Forward-Backward Block-wise Channel Tracking in High-speed Underwater Acoustic Communication

Peng Chen, Yue Rong, Sven Nordholm
Department of Electrical and Computer Engineering
Curtin University

Zhiqiang He
Key Lab of Universal Wireless Communications
Beijing University of Posts and Telecommunications

***Abstract*—Underwater acoustic (UA) communication channel is extremely bandlimited and fast time-varying. Block-by-block decision-directed channel tracking is a bandwidth efficient channel estimation method for pilot-aided single-carrier UA communication systems. However, conventional forward-only decision-directed method suffers from error propagation where the system bit-error-rate (BER) increases with the interval between the pilot sequence and data symbols. To mitigate the error propagation effect, in this paper, a backward decision-directed algorithm is proposed to detect data blocks which are at large internal from the previous pilot sequence but close to the next one. The proposed algorithm is applied to detect data received during the experiment conducted in December 2012 in the Indian Ocean off the Rottnest Island, Western Australia. The results show that using the proposed algorithm, the average uncoded BER of the last data block in one frame is much lower than the BER yielded by the forward-only tracking method and is only sightly higher than the BER of the first data block.**

***Index Terms*—Channel estimation, time-varying channel, Underwater acoustic communication**

I. Introduction

The underwater acoustic (UA) channel is extremely bandlimited and reverberant making it one of the most challenging channels for communication [1]. Firstly, the propagation loss of acoustic waves in water is approximately proportional to square of the frequency [1]. Therefore, UA communication signals are usually transmitted at a low carrier frequency, and thus the bandwidth available for UA communication is extremely limited compared with that of terrestrial radio channels [2]. Secondly, the speed of UA wave near the sea surface is typically around 1520 m/s which is five orders of magnitude smaller than the speed of light [3]. Thirdly, the speed of UA wave is affected by many factors, such as temperature, salinity, and the pressure of water. These features of UA medium introduce rapid dispersion in both time and frequency domains to UA communication channels. The time-domain dispersion due to delay spread results in severe inter-symbol interference. The frequency-domain dispersion caused by the drift of the transmitter, receiver and/or the motion of water leads to rapidly time-varying communication channel. Therefore, efficient channel estimation and tracking are crucial to coherent high-speed UA communication [4].

It has been shown in [5] that many shallow-water UA channels have a sparse structure, which means that although the UA channel impulse response generally has extremely large delay spread, most of the channel energy is carried by only a few propagation paths. By exploiting the sparsity of the UA channel impulse response, channel estimators at receiver can have reduced number of taps, which reduces the noise involved in channel estimation. Consequently, the channel estimation can have an improved accuracy as well as a reduced computational complexity [4], [6].

One of the methods to exploit the sparse structure in channel estimation is the matching pursuit (MP) algorithm [7] or its orthogonal vision named the orthogonal matching pursuit (OMP) algorithm [8], both of which are considered as compressed sensing (CS) techniques. In particular, sparse channel estimation can be implemented by first selecting the most important paths of the sampled channel impulse response via a greedy L_p-norm regularized method and then estimating coefficients for all selected paths. In [7], [8], the MP and OMP algorithms have been applied to estimated linear time-invariant (LTI) frequency selective radio channels. However, both algorithms work well only in quasi-static channels. For fast time-varying UA channels, efficient channel tracking method should be developed.

A block-wise decision-directed channel tracking method has been developed in [9], where each received data frame is subdivided into data blocks, and each data block is decoded by using the channel state information (CSI) estimated from the detected symbols of the previous data block. The authors of [9] adopted the least-squares (LS) approach to perform channel estimation at each data block. In [10], the OMP approach has been applied to estimate the CSI at each data block by exploiting the sparsity of UA channel, which yields a better performance than the LS approach.

The forward-only decision-directed channel tracking algorithms in [9] and [10] suffer from error propagation where the system bit-error-rate (BER) increases with the interval between the pilot sequence and data symbols. To mitigate the error propagation effect, in this paper, we propose a block-wise forward-backward channel tracking method to detect data blocks close to the next pilot sequence for UA communication. In the backward tracking mode, the current block is decoded using the CSI estimated from the next data block instead of the previous one. The proposed algorithm is tested in our UA communication experiment conducted in December 2012 in the Indian Ocean off the Rottnest Island, Western Australia. The results show that using the proposed algorithm, the average uncoded BER of the last data block in one frame is

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much lower than the BER yielded by the forward-only tracking method and is only sightly higher than the BER of the first data block.

II. System Model

As shown in Fig. 1, each data frame contains two training blocks with identical sequences followed by the data load. Let us introduce T_s as the symbol duration, N_T as the length of each training sequence, and N_D as the length of the data sequence. Obviously, each frame has $N_f = 2N_T + N_D$ symbols and its duration is $T_f = T_s N_f$.

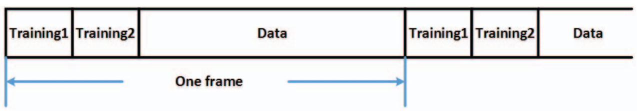

Fig. 1. Frame structure of the system.

We assume that the channel state is quasi-stationary within a block of N symbols, and thus the data sequence in one frame can be divided into $P = N_D/N$ blocks. The channel impulse response of the tth data block, $t = 1, \cdots, P$, can be represented by

$$\boldsymbol{h}(t) = [h_0(t), h_1(t), \cdots, h_{L-1}(t)]^T$$

where L denotes the maximum delay spread of the channel impulse response, and $(\cdot)^T$ stands for the matrix transpose. The tth data block $\boldsymbol{r}(t) = [r_0(t), r_1(t), \cdots, r_{N-1}(t)]^T$ at the receiver side can be written as

$$\boldsymbol{r}(t) = \boldsymbol{D}(t)\boldsymbol{h}(t) + \boldsymbol{n}(t) \tag{1}$$

where

$$\boldsymbol{D}(t) = \begin{pmatrix} d_0(t) & d_N(t-1) & \cdots & d_{N-L+2}(t-1) \\ d_1(t) & d_0(t) & \cdots & d_{N-L+3}(t-1) \\ \vdots & \vdots & \ddots & \vdots \\ d_{N-1}(t) & d_{N-2}(t) & \cdots & d_{N-L}(t) \end{pmatrix}$$

with $d_i(t)$ denoting the ith transmitted symbol of the tth data block, and $\boldsymbol{n}(t) = [n_0(t), n_1(t), \cdots, n_{N-1}(t)]^T$ is the additive noise.

Fig. 2 shows the block diagram of our UA communication system. It can be seen that at the receiver, the frame head is firstly found by the synchronization algorithm. Then the receiver performs frequency offset estimation and compensation for each data block. The above operations are performed to the pass-band received signals. After the frequency offset compensation, the receiver removes the carrier frequency and passes the signals through a matched filter followed by the down sampling operation. Then block-wise channel estimation/tracking and equalization are performed to the down-sampled baseband signal. The details of frequency offset compensation and channel estimation/tracking are shown below.

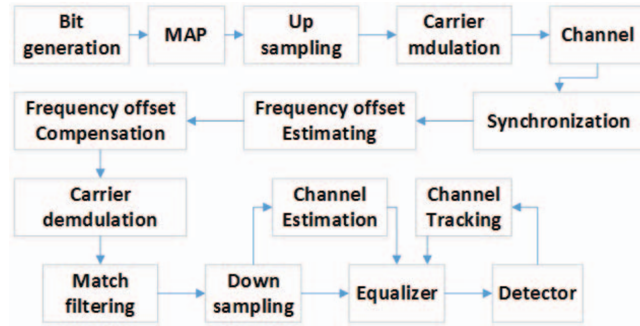

Fig. 2. System block diagram.

III. Frequency Offset Compensation

We assume that the Doppler shift is constant within one data block, but has a constant acceleration rate between data blocks which is caused by the medium and the relative motion between the transmitter and receiver. Thus, the Doppler shift at the tth data block, $t = 1, \cdots, P$, in one frame can be modelled as

$$f_D(t) = f_D(0) + \alpha t N T_s / c \tag{2}$$

where $f_D(0)$ is the initial Doppler shift at the beginning of the data sequence, α is the acceleration rate of the Doppler shift, and c denotes the speed of sound in water.

The steps of frequency offset estimation and compensation in the ith data frame are summarized bellow.

(1) Obtain an estimation of the initial frequency offset $\hat{f}_D(0)$ using the second pilot sequence of the ith frame.

(2) Set the searching range from $f_{D,h} = \hat{f}_D(0) + f_R$ to $f_{D,l} = \hat{f}_D(0) - f_R$ with a chosen parameter f_R.

(3) Calculate $f_c = (f_{D,h} + f_{D,l})/2$ and compensate the received pilot sequence using f_c.

(4) Estimate the residue frequency offset $f_{D,r}$. If $f_{D,r}$ is sufficiently small, take f_c as the estimated Doppler shift of the ith frame and go to step (6). Otherwise, go to step (5).

(5) Set $f_{D,h} = f_c$ if $f_{D,r} \leq 0$. Otherwise, set $f_{D,l} = f_c$. Go to step (3).

(6) Estimate the frequency offset f_c of the $(i+1)$-th frame through step (1) to step (5), then go to step (7).

(7) Calculate the frequency offsets for all data blocks of the ith frame by interpolating f_c of two adjacent frames. Linear interpolation is adopted here following (2). Finally, the estimated frequency offsets are used to remove the Doppler shift at the pilot and data sequences.

IV. Channel Estimation and Tracking

In the forward decision-directed mode, an initial estimation of the CSI is obtained by using the second training sequence of each frame. Then the detected symbols in one block are used to track the channel changes and the updated CSI is used to equalize the next received data block.

In the backward decision-directed mode, an initial estimation of the CSI is obtained by using the training sequence of the next frame. The estimated CSI is used to equalize the last data block of the current frame. Then the estimated symbols of the last data block is used to estimate the CSI again, and this estimated CSI is used to equalize the second last data block. This process continuous till the data block in the middle of one frame. Note that the first several received symbols of the next data block are interfered by the symbols in the current block. Let G denote the number of symbols between the start point of the next data block and the start point of the received data used to perform backward channel estimation. A large G reduces the interference from the current block. However, a larger G increases the mismatch between the estimated and the real channel of the current data block. The received signal vector used to perform channel estimation/tracking can be written as

$$\boldsymbol{r}(t) = \hat{\boldsymbol{D}}(t)\boldsymbol{h}(t) + \boldsymbol{I}(t) + \boldsymbol{n}(t) \tag{3}$$

where

$$\hat{\boldsymbol{D}}(t) = \begin{pmatrix} d_0(t) & d_N(t\text{–}1) \cdots & d_{N-G+2}(t\text{–}1) & 0 \\ d_1(t) & d_0(t) \quad \cdots & d_{N-G+3}(t\text{–}1) & d_{N-G+2}(t\text{–}1) \\ \vdots & \vdots \quad\; \vdots & \vdots & \vdots \\ d_{N-1}(t) & d_{N-2}(t) \cdots & \cdots & \cdots \end{pmatrix}$$

and $\boldsymbol{I}(t)$ denotes the interference caused by the previous data block. In this paper, the interference $\boldsymbol{I}(t)$ is ignored during channel estimation/tracking.

V. Compressed Sensing Method

CS is a technique that can recover signal accurately from its measurements provided that the signal is sparse. Let us consider the following measurement model

$$\boldsymbol{r} = \boldsymbol{D}\boldsymbol{h} + \boldsymbol{n}$$

where $\boldsymbol{D}$ is an $N \times L$ sensing matrix, $\boldsymbol{h}$ denotes an $L \times 1$ signal vector to be recovered, $\boldsymbol{r}$ presents the corresponding $N \times 1$ measurement signal vector, and $\boldsymbol{n}$ is an $N \times 1$ noise vector. Generally, the LS and/or the minimal mean-squared error (MMSE) methods can be applied to recover $\boldsymbol{h}$. However, if $\boldsymbol{h}$ is S-sparse, which means that $\boldsymbol{h}$ has $S(S \leq L)$ non-zero entries, and $\boldsymbol{D}$ is designed to capture the dominant information of $\boldsymbol{h}$ into $\boldsymbol{r}$, $\boldsymbol{h}$ can be recovered by the CS technique.

Many algorithms such as OMP, basis pursuit (BP), and compressed sampling matching pursuit (CoSaMP) have been developed for sparse signal recovery. In this paper, the OMP algorithm is adopted to perform channel estimation. Details of this algorithm are shown in Table I, where $b_j(s)$ is the jth element of $\boldsymbol{b}$ in the sth iteration and $\boldsymbol{D}_{:,p}$ denotes the pth column of $\boldsymbol{D}$.

VI. Experiment Arrangement

The experiment was conducted in December 2012, in the Indian Ocean off the coast of the Rottnest Island, Western Australia (Fig. 3). The average water depth was about 50 meter. As shown in Fig. 4, a single hydrophone at the receiver was attached through a cable at one meter above the seabed. A transducer attached to a drifting vessel through cable for data transmission was located approximately 20 meters below the sea surface. Signals were transmitted when the vessel and transducer were at the positions as denoted by the red dots with labels of T52, T54, T55, T56, T57, T58, T59 , T60 and T61 in Fig. 3, which correspond to 125m, 250m, 500m, 1km, 2km, 4km, 6km, 8km, and 10km from the receiver, respectively. It should be noted that both transmitter and receiver were drifting while signals were transmitted, which leads to significant Doppler spreading. GPS data showed that the average drifting speed of the vessel was 0.96 m/s and the peak drift speed was 1.7 m/s when the communication distance is 1 km.

BPSK modulated pseudo random sequence was used for

TABLE I
The OMP algorithm.

Initialization
$\hat{\boldsymbol{h}} = \boldsymbol{0}, \boldsymbol{y}(0) = \boldsymbol{r}, \boldsymbol{u}(0) = \varnothing, \tilde{\boldsymbol{D}}(0) = \varnothing$
For $s = 1, \cdots, S$
Calculate the correlation vector $\boldsymbol{b}(s) = \boldsymbol{D}^H \boldsymbol{y}(s-1)$
Find the index $p = \arg\max_{j=1\cdots L, j \notin \boldsymbol{u}(s-1)} (b_j(s))$
Update the index set $\boldsymbol{u}(s) = \boldsymbol{u}(s-1) \cup p$
Update $\tilde{\boldsymbol{D}}(s) = \tilde{\boldsymbol{D}}(s-1) \cup \boldsymbol{D}_{:,p}$
Update $\tilde{\boldsymbol{h}} = [\tilde{\boldsymbol{D}}(s)^H \tilde{\boldsymbol{D}}(s)]^{-1} \tilde{\boldsymbol{D}}(s)^H \boldsymbol{r}$
Update the residual measurement $\boldsymbol{y}(s) = \boldsymbol{r} - \tilde{\boldsymbol{D}}(s)\tilde{\boldsymbol{h}}$
end for
$\hat{h}_{u_i} = \tilde{h}_i$ for $i = 1, 2, \cdots, S$

Fig. 3. General location of the experiment environment.

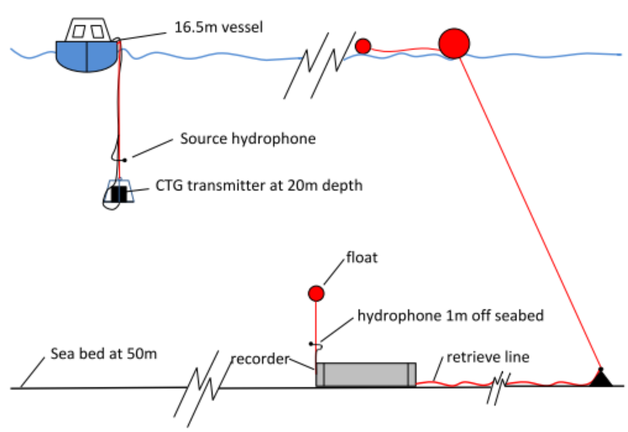

Fig. 4. Transmitter and receiver diagram.

TABLE II
EXPERIMENTAL SYSTEM PARAMETERS.

bandwidth	4 kHz
carrier frequency	12 kHz
sampling rate	96 kHz
pilot sequence length	511 symbols
data length of each frame	2046 symbols
data blocks in each frame	4

the training sequence. For data sequences, 8PSK and QPSK signals were transmitted at ranges of 125m, 250m, 500m, 1km, 2km, and 4km. QPSK and BPSK signals were transmitted at the ranges of 6km and 8km. At the range of 10km, only BPSK signal was transmitted. Other parameters are shown in Table II.

VII. EXPERIMENT RESULTS

Tables III and IV show the error propagation effect of the forward decision-directed method at the 2km and 8km ranges, respectively. The BER results of both the LS and OMP based channel estimation methods are shown. It can be seen that for the 2km range, both the LS and OMP methods have only a BER of 9% in the first data block. Once the detected symbols in the first data block are used to estimate the CSI for symbