Laser atmospheric channel estimation based on fast Bayesian matching pursuit

Ma Pengge[1], Chen Enqing[2], Pang Dongdong[2], Yang Yi[3]

(1. School of Electronic Communication Engineering, Zhengzhou University of Aeronautics, Zhengzhou 450015, China;
2. School of Information Engineering, Zhengzhou University, Zhengzhou 450001, China;
3. Luoyang Institute of Electro-Optic Equipment, AVIC, Luoyang 471000, China)

Abstract: Channel estimation refers to the method and process of receiving channel state information.The accuracy of channel estimation determines the performance of the receiver, so channel estimation must be carried out before equalization.Nowadays, the laser channel estimation for optics transmission becomes a key technology in free space optical communication in multiple-input multiple-output orthogonal frequency division multiplexing (FSO-MIMO-OFDM) system. Although the traditional method of compression sensing, as an effective method for channel estimation, has the ability to recover and reconstruct the original signal, it has paid a certain cost in computational complexity. A novel fast Bayesian matching pursuit (FBMP) algorithm was proposed to overcome the low reconstruction precision and high complexity of the existing methods. Through the prior model selection and approximate minimum mean squared error (MMSE) estimation of the parameter vector, the FBMP algorithm provided an efficient way to estimate the channel impulse response and was characterized by high reconstruction accuracy and low complexity. Simulation results show that the proposed method can significantly improve the performance of the system compared with the traditional compressed sensing(CS).

Key words: compressed sensing; sparse channel estimation; fast Bayesian matching pursuit; FSO-MIMO-OFDM

CLC number: TN911　　**Document code:** A　　**DOI:** 10.3788/IRLA201746.0922002

基于快速贝叶斯匹配追踪的激光大气信道估计

马鹏阁[1],陈恩庆[2],庞栋栋[2],羊　毅[3]

(1. 郑州航空工业管理学院 电子通信工程学院,河南 郑州 450015;
2. 郑州大学 信息工程学院,河南 郑州 450001;
3. 中航工业集团公司洛阳电光设备研究所,河南 洛阳 471000)

摘　要: 信道估计是指接收机获知信道状态信息的方法和过程。信道估计的准确度决定了接收机

收稿日期:2017-01-10;　**修订日期**:2017-02-13

基金项目:国家自然科学基金(61331021);航空科学基金(2014ZC13004);河南省高校科技创新团队(17IRTSTHN014);河南省科技计划(152102210139)

作者简介:马鹏阁(1976-),男,副教授,博士,主要从事激光雷达目标检测与识别方面的研究。Email:mapenge@163.com

的工作性能，所以均衡之前，必须先进行信道估计。目前，激光光学传输信道估计成为多输入多输出正交频分复用的自由空间光通信系统的关键技术。传统的压缩感知方法作为一种信道估计的有效方法，具有恢复和重构原始信号的能力，但在计算复杂度上付出了一定的代价。快速贝叶斯匹配追踪算法克服了现有方法重构精度低和复杂度高缺点。通过先验模型选择和近似的最小均方误差的参数向量的估计，快速贝叶斯匹配追踪算法提供了估计信道冲激响应的一种有效方式。仿真结果表明，与传统的基于压缩感知的方法相比，该方法能显著提高系统的性能。

关键词： 压缩感知； 空闲信道估计； 快速贝叶斯匹配追踪；
多输入多输出正交频分复用的自由空间光通信

0 Introduction

The channel of free space optics (FSO) system for atmospheric scattering channel, will be affected by dust, rain, fog and other particles, while the cyclic guard interval is introduced in, at the receiving end can be used in simple frequency domain equalization and eliminate multipath interference caused by atmospheric scattering, but in the frequency domain equalization must be known before the channel frequency accuracy on each sub carrier response. FSO communicating[1] in MIMO-OFDM system with a machine brings out many advantages in practice, yet results in several technological challenges, such as how to significantly increase the transmission accuracy and improve the spectral efficiency. The key is how to obtain the channel state information (CSI) accurately in MIMO-OFDM system for speech signal transmission.

