(j)} \mid x_{n-1}^{(j)})}{q(x_n^{(j)} \mid x_{0:n-1}^{(j)}, y_{0:n})}. \tag{15}$$

Return to the factor graph shown in Fig.1b, in which the sum-product algorithm can be developed (Worthen and Stark, 2001; Loeliger, 2004). Furthermore, the importance sampling method is used to approximate the integrals by the sums. The sum-product algorithm can be initialized by drawing samples $x_0^{(j)}$ from the initial probability density $p(x_0)$ and setting $w_0^{(j)}=1$ for $j=1,\ldots,M$. For the jth sample $x_0^{(j)}$, the probability of which can be written as $p(x_0)\delta(x_0 - x_0^{(j)})$. For simplicity, let f_i denote the function nodes $p(x_i|x_{i-1})$ and g_i denote the function nodes $p(y_i|x_i)$ in Fig.1b. Let $\mu_{a\rightarrow b}$ denote the message passed from node a to node b. Based on the sum-product update rule in factor graphs, we have

$$\left.\begin{aligned}&\mu_{x_0\to f_1}=p(x_0)\delta(x_0-x_0^{(j)})p(y_0|x_0),\\&\mu_{f_1\to x_1}=\int p(x_0)\delta(x_0-x_0^{(j)})p(y_0|x_0)p(x_1|x_0)\mathrm{d}x_0\\&\qquad\propto p(x_1|x_0^{(j)},y_0),\\&\mu_{f_1\to x_1}\cdot\mu_{g_1\to x_1}=p(x_1|x_0^{(j)},y_0)p(x_1|y_1)\propto p(x_1|x_0^{(j)},y_{0:1}).\end{aligned}\right\}\tag{16}$$

The jth sample of x_1 can be generated from probability $p(x_1\mid x_0^{(j)},y_{0:1})$. Consider using importance sampling, $x_1^{(j)}$ is drawn from $q(x_1\mid x_0^{(j)},y_{0:1})$, and then the message passed from x_1 to f_2 can be written as

$$\mu_{x_1\to f_2}=p(x_1\mid x_0^{(j)},y_{0:1})\delta(x_1-x_1^{(j)}),\tag{17}$$

and the messages up to the time n can be generated as

$$\left.\begin{aligned}&\mu_{x_{n-1}\to f_n}=p(x_{n-1}|x_{0:n-2}^{(j)},y_{0:n-1})\delta(x_{n-1}-x_{n-1}^{(j)})\\&\mu_{f_n\to x_n}=\int p(x_{n-1}|x_{0:n-2}^{(j)},y_{0:n-1})\delta(x_{n-1}-x_{n-1}^{(j)})p(x_n|x_{n-1})\mathrm{d}x_{n-1}\\&\qquad\propto p(x_n|x_{0:n-1}^{(j)},y_{0:n-1})\\&\mu_{f_n\to x_n}\cdot\mu_{g_n\to x_n}=p(x_n|x_{0:n-1}^{(j)},y_{0:n-1})p(y_n|x_n)\propto p(x_n|x_{0:n-1}^{(j)},y_{0:n})\end{aligned}\right\}\tag{18}$$

Note that y_n is independent of $x_{0:n-1}$ and $y_{0:n-1}$, the sample $x_n^{(j)}$ can be generated from $q(x_n\mid x_{0:n-1}^{(j)},y_{0:n})$. It is shown that the above sum-product algorithm aided by importance sampling is indeed the Sequence Monte Carlo method.

