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Technical note

Distributed compressed sensing estimation of underwater acoustic OFDM channel

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ABSTRACT

Orthogonal frequency division multiplexing (OFDM) is recently drawing more and more attention for its high bandwidth efficiency over underwater acoustic (UWA) channels. However, the classic OFDM channel estimation algorithms, e.g. Least Square (LS), Minimum Mean Square Error (MMSE) are subject to significant performance degradation caused by doubly selective UWA channels. It has been recognized that the sparsity contained in UWA channels offers the possibility to improve the performance by compressed sensing (CS) estimation methods such as Orthogonal Matching Pursuit (OMP). Moreover, it has also been observed that multipath arrivals associated with adjacent OFDM symbols usually exhibit varying magnitude but similar delay, which means that UWA channels of several continuous symbols can be modeled as sparse sets with common support. In this paper, a Distributed Compressed Sensing (DCS) method is proposed to transform the problem of OFDM channel estimation into reconstruction of joint sparse signals. By exploiting this type of joint sparsity among adjacent OFDM symbols, we establish the DCS OFDM channel model, and then utilize the Simultaneous Orthogonal Matching Pursuit algorithm (SOMP) to optimize the model. Finally the experimental performance under field test is provided to illustrate the superiority of the proposed DCS channel estimation method, compared to the classic algorithm as well as CS counterparts.

1. Introduction

With rapidly increasing requirement on efficient acquisition and transmission of underwater observation information associated with ocean environmental monitoring, underwater project engineering and sea bottom resource exploitation tasks, there is an urgent need for R&D of high data rate underwater acoustic communication systems [1]. Unfortunately, compared with wireless channel, underwater acoustic channel is much more complicated due to the strictly limited bandwidth, extensive multi-path spread, Doppler shift and background noise. Design and implementation of high data rate underwater acoustic communication pose a considerable challenge [2] to the research community.

OFDM has recently emerged as a promising alternative to single-carrier systems for underwater acoustic communication because of its robustness to long delay spreads and frequency selectivity [3–5]. As well, OFDM provides high data rate for underwater acoustic communication which can be used for underwater acoustic speech or photo communication occasions. However, underwater OFDM systems are sensitive to Doppler shifting and phase noise [6], which will destroy the orthogonality of OFDM subcarriers, and pose difficulties in channel estimation and coherence detection [7].

Various channel estimation methods developed based on the assumption of the rich multi-path channel model, have been summarized in the literature [8]. Qiao et al. [9] pose an iterative Lease Square (LS) channel estimation algorithm for MIMO OFDM systems, the algorithm can greatly improve estimation accuracy, and the low-pass filtering in time domain reduces AWGN and ICI significantly. Jeong and Lee [10] pose a low complexity channel tracking for adaptive MMSE channel Estimation in OFDM system, the experimental result shows that the proposed channel parameter estimator tracks channel condition reliably in various channel conditions without significant increase in computational complexity. Morelli and Mengali [11] pose a maximum likelihood estimator (MLE) for OFDM system. However, the algorithms mentioned above require larger number of pilots or preambles to guarantee the estimated channel accuracy, which, unfortunately, will reduce

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the bandwidth efficiency and increase a high computation overhead. Meanwhile, there will exist significant estimated noise in non-zeros taps.

The underwater acoustic channels are considered to be sparse both in time and frequency domain, i.e., the delay-Doppler spread function has a limited number of nonzero elements [12]. The compressed sensing (CS) methods have been widely used for channel estimation to exploit the channel sparsity [13–16]. Wu and Tong [13] propose the Non-uniform norm constraint LMS algorithm for sparse underwater acoustic channel estimation. Singh et al. [14] investigate the compressed sensing algorithms for estimation of OFDM channel. By adopting the compressed sensing methods, the length of training sequence can be significantly cut to improve efficiency, and the estimation noise at non-zero taps can be effectively suppressed [17].

While the UWA channels typically consists of sparse multipath arrivals, the multipath structure of adjacent OFDM symbols appears similar sparse structure because the delay of multipath arrivals tend to exhibit much slower variation than the corresponding magnitude does [18]. It means that UWA channels of several continuous symbols can be modeled as sparse sets with common support. Baron et al. [19] study three joint sparsity models (JSMs): JSM1 has sparse common component, JSM2 has common sparse supports and JSM3 has non-sparse common component. Underwater acoustic OFDM channels among adjacent symbols can be described as a JSM2 type model. Based on the basic concept of CS, Distributed compressed sensing (DCS) is proposed to exploit the joint sparseness contained among different sparse signals so as to achieve further performance enhancement. The temporal, spatial correlation among multiple sparse targets have been employed for DCS sparse recovery in wireless networks [20].

In this paper, a temporal joint sparse recovery approach is proposed to exploit the sparse correlation among adjacent OFDM symbols to improve the performance of OFDM channel estimation. By converting the problem of OFDM channel estimation into reconstruction of joint sparse signals with common support, a joint sparse model under the framework of DCS is adopted to derive a joint sparse recovery OFDM channel estimation algorithm. The performance of the proposed method is quantitatively evaluated with the experimental bit error rate (BER) of an UWA OFDM communication system. Finally, underwater OFDM communication experimental results obtained in Xiamen harbor are provided to demonstrate the effectiveness of the proposed method in improving the performance of underwater acoustic OFDM communication, compared to the classic channel estimation methods.

The rest of this paper is organized as follows. In Section 2, the model of OFDM and distributed compressed sensing are derived. The experimental performance analysis and comparison are provided in Section 3. Some conclusions are made in Section 4.