Due to the sparse structures of the rich multipath channels, the channel can be modeled as a tapped delay line (TDL) in the time domain, since the large delay spread and the sparseness of resolvable multipath allow only a few taps to be nonzero[2]. Conventional channel estimation methods could not take advantage of the multipath channel inner sparse prior knowledge. Therefore, the accuracy and effectiveness of channel estimation are not accurate enough. CS has recently been applied for pilot-aided sparse channel estimation. Recently, CS[3] has been studied for sparse signal recovery from a few of linear measurements for long time in applied sparse channel estimation. CS as one of the channel estimation methods has been extensively studied in[4]. However, the performance of CS-based channel estimation scheme hangs on reliable sparse recovery algorithms. We investigate some representative existing approaches including matching pursuit (MP), orthogonal matching pursuit (OMP)[5], and stage wise orthogonal matching pursuit (SOMP)[6], etc. Above-mentioned algorithms belong to greedy algorithms whose complexity depends on the number of iterations or finding set of support. These algorithms have lower reconstruction precision, though they can be implemented easily. Therefore they have relatively poor performance and limited applications. Meanwhile, certain algorithms such as Basic Pursuit (BP)[7] belong to convex optimization algorithms whose computational complexity is about $O(N^3)$[8]. Despite the algorithms can exactly recover sparse signal, its long computational time resulting in high complexity is not applicable for large scale data of speech communication system.

Recently, a Bayesian approach was adopted for sparse channel estimation via model selection and model averaging in Ref. [9]. Sparse Bayesian Learning (SBL)[10] is one of the Bayesian-based approaches adopted for sparse channel estimation for OFDM systems in Ref. [11]. Compared with other channel estimation algorithms, Bayesian-based scheme have higher performance recourse to probabilistic priors.

We introduce a CS recovery algorithm-FBMP proposed in Ref.[12] which can reduce the complexity by a fast metric update and can be implemented easily in contrast to SBL approach. Through the prior model selection of sparse multipath channels and parameter estimation, FBMP based channel estimation techniques are capable of obtaining more efficient estimator and faster convergence rate.

1 Channel model for speech transmission in FSO-MIMO-OFDM

The total number of subcarriers is L in FSO-MIMO-OFDM systems. There are N_t transmit antennas and N_r receive antennas to transmit speech signal. After speech encoding and modulation, the data bits are divided into N_t streams, and then the serial data symbols are converted into parallel blocks. Then each block performs pilot insertion, L point IFFT and cyclic extension. It is worth noting that the modulated signals are then space-time coded using Alamouti Space Time Block Coding(STBC)[13] scheme. The impulse response of the channel vector is represented as

$$h^{(i,j)}(t)=\sum_{n=0}^{N-1}\alpha_n^{(i,j)}\delta(t-\tau_n) \tag{1}$$

Where, $\alpha_n^{(i,j)}$ is the fading coefficient of the n-th multipath; τ_n is the relative delay of the n-th multipath. It is assumed that all the channels between N_t transmit antennas and N_r receive antennas hold the same delay profile. N is the number of multipath. The sparsity of time-domain channel is determined by the channel power.

After the removal of FFT and CP, the original speech signal at the j-th receive antenna can be written as

$$Y^{(j)}=\sum_{i=1}^{N_t}(Fh^{(i,j)})\circ X^{(i)}+W^{(j)},\ j=1,\cdots,N_r \tag{2}$$

There, $Y^{(j)}=[Y_1^{(j)},\ \cdots,Y_L^{(j)}]^{\mathrm{T}}$ is the frequency-domain received signal vector at j-th receive antenna; F is $L\times N$ discrete Fourier transform(DFT) matrix, whose (l,n)-th element is $F_{l,n}=\mathrm{e}^{-j2\pi ln/L}$; $W^{(j)}=[W_1^{(j)},\ \cdots,W_L^{(j)}]^{\mathrm{T}}$ is the complex noise; $X^{(i)}=[X_1^{(i)},\cdots,X_L^{(i)}]^{\mathrm{T}}$ is the modulated symbol vector at the i-th transmit antenna; "$\circ$" represents multiplication by element.