NEWLY-BUILT BLIND DETECTOR FOR OFDM

For the OFDM system described by Eqs.(6) and (10), let $X_{0:k}=\{X_0,X_1,\ldots,X_k\}$ and $Y_{0:k}=\{Y_0,Y_1,\ldots,Y_k\}$ respectively denote the transmitted signals and the received signals in frequency domain up to the kth subcarrier. The aim of the blind receiver is to estimate the *a posterior* symbol probability

$$p(X_k=a_i\mid Y_{0:k}),\ \ a_i\in\mathcal{S};\ k=0,\ldots,N-1\tag{19}$$

based on the received signals up to the kth subcarriers $Y_{0:k}$ and the *a priori* symbol probability of X_k, without knowing the channel $\boldsymbol{h}$. From Eq.(14), the approximation of Eq.(19) can be written as

$$P(X_k=a_i\mid Y_{0:k})\cong\sum_{j=1}^{M}\delta(X_k-a_i)\tilde{w}_k^{(j)},\ a_i\in\mathcal{S}\tag{20}$$

with samples $\{X_k^{(j)}\}_{j=1}^{M}$ drawn from the trial distribution $q(X_k\mid X_{0:k-1}^{(j)},Y_{0:k})$, and a useful choice of the trial distribution is of the form

$$q(X_k\mid X_{0:k-1}^{(j)},Y_{0:k})=p(X_k\mid X_{0:k-1}^{(j)},Y_{0:k}),\tag{21}$$

and thus the weights in Eq.(15) can be rewritten as (Yang and Wang, 2002; Lu and Wang, 2001)

$$w_k^{(j)}\propto w_{k-1}^{(j)}\cdot p(Y_k\mid X_{0:k-1}^{(j)},Y_{0:k-1}).\tag{22}$$

Detector via SMC in factor graphs

Let $p(Y_{0:N-1},X_{0:N-1},\boldsymbol{h})$ denote the joint probability mass function of the received signals $Y_{0:N-1}$, the transmitted signals $X_{0:N-1}$ and the channel vector $\boldsymbol{h}$, which factors as

$$p(Y_{0:N-1},X_{0:N-1},\boldsymbol{h})=\prod_{i=0}^{N-1}p(Y_i\mid X_i,\boldsymbol{h})p(X_i)p(\boldsymbol{h}),\tag{23}$$

whose factor graph is shown in Fig.2, where $T(X_0,X_1,\ldots,X_{N-1})$ denotes the code constraint. Since the interleaver after channel encoding is employed, the transmitted symbols can be supposed to be independent, i.e. $T(X_0,X_1,\ldots,X_{N-1})=p(X_0)p(X_1)\ldots p(X_{N-1})$. We can develop the sum-product algorithm aided by important sampling in the factor graph shown in Fig.2. For simplicity, let f_k denote function node $p(Y_k|X_k,\boldsymbol{h})$ and T denote function node $T(X_0,X_1,\ldots,X_{N-1})$. Up to the 0th subcarrier, the messages are generated as follows

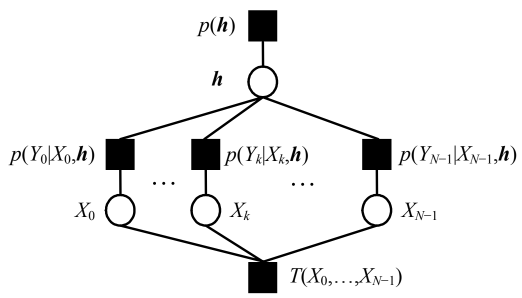

Fig.2 Factor graph for the OFDM system

$$\left.\begin{aligned}&\mu_{f_0\to X_0}=\int p(\boldsymbol{h})p(Y_0\mid X_0,\boldsymbol{h})\mathrm{d}\boldsymbol{h}=p(Y_0\mid X_0),\\&\mu_{f_0\to X_0}\cdot\mu_{T\to X_0}=p(Y_0\mid X_0)p(X_0)\propto p(X_0\mid Y_0).\end{aligned}\right\}\quad(24)$$