2. System model

2.1. Transmitting model

We consider an OFDM baseband system with K equally spaced subcarriers at frequencies

$$f_k = k\Delta f,\ k = 0, \ldots K-1 \tag{1}$$

where Δf is the K subcarrier separation, therefore, the entire signal bandwidth is $B = K\Delta f$, and each OFDM symbol lasts $T_0 = 1/\Delta f$. The K subcarriers can be allocated as either data symbols or pilot symbols, depending on the packet structure. Define the K subcarrier symbols of i-th OFDM symbol as $\mathbf{b}_i$:

$$\mathbf{b}_i = [b(i,0),\ \ldots,\ b(i,K-1)]^T \tag{2}$$

The transmitted time-domain discrete signal OFDM symbol can be expressed as:

$$\mathbf{x} = \mathbf{F}^H \mathbf{b}_i \tag{3}$$

where F is the $K \times K$ unitary normalized Discrete Fourier Transform (DFT) matrix,

$$F = \frac{1}{K}\begin{bmatrix} \exp(j2\pi\frac{0}{K}\cdot 0) & \exp(j2\pi\frac{1}{K}\cdot 0) & \cdots & \exp(j2\pi\frac{K-1}{K}\cdot 0) \\ \exp(j2\pi\frac{0}{K}\cdot 1) & \exp(j2\pi\frac{1}{K}\cdot 1) & \cdots & \exp(j2\pi\frac{K-1}{K}\cdot 1) \\ \vdots & \vdots & \ddots & \vdots \\ \exp(j2\pi\frac{0}{K}\cdot(K-1)) & \exp(j2\pi\frac{1}{K}\cdot(K-1)) & \cdots & \exp(j2\pi\frac{K-1}{K}\cdot(K-1)) \end{bmatrix} \tag{4}$$

To prevent the inter-block interference (IBI) induced by multipath, last N_{cp} samples of an OFDM symbol which are called cyclic prefix (Cp) are copy to the beginning of each symbol. In general, the length of cyclic prefix is larger than that of the longest channel response delay.

2.2. Channel model

We assume that the channel between transmitter and receiver is a linear time-invarint (LTI) finite impulse response (FIR) filter with impulse response [21] written as:

$$h(t) = \sum_{i=0}^{L-1} h_i \delta(t - \tau_i) \tag{5}$$

where L denotes the length of channel which depends on the maximum channel delay spread, h_i and τ_i denote channel tap coefficient and the channel delay respectively.

After removing the Cp, the discrete received signal can be expressed as

$$y(n) = x(n) \otimes h(n) + w(n) = \sum_{i=0}^{L-1} x(i)h(n-i) + w(n) \tag{6}$$

where $w(n)$ is the additive noise. Eq. (5) can be written as matrix form as:

$$\mathbf{y} = \mathbf{A}\mathbf{h} + \mathbf{w} \tag{7}$$

where $\mathbf{A}$ is the Toeplizt matrix. The received signal y is converted to the frequency domain by applying DFT as:

$$\mathbf{Y} = \mathbf{F}\mathbf{y} = \mathbf{F}diag(\mathbf{x})\mathbf{h} + \mathbf{W} = \mathbf{S}\mathbf{h} + \mathbf{W} \tag{8}$$

where vector $\mathbf{x}$ is the frequency domain of transmitting signal, $\mathbf{W} = \mathbf{F}\mathbf{w}$ is the frequency domain noise and $\mathbf{S} = \mathbf{F}diag(\mathbf{x})$.

For the purpose of OFDM channel estimation, pilots are usually equally inserted into an OFDM data symbol, so Eq. (8) can be written as

$$\mathbf{Y}_p = \mathbf{F}diag(\mathbf{X}_p)\mathbf{h} + \mathbf{W}_p = \mathbf{S}_p\mathbf{h} + \mathbf{W}_p \tag{9}$$

The subscript p denotes pilot, which is used for channel estimation. The classic channel estimation methods such as LS or MMSE algorithms are popularly adopted to solve Eq. (9)[9,10].

2.3. CS channel estimation

Due to the sparsity feature of UW channels, the problem of the UWA channel estimation can be converted into a sparse recovery one, namely, it can be expressed as:

$$\hat{\mathbf{h}} = \arg\min \|\mathbf{h}\|_1 \text{ subject to } \mathbf{y} = \mathbf{S}\mathbf{h} \tag{10}$$

where the vector $\mathbf{y}$ is received training sequences and matrix $\mathbf{S}$ is called atoms, the length of $\mathbf{h}$ can be much shorter than that of training sequences $\mathbf{y}$ [22], because of the sparseness. We can use compressed sensing method to improve the channel estimation performance and reduce the computation.

2.4. DCS estimation of OFDM channels

For sparse signals with common support, the concept of DCS is capable of further improving the performance of sparse reconstruction [19]. As the UWA OFDM channels of adjacent data symbols exhibit significant temporal correlation, i.e., multipath arrivals are associated with similar time delay and different magnitude, according to the Joint Sparsity Models 2 (JSM2) of DCS theory, the UWA channels can be modeled as sparse signals with common temporal support, which enable the adoption of DCS recovery to improve the estimation performance, or alternatively decrease the number of pilots.