Pilots of different transmit antennas insert different subcarriers in the frequency domain. Before the channel estimation, the received signal vector of the j-th receiving antenna is separated from the pilot frequency of the i-th transmitting antenna, and can be represented as a received signal vector

$$Y_p^{(i,j)}=f_M^{(i)}Fh^{(i,j)}\circ X_p^{(i)}+f_M^{(i)}W^{(i,j)} \tag{3}$$

Where, M is the number of pilot; $f_M^{(i)}$ is the M-by-N ($N\gg M$) pilot extraction matrix,and can be written as

$$f_M^{(i)}=(e_{p1}\ \cdots\ e_{pM})^{\mathrm{T}} \tag{4}$$

Where, e_{pi} is the unit column vector, $p_{i\text{-th}}$ element is 1. The other elements is 0, and $T=\{p_1,p_2,\cdots,p_M\}$ is the index set that represents the pilot position. Since pilots are known receivers, the following equations can be implemented for channel estimation.

$$R^{(i,j)}=Y_P^{(i,j)}\circ\hat{X}_P^{(i)}=f_m^{(i)}Fh^{(i,j)}+W'=\Theta h^{(i,j)}+W' \tag{5}$$

Where $\Theta=f_m^{(i)}F\in C^{M\times N}$, $R^{(i,j)}\in C^M$ and $h^{(i,j)}\in C^N$ is sparse and the vector that we want to obtain. $W'=f_m^{(i)}W^{(i,j)}\circ\hat{X}_P^{(i)}$. Because Θ and $R^{(i,j)}$ are readily available in the receiver. $h^{(i,j)}$ can be restored by the CS algorithm.

2 FBMP algorithm for sparse channel estimation

2.1 Signal model for compressed sensing

In order to apply the FBMP algorithm proposed in Ref.[12], we let $r=R^{(i,j)}$, $h=h^{(i,j)}$ and $w=W'$ in the following. Hence, Eq.(5) also can be written as

$$r=\Theta h+w \tag{6}$$

Where, the w is white Gaussian noise with variance σ^2, i.e., $w\sim N(0,\sigma^2 I_M)$. Due to $\Theta\in C^{M\times N}$ ($N\gg M$), Eq.(6) is an over-determined case and h is a suitably sparse parameter vector (i.e., $\|h\|_0\ll N$).

To model sparsity, we assume that $\{h_n\}_{n=0}^{N-1}$, the component of h, are i.i.d. random variables drawn from a two-dimensional Gauss mixing matrix. We know that few elements of the vector h are nonzero because of the sparsity of the multipath channel. Since this priori information, we introduce a new parameter vector z which is also sparse and the nonzero locations in specify which of the elements in h are nonzero. For each h_n, a mixture parameter $z_n\in\{0,1\}$ is used to index the component distribution. Especially, when $z_n=q$ ($q\in\{0,1\}$), then the coefficient h_n is modeled as a circular Gaussian with mean 0 and variance σ_q^2:

$$h_n|\{z_n=q\}\sim N(0,\sigma_q^2) \tag{7}$$

The mixture parameters $\{z_n\}_{n=0}^{N-1}$ are treated as random variables such that $P_r\{z_n=1\}=p_1$ and $P_r\{z_n=0\}=1-p_1$. We choose $\sigma_0^2=0$, so that the case $z_n=0$ implies $h_n=0$, whereas the case $z_n=1$ allows $h_n\neq 0$. In addition, we choose $p_1\leqslant 1$ which ensures that (with high probability) the coefficient vector h has relatively few nonzero values.

Using $h=[h_0,\cdots,h_{N-1}]^{\mathrm{T}}$ and $z=[z_0,\cdots,z_{N-1}]^{\mathrm{T}}$, the priors can be written as:

$$h|z\sim N(0,R(z)) \tag{8}$$

Where, the $R(z)$ is the covariance matrix with respect to the discrete random vector $z=[z_0,\cdots,z_{N-1}]^{\mathrm{T}}$. And here, we set $R(z)$ to be a diagonal matrix with $[R(z)]_{n,n}=\sigma_{z_n}^2$, implying $h_n|\{z_n=1\}\sim N(0,\sigma_1^2)$ that and $h_n|\{z_n=0\}\sim N(0,\sigma_0^2)$.