The jth sample $X_0^{(j)}$ can be generated from $p(Y_0|X_0)$, and then we have

$$\left.\begin{aligned}&\mu_{X_0\to f_0}=p(X_0\mid Y_0)\delta(X_0-X_0^{(j)}),\\&\mu_{f_0\to \boldsymbol{h}}=p(X_0\mid Y_0)\delta(X_0-X_0^{(j)})p(Y_0\mid X_0,\boldsymbol{h})\\&\qquad\propto p(Y_0\mid X_0^{(j)},\boldsymbol{h}),\\&\mu_{f_1\to X_1}=\int p(\boldsymbol{h})p(Y_0\mid X_0^{(j)},\boldsymbol{h})\,p(Y_1\mid X_1,\boldsymbol{h})\mathrm{d}\boldsymbol{h}\\&\qquad\propto p(Y_1\mid X_1,X_0^{(j)},Y_0),\\&\mu_{f_1\to X_1}\cdot\mu_{T\to X_1}=p(Y_1\mid X_1,X_0^{(j)},Y_0)p(X_1)\\&\qquad\propto p(X_1\mid X_0^{(j)},Y_{0:1}).\end{aligned}\right\}\quad(25)$$

The jth sample $X_1^{(j)}$ can be generated from $p(X_1\mid X_0^{(j)},Y_{0:1})$, and then we have

$$\left.\begin{aligned}&\mu_{X_1\to f_1}=p(X_1|X_0^{(j)},Y_{0:1})\delta(X_1-X_1^{(j)}),\\&\mu_{f_1\to\boldsymbol{h}}=p(X_1|X_0^{(j)},Y_{0:1})\delta(X_1-X_1^{(j)})p(Y_1|X_1,\boldsymbol{h})\\&\qquad\propto p(Y_{0:1}|X_{0:1}^{(j)},\boldsymbol{h}).\end{aligned}\right\}\quad(26)$$

The messages up to the kth subcarrier can be written as

$$\left.\begin{aligned}&\mu_{f_k\to X_k}=\int p(\boldsymbol{h})p(Y_{0:k-1}\mid X_{0:k-1}^{(j)},\boldsymbol{h})p(Y_k\mid X_k,\boldsymbol{h})\mathrm{d}\boldsymbol{h}\\&\qquad\propto p(Y_k\mid X_k,X_{0:k-1}^{(j)},Y_{0:k-1}),\\&\mu_{f_k\to X_k}\cdot\mu_{T\to X_k}=p(Y_k\mid X_k,X_{0:k-1}^{(j)},Y_{0:k-1})\cdot\\&\qquad p(X_k\mid X_{0:k-1}^{(j)},Y_{0:k-1})\propto p(X_k\mid X_{0:k-1}^{(j)},Y_{0:k}),\\&\mu_{X_k\to f_k}=p(X_k\mid X_{0:k-1}^{(j)},Y_{0:k})\delta(X_k-X_k^{(j)}).\end{aligned}\right\}\quad(27)$$

Note that X_k is independent of X_{k-1} and Y_{k-1}, and $X_k^{(j)}$ is generated from $p(X_k\mid X_{0:k-1}^{(j)},Y_{0:k})$. If the number of samples is M, then the sum-product algorithms for j=1,…,M are developed in parallel. Let

$$\begin{aligned}\alpha_{k,i}^{(j)}&\triangleq p(Y_k|X_{0:k-1}^{(j)},Y_{0:k-1},X_k=\alpha_i)P(X_k=\alpha_i|X_{0:k-1}^{(j)},Y_{0:k-1})\\&\propto P(X_k=a_i|X_{0:k-1}^{(j)},Y_{0:k}),\ a_i\in\mathcal{S},\end{aligned}\quad(28)$$

and the predictive distribution can be computed as

$$\begin{aligned}p(Y_k|X_{0:k-1}^{(j)},Y_{0:k-1})&=\sum_{a_i\in\mathcal{S}}\{p(Y_k|X_{0:k-1}^{(j)},Y_{0:k-1},X_k=a_i)\\&\cdot P(X_k=a_i|X_{0:k-1}^{(j)},Y_{0:k-1})\}=\sum_{a_i\in\mathcal{S}}\alpha_{k,i}^{(j)}.\end{aligned}\quad(29)$$

As the signal models are regarded as Gaussians, we can compute the messages in Eq.(27) straightforwardly. Assume that $\boldsymbol{h}$ has *a priori* Gaussian distribution, i.e., $p(\boldsymbol{h})\sim\mathcal{N}_c(\boldsymbol{h}_{-1},\boldsymbol{\Sigma}_{-1})$, then we have

$$\begin{aligned}p(\boldsymbol{h})p(Y_{0:k-1}\mid X_{0:k-1}^{(j)},\boldsymbol{h})&\propto p(\boldsymbol{h}\mid X_{0:k-1}^{(j)},Y_{0:k-1})\\&\sim\mathcal{N}_c(\boldsymbol{h}_{k-1}^{(j)},\boldsymbol{\Sigma}_{k-1}^{(j)}),\end{aligned}\quad(30)$$

where

$$\left.\begin{aligned}&\boldsymbol{h}_k^{(j)}\triangleq\boldsymbol{\Sigma}_k^{(j)}\left[\boldsymbol{\Sigma}_{-1}^{-1}\boldsymbol{h}_{-1}+\frac{1}{\sigma_n^2}\sum_{i=0}^{k}(X_i^{(j)}\boldsymbol{Q}'(i,:))^{\mathrm{H}}Y_i\right],\\&\boldsymbol{\Sigma}_k^{(j)}\triangleq\left[\boldsymbol{\Sigma}_{-1}^{-1}+\frac{1}{\sigma_n^2}\sum_{i=0}^{k}(X_i^{(j)}\boldsymbol{Q}'(i,:))^{\mathrm{H}}X_i^{(j)}\boldsymbol{Q}'(i,:)\right]^{-1}.\end{aligned}\right\}\quad(31)$$

Following the matrix inversion lemma, Eq.(31) can be rewritten as (Yang and Wang, 2002)

$$\left.\begin{aligned}&\boldsymbol{h}_k^{(j)}=\boldsymbol{h}_{k-1}^{(j)}+\frac{Y_k-\mu_k^{(j)}}{\sigma_k^{2(j)}}\boldsymbol{\xi},\\&\boldsymbol{\Sigma}_k^{(j)}=\boldsymbol{\Sigma}_{k-1}^{(j)}-\frac{1}{\sigma_k^{2(j)}}\boldsymbol{\xi}\boldsymbol{\xi}^{\mathrm{H}},\\&\boldsymbol{\xi}\triangleq\boldsymbol{\Sigma}_{k-1}^{(j)}(X_k^{(j)}\boldsymbol{Q}'(k,:))^{\mathrm{H}}.\end{aligned}\right\}\quad(32)$$

It is shown that the conditional channel response is a Gaussian random variable. From Eq.(27) we have

$$\left.\begin{aligned}&p(Y_k\mid X_k,X_{0:k-1}^{(j)},Y_{0:k-1})\sim\mathcal{N}_c(\mu_k^{(j)},\sigma_k^{2(j)}),\\&\mu_k^{(j)}=X_k\boldsymbol{Q}'(k,:)\boldsymbol{h}_{k-1}^{(j)},\\&\sigma_k^{2(j)}=\sigma_n^2+X_k\boldsymbol{Q}'(k,:)\boldsymbol{\Sigma}_{k-1}^{(j)}(X_k\boldsymbol{Q}'(k,:))^{\mathrm{H}}.\end{aligned}\right\}\quad(33)$$

Assume that the symbol X_k has an *a priori* Gaussian distribution, i.e., $p(X_k)\sim\mathcal{N}_c(\bar{X}_k,V_k)$, and then from Eq.(27) the trial distribution can be computed as

$$\left.\begin{aligned}&p(X_k\mid X_{0:k-1}^{(j)},Y_{0:k})\propto p(Y_k\mid X_k,X_{0:k-1}^{(j)},Y_{0:k-1})p(X_k)\\&\qquad\sim\mathcal{N}_c(\nu_k^{(j)},\varsigma_k^{2(j)}),\\&\nu_k^{(j)}=\varsigma_k^{2(j)}\left[V_k^{-1}\bar{X}_k+\frac{1}{\sigma_k^{2(j)}}(\boldsymbol{Q}'(k,:)\boldsymbol{h}_{k-1}^{(j)})^{\mathrm{H}}Y_k\right],\\&\varsigma_k^{2(j)}=\left[V_k^{-1}+\frac{1}{\sigma_k^{2(j)}}(\boldsymbol{Q}'(k,:)\boldsymbol{h}_{k-1}^{(j)})^{\mathrm{H}}\boldsymbol{Q}'(k,:)\boldsymbol{h}_{k-1}^{(j)}\right]^{-1},\end{aligned}\right\}\quad(34)$$

