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Exploiting joint sparsity for underwater acoustic MIMO communications

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ABSTRACT

MIMO communication has been recognized as a potential solution for high speed underwater acoustic communication, which unfortunately encounters significant difficulties posed by simultaneous presence of multipath and Co-channel interference (CoI). Sparsity contained in the multipath structure of underwater acoustic channels offers an effective way for improving channel estimation quality and thus enhancing the communication performance in the form of time reversal or channel estimation based equalization. However, for MIMO channels with extensive multipath and CoI, the performance gain achieved by classic sparsity exploitation channel estimation methods such as orthogonal matching pursuit (OMP) is still not enough to yield satisfactory performance. Under quasi-stationary assumption, underwater acoustic channels of adjacent data blocks exhibit correlated multipath structure, namely, multipath arrivals with similar time delay but different magnitude, which has not been exploited. In this paper, a joint sparse recovery approach is proposed to exploit the sparse correlation among adjacent data blocks to improve the performance of channel estimation. Under the framework of distributed compressed sensing (DCS), a joint sparse model which treats the multipath arrivals as sparse solutions with common time support is adopted to derive a joint sparse recovery algorithm for efficient channel estimation, the results of which are used to initialize and periodly update a channel estimation based time reversal receiver. Finally, underwater MIMO communication experimental results obtained in a shallow water channel are provided to demonstrate the effectiveness of the proposed method, compared to the same type of receiver that do not exploit the joint sparse.

1. Introduction

Rapidly growing of ocean related missions such as environmental monitoring, underwater project engineering and resource exploitation urges the R&D of high data rate underwater acoustic (UWA) communication systems, which is unfortunately seriously hindered by extreme difficulties of underwater acoustic channels such as narrow bandwidth, multipath, Doppler spread and background noise [1–3].

With popularly successful applications in wireless fields, MIMO communication offers a potential solution for high data rate underwater acoustic communication. Unfortunately, simultaneous presence of multipath and CoI poses significant difficulty to estimation of acoustic MIMO channels. As it has been recognized that channel estimation is capable to improve the performance of underwater acoustic communication in the form of channel equalization such as time reversal processor or decision feedback equalizer (DFE), extensive investigations have been carried out. In [4] a channel estimation based space-time equalizer consisting of multiple DFE equalizers is used for UWA MIMO communications. Song et al. [5] proposed a low complexity time reversal MIMO receiver by coupling multi-channel time reversal processors with a single channel DFE equalizer.

For MIMO channels with extensive multipath and CoI, conventional estimation methods such as Least squares (LS) algorithms is subject to significant degradation. As sparsity contained in the multipath structure of underwater acoustic channels offers an effective way for improving channel estimation quality [6,7], compressed sensing (CS) channel estimation method has been employed to yield performance enhancement by exploitation of sparseness contained in underwater acoustic channels [8]. However, for MIMO channels with serous CoI, performance gain achieved by sparsity exploitation of UWA channel is still not enough to meet the need of MIMO acoustic communication.

The quasi-stationary assumption of UWA channels [9] that applicable to most UWA channels with moderate or slight time variations indicates, UWA channels of adjacent data blocks exhibit correlated multipath structure under the condition that the length of data block does not exceed the period within which the channel

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remain static. Namely, among multiple continuous data blocks the multipath arrivals have similar time delay but different magnitude. While the sparseness contained in individual UWA channel has been utilized extensively, this type of cross-block correlation has not been exploited.

Based on the basic concept of CS, the DCS is proposed to exploit the joint sparseness among different sparse signals to achieve further performance enhancement. The temporal, spatial correlation among multiple sparse targets has been employed for DCS sparse recovery in wireless network [10,11]. In this paper, a temporal joint sparse recovery approach is proposed to exploit the sparse correlation among adjacent blocks to improve the performance of MIMO channel estimation. Under the framework of DCS, a joint sparse model which treats the multipath arrivals as sparse solutions with common time support and different magnitude is adopted to derive a joint sparse recovery algorithm for efficient estimation of MIMO channels. The enhanced estimation performance achieved with joint sparse recovery contribute to improve the MIMO communication quality in the form of a multichannel time reversal receiver [5], which is initialized and periodly updated by the results of channel estimation. Finally, underwater MIMO communication experimental results obtained in Xiamen harbor are provided to demonstrate the effectiveness of the proposed method in improving the performance of MIMO acoustic communication, indicating the advantages of joint sparsity exploitation compared to classic sparse exploitation.

2. Problem formulation

2.1. System model of MIMO acoustic communication

The receiving signal of a MIMO acoustic communication system with N transmitters and M receivers can be written as [5]:

$$y_m(k) = \sum_{n=1}^{N}\sum_{l=0}^{L-1} s_n(k-l)h_{n,m}(k,l) + w_m(k), \tag{1}$$

where $y_m(k)$,$w_m(k)$ is the receiving signal and additive noise at the mth receiver, $s_n(k)$, $h_{n,m}(k,l)$ is transmitting signal of the nth transmitter, and channel impulse response between n-m couple, k is time index for observation time, l is time index for time delay. Under the quasi-stationary assumption that the channel remains stable in P samples, (1) can be expressed as:

$$\mathbf{y}_m = \sum_{n=1}^{N}\mathbf{A}_n\mathbf{h}_{n,m} + \mathbf{w}_m \tag{2}$$

where the Toeplitz type matrix $\mathbf{A}_n$ [5] is:

$$\mathbf{A}_n = \begin{bmatrix} s_n(k+L), & s_n[k+L-1], & \cdots, & s_n[k+1] \\ s_n[k+L+1], & s_n[k+L], & \cdots, & s_n[k+2] \\ & \vdots & & \\ s_n[k+L+P-1], & s_n[k+L+P-2], & \cdots, & s_n[k+P] \end{bmatrix} \tag{3}$$

with:

$$\begin{aligned} \mathbf{y}_m &= [\,y_m(k+L) \quad y_m(k+L+1) \quad \ldots \quad y_m(k+L+P-1)\,]^T \\ \mathbf{s}_m &= [\,s_m(k+L) \quad s_m(k+L+1) \quad \ldots \quad s_m(k+1)\,]^T \\ \mathbf{h}_{n,m} &= [\,h_{n,m}(k) \quad h_{n,m}(k+1) \quad \ldots \quad h_{n,m}(k+L-1)\,]^T \\ \mathbf{w}_m &= [\,w_m(k+L) \quad w_m(k+L+1) \quad \ldots \quad w_m(k+L+P-1)\,]^T \end{aligned} \tag{4}$$

(2) can be further expressed as:

$$\mathbf{y}_m = \mathbf{A}\mathbf{h}_m + \mathbf{w}_m \tag{5}$$

where: $\mathbf{A} = [\mathbf{A}_1, \quad \mathbf{A}_2, \quad \ldots \quad \mathbf{A}_N]$, $\mathbf{h} = [\,\mathbf{h}_{1,m}, \quad \mathbf{h}_{2,m}, \quad \ldots \quad \mathbf{h}_{N,m}\,]^T$, the superscript $[*]^T$ denotes transpose operation.

The MIMO channel $\mathbf{h}$ can be estimated with the classic LS [5] or MMSE type method [1]. Considering that UWA channels exhibit sparse features, sparsity exploitation algorithm such as the OMP [5] is capable to improve the estimation performance. For multichannel receiver, estimation output of each channel is used to construct the time reversal processor of corresponding channel. In [5], a low-complexity MIMO receiver is proposed to combine the multichannel time reversal processor to deal with the ISI, which is followed by a single channel DFE equalizer to address the residual multipath.

2.2. DCS estimation of MIMO channels

For sparse signals with common support, DCS is capable to further improve the performance of sparse recovery by exploiting the joint sparsity [11,12]. To be specific, when the length of data block is far more less than the period within that the channel remains static, UWA channels of adjacent data blocks will exhibit significant correlation, i.e., multipath arrivals have similar time delay but different magnitude. According to the Joint Sparsity Models 2 (JSM2) of DCS theory [12], among multiple adjacent data bocks the UWA channels can be modeled as sparse solutions with common support, the common support is time delay of the correlated multipath arrivals. It means that UWA channels of adjacent data blocks measured independently can be reconstructed jointly by employing DCS method to improve the recovery performance or alternatively cut down the length of training sequence P to save overhead.

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

$$\mathbf{h}_i = \Psi_i\boldsymbol{\Omega} + \mathbf{d}_i \quad i \in (1, 2, \ldots, T) \tag{6}$$

where T is the number of data blocks used for joint sparse recovery. The UWA channels associated with T adjacent data blocks consist of two types of components: first, the common multipath components with the common support $\boldsymbol{\Omega}$ and different magnitude Ψ_i; second, different multipath arrivals $\mathbf{d}_i$ with different time delay. According to the JSM2 model, estimation of MIMO UWA channels can be converted to the following DCS problem:

$$\begin{aligned} \widehat{\mathbf{H}}_{n,m} &= \arg\min \sum_{i=1}^{T}(\|\mathbf{h}^i_{n,m}\|_1) \\ s.t.\ &\|\mathbf{Y}_m - \mathbf{A}_n\mathbf{H}_{n,m}\|_2^2 \leqslant \varepsilon \end{aligned} \tag{7}$$

where, $\mathbf{h}^i_{n,m}$ is the channel associated with the i-th data block between the nm-th couple, ε is a noise factor. Thus, we have:

$$\begin{aligned} &\mathbf{H}_{n,m} = [\mathbf{h}^1_{n,m}, \mathbf{h}^2_{n,m}, \ldots, \mathbf{h}^T_{n,m},]^H, \ \mathbf{H}_{n,m} \in C^{LT\times 1}, \\ &\mathbf{Y}_m = [\mathbf{y}^1_m, \mathbf{y}^2_m, \ldots, \mathbf{y}^T_m]^H, \ \mathbf{Y}_m \in C^{PT\times 1}, \end{aligned}$$

where the superscript $[*]^H$ denotes Hermitian operation, $\mathbf{y}^i_m$ is the i-th data block received in the m-th receiver, defined as:

$$\begin{aligned} \mathbf{y}^i_m = [&y^i_m(k+L+i*B), y^i_m(k+L-1+i*B), \ \ldots, \\ &y^i_m(k+L+P-1+i*B)]^H, \ \mathbf{y}^i_m \in C^{P\times 1} \end{aligned} \tag{8}$$

where B ($B \geqslant P$) is the length of each data block, $i \times B$ is the offset of data block. Thus the measurement matrix $\mathbf{A}_n$ can be expressed as:

$$\mathbf{A}_n = \begin{bmatrix} \mathbf{X}_1 & \mathbf{0} & \ldots & \mathbf{0} \\ \mathbf{0} & \mathbf{X}_2 & \ldots & \mathbf{0} \\ \vdots & \vdots & \vdots & \vdots \\ \mathbf{0} & \mathbf{0} & \mathbf{0} & \mathbf{X}_T \end{bmatrix}, \quad \mathbf{A}_n \in C^{PT\times LT} \tag{9}$$

$$\mathbf{X}_i = \begin{bmatrix} s_n[k+L+i*B], & s_n[k+L-1+i*B], & \cdots, & s_n[k+1+i*B] \\ s_n[k+L+1+i*B], & s_n[k+L+i*B], & \cdots, & s_n[k+2+i*B] \\ \vdots & \vdots & & \vdots \\ s_n[k+L+P-1+i*B], & s_n[k+L+P-2+i*B], & \cdots, & s_n[k+P+i*B] \end{bmatrix}, \ \mathbf{X}_i \in C^{P\times L} \tag{10}$$

2.3. SOMP algorithm

The DSC estimation of the MIMO UWA channels can be addressed with the simultaneous OMP (SOMP) algorithm as following [11]:

Input: T adjacent receiving data blocks $\mathbf{Y}_m = [\mathbf{y}_m^1, \mathbf{y}_m^2, \ldots, \mathbf{y}_m^T]^H$, $\mathbf{Y}_m \in C^{PT\times 1}$; $\mathbf{A}_n \in C^{PN\times LN}$; the maximum iterations K; threshold of residual error.

Initialization:

Initializing the residual error as $(\mathbf{R}^i)_0 = \mathbf{y}_m^i$, $(\mathbf{R}^i)_0 \in C^{P\times 1}$, $i \in (1, 2, \ldots, T)$, where $(\bullet)_i$ denotes the i-th iteration, superscript denotes index of the data block. Initializing the index of atom as $\mathbf{\Omega} = \varnothing$, initial atom set as $\mathbf{Phit}^i = \varnothing$. The multipath magnitude of the i-th data block is $\widehat{\mathbf{h}}_{n,m}^i = \varnothing, i \in (1, 2, \ldots, N)$ and the initial iteration number is $t = 1$.