According to Bayes rule, the relationship of z, h and r is shown as the equation in the following.

$$p(r,h|z)=\frac{p(r,h,z)}{p(z)}=\frac{p(r|h,z)p(h,z)}{p(z)}=\frac{p(r|h,z)p(h|z)p(z)}{p(z)}=p(r|h,z)p(h|z) \tag{9}$$

Because the relationship of z and h, the $p(r|h,z)$ is equivalent to $p(r|h)$, so the Eq.(9) can be written as:

$$p(r,h|z)=p(r|h)p(h|z) \tag{10}$$

From the model we can gain

$$\begin{bmatrix} r \\ h \end{bmatrix}\Big|z\sim N\left(0,\begin{bmatrix} \Phi(z) & \Theta R(z) \\ R(z)\Theta^{\mathrm{T}} & R(z) \end{bmatrix}\right) \tag{11}$$

Where

$$\Phi(z):=\Theta R(z)\Theta^{\mathrm{T}}+\sigma^2 I_M \tag{12}$$

2.2 Estimation of parameter z based on FBMP

According to the aforementioned model, the solution of h can be reduced to estimation of z. So, we first to analyze the parameter z.

The posterior can be written as

$$p(z|r)=\frac{p(r|z)p(z)}{\sum_{z'\in Z}p(r|z')p(z')} \tag{13}$$

Where $Z=\{0,1\}^N$. Because $\{p(r|z)p(z)\}_{z\in Z}$ has the same monotonicity with $\{p(z|r)\}_{z\in Z}$ and the latter is more practical to compute, we can compute $\{p(r|z)p(z)\}_{z\in Z}$ in order to estimate the parameter z. Working in the log domain, we find

$$\begin{aligned}\mu(z)&:=\ln p(r|z)p(z)=\ln p(r|z)+\sum_{n=0}^{N-1}\ln p(z_n)=\\ &\ln p(r|z)+\|z\|_0\ln p_1+(N-\|z\|_0)\ln(1-p_1)=\\ &\ln p(r|z)+\|z\|_0\ln\frac{p_1}{1-p_1}+N\ln(1-p_1)=\\ &-\frac{N}{2}\ln 2\pi-\frac{1}{2}\ln\det(\Phi(z))-\frac{1}{2}r^{\mathrm{T}}\Phi(z)^{-1}r+\\ &\|z\|_0\ln\frac{p_1}{1-p_1}+N\ln(1-p_1)\end{aligned} \tag{14}$$

Where combined with Eq.(13),

$$\begin{aligned}\ln p(r|z)&=\ln\frac{1}{(2\pi)^{N/2}|\Phi(z)|^{1/2}}\exp\left(-\frac{1}{2}r^{\mathrm{T}}\Phi(z)^{-1}r\right)=\\ &-\frac{N}{2}\ln 2\pi-\frac{1}{2}\ln\det(\Phi(z))-\frac{1}{2}r^{\mathrm{T}}\Phi(z)^{-1}r\end{aligned} \tag{15}$$

We refer to $\mu(z)$ as the basis selection metric.

Now we describe an efficient mean to estimate z which is called Fast Bayesian Matching Pursuit.