and then by setting $X_k=\alpha_i$ ($a_i\in\mathcal{S}$) in Eq.(34), the probability $\alpha_{k,i}^{(j)}$ can be computed as

$$\alpha_{k,i}^{(j)}=\frac{1}{\pi\varsigma_k^{2(j)}}\exp\left\{-\frac{\left\|a_i-\nu_k^{(j)}\right\|^2}{\varsigma_k^{2(j)}}\right\},\quad a_i\in\mathcal{S}. \tag{35}$$

After computing the probability $\alpha_{k,i}^{(j)}$, we can draw $X_k^{(j)}=a_i$ from the set $\mathcal{S}$.

The above calculation shows that generating samples of the channels and the data symbols are performed alternately. The trial distribution, from which samples of the data symbol on the kth subcarrier are drawn, is computed based on the channel up to the ($k-1$)th recursion. And the channel up to the kth recursion can be updated based on the samples of the data symbol on the kth subcarrier. However, at the beginning of SMC algorithm, channels or data symbols, whose samples should be generated first, that is a question. The channels are proposed to be drawn first in previous SMC blind detection (Yang and Wang, 2002; Lu and Wang, 2001). While in this paper, we try to draw the samples of the data symbols first, which can provide some advantages.

Newly-built SMC detector

It is well known that as OFDM is without noise, any L of the N available tones can be used for training to recover the channel $\boldsymbol{h}$ exactly, assuming the maximum channel length is L. While in AWGN, the MMSE estimate of $\boldsymbol{h}$ occurs when the set of L pilot tones is one of the sets $\{k,k+N/L,\ldots,k+(L-1)N/L\}$, $k=0,1,\ldots,N/L-1$, i.e., pilot tones should be equispaced (Negi and Cioffi, 1998). Suppose we have chosen one set $k(0),\ldots,k(L-1)$, which are not pilot tones but data symbols in the blind receiver via SMC, which are called as virtual-pilots. Through drawing the samples of virtual-pilots, the samples of the channel vector can be generated, as the channel vector of L order can be computed based on L virtual-pilots.

Theorem 1 Assuming the virtual-pilot tones are data symbols employing M-QAM modulation (including M-PSK), for a generated sample of virtual-pilot tones, in relation to which there are at most $M-1$ ambiguous samples, which results in phase ambiguity.

Theorem 2 In OFDM systems, in order to resolve phase ambiguity, only one subcarrier is necessary to be used as pilot tone, which is used to generate the samples of the channel vector together with the samples of virtual-pilot tones.

Proof See Appendix A.

As shown in Fig.3, among these pilot tones, actually, only one pilot tone is training symbol, which is necessary to resolve the phase ambiguity inherent to any blind receiver, the others are data symbols, which are called virtual-pilots.

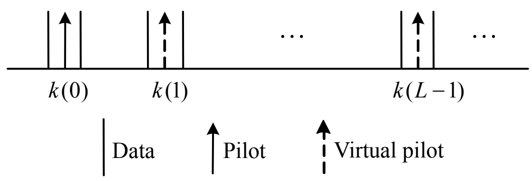

Fig.3 Pilot allocation sheme

Let $X_p^{(j)}=\{X_{k(0)}^{(j)},X_{k(1)}^{(j)},\ldots,X_{k(L-1)}^{(j)}\}$ ($j=1,\ldots,M$) be the initial samples of the symbols on the pilot tones including one pilot and the other $L-1$ virtual-pilots, and then from Eq.(31), the initial samples of the channel vector can be computed as

$$\left.\begin{aligned}&\boldsymbol{h}_{-1}^{(j)}\triangleq\boldsymbol{\Sigma}_{-1}^{(j)}\left[\boldsymbol{\Sigma}_{-1}^{-1}\boldsymbol{h}_{-1}+\frac{1}{\sigma_n^2}\sum_{i=0}^{L-1}\boldsymbol{\Xi}^{\mathrm{H}}Y_{k(i)}\right],\\&\boldsymbol{\Xi}\triangleq X_{k(i)}^{(j)}\boldsymbol{Q}'(k(i),:),\\&\boldsymbol{\Sigma}_{-1}^{(j)}\triangleq\left[\boldsymbol{\Sigma}_{-1}^{-1}+\frac{1}{\sigma_n^2}\sum_{i=0}^{L-1}\boldsymbol{\Xi}^{\mathrm{H}}\boldsymbol{\Xi}\right]^{-1}.\end{aligned}\right\} \tag{36}$$

After generating the initial samples of the channel vector, the SMC algorithm is performed by drawing the samples of data symbols and generating the samples of the channel vector in turn. The newly-built blind detector for OFDM systems via SMC in the factor graph is described as follows:

Initialization: Draw the initial samples $\{X_p^{(j)}\}_{j=1}^M$, and compute the initial samples of the channel vector based on Eq.(36); Set $\{w_{-1}^{(j)}\}_{j=1}^M=1$

For ($k=0,\ldots,N-1$) {
 If k in the set $k(0),\ldots,k(L-1)$
  For ($j=1,\ldots,M$) {
   Set $X_k^{(j)}$ to be the initial sample;

$w_k^{(j)} = w_{k-1}^{(j)}$;

$\boldsymbol{h}_k^{(j)} = \boldsymbol{h}_{k-1}^{(j)}, \boldsymbol{\Sigma}_k^{(j)} = \boldsymbol{\Sigma}_{k-1}^{(j)}$;

}

Else

For (j=1,…,M) {

For each $a_i \in \mathcal{S}$ compute $\alpha_{k,i}^{(j)}$ based on Eq.(35);

Draw $X_k^{(j)} = a_i$ from the set $\mathcal{S}$ with probability $\alpha_{k,i}^{(j)}$;

Compute the importance weight:

$$w_k^{(j)} = w_{k-1}^{(j)} \cdot \sum\nolimits_{a_i \in \mathcal{S}} \alpha_{k,i}^{(j)};$$

Update the *a posterior* mean and covariance of channel vector based on Eq.(32);

}

}

Compute the *a posteriori* probability of the data symbol

$$p(X_k = a_i \mid Y_{0:N-1}) \cong \sum_{j=1}^{M} \delta(X_k^{(j)} - a_i)\tilde{w}_{N-1}^{(j)}. \quad (37)$$

It can be seen that the initial samples $\{X_p^{(j)}\}_{j=1}^{M}$ are drawn from a sample space composed of totally $2J(L-1)$ points with $X_{k(0)}$ being a pilot tone whose value is known, while the size of the channel space is infinite, apparently drawing samples of the vector $\boldsymbol{X}_p$ is simpler than drawing samples of the channel vector $\boldsymbol{h}$ directly.

SIMULATION RESULTS

In our simulation, we employ Jakes channel model with L=4, with the power profile for each tap being 0, −3, −6, −9 dB respectively. We also simulate the system with channel order L=2 with the power profile for each tap being 0, −3 dB respectively. For simplicity, the entire channel bandwidth, i.e. 400 kHz, is divided into 64 subcarriers, i.e. N=64. A convolutional code with rate 1/2, constraint length 3 and generator (5, 7) in octal notation is used, and the BPSK and QPSK modulation methods are employed. Both previous blind SMC detection and the newly-built one are simulated. For the previous blind SMC detection, differential encoding is necessary with the first symbol being used as reference. While in our proposal, differential encoding is not necessary, one pilot is inserted in each OFDM block to resolve phase ambiguity, and subcarries {4, 20, 36, 52} are one pilot and three virtual-pilots, which are equispaced on FFT grid as shown in Fig.3.

