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Prediction based sparse channel estimation for underwater acoustic OFDM

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ABSTRACT

Channel prediction has been becoming the key technique in adaptive underwater acoustic communication systems because it is always a challenge to transmit the exact channel state information back to transmitter in the range of several kilometers. In this paper, we focus on exploring a time domain predictor by exploiting the sparse features of underwater acoustic channel for OFDM systems. At the same time, it takes the presence of Doppler shifts into account. Different channel estimation methods are compared for a better channel prediction performance. The complexity of the proposed algorithm is low, because only a small number of significant channel paths are predicted. Simulated results and experimental results show that our proposed method has a better performance, and it is able to present a time domain predictor in an underwater acoustic channel and provide reliable channel state information (CSI) to the transmitter. According to the reliable CSI, an adaptive underwater acoustic communication system can be established and function well.

1. Introduction

Recently, orthogonal frequency division multiplexing (OFDM) has received much attention in the research of underwater acoustic communications because of the significant advantage to overcome the complexity such as excessive multipath delay spread, time variability and severe Doppler-drift in underwater acoustic channels [1]. In this paper, we focus on channel prediction for an underwater acoustic OFDM receiver. Previous channel predictors were often realized at each OFDM subcarrier in the frequency domain due to the parallel transmission scheme of OFDM systems [2]. The variable at each subcarrier was a combination of multiple taps, which made it is difficult to accurately predict the channel. In time domain, some effective channel predictors have been proposed [3,4]. However, the discussed methods have a high complexity.

At the same time, underwater acoustic channels have several distinct features [5]. According to [6–9], the transmission paths had the property of sparsity. It means that there were not so many channel taps with significant energy compared to the number of subchannels of OFDM. And now several approaches had been proposed to exploit sparse features in channel estimation.

One of the most widely used approaches was significant tap selection method [10,11], which used a measure to determine which channel tap was significant.

In [12,13], the matching pursuit type algorithm was adopted to estimate channel taps iteratively by maximizing the correlation of a column of the mixture matrix with the residual signal. In [14,15], compressed sensing was used, which provided effective solutions to exploit channel sparsity. So it is a good choice to predict in time domain based on channel sparsity.

In this paper, it explores a time domain predictor by exploiting the sparse features of underwater acoustic channel for OFDM systems. The ultimate goal is to realize channel prediction, which is the key technique in adaptive underwater acoustic communication systems. In an adaptive communication system, the channel impulse response characteristic, i.e. the channel state information (CSI), is measured at the receiver and fed back to the transmitter. Since sound propagates at a lower speed (nominally 1500 m/s) compared to the propagation speed of electromagnetic wave in the air (nominally 3.0×10^8 m/s), it is a challenging task for adaptive underwater acoustic communications in the range of several kilometers because of the long feedback transmission delay. The solving approach is to adopt channel prediction in an adaptive communication system.

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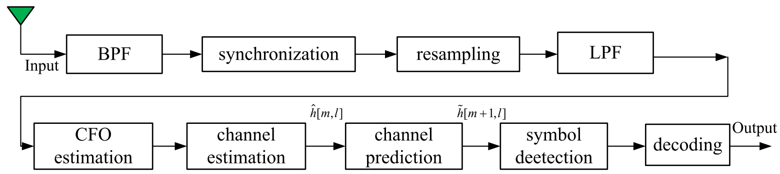

Fig. 1. The detailed receiver diagram.

However, motion often introduces additional Doppler shifts in underwater acoustic channels [16]. The Doppler shifts introduce strong intercarrier interference if an effective Doppler compensation scheme is not performed. At the same time, proper Doppler compensation is needed to ensure stability over intervals of time that are long enough to support channel prediction several seconds ahead. What is more, Doppler shifts are needed to feedback to transmitter in order to ensure the adjustment of parameters at the transmitter. Therefore Doppler estimation is also a necessary step in the receiver.

The approach in this paper is described as follows. Firstly this paper focuses on dealing with Doppler shifts. After necessary preprocessing steps such as resampling, the residual Doppler shift can be mathematically modeled as carrier frequency offset (CFO) [16], which can be estimated and compensated based on null subcarriers for underwater acoustic OFDM. Secondly this paper exploits the sparse structure of the underwater acoustic channel to simplify the prediction problem. Specifically, it estimates only a few significant paths of the channel by separating the negligible taps from the significant channel taps before performing prediction. Finally, it treats the statistical properties of the underlying random process of the channel fading as unknown, and computes the parameters of a linear predictor adaptively, by applying the recursive least-squares (RLS) algorithm [3,17]. The complexity of the proposed algorithm remains low since only a small number of significant channel paths are predicted. Simulated results and experimental results demonstrate that the proposed method is capable of presenting a time domain predictor in an underwater acoustic channel and providing reliable CSI to the transmitter.

The paper is organized as follows. Section 2 describes the system model that characterizes an underwater acoustic channel. Section 3 presents a CFO compensation method by using null subcarriers and introduces a linear RLS predictor for the channel tap coefficients. Section 4 presents simulated results and illustrates the performance evaluation. Section 5 provides experimental results that demonstrate the performance of the time domain predictor, and Section 6 is the conclusion.

2. System model

This paper considers a cyclic-prefixed (CP) OFDM system with the OFDM symbol duration T and the cyclic prefix length T_{CP}. The subcarrier spacing is $\Delta f = \frac{1}{T}$. Assume that there are a total of subcarriers, located at

$$f_k = f_c + k\Delta f, \quad k = -\frac{K}{2}, \ldots, \frac{K}{2} - 1 \tag{1}$$

where f_c is the carrier frequency. Let $d[k]$ denote the information symbol to be transmitted on the kth subcarrier. The sets of data subcarriers, pilot subcarriers, and null subcarriers are respectively denoted as S_D, S_P and S_N. The set of active subcarriers is $S_A = S_D + S_P$. The transmitted signal in the baseband is

$$x(t) = \sum_{k \in S_A} d[k] e^{j2\pi k\Delta f t} \tag{2}$$

After passing through the underwater acoustic channel and the receiver pre-processing such as the resampling operation [16], the received signal in the presence of residual Doppler shift can be expressed as

$$y(t) \approx e^{j2\pi\varepsilon t} \sum_{k \in S_A} H[k] d[k] e^{j2\pi k\Delta f t} + v(t) \tag{3}$$

where ε is the residual Doppler shift which can be viewed as the carrier frequency offset (CFO), $v(t)$ is the additive noise, and $H[k]$ is the channels frequency response at the kth subcarrier associated with a multipath channel of N_{pa} paths having complex amplitude ε_p and delay τ_p on the pth path

$$H[K] = \sum_{p=1}^{N_{pa}} \varepsilon_p e^{-j2\pi k\Delta f \tau_p} \tag{4}$$

Sampling $y(t)$ at a rate $\frac{T}{K}$, the discrete samples are

$$y[n] = e^{j2\pi\varepsilon nT/K} \sum_{k \in S_A} H[k] d[k] e^{j2\pi kn/K} + v[n] \tag{5}$$

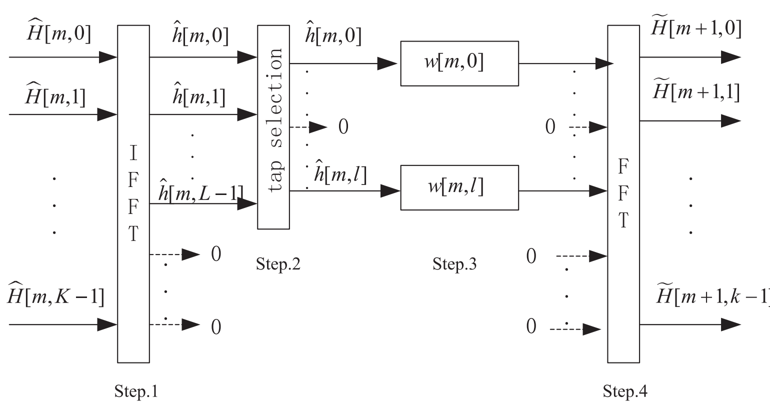

Fig. 2. Time domain predictor for sparse channel.