Step 1:

Selecting atom $\mathbf{X}_i$ from $\mathbf{A}_n$ to perform inner product with residual error $(\mathbf{R}^i)_{t-1}$, summing the inner product outputs of T data blocks to determine the location corresponding to the maximum result $(\lambda)_t$, saving $(\lambda)_t$ and the associated atom, i.e., the $\mathbf{X}_i$ associated with $(\lambda)_t$ is denoted as $\mathbf{X}_{\mathbf{i},(\lambda)_t}$.

$$\begin{aligned} &(\lambda)_t = \arg\max \sum_{i=1}^{T} |\langle \mathbf{X_i}, (\mathbf{R_i})_{t-1}\rangle| \\ &\mathbf{\Omega} = \mathbf{\Omega} \cup (\lambda)_t \\ &\mathbf{Phit}^i = \mathbf{Phit}^i \cup \mathbf{X}_{\mathbf{i},(\lambda)_t} \end{aligned} \tag{11}$$

Step2:

Calculating the multipath magnitude of each data block with LS method as:

$$\beta_i = [(\mathbf{X}_{i,(\lambda)_t})^H \mathbf{X}_{i,(\lambda)_t}]^{-1} \mathbf{X}_{i,(\lambda)_t} \mathbf{y}_m^i, \quad i \in (1, 2, \ldots, T) \tag{12}$$

Saving $\widehat{\mathbf{h}}_{n,m}^i = \widehat{\mathbf{h}}_{n,m}^i \cup \beta_i, i \in (1, 2, \ldots, T)$, then calculating the residual error:

$$(\mathbf{R}^i)_t = \mathbf{y}_m^i - \mathbf{Phit}^i * \widehat{\mathbf{h}}_{n,m}^i \tag{13}$$

Step3:

Iterations stop if the current residual is smaller than the threshold or the number of iterations surpass the defined number, else continue with $t = t + 1$.

Output:

Thus the multipath coefficient $\widehat{\mathbf{h}}_{n,m}^i, i \in (1, 2, \ldots, T)$ and the corresponding time delay $\mathbf{\Omega}$ are obtained.

The iteration procedures above indicate that the proposed DCS method is capable of not only utilizing the sparse feature of individual channel associated with each data block, but also exploiting the correlation of multipath arrivals among multiple data block for joint reconstruction. Note that when $T = 1$ the SOMP algorithm shrinks to the classic OMP algorithm.

3. Experiment and discussions

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 12 m. The transmitting couple was suspended to depth of 4 m and 6 m from a boat, with the 8-element receiving vertical array suspended to a depth range of 2–8 m with a space of 1.5 m at the pier. The distance between the transmitter and receiver was 1000 m as shown in Fig. 1.

In the field experiment, a 2TX-8RX MIMO acoustic communication system is adopted with a channel estimation based multichannel time reversal receiver as proposed in [5]. The channel response obtained with the DCS method are employed as the coefficient of the time reversal processor for each channel. For the purpose of comparison, the proposed joint sparse recovery (DCS) MIMO channel estimation method, the OMP method as well as the classic LS method is selected for the time reversal MIMO receiver. Moreover, for the proposed DCS method, different number of continuous data blocks, i.e., 2 data blocks (J2DCS), 4 data blocks (J4DCS) and 8 data blocks (J8DCS) are used for joint sparse recovery respectively.

The modulation format was QPSK with a bit rate of 8 kilobits per second and a carrier frequency of 16 kHz. The bandwidth of the transducer couple was 13–18 kHz. Original sampling rate of the received data is 96 ksps. Note that sampling interval of the baseband sequence is 1/2 of the symbol duration to provide robustness of carrier phase fluctuations in underwater acoustic channel. The raw received signal recorded during the sea experiment has an SNR of 14 dB.

In the experiment, the multichannel time reversal receiver adopts 8 channels for multi-channel time reversal processing. The length of the time reversal processor is the same with that of channel estimator, set as $L = 150$. The multichannel time reversal receiver adopted the periodly training mode [5]. Namely, after the initial channel estimation to set the initial coefficient of the time reversal processor, every 600 symbols the time reversal processor is updated with the output of the channel estimation algorithm, in which the previously detected bits are adopted as training sequence. The single-channel adaptive DFE followed the combing time reversal is updated with RLS algorithm. The filter length of the RLS updating forward and backward is set as 24, 12 respectively, with the RLS forgetting factor of 0.998 [4].

The channel impulse response (CIR) of the TX2nd-RX2nd channel obtained during the experiment with LS, OMP, J2DCS and J8DCS is shown in Fig. 2(a)–(d) respectively, which indicates that the experimental shallow water channel exhibits typical multipath pattern. While the channel response obtained with LS method contains significant estimation noise at those near zero taps, it is evident from Fig. 2 that the results obtained via OMP method and DCS type methods exhibit a good noise suppression effect due to the exploitation of sparsity, or joint sparsity. Moreover, one may also observe that DCS type methods generally outperform the OMP method in identification of weak multipath components, the quality of which is proportional to the number of blocks adopted for

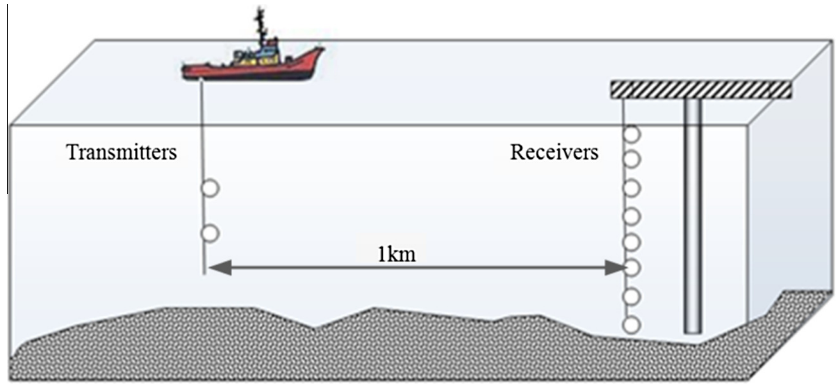

Fig. 1. Setup of the acoustic MIMO communication experiment.

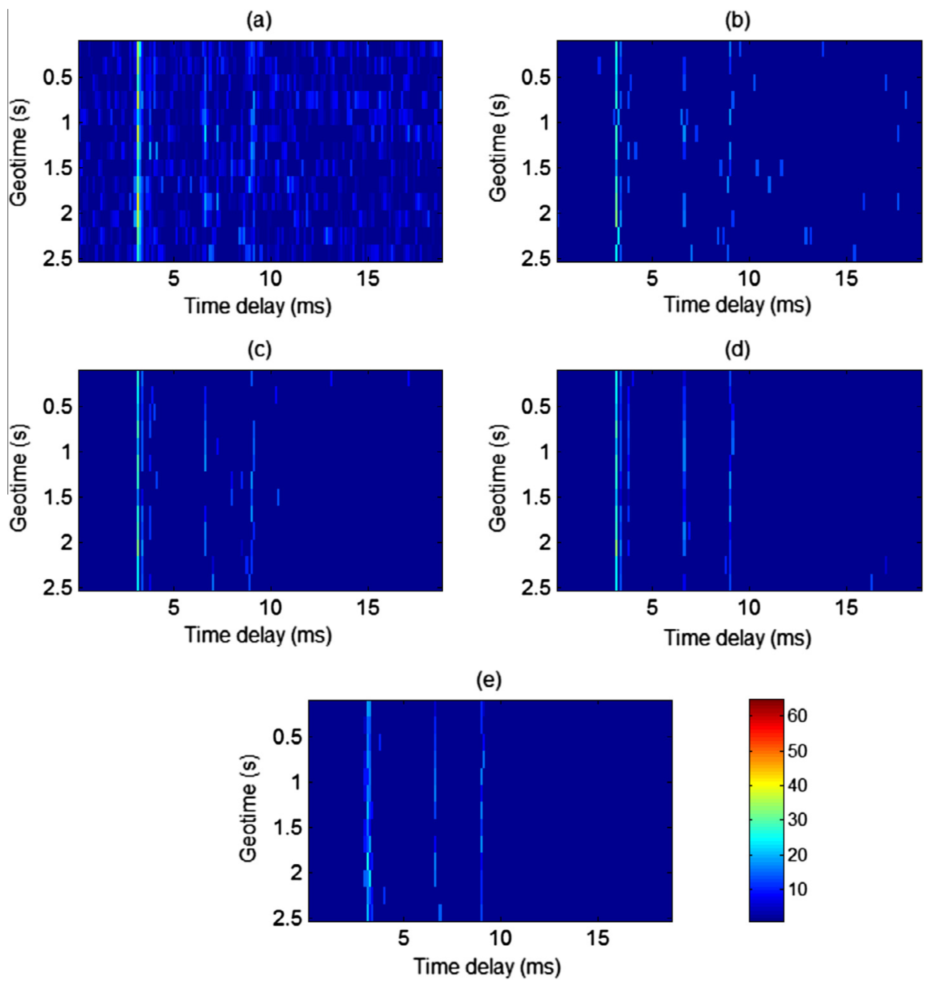

Fig. 2. MIMO TX2nd-RX2nd channel response obtained with different estimation methods. (a) LS, (b) OMP, (c) J2DCS, (d) J4DCS, (e) J8DCS.

joint sparse recovery. Namely, J8DCS achieved the best details of weak multipath arrivals, followed by J4DCS and J2DCS.

Meanwhile, the CIR of the TX2nd-RX6nd channel obtained with LS, OMP, J2DCS and J8DCS is shown in Fig. 3(a)–(d) respectively. One may observe from Fig. 3 that, while the energetic taps of the CIR were estimated with better accuracy by using more data blocks for joint estimation, a weak and fast fluctuating arrival at around 9 ms of time delay domain was missed by the J8DCS estimator as shown in Fig. 3(e). This means that, when too many data blocks are employed for joint sparse recovery, it will be difficult to detect the rapidly time-varying multipath arrivals which do not remain stable within the period of those data blocks.

The BER results with respect to training length *P* obtained by the multichannel time reversal receivers driven by different MIMO channel estimation methods are provided in Fig. 4. It is evident that under different *P* parameter the proposed receiver yields the best BER result compared to the OMP and LS methods, further validating the superiority of the joint sparse recovery in the presence of multipath and CoI. The classic LS receiver produces the worst BER, as no any sparse exploitation is adopted.

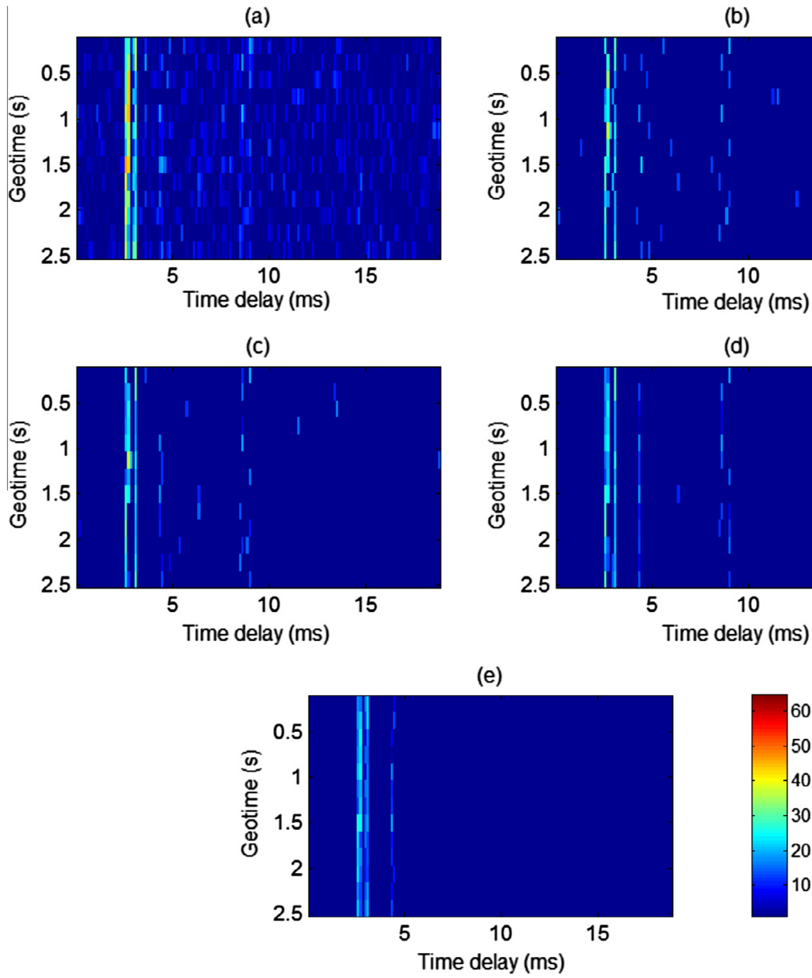

Fig. 3. MIMO TX2nd-RX6th channel response obtained with different estimation methods. (a) LS, (b) OMP, (c) J2DCS, (d) J4DCS, (e) J8DCS.

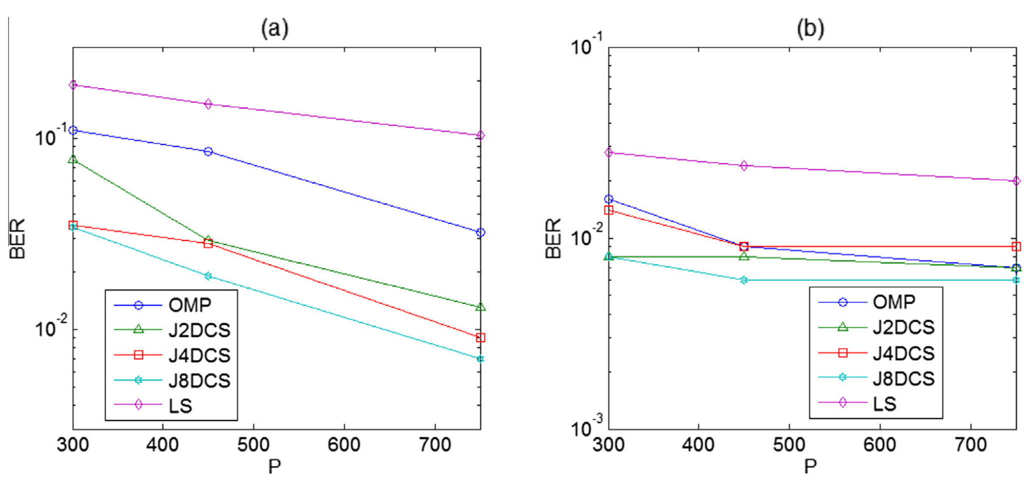

Fig. 4. BER of MIMO receiver with different estimation methods under different training length P (a) TX1, (b) TX2.

Moreover, in view of DCS channel methods with different number of data blocks used for joint sparse recovery, both the J4DCS and J8DCS did not yield distinct performance improvement compared to J2DCS. It is attributed to the time variations of the physical UWA channels, which lead to significant correlation loss when a large number of data blocks are used for joint sparse recovery.

The constellation outputs corresponding to TX2nd obtained with the LS method, OMP method, J2DCS, J4DCS and J8DCS based receiver are provided in Fig. 5(a)–(e) respectively, from which one may see that the LS receiver corresponds to a poor constellation quality, as there will exist considerable estimation noise at zero taps. The OMP receiver achieves better separating effect

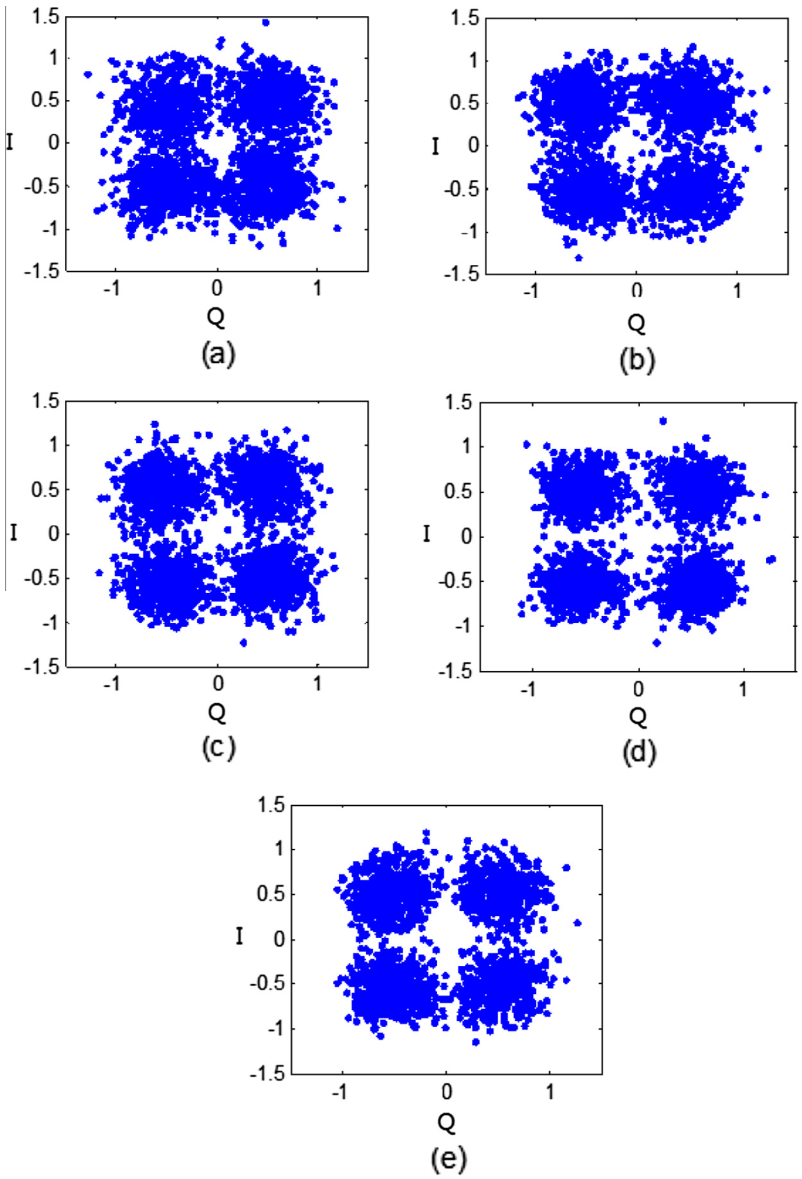

Fig. 5. Constellation output of MIMO receiver for TX2nd with different estimation methods. (a) LS, (b) OMP, (c) J2DCS, (d) J4DCS, (e) J8DCS.

compared to the LS method. However, as the OMP method only takes advantage of the sparseness contained in individual data block, quality of constellation of the OMP receiver is still inferior to that of the proposed DCS receiver, which is capable to make use of the common sparsity among continuous data blocks. Meanwhile, due to time variations of physical UWA channel, constellation output of J4DSC and J8DCS exhibit almost the same quality as the J2DSC, which is generally consistent with the BER result in Fig. 3.

The above experimental results reveal that, for underwater communication channels that exhibit similar multipath structure over several data symbols, DCS estimation of MIMO channels is capable of yielding performance improvement at the presence of multipath and CoI. Moreover, contribution of the algorithm factors, i.e., training length and number of symbols for joint estimation, on the performance superiority is quantitatively analyzed and compared in terms of BER and constellation output of MIMO receiver. Note that, while the analysis and comparison regarding the proposed DCS channel estimation method are obtained by only one experimental result, qualitative relationship between the exploitation of joint sparsity and the temporal stability of channel provides a meaningful reference for similar scenarios. Specifically, adoption of more symbols for joint channel estimation means further exploitation of sparse recovery from the viewpoint of DCS theory. However, time scale over which the path remains correlated will limit the utilization of large symbol number for DCS estimation.

4. Conclusion

Consider the difficulties posed by multipath and CoI to MIMO communications, a novel channel estimation method employing the joint sparsity of channel multipath structure among continuous data blocks is proposed to improve the performance of the channel estimation based time reversal receiver. With joint sparse reconstruction MIMO channel estimation under the framework of DCS, the sea trial performed at shallow water channel show that the proposed joint sparse recovery method exhibits better performance than the same type of receiver driven by LS or OMP methods that do not utilize the cross-block correlation. Furthermore, while the performance gain yielded by exploitation of joint sparse is evident, experimental demonstration also indicated that, employment of more data blocks for joint sparse recovery does not always guarantee distinct performance improvement due to the time variations of UWA channels.

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References

[1] Yang Z, Zheng YR. Iterative channel estimation and turbo equalization for multiple-input multiple-output underwater acoustic communications. IEEE J Oceanic Eng 2016;41(1):232–42.

[2] Ling Jun, Tan Xing, Yardibi T, Li Jian, Nordenvaad ML, He Hao, Zhao Kexin. On Bayesian channel estimation and FFT-based symbol detection in MIMO underwater acoustic communications. IEEE J Oceanic Eng 2016;39(1):59–73.

[3] 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.

[4] Song B, Ritcey J. Spatial diversity equalization for MIMO ocean acoustic communication channels. IEEE J Ocean Eng 1996;21(4):505–12. October.

[5] Song A, Badiey M, McDonal VK, et al. Time reversal receivers for high data rate acoustic multiple-input-multiple-output communication. IEEE J Oceanic Eng 2011;36(4):525–38.

[6] Wu FY, Tong F. Gradient optimization p-norm-like constraint LMS algorithm for sparse system estimation. Signal Process Apr. 2013;93(4):967–71.

[7] Wu FY, Tong F. Non-uniform norm constraint LMS algorithm for sparse system identification. IEEE Commun Lett 2013;17(2):385–8. February.

[8] Cotter SF, Rao BD. Sparse channel estimation via matching pursuit with application to equalization. IEEE Trans Commun 2002;50(3):374–7.

[9] Stojanovic M. Efficient processing of acoustic signals for high-rate information transmission over sparse underwater channels. Phys Commun 2008;1(2):146–61.

[10] Chitre MS, Shahabodeen S, Stojanovic M. Underwater acoustic communications and networking: recent advances and future challenges. Mar Technol Soc 2008;42(1):103–16.

[11] Baron D, Wakin MB, Duarte MF, et al. Distributed compressed sensing. Rice University; 2006.

[12] 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.