Fig.4a shows the bit error rate (BER) of the newly-built SMC blind detection compared with the previous SMC detection. It is seen that the performance of the proposal is close to the lower bound achieved by coherent detection using pilot-aided

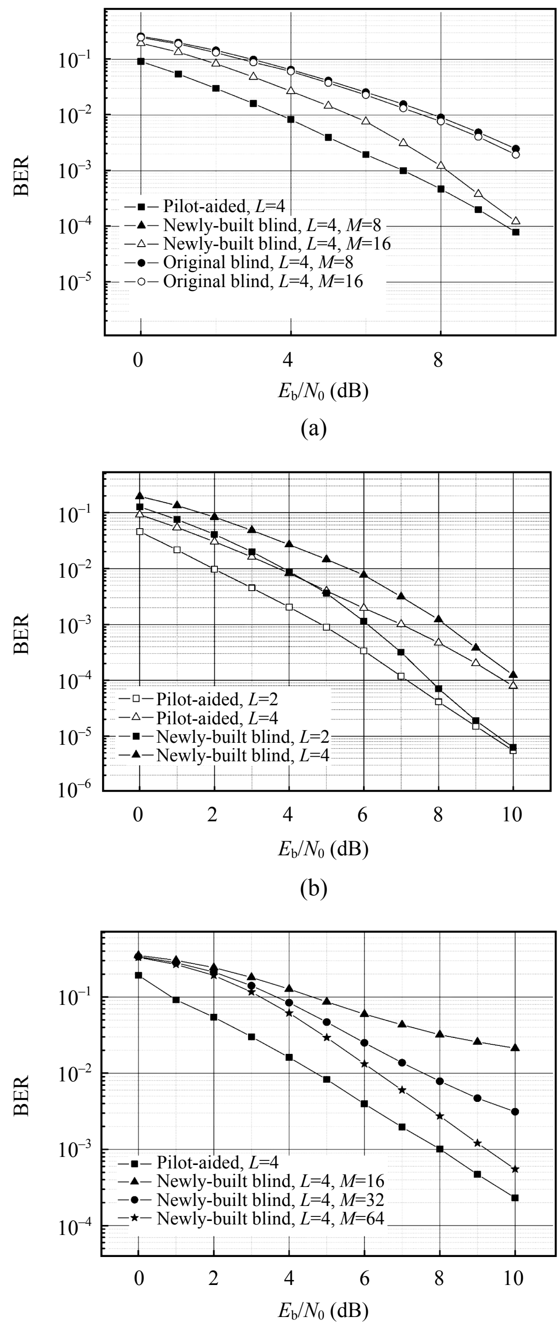

Fig.4 BER performance of the newly-built blind SMC detection for OEM (a) compared with the previous one; (b) compared with different channel orders; (c) compared with QPSK modulation and different numbers of samples

estimation of channel at high SNR, while the proposal does not perform as well as the pilot-aided scheme at low SNR, with the previous blind SMC detection undergoing performance degradation compared with the lower bound. For the coded OFDM, the proposed blind detection outperforms the previous blind SMC detection because more channel information can be retrieved in the proposal than in the previous approach. The BER performance of the proposed blind detection for channel model order L=2 and L=4 with samples M=8 is compared in Fig.4b, showing that the former is better than the latter, as the performance of channel estimation over the channel model L=2 is better than the channel model L=4. Fig.4c shows the BER performance of the proposal for QPSK modulation scheme with different numbers of samples, which are M=16, 32 and 64 respectively, It is shown that the BER performance is improved with the increase of samples.

CONCLUSION

In this paper, we present a newly-built blind detection for OFDM systems via SMC in factor graphs. The blind detection is developed based on the sum-product algorithm and importance sampling method. We generate initial samples of the virtual-pilot tones instead of drawing initial samples of the channel vector directly. And then the newly-built blind detection is developed without differential encoding and fewer Monte Carlo samples should be generated. It is shown that the newly-built blind detection can be constructed more simply and provide performance improvement.