Define the following vectors

$$\boldsymbol{y} = [y[0], y[1], \ldots, y[K-1]]^T \tag{6}$$

$$\boldsymbol{d} = [d[0], d[1], \ldots, d[K-1]]^T \tag{7}$$

$$\boldsymbol{v} = [y[0], v[1], \ldots, v[K-1]]^T \tag{8}$$

and two diagonal matrices as

$$\boldsymbol{D}(\varepsilon) = diag(1, e^{j2\pi\varepsilon T/K}, \ldots, e^{j2\pi(K-1)\varepsilon T/K}) \tag{9}$$

$$\boldsymbol{\Lambda}_H = diag(H[0], H[1], \ldots, H[K-1]) \tag{10}$$

The matrix–vector representation of the channel input–output relationship is

$$\boldsymbol{y} = \boldsymbol{D}(\varepsilon)\boldsymbol{F}^H \boldsymbol{\Lambda}_H \boldsymbol{d} + \boldsymbol{v} \tag{11}$$

where F is the $K \times K$ Fourier transform matrix with the (p,q) entry $e^{-j2\pi pq/K}$ and $(\cdot)^H$ stands for complex conjugate.

3. Receiver design

Firstly this paper presents the technical approach to estimate the frequency-dependent Doppler shifts in Section 3.1, and then specifies the time domain prediction method in Section 3.2. The detailed receiver diagram is depicted in Fig. 1.

3.1. Doppler effect estimation

According to [16], the residual Doppler shift can be modeled as carrier frequency offset (CFO) by resampling and can be estimated based on null subcarriers for underwater acoustic OFDM.

This section focuses on CFO compensation after resampling. A CFO estimate is defined for each OFDM block by finding a selection matrix that picks the frequency domain measurements out of all the subcarriers. The energy of the null subcarriers is used as the cost function to find the CFO estimate as

$$\hat{\varepsilon} = \underset{\varepsilon}{argmin} \, ||\Theta_{null} F D^H(\varepsilon) y||^2 \tag{12}$$

where $||\cdot||$ denotes the 2-norm. CFO estimation can be solved via a one-dimensional search on ε.

3.2. The time channel prediction method

In an OFDM system, the entire channel is divided into many narrow parallel subchannels, and the frequency domain prediction methods will be limited based on the following reasons. Firstly, as introduced in Section 1, the subchannel of OFDM is not as predictable as the channel tap in time domain. Secondly, the number of OFDM subcarriers is much larger than that of taps in sparse channel, which leads to a high prediction complexity. At last, the nonsignificant channel taps can be neglected to eliminate the noise perturbation and to make the prediction more accurate. So the time domain channel prediction method is adopted in this paper and it is described in Section 3.2.1.

3.2.1. Tap selection

This paper adopts compressed sensing (CS) to estimate channel based on equal-spaced pilots. On the one hand, compressive sensing (CS) techniques have been extensively used to deal with sparse signal. On the other hand, in the process of channel estimation by CS, tap selection is done. It means that additive steps for tap selection are not needed by using CS to estimate channel, which brings the improvement of the performance and it is discussed specifically in Section 4. Current reconstruction methods include basic pursuit (BP) [18,19], orthogonal matching pursuit (OMP) [20] and regularized orthogonal matching pursuit (ROMP) [21]. In this paper, OMP algorithm is used for channel estimation.

Fig. 2 presents the common method for time domain prediction [3]. By using OMP, it skips step. 1 and step. 2. The time domain channel estimation can be obtained as

$$\hat{h}[m,l] = \begin{cases} h[m,l] + \zeta[m,l], & \text{significant taps} \\ 0, & \text{zero-valued taps} \end{cases} \tag{13}$$

where $\zeta[m,l]$ is the noise in time domain.

3.2.2. Adaptive prediction

Since underwater acoustic channel is time-varying in practice, the predictor should adjust itself with the goal of tracking the change of channel. As we all known, least-mean-squares (LMS) algorithm and recursive least-squares (RLS) algorithm are the main adaptive methods used for channel prediction. LMS predictor is simple to implement, and it has a poorer ability to track

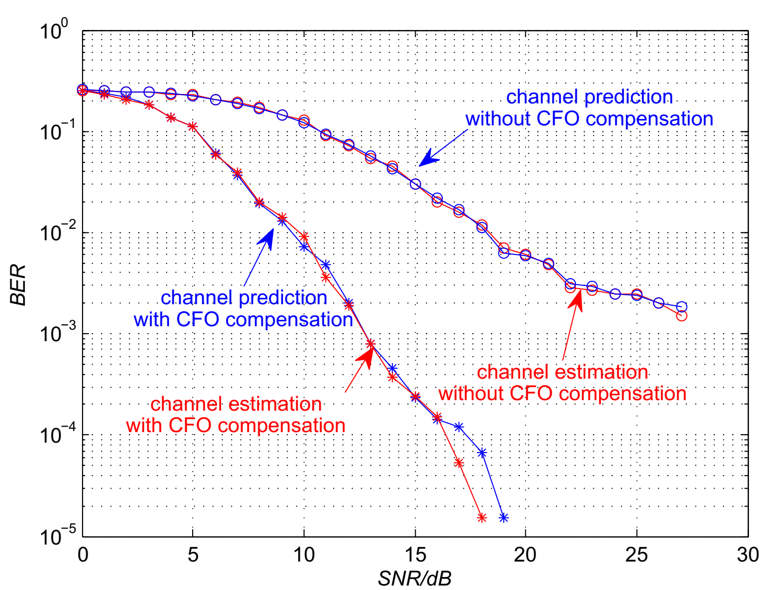

Fig. 3. Performance of channel prediction with and without CFO compensation.

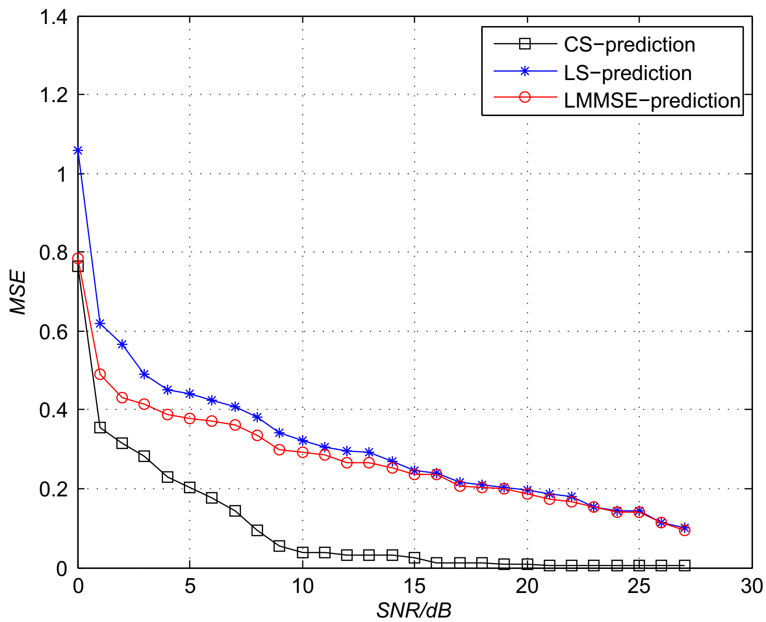

Fig. 4. MSE comparison for channel coefficient and different channel predictors.

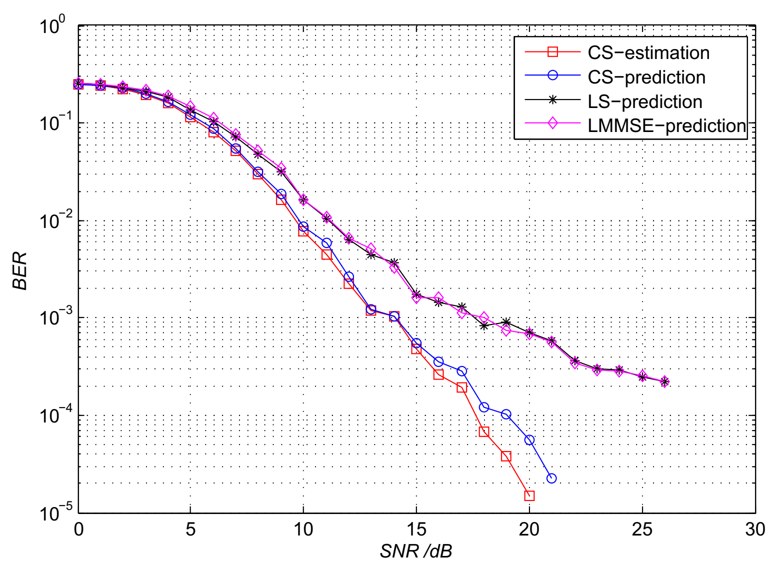

Fig. 5. BER comparison for different channel predictors.

time-varying channel. In contrast, RLS predictor has a superior tracking ability, but with a much higher complexity. As a result, when computational complexity is a primary concern, the RLS will not be broadly adopted because of too many predictors involved in such methods.

In this paper, by exploiting the sparse features of underwater acoustic channel, the proposed prediction method only uses a small number of predictors. So the RLS can be adopted for channel prediction without worrying about the prediction complexity. For those significant channel taps, the RLS predictor is depicted as

$$\tilde{h}[m+1,l] = \boldsymbol{w}^{H}[m,l]\hat{\boldsymbol{h}}[m,l] \tag{14}$$

where

$$\boldsymbol{w}[m,l] = [w_0[m,l], w_1[m,l], \ldots, w_{n-1}[m,l]]^T \tag{15}$$

$$\hat{\boldsymbol{h}}[m,l] = [\hat{\boldsymbol{h}}[m,l], \hat{\boldsymbol{h}}[m-1,l], \ldots, \hat{\boldsymbol{h}}[m-n+1,l]]^T \tag{16}$$

$\boldsymbol{w}[m,l]$ is the prediction coefficient vector and $\hat{\boldsymbol{h}}[m,l]$ is the estimated time domain channel coefficient vector. n is prediction order. The updated equation of RLS is as follows.

$$\boldsymbol{w}[m,l] = \boldsymbol{w}[m-1,l] + \boldsymbol{k}[m-1,l]e[m|m-1,l] \tag{17}$$

where

$$e[m|m-1,l] = \hat{h}[m,l] - \boldsymbol{w}^{H}[m-1,l]\hat{\boldsymbol{h}}[m-1,l] \tag{18}$$

is prediction error, and

$$\boldsymbol{k}[m,l] = \frac{\boldsymbol{p}[m-1,l]\hat{\boldsymbol{h}}[m,l]}{\lambda + \hat{\boldsymbol{h}}^{H}[m,l]\boldsymbol{p}[m-1,l]\hat{\boldsymbol{h}}[m,l]} \tag{19}$$

is the RLS gain vector, where λ is forgetting factor. the matrix $\boldsymbol{p}[m.l]$ can be calculated recursively as

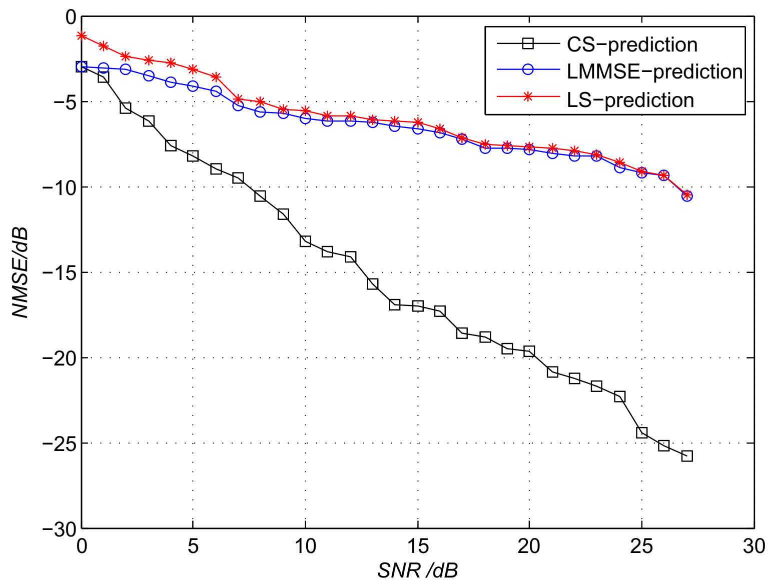

Fig. 6. NMSE performance comparison for different channel predictors.

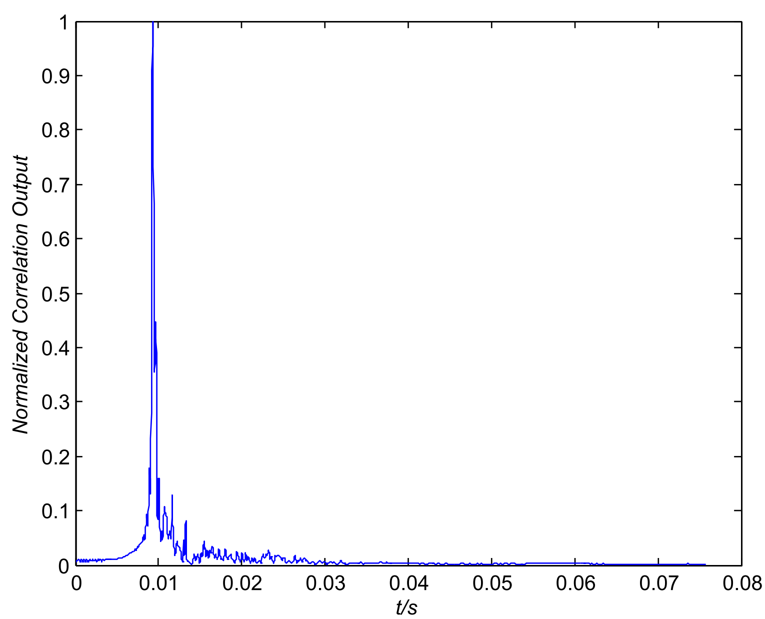

Fig. 7. Channel profile based on preamble correlation, 7 m.

$$\begin{aligned}\boldsymbol{p}[m,l] &= \frac{1}{\lambda}[\boldsymbol{p}[m-1,l] - \frac{\boldsymbol{p}[m-1,l]\hat{\boldsymbol{h}}[m,l]\hat{\boldsymbol{h}}^H[m,l]\boldsymbol{p}[m-1,l]}{\lambda + \hat{\boldsymbol{h}}^H[m,l]\boldsymbol{p}[m-1,l]\hat{\boldsymbol{h}}[m,l]}] \\ &= \frac{1}{\lambda}(\boldsymbol{I} - \boldsymbol{k}[m,l]\hat{\boldsymbol{h}}^H[m,l])\boldsymbol{p}[m-1,l]\end{aligned} \tag{20}$$

4. Simulated results

The multipath channel consists of 15 discrete paths, where the inter-arrival time follows an exponential distribution with a mean of 1 ms. The amplitudes are Rayleigh distributed with average power decreasing exponentially with the delay. The CP-OFDM signal parameters are follows. Out of 1024 subcarriers, 96 are null subcarriers with 24 on each edge for band protection and 48 distributed evenly in the middle [16]. The CFO term is randomly generated

$$\varepsilon \in [-\Delta f/2, \Delta f/2] \tag{21}$$

The data symbols are drawn from a QPSK constellation, and 256 pilot subcarriers are used for channel estimation [16]. A 64-state rate-1/2 convolutional code is used for channel coding. The bit-error-rate (BER) after Viterbi decoding will be used as the performance metric.

In this paper, three channel prediction methods are compared.

(1) LS-prediction method shows least square (LS) is used to estimate channel and prediction on each of the first L_{CP} channel taps in the time domain; that is, $\hat{h}[m,l],\ l = 0,1,\ldots,L_{CP}-1$.
(2) LMMSE-prediction method shows linear minimum mean square error (LMMSE) is used for channel estimation and prediction on each of the first L_{CP} channel taps; that is, $\hat{h}[m,l],\ l = 0,1,\ldots,L_{CP}-1$.

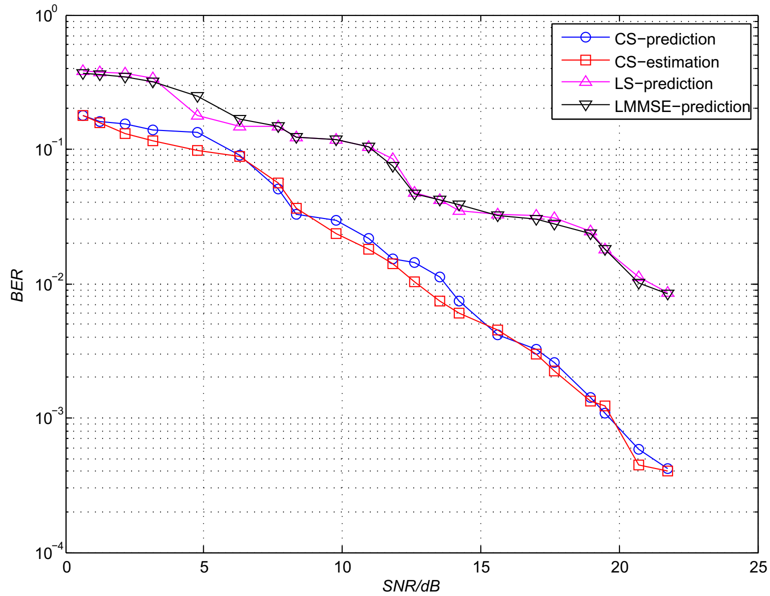

Fig. 8. BER comparison of semi-experimental data sets with different prediction methods.

Table 1
Experimental pool experiments.

	Estimation results	CS-prediction results	LS-prediction results	LMMSE-prediction results
1	0.0060	0.0060	0.0437	0.0412
2	0.0015	0.0015	0.0322	0.0303
3	0	0	0.0032	0.0031
4	0.0045	0.0045	0.0351	0.0308
5	0	0	0.0027	0.0021
6	0.0074	0.0074	0.0474	0.0442

(3) CS-prediction method shows this paper adopts CS for channel estimation. Prediction on each of the first L_{CP} channel taps, which are selected in the process of channel estimation.

The three methods all adopt RLS predictors for prediction. The RLS predictors have the same parameters: the order $n = 5$ and the forgetting factor $\lambda = 0.99$.

Firstly the effect of CFO for channel prediction is investigated. Fig. 3 shows the performance of channel prediction with and without CFO compensation by using CS-prediction method. One can observe that the receiver with CFO compensation outperforms the receiver without CFO compensation, and the performance gap between the CFO cancellation and without CFO cancellation is large. It shows that the CFO compensation method in advance of the channel prediction is necessary.

Table 2
System specification.