Under the JSM2 framework, UWA channel $\mathbf{h}_i$ of the i-th data block can be described as:

$$\mathbf{h}_i = \Psi_i \mathbf{\Omega} + \mathbf{d}_i \ i \in (1,2,\ldots,N) \tag{11}$$

where N is the number of OFDM data symbols used for joint sparse recovery. Thus, the UWA OFDM channels of N adjacent OFDM data symbols consist of two types of multipath arrivals, namely, multipath arrivals with the common support $\mathbf{\Omega}$ but different magnitudes, and those with different time delay $\mathbf{d}_i$.

According to the JSM2 model, estimation of MIMO UWA channels can be converted to the following DCS problem:

$$\hat{\mathbf{H}} = \arg\min \sum_{i=1}^{N} (\|\mathbf{h}_i\|_1) \quad s.t. \|\mathbf{Y}_p - \mathbf{S}_p \mathbf{H}\|_2^2 \leqslant \boldsymbol{\varepsilon} \tag{12}$$

where $\boldsymbol{\varepsilon}$ is the noise factor, $\mathbf{h}_i$ is the channel associated with i-th OFDM symbol, N is the number of associate OFDM data symbols, P is the number of pilots in an OFDM data symbols.

$\mathbf{H} = [\mathbf{h}_1, \mathbf{h}_2, \ldots \mathbf{h}_N]$, $\mathbf{H} \in C^{NL\times 1}$, $\mathbf{Y} = [\mathbf{Y}_{p,1}, \mathbf{Y}_{p,2}, \ldots \mathbf{Y}_{p,N}]$, $\mathbf{Y} \in C^{PN\times 1}$, where $\mathbf{Y}_{p,i}$ is the received signal of i-th OFDM pilots in frequency domain. The measurement matrix can be expressed as

$$\mathbf{S}_p = \begin{bmatrix} \mathbf{S}_{p,1} & \mathbf{0} & \cdots & \mathbf{0} \\ \mathbf{0} & \mathbf{S}_{p,2} & \cdots & \mathbf{0} \\ \vdots & \vdots & \ddots & \vdots \\ \mathbf{0} & \mathbf{0} & \cdots & \mathbf{S}_{p,N} \end{bmatrix}, \ \mathbf{S}_p \in C^{PN\times NL} \tag{13}$$

2.5. SOMP algorithm

Accordingly, the DCS estimation of the underwater OFDM channels can be addressed with the simultaneous OMP (SOMP) algorithm. Specifically:

Input: N adjacent receiving OFDM pilot symbols $\mathbf{Y} = [\mathbf{Y}_{p,1}, \mathbf{Y}_{p,2}, \ldots \mathbf{Y}_{p,N}]$, $\mathbf{Y} \in C^{PN\times 1}$, $\mathbf{S}_p \in C^{PN\times NL}$, the maximum iteration T and the threshold of residual error.

Initialization:

Residual error $R_i^0 = Y_{p,i}$, $R_i^0 \in C^{P\times 1}$, $i \in (1,2,\ldots,N)$, where the superscript denotes the i-th iteration, the subscript denotes the parameters corresponding to i-th OFDM symbol. Initialize the index of atom as $\mathbf{\Omega} = \varnothing$, initialize atom set as $\mathbf{Phit}_i = \varnothing$. The multi-path magnitude of the i-th OFDM symbol is $\hat{\mathbf{h}}_i = \varnothing$. The initial iteration number is t = 1.

Step 1:

Selecting atom $\mathbf{S}_{p,i}$ from the $\mathbf{S}_p$ to perform inner product with residual error R_i^{t-1}, summing the inner product outputs of N OFDM symbols to determine the location corresponding to the maximum result λ^t, saving λ^t and the associated atom, i.e., the $\mathbf{S}_{p,i}$ associated with λ^t is denoted as $\mathbf{S}_{p,i,\lambda^t}$

$$\begin{aligned} &\lambda^t = \arg\max \sum_{i=1}^{N} |\langle \mathbf{S}_{p,i}, \mathbf{R}_i^{t-1} \rangle| \\ &\mathbf{\Omega} = \mathbf{\Omega} \cup \lambda^t \\ &\mathbf{Phit}_i = \mathbf{Phit}_i \cup \mathbf{S}_{p,i,\lambda^t} \end{aligned} \tag{14}$$

Step 2:

Calculate the multi-path magnitude of each OFDM symbol with LS method as:

$$\beta_i = [(\mathbf{S}_{p,i,\lambda^t})^H \mathbf{S}_{p,i,\lambda^t}]^{-1} \mathbf{S}_{p,i,\lambda^t} \mathbf{Y}_{p,i} \ i \in (1,2,\ldots,\ N) \tag{15}$$

Save the coefficients $\hat{\mathbf{h}}_i = \hat{\mathbf{h}}_i \cup \beta_i, \ \ i \in (1,2,\ldots,N)$, then calculate the residual error:

$$\mathbf{R}_i^t = \mathbf{Y}_{p,i} - \mathbf{Phit}_i^t \cdot \hat{\mathbf{h}}_i^t \tag{16}$$

Step 3:

Iterations stop when the current residual is smaller than the threshold or the number of iterations surpasses the defined number, otherwise keep on with iterations with $t = t + 1$

Output:

Thus the multi-path coefficients $\mathbf{h}_i, \ \ i \in (1,2,\ldots,N)$ and the corresponding time delay $\mathbf{\Omega}$ are obtained.

The iteration procedures above indicate that, the proposed DCS channel estimation method not only makes use of the sparse feature of each OFDM symbol's channel itself, but also exploits the joint sparse relationship of channels among adjacent OFDM symbols. Note that, when $N = 1$, the SOMP algorithm shrinks to the classic OMP algorithm.

2.6. Comparison of computational complexity

The computational complexity of the OMP as well as the SOMP algorithm is provided in Table 1 [23], where P is the number of pilots, L is the length of channel impulse response, t is the iteration number. From Table 1 one may observe that the SOMP algorithm adopting N symbols for joint estimation will lead to a computational complexity N times higher than that of the OMP algorithm.

3. Experiment and discussions

3.1. Setup of at-sea experiment

The experimental field data was collected from a shallow water acoustic channel with slight wind condition at Wuyuan Bay, Xiamen, China. The depth of the experiment area is about 10 m. The OFDM signal was transmitted from a transducer, at a depth of 2 m. The transmitted signal was received by two receivers submerged at the depth of 2 m and 6 m respectively. The transmitting transducer was suspended under a pier and the receivers are mounted at the rear of one anchored ship, with a distance of 1000 m as shown in Fig. 1. The channels from transmitting transducer to the upper and the lower receiver are defined as channel

Table 1
Complexity comparison.

Parameters	Complexity
OMP	$\mathcal{O}(PL + Pt + Pt^2 + t^3)$
SOMP (N = 2)	$2 * \mathcal{O}(PL + Pt + Pt^2 + t^3)$
SOMP (N = 4)	$4 * \mathcal{O}(PL + Pt + Pt^2 + t^3)$

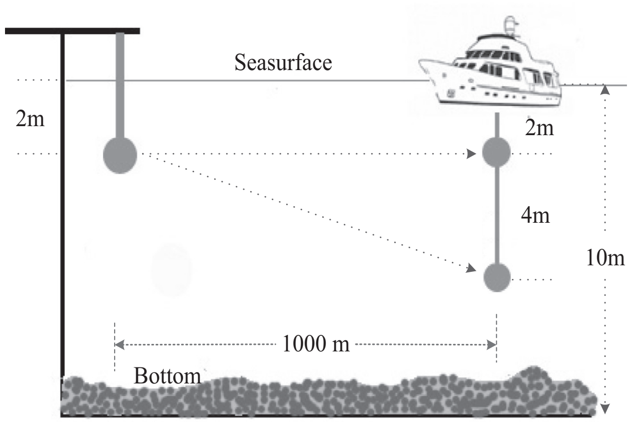

Fig. 1. Setup of OFDM acoustic communication experiment.

Table 2
Parameters of at-sea experiment.

Description	Value
Sampling frequency (fs)	96,000 Hz
Carrier frequency (fc)	15,500 Hz
Bandwidth (B)	5000 Hz
Number of subcarriers (K)	256
Symbol duration (T)	128 ms
Length of cyclic prefix (L_{cp})	32 ms
Mapping type	QPSK

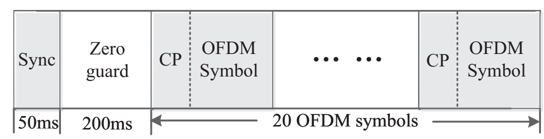

Fig. 3. Frame structure of OFDM packet.

1 and channel 2 respectively. The sound speed profile is provided in Fig. 2.

The parameters of at-sea experiment are presented in Table 2. Note that the number of total carriers contains that of data subcarriers and pilot subcarriers, which are designed for information delivering and channel estimation respectively.

The frame structure of OFDM packet is presented in Fig. 3. The Linear Frequency Modulation (LFM) pulse with a length of 50 ms is used as the synchronizing head of one frame. There are totally 20 OFDM symbols in one packet. The correlation method in [24] is adopted to estimate the bulk Doppler, which is compensated by resampling.

To evaluate the performance of the proposed method, we adopted different numbers of pilot subcarriers, which are equally insert in one OFDM symbol. For the purpose of comparison, the proposed joint sparse recovery (DCS) OFDM channel estimation method, the OMP method and the LSQR [22]method are selected for channel estimation respectively. The results of channel estimation are used for OFDM demodulation in the form of a classic channel equalizer [25] to facilitate the performance evaluation of the channel estimation algorithms.

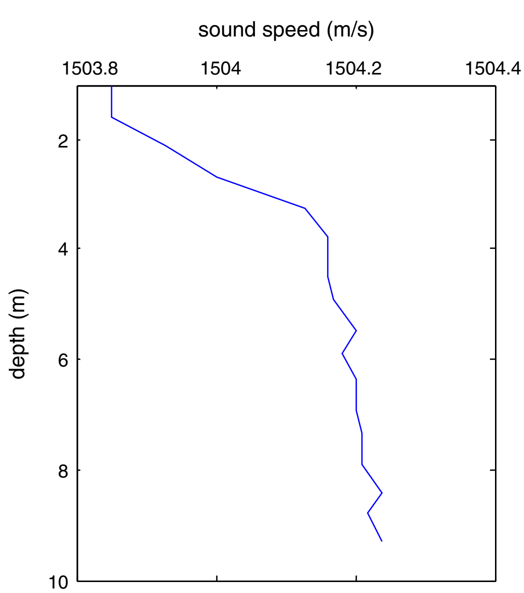

Fig. 2. Sound speed profile.

With the proposed algorithm, 2 adjacent OFDM symbols (corresponding method denotes SOMP2), and 4 continuous OFDM symbols (corresponding method denotes SOMP4) are used for joint sparse recovery respectively to examine the relationship between performance improvement and the OFDM symbols adopted for joint sparse reconstruction. The performance of different OFDM channel estimation algorithms is also analyzed under different pilot number. The original SNR of the channel 1, channel 2 are 20.5 d and 19.7 dB respectively, with an estimated bulk Doppler of about −2.0 Hz.

3.2. The results of experiment and discussion

The multi-path intensity profile (MIP) of channel 2 obtained during the experiment with LSQR, OMP, SOMP2 and SOMP4 is shown in Fig. 4(a), (b), (c) and (d) respectively. We set the pilot number at 60, and set the sparse degree at 6 in the OMP, SOMP2 and SOMP4 methods.

Fig. 4 indicates that the experimental channel exhibits a typical sparse pattern with distinct multipath arrivals. One can see that there exists considerable estimation noise in non-zero taps which is obtained by LSQR method as shown in Fig. 4(a), because the LSQR algorithm is non-sparse algorithm and it requires a large pilot number to ensure the positive definite solution which unfortunately occupies the bandwidth.

With the result of classic OMP method in Fig. 4(b) and that of the proposed DCS methods (SOMP2 and SOMP4) shown in Fig. 4 (c) and (d), it is evident that the proposed DCS methods yield a better estimation performance on weak multipath arrivals. The reason is that, as Eq. (14) shows, the proposed DCS not only explores the sparseness of individual OFDM underwater channel, but also utilizes the joint sparse relationship among adjacent OFDM symbols. Furthermore, we can also observe that the SOMP4 method yields a better performance of estimation noise suppression than the SOMP2 does.

Fig. 5 provides the curves between pilot number and BER of channel 2. We can observe that the BER obtained by SOMP4 is the lowest, which illustrates the effectiveness of the proposed method. From Fig. 5 we can also conclude that, for the proposed SOMP methods, a small pilot number corresponds to higher performance improvement. Specifically, when the number of pilots is 50, the BERs associated with LSQR, OMP, SOMP2 and SOMP4 are 0.1875, 0.1145, 0.1006, and 0.0852 respectively. Under a pilot number of 100, the BERs corresponding to LSQR, OMP, SOMP2 and SOMP4 are0.035, 0.0262, 0.0238 and 0.0214 respectively. Thus, Fig. 5 demonstrates that, under small pilot number, the proposed

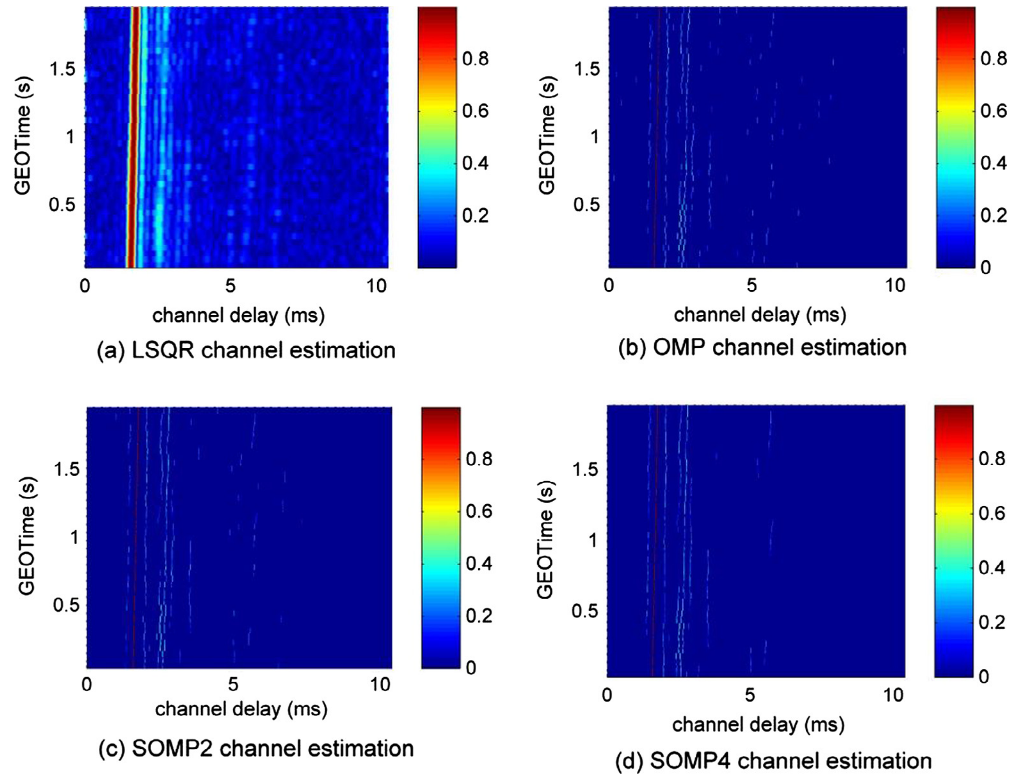

Fig. 4. Channel impulse response of channel 2 obtained by different algorithms.

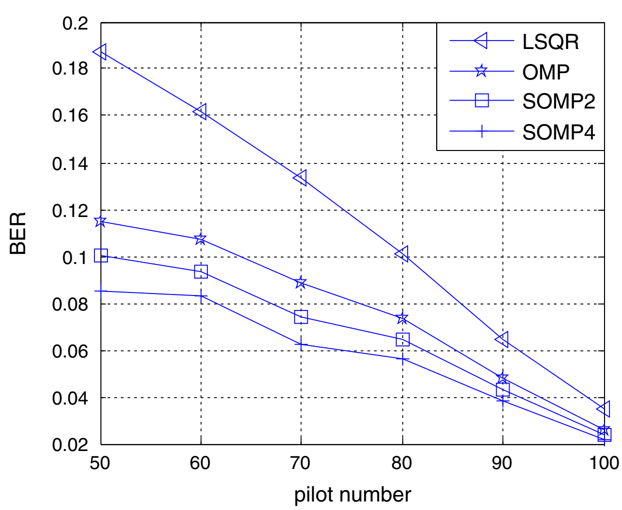

Fig. 5. Pilot number versus BER of channel 2.

method can achieve much performance gain upon the classic methods.

In Fig. 6, the constellation results of channel 2 obtained by different algorithms are shown with a pilot number of 100. One can observe that the SOMP4 obtains the best separated constellation result, which indicates the best communication performance. The result of constellation is consistent with that of Fig. 4 and Fig. 5 as analyzed before.

3.3. Performance analysis under time variations

In order to investigate the performance of proposed method under time-varying channel, we compare the OFDM communication performance associated with two receivers that exhibiting different time variations. Similar to [26], the channel correlation coefficient is defined to quantitatively evaluate the extent of time variations of experimental UWA channels associated with adjacent OFDM symbols:

$$\rho_i = \frac{E\{\mathbf{h}_i \mathbf{h}_{i+1}^H\}}{\sqrt{E\{\mathbf{h}_i \mathbf{h}_i^H\} E\{\mathbf{h}_{i+1} \mathbf{h}_{i+1}^H\}}} \quad i \in (1, 2, \ldots, N-1) \tag{17}$$

where the superscript H denotes the Hermite transpose, $\mathbf{h}_i$ and $\mathbf{h}_{i+1}$ denotes the channel response associated with the ith and $i+1$th symbol respectively, N is number of total symbols.

As the upper receiver is subject to surface fluctuations caused by wind and the current, the corresponding channel 1 exhibits more significant time variations than channel 2 does. Shown in Fig. 7 is the Channel impulse response of channel 1 obtained by SOMP2, with that of channel 2 provided in Fig. 4(c). One can see that the time variations of channel 1 are more obvious than that of channel 2, corresponding to a Doppler shift of about −2.1 Hz and −1.6 Hz respectively.

In Fig. 8, the BER with respect to the channel correlation coefficient of adjacent OFDM symbols is provided for channel 1 and channel 2, where (a) and (b) are the BER corresponding to channel 1 and channl 2 respectively, and (c) and (d) are channel correlation coefficients of adjacent two OFDM symbols obtained by Eq. (17) corresponding to channel 1 and channel 2 respectively.

From Fig. 8(a) and (b), we can see that, the proposed DCS channel estimation methods generally present better performance than classic OMP does for both channel1 and channel2. In view of Fig. 8 (c) and (d), it is evident that the channel correlation coefficient of channel 2 is considerably higher than that of channel 1, due to more surface-induced time variations of channel 1 as mentioned previously. As a result, channel 2 outperforms channel 1 in terms

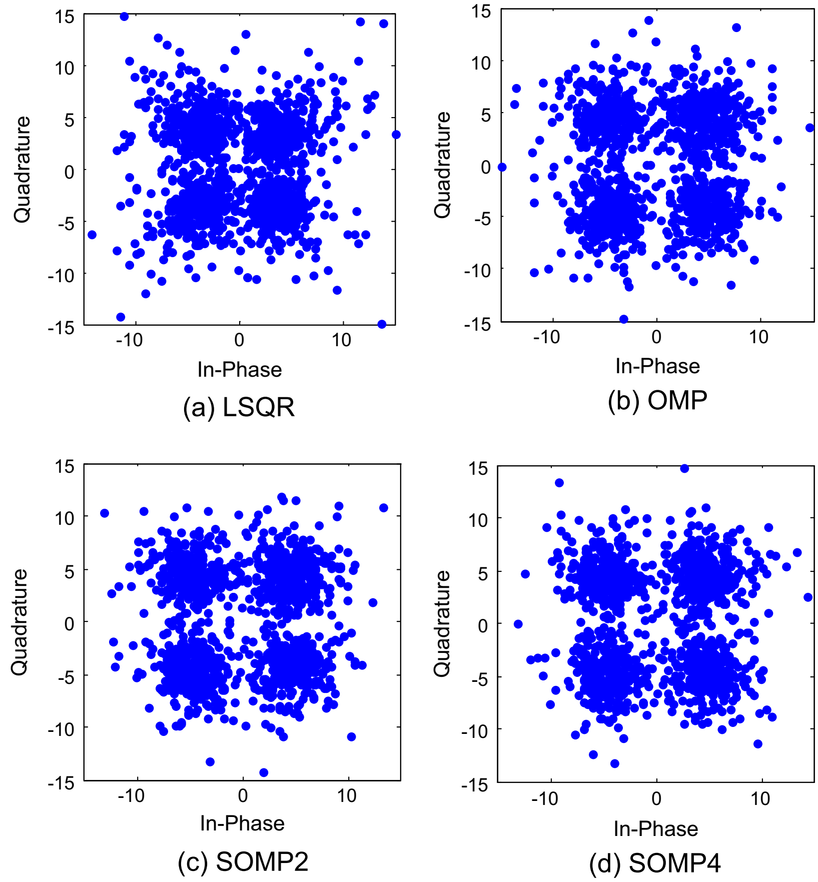

Fig. 6. Constellation obtained by different algorithms.

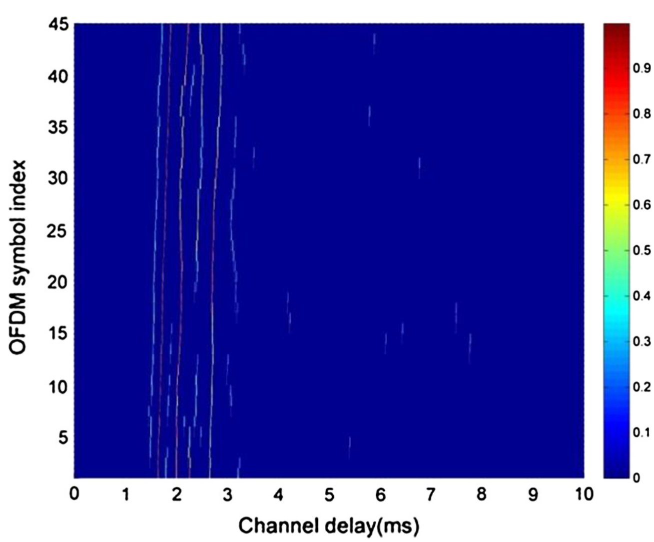

Fig. 7. Channel impulse response of channel 1.

of the BER improvement upon classic OMP algorithm achieved by the proposed algorithm.

As Fig. 8 indicates, the fluctuation of BER curve is highly consistent with that of the channel correlation coefficient, i.e., the higher channel correlation coefficients corresponds to better performance of DCS methods, while the lower channel correlation coefficients leading to the worse performance of DCS methods. The reason is that, as a large channel correlation coefficient means high similarity between channels of adjacent symbols, the channels can be well modeled by sparse set with common support. Thus the proposed DCS method is capable of improving the estimation performance via joint sparse reconstruction compared to the classic algorithm. Specifically, as show in Fig. 8(a) and (c), when the channel correlation coefficient is 0.81 at the 12th OFDM symbol from channel 1, the BERs of OMP, SOMP2 and SOMP4 methods are 0.100, 0.0957 and 0.0826 respectively which means that DCS type methods produce better performance. On the other hand, a small channel correlation coefficient corresponds to considerable time variations between adjacent OFDM channels, which cause more different components that cannot be formulated by common support, thus lead to performance degradation of DCS algorithm.

Moreover, at the presence of extremely significant time variations, the proposed DCS algorithm may even exhibits worse performance than classic method does. For example, as Fig. 8(a) and (c) indicating, the channel correlation coefficient at 7th symbol is only 0.0322, implying the presence of extreme time variations. As a result, the corresponding BERs obtained by OMP, SOMP2 and SOMP4 are 0.1174, 0.1304 and 0.1217 respectively, which means that the performance of classic OMP method is better than that of the proposed DCS method when the channel encounters extremely rapid time-variations.

Thus, while the experimental results reveal that the proposed DCS channel estimation is capable of achieving an overall performance improvement by exploiting the cross-correlation between the adjacent OFDM symbols, the impact of significant time variations on the effectiveness of joint channel estimation should be taken into account to achieve comprehensive performance improvement.

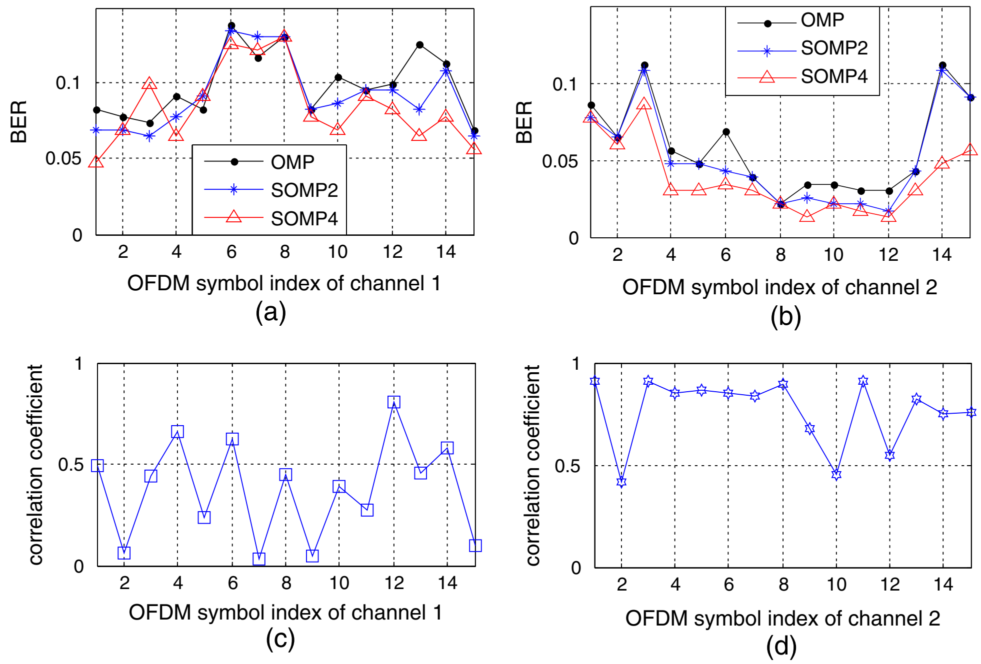

Fig. 8. BER with respect to channel correlation coefficient of channel 1 and channel 2.

4. Conclusion

While the sparsity contained in UWA channels have been popularly employed to improve the performance of channel estimation by CS methods, for UWA channels of adjacent symbols, similar delay pattern of multipath arrivals provides attractable possibility for further performance enhancement under the framework of DCS. In this paper, we investigated the joint estimation of underwater acoustic OFDM channels by modeling the channels of continuous OFDM systems as sparse set with common support. By establishing the DCS model of OFDM channels and utilizing the SOMP algorithm to optimize the model, the channel estimation performance under different number of training pilots is analyzed. Finally at-sea experimental results are provided to show that the proposed method outperforms classic LSQR and OMP methods due to the exploitation of the common sparseness. Moreover, the impact of time variations on the performance of the proposed joint estimation method is also quantitatively analyzed and discussed based on the experimental data.

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References

[1] Rouseff D, Badiey M, Song A. Effect of reflected and refracted signals on coherent underwater acoustic communication: results from the Kauai experiment (KauaiEx 2003). J Acoust Soc Am 2009;126(5):2359–66.
[2] Chitre M, Shahabudeen S, Freitag L, et al. Recent advances in underwater acoustic communications & networking [C]//OCEANS 2008. IEEE 2008;2008:1–10.
[3] Li B, Huang J, Zhou S, Ball K, Stojanovic M, Freitag L, Willett P. MIMO-OFDM for high rate underwater acoustic communications. IEEE J Ocean Eng 2009;34(4):634–45.
[4] Li B, Zhou S, Stojanovic M, Freitag L, Willet P. Multicarrier communications over underwater acoustic channels with nonuniform Doppler shifts. IEEE J Ocean Eng 2008;33(2):198–209.
[5] Radosevic A, Ahmed R, Duman TM, et al. Adaptive OFDM modulation for underwater acoustic communications: design considerations and experimental results. Ocean Eng IEEE J 2014;39(2):357–70.
[6] Zhang Y, Liu H. MIMO-OFDM systems in the presence of phase noise and doubly selective fading. Veh Technol IEEE Trans 2007;56(4):2277–85.
[7] Wang Z, Zhou S, Preisig JC, et al. Clustered adaptation for estimation of time-varying underwater acoustic channels. Signal Process IEEE Trans 2012;60(6):3079–91.
[8] Ozdemir M, Arslan H. Channel estimation for wireless OFDM systems. IEEE Commun Surv Tutorials 2007;9(2):18–48.
[9] Qiao Y, Yu S, Su P, et al. Research on an iterative algorithm of LS channel estimation in MIMO OFDM systems. IEEE Trans Broadcast 2005;51(1):149–53.
[10] Jeong K, Lee J. Low complexity channel tracking for adaptive MMSE channel estimation in OFDM [C]//Information Sciences and Systems, 2007. In: CISS'07. 41st Annual conference on. IEEE; 2007. p. 548–52.
[11] Morelli M, Mengali U. A comparison of pilot-aided channel estimation methods for OFDM systems. Signal Process IEEE Trans 2001;49(12):3065–73.
[12] Li W, Preisig J. Estimation of rapidly time-varying sparse channels. IEEE J Ocean Eng 2007;32(4):927–39.
[13] Wu FY, Tong F. Non-uniform norm constraint LMS algorithm for sparse system identification. IEEE Commun Lett 2013;17(2):385–8.
[14] Singh I, Kalyani S, Giridhar K. A practical compressed sensing approach for channel estimation in OFDM systems. Commun Lett IEEE 2015;19(12):2146–9.
[15] Wu FY, Tong F. Gradient optimization p-norm-like constraint LMS algorithm for sparse system estimation. Signal Process 2013;93(4). 967–961.
[16] Taubock G, Hlawatsch F, Eiwen D, Rauhut H. Compressive estimation of doubly selective channels in multicarrier systems: leakage effects and sparsity enhancing processing. IEEE J Sel Top Signal Proces 2010;4(2):255–71.
[17] Song A, Abadi A, Badiey M, et al. Experimental demonstration of underwater acoustic communication by vector sensors. IEEE J Ocean Eng 2011;36(3):454–61.
[18] Stojanovic M. Efficient processing of acoustic signals for high-rate information transmission over sparse underwater channels. Phys Commun 2008;1(2):146–61.
[19] Baron D, Wakin MB, Duarte MF, et al. Distributed compressed sensing. IEEE Trans Inform Theory 2006;52(12):5406–25.
[20] Corroy S, Mathar R. Distributed compressed sensing for the MIMO MAC with correlated sources. In: Communications (ICC), 2012 IEEE international conference on. IEEE; 2012. p. 2516–20.
[21] Liu Z, Yang TC. On the design of cyclic prefix length for time-reversed OFDM. Wireless Commun IEEE Trans 2012;11(10):3723–33.
[22] Berger CR, Wang Z, Huang J, et al. Application of compressive sensing to sparse channel estimation. Commun Mag IEEE 2010;48(11):164–74.
[23] Sturm BL, Christensen MG. Comparison of orthogonal matching pursuit implementations[C]//EUSIPCO; 2012. p. 220–4.
[24] Song A, Badiey M, McDonald VK, et al. Time reversal receivers for high data rate acoustic multiple-input–multiple-output communication. IEEE J Ocean Eng 2011;36(4):525–38.
[25] Jeon WG, Chang KH, Cho YS. An equalization technique for orthogonal frequency-division multiplexing systems in time-variant multipath channels. IEEE Trans Commun 1999;47(1):27–32.
[26] Xue X, Wei D, Gong S. The study of MIMO channel correlation coefficient in the rainfall environment for satellite communications//Microwave, antenna, propagation and EMC technologies for wireless communications (MAPE). In: 2013 IEEE 5th international symposium on. IEEE; 2013. p. 378–82.