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APPENDIX A

For a generated sample of virtual-pilot tones, which is $X_{k(0)}^{(j)},\ldots,X_{k(L-1)}^{(j)}$, the sample of channel vector can be written as

$$\boldsymbol{h}^{(j)} \triangleq \left[\sum_{i=0}^{L-1}\left(X_{k(i)}^{(j)}\boldsymbol{Q}'(k(i),:)\right)^{\mathrm{H}} X_{k(i)}^{(j)}\boldsymbol{Q}'(k(i),:)+\sigma_n^2\boldsymbol{I}\right]^{-1}\cdot \left[\sum_{i=0}^{L-1}\left(X_{k(i)}^{(j)}\boldsymbol{Q}'(k(i),:)\right)^{\mathrm{H}} Y_{k(i)}\right]. \quad \text{(A1)}$$

Consider constant modulus modulation, M-PSK, and assume $(X_{k(i)}^{(j)})^{\mathrm{H}} X_{k(i)}^{(j)}=1$, thus Eq.(A1) can be rewritten as

$$\boldsymbol{h}^{(j)} \triangleq \left[\sum_{i=0}^{L-1}\left(\boldsymbol{Q}'(k(i),:)\right)^{\mathrm{H}} \boldsymbol{Q}'(k(i),:)+\sigma_n^2\boldsymbol{I}\right]^{-1}\cdot \left[\sum_{i=0}^{L-1}\left(X_{k(i)}^{(j)}\boldsymbol{Q}'(k(i),:)\right)^{\mathrm{H}} Y_{k(i)}\right]. \quad \text{(A2)}$$

For the symbol X_k from set $\mathcal{S}$, $\mu_k^{(j)}$ can be evaluated as

$$\mu_k^{(j)} \triangleq \boldsymbol{Q}'(k(i),:)\left[\sum_{i=0}^{L-1}\left(\boldsymbol{Q}'(k(i),:)\right)^{\mathrm{H}} \boldsymbol{Q}'(k(i),:)+\sigma_n^2\boldsymbol{I}\right]^{-1}\cdot \left[\sum_{i=0}^{L-1}X_k\left(X_{k(i)}^{(j)}\right)^{\mathrm{H}}\boldsymbol{Q}'(k(i),:)Y_{k(i)}\right]. \quad \text{(A3)}$$

It is known that for M-PSK modulation and $s\in\mathcal{S}$, $s'=s\cdot e^{2\pi m/M}$ ($1\le m\le M-1$) is also in symbol alphabet $\mathcal{S}$, and then we have

$$X_k\left(X_{k(i)}^{(j)}\right)^{*} = X_k e^{2\pi m/M}\left(X_{k(i)}^{(j)}e^{2\pi m/M}\right)^{*}. \quad \text{(A4)}$$

Let

$$\left.\begin{array}{l} X_p^{(j)}=\{X_{k(0)}^{(j)},\ldots,X_{k(L-1)}^{(j)}\},\ \tilde{X}_p^{(j)}=\{\tilde{X}_{k(0)}^{(j)},\ldots,\tilde{X}_{k(L-1)}^{(j)}\},\\ \tilde{X}_{k(i)}^{(j)}=X_{k(i)}^{(j)}e^{2\pi m/M},\ \tilde{X}_k=X_k e^{2\pi m/M}. \end{array}\right\} \quad \text{(A5)}$$

It is shown that, when $\mu_k^{(j)}$ is computed, the combination of symbol X_k and virtual-pilot tones $X_p^{(j)}$ cannot be distinguished from the combination of $\tilde{X}_k$ and $\tilde{X}_p^{(j)}$.

As $X_{k(i)}^{(j)} \ne X_{k(i)}^{(j)}e^{2\pi m/M}$ for $1\le m\le M-1$, if any subcarrier from the set $k(0),\ldots,k(L-1)$ can be used as a pilot tone, then there exists no combination of $\tilde{X}_k$ and $\tilde{X}_p^{(j)}$, which can not be distinguished from the combination of X_k and $X_p^{(j)}$, and then the phase ambiguity is resolved.