More specifically, z_n denote a vector which is same to z except for the n^{th} coefficient and we set $[z_n]_n=1$ and $[z]_n=0$. Then we compute the metric increment: $\Delta_n(z):=\mu(z_n)-\mu(z)$. What must be noted is that the metric at the root node (i.e., $z=0$) is

$$\mu(0)=-\frac{N}{2}\ln 2\pi-\frac{M}{2}\ln\sigma^2-\frac{1}{2\sigma^2}\|r\|_2^2+N\ln(1-p_1) \tag{16}$$

Via Eq.(12) we can know that

$$\Phi(0)=\sigma^2 I_M \tag{17}$$

To obtain the fast metric update, we start with the property that

$$\Phi(z_n)=\Theta R(z_n)\Theta^{\mathrm{T}}+\sigma^2 I_M=\Theta(R(z)+A)\Theta^{\mathrm{T}}+\sigma^2 I_M=$$
$$\Theta R(z)\Theta^{\mathrm{T}}+\Theta A\Theta^{\mathrm{T}}+\sigma^2 I_M=\Phi(z)+\sigma_1^2\theta_n\theta_n^{\mathrm{T}} \tag{18}$$

Where the A is a $N\times N$ matrix whose elements are all zero but $[A]_{n,n}$, and $[A]_{n,n}=\sigma_{z_n}^2=\sigma_1^2$. θ_n expresses the n-th column of matrix Θ.

As is shown in the Appendix, we can obtain:

$$\Phi(z_n)^{-1}=\Phi(z)^{-1}-\sigma_1^2\beta_n\varphi_n\varphi_n^{\mathrm{T}} \tag{19}$$

$$\varphi_n:=\Phi(z)^{-1}\theta_n \tag{20}$$

$$\beta_n:=(1+\sigma_1^2\theta_n^{\mathrm{T}}\varphi_n)^{-1} \tag{21}$$

Combined with Eq.(14), yield

$$\mu(z_n)=\mu(z)+\frac{1}{2}\ln\beta_n+\frac{\sigma_1^2}{2}\beta_n(r^{\mathrm{T}}\varphi_n)^2+\ln\frac{p_1}{1-p_1} \tag{22}$$

$$\Delta_n(z):=\mu(z_n)-\mu(z)=\frac{1}{2}\ln\beta_n+\frac{\sigma_1^2}{2}\beta_n(r^{\mathrm{T}}\varphi_n)^2+\ln\frac{p_1}{1-p_1} \tag{23}$$

In summary, $\Delta_n(z)$ in Eq.(23) quantifies the change due to the activation of the n^{th} tap of z.

From Eqs.(19)-(21), the complexity of computing $\{\beta_n\}_{n=0}^{N-1}$ is $O(NM^2)$. Then, exploiting the structure of $\Phi(z)^{-1}$, we can save the cost to be linear in M.

We set that $t=[t_1,t_2,\cdots,t_P]^{\mathrm{T}}$ consists of the induces of active elements in z. Then, from Eq.(17) and Eq.(19),

$$\Phi(z)^{-1}=\frac{1}{\sigma^2}I_M-\sigma_1^2\sum_{i=1}^{P}\beta_{t_i}\varphi_{t_i}\varphi_{t_i}^{\mathrm{T}} \tag{24}$$

When activating index $n=t_i$ in the mixture parameter vector, φ_{t_i} and β_{t_i} represent the values of φ_n and β_n. From Eq.(20), we are required to compute

$$\varphi_n=\frac{1}{\sigma^2}\theta_n-\sigma^2\sum_{i=1}^{P}\beta_{t_i}\varphi_{t_i}\underbrace{\varphi_{t_i}^{\mathrm{T}}\theta_n}_{:=c_n^{(i)}} \tag{25}$$

When activating the n^{th} tap in z. The key point is that we need to compute the coefficients $\{c_n^{(i)}\}_{n=o}^{N-1}$ only when index t_i is activated. Moreover, $\{c_n^{(i)}\}_{n=0}^{N-1}$ only need to be calculated for extracting induces t_i. These are the foundation of the FBMP algorithm. Table 1 shows the steps of FBMP algorithm and distinctly verifies that the iteration complexity of that algorithm is $O(NMPD)$.