Parameter	Value
FFT length	1024
Guard interval	85.333 ms
Symbol duration	255.848 ms
Effective bandwidth	6 kHz
Center frequency	11 kHz
Effective speed	8 kbit/s
Mapping	QPSK
Pilot type	Comb-type

Fig. 4 presents MSE comparison for channel coefficient and different channel predictors. It is shown that CS-prediction method almost accurately obtains all the channel coefficients. There is a little bit of gap between CS-predictor and channel coefficient at low threshold SNR. With the increasing of SNR, the gap of them will be smaller and smaller. LS-prediction method and LMMSE-prediction method can only achieve some significant channel coefficients. The gaps between them and channel coefficient are large.

By varying the SNR level, the performance of bit error rate (BER) comparison for different predictors is shown in Fig. 5. It shows that three methods have a good performance for channel prediction. CS-prediction method leads to a better performance than LS-prediction method and LMMSE-prediction method. It is because CS-prediction method can separate more negligible taps by exploiting the features of sparse channel. What is more, the BER performance of CS-prediction method is very close to the BER performance got from channel estimation.

The performance of different predictors is also compared in terms of NMSE, defined as

$$\mathrm{NMSE} = \frac{E[||h(m) - \hat{h}(m)||^2]}{E[||h(m)||^2]} \tag{22}$$

where

$$h(m) = [h(m,0), h(m,1), \ldots, h(m,K-1)]^T \tag{23}$$

$$\hat{h}(m) = [\hat{h}(m,0), \hat{h}(m,1), \ldots, \hat{h}(m,K-1)]^T \tag{24}$$

are predicted time domain channel coefficient vectors.

Table 3
Shallow water experimental results.

	Estimation results	CS-prediction results	LS-prediction results	LMMSE-prediction results
1	0.0019	0.0020	0.0334	0.0290
2	0.0238	0.0074	0.3705	0.3036
3	0.0119	0.0089	0.3869	0.3497
4	0.0030	0.0060	0.0354	0.0348
5	0.0016	0.0028	0.0328	0.0268
6	0.0104	0.0119	0.3690	0.2560

The NMSE performance versus the estimation SNR for different predictors is shown in Fig. 6. According to Fig. 6, it is obviously shown that CS-prediction method has a better performance than LS-prediction method and LMMSE-prediction method.

5. Experimental results

5.1. Experimental pool experiments

This experiment was held at the experimental pool in Xiamen University. There were one transmitter and one receiving hydrophone located in an area of the size 18 m $\times$ 5 m. They were both located at the depth of 0.8 m below the surface and the distance between them is 7 m. The parameters of OFDM were the same as in the simulations.

The estimated channel for one OFDM block is shown in Fig. 7. It can be seen that the channel for the 7 m case has larger energy.

In the receiver, it get the performance of OFDM signal in the pool. Then the SNR can be estimated. White Gaussian noise is added to the received signal to generate several semi-experimental data sets with different SNRs.

Fig. 8 shows the demodulation performance of the semi-experimental data sets with different prediction methods, and Table 1 shows the demodulation performance of the different pool experimental data sets. They both show that CS-prediction method outperforms LS-prediction method and LMMSE-prediction method. The BER performance of CS-prediction method is close to estimated results.

5.2. Shallow water experiments

This experiment was carried out in the shallow water near Xiamen University. System specification for the experiment is shown in Table 2. The relative distance of the transmitter and the receiver was 105 m. The transmitter and the receiver were located at the depth of 4 m below the surface.

Table 3 presents the results of shallow water experiments. It is obviously shown that three prediction methods can be used to channel prediction for underwater acoustic OFDM channel. At the same time, CS-prediction method leads to a better performance than LS-prediction method and LMMSE-prediction method. BER performance of CS-prediction method is very near to estimated results.

6. Conclusions

This paper proposes a time domain predictor for underwater acoustic communication in order to provide reliable CSI to the transmitter, and the Doppler shift is also considered. According to the reliable CSI, an adaptive underwater acoustic communication system can be established and function well. Simulated results and experimental results show that the proposed channel prediction method based on CS has a better performance, and the complexity of the proposed algorithm is low because only a small number of significant channel paths are predicted.

Acknowledgments

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