Tab.1 Fast Bayesian matching pursuit

FBMP algorithm

$\mu_{0,1}=-\frac{N}{2}\ln 2\pi-\frac{M}{2}\ln\sigma^2-\frac{1}{2\sigma^2}\|r\|_2^2+N\ln(1-p_1)$;
for $n=1:N$,
  $\tilde{\varphi}_{1,n}=\sigma^{-2}\theta_n$;
  $\tilde{\beta}_{1,n}=(1+\sigma_1^2\theta_n^{\mathrm{T}}\tilde{\varphi}_n)^{-1}$
  $\tilde{\mu}_{1,n}=\mu_{0,1}+\frac{1}{2}\ln\tilde{\beta}_n+\frac{\sigma_1^2}{2}\tilde{\beta}_n(r^{\mathrm{T}}\tilde{b}_{1,n})^2+\ln\frac{p_1}{1-p_1}$;
end
for $n=1:D$;
  $n_*=n$ corresponding to k^{th} largest $\tilde{\mu}_{1,n}$;
  $\mu_{1,k}=\tilde{\mu}_{1,n}$; $\varphi_{1,k}^{(1)}=\tilde{\varphi}_{1,n^*}$; $c_{1,k}^{(1)}=\Theta^{\mathrm{T}}\varphi_{1,k}^{(1)}$; $\beta_{1,k}^{(1)}=\tilde{\beta}_{1,n^*}$;
  $t_{1,k}^{(1)}=n_*$;
end
for $p=2:P$
  for $d=1:D$
    for $n=1:N$
    $\tilde{\varphi}_{d,n}=\sigma^{-2}\theta_n-\sum_{i=1}^{p-1}\varphi_{p-1}^{(i)}\beta_{p-1}^{(i)}[c_{p-1,d}^{(i)}]_n$;
    $\tilde{\beta}_{d,n}=(1+\sigma_1^2\theta_n^{\mathrm{T}}\tilde{\varphi}_{d,n})^{-1}$;
    $\tilde{\mu}_{d,n}=\mu_{p-1,d}+\frac{1}{2}\ln\tilde{\beta}_{d,n}+\frac{\sigma_1^2}{2}\tilde{\beta}_{d,n}(r^{\mathrm{T}}\tilde{b}_{d,n})^2+\ln\frac{p_1}{1-p_1}$;
    if $n\in\{t_{p-1,d}^{(i)}\}_{i=1}^{p-1}$ then $\tilde{\mu}_{d,n}=-\infty$
    end
  end
  for $k=1:D$
    $\{d_*,n_*\}=\{d,n\}$ corresponding to k^{th} largest $\tilde{\mu}_{d,n}$;
    $\mu_{p,k}=\tilde{\mu}_{d^*,n^*}$; $\varphi_{p-k}^{(p)}=\tilde{\varphi}_{d^*,n^*}$; $c_{p-k}^{(p)}=\Theta^{\mathrm{T}}\varphi_{p-k}^{(p)}$; $\beta_{p-k}^{(p)}=\tilde{\beta}_{d^*,n^*}$;
    $t_{p-k}^{(p)}=n_*$;
    for $i=1:p=1$,
      $\varphi_{p,k}^{(i)}=\varphi_{p-1,k}^{(i)}$; $c_{p,k}^{(i)}=c_{p-1,k}^{(i)}$; $\beta_{p,k}^{(i)}=\beta_{p-1,k}^{(i)}$; $t_{p,k}^{(i)}=t_{p-1,k}^{(i)}$;
    end
  end
end

2.3 Estimation of sparse channel *h*

In section 2.2, we have got the mixture parameter z. However our primary goal is to estimate the sparse channel h when the mixture parameter z is known. Here, we use "minimum mean square error" (MMSE) to estimate the parameter vector h.

The MMSE estimate of h from r is

$$\hat{h}_{\mathrm{mmse}}:=E\{h|r\}=\sum_{z\in Z_*}p(z|r)E\{h|r,z\} \tag{26}$$

Where z from Eq.(11) it is straight forward to obtain in Ref.[14]

$$E\{h|r,z\}=R(z)\Theta^{\mathrm{T}}\Phi(z)^{-1}r \tag{27}$$

So, via Eq. (26), the parameter vector h, i.e., channel impulse response $h^{(i,j)}$, has been obtained.

3 Simulation results and analysis

The simulations are carried out to evaluate the performance of the FBMP algorithm from Tab.1 by using 2×2 MIMO-OFDM systems. The simulation parameters are shown in the Tab.2. The channel length is chosen as N=50. There are 6 main paths (sparsity of channel: K=6) in Rayleigh fading channels, so we set p_1=0.12 because the p_1 denotes the probability of $h_n \neq 0$ which means main paths in multipath channel.

Tab.2 Simulation parameters

Parameters	Specification
FFT size	256
No. of carriers	256
Guard interval	32
Signal constellation	QPSK
Channel model	Rayleigh fading
No. of frames	1 000

When referring to the "normalized mean-squared error"(NMSE) of an estimate $\hat{h}$, we mean $E\{\|\hat{h}-h\|_2^2/\|h\|_2^2\}$. And the Signal to Noise Ratio (SNR) means $10\lg10(|h|^2/|h-\hat{h}|^2)$.

Furthermore, traditional algorithm LS, CS-based OMP algorithms are chosen to compare with FBMP algorithm.

Figure 1 depicts the NMSE versus and the SNR, which is averaged over 1 000 OFDM block at every SNR value. Where, the SNR value is known to us from 0 dB to 30 dB. Figure 1 shows the performance of FBMP compared with the LS, OMP algorithms. We can see that the NMSE of FBMP is about 5 dB lower than OMP method and about 20 dB lower than LS method for SNR in 15 dB and the performance superiority is more and more obvious with the increasing of SNR.

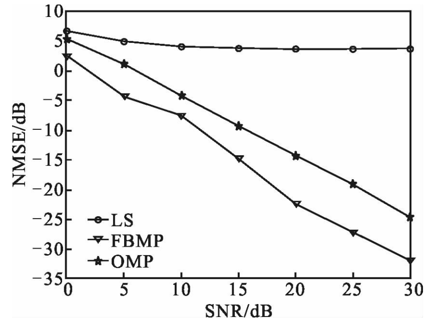

Fig.1 NMSE comparison of different estimation methods

Figure 2 shows the Bit Error Rate (BER) versus the SNR of channel estimation in MIMO-OFDM system with the LS, OMP and FBMP algorithms. From the Fig.2, we can observe that performance of the FBMP algorithm is superior to other two algorithms. Therefore, it can be seen that the former shows the better performance and more efficient to estimate channel in MIMO-OFDM.

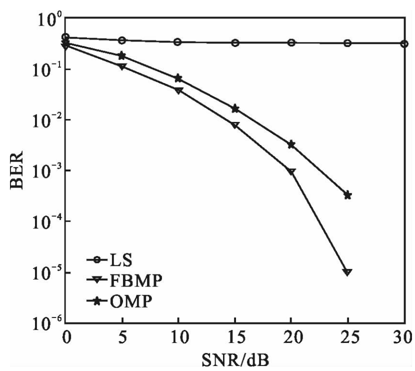

Fig.2 BER comparison of different estimation methods

Figure 3 denotes the SNR versus the different number of pilot, which is averaged over 1 000 OFDM block at every number of pilot. Fig.3 shows the SNR

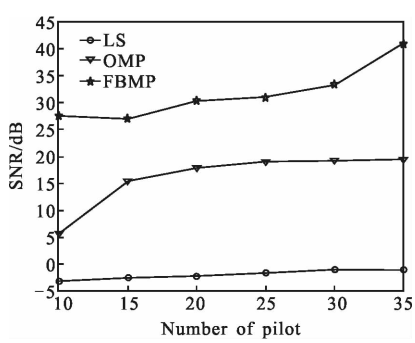

Fig.3 SNR comparison of different number of pilot for the three estimation methods

of FBMP compared with the LS, OMP algorithms in channel estimation in MIMO-OFDM system. We can see that SNR value of FBMP is always higher than LS and OMP with the number of pilot ranging from 10 to 35.

Figure 4 shows the BER versus the SNR with different sparsity(K=2, 4, 6, 8, 10) for FBMP algorithm. In this simulation, the actual sparsity of channel is 6. The Figure 4 shows that BER of FBMP gradually declines with the sparsity growth, and when K=2 and K=4, the performance of the algorithm is relatively poor and the curves of K=6, K=8, K=10 are very similar. This shows that only when the priori sparsity K is equal to or greater than the actual channel sparsity can we obtain accurate channel state information.

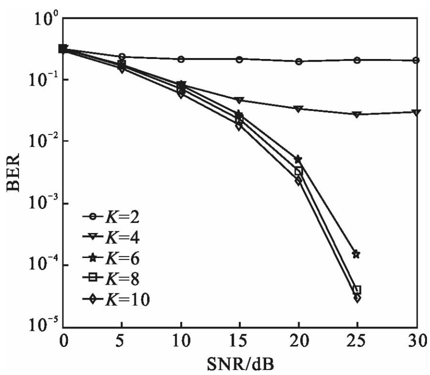

Fig.4 SNR comparison of different sparsity for the FBMP algorithm

4 Conclusion

This paper focused on the speech signal transmission in FSO-MIMO-OFDM system and mainly studied the channel estimation technology based on compressed sensing and reconstruction algorithm FBMP. Compared with traditional LS and CS-based OMP and SP channel estimation method, FBMP based channel estimation technique were capable of obtaining efficient sparse channel estimates by making full use of channel sparse prior in FSO-MIMO-OFDM systems.

References:

[1] Ma Pengge, Qi Lin, Yang Yi, et al. Study on airborne multi-pulse ladar target signal simulator [J]. ***Acta Optica Sinica***, 2012, 32(1): 271-276. (in Chinese)

[2] Donoho D L. Compressed sensing [J]. ***IEEE Trans Inf Theory***, 2006, 52(4): 1289-1306.

[3] Berger C R, Wang Z, Huang J, et al. Application of compressive sensing to sparse channel estimation [J]. ***IEEE Communications Magazine***, 2010, 48(11):164-174.

[4] Cai T T, Wang L. Orthogonal matching pursuit for sparse signal recovery with noise [J]. ***IEEE Transactions on Information Theory***, 2011, 57(7): 4680-4688.

[5] Donoho D L, Tsaig Y, Drori I, et al. Sparse solution of underdetermined linear equations by stagewise orthogonal matching pursuit [R]. Stanford Statistics Technical Report, 2006.

[6] Candes E and Tao T. Decoding by Linear Programming[J]. ***IEEE Trans Inf Theory***, 2005, 51(12): 4203-4215.

[7] Richard G. Baraniuk. Compressed sensing [J]. ***IEEE Signal Processing Magazine***, 2007, 24(4): 118-121.

[8] Larsson E, Selen Y. Linear regression with a sparse parameter vector [J]. ***IEEE Transactions on Signal Processing***, 2007, 55(2): 451-460.

[9] Barbu O E, Manchón C N, Rom C, et al. OFDM receiver for fast time-varying channels using block-sparse bayesian learning [J]. ***IEEE Transactions on Vehicular Technology***, 2016, 65(12): 10053-10057.

[10] Wipf D P, Rao B D. Sparse Bayesian learning for basis selection[J]. ***IEEE Transactions on Signal Processing***, 2004, 52(8): 2153-2164.

[11] Prasad R, Murthy C R. Joint channel estimation and data detection in MIMO-OFDM systems using sparse Bayesian learning[C]//Communications IEEE, 2014: 1-6.

[12] Prasad R, Murthy C R. Bayesian learning for joint sparse OFDM channel estimation and data detection [C]//Global Telecommunications Conference (GLOBECOM 2010), 2010 IEEE, 2010: 1-6.

[13] Schniter P, Potter L C, Ziniel J. Fast bayesian matching pursuit [C]//Information Theory and Applications Workshop. 2008: 326-333.

[14] Alamouti S. A simple transmit diversity teachnique for wireless communications [J]. ***IEEE J Ael Areas Comm***, 1998, 16(8): 1451-1458.

[15] Poor H V. An introduction to signal detection and estimation (Adapted from a one semester graduate course taught at the University of Illinois) [J]. ***Springer Texts in Electrical Engineering***, 2015, 333(1): 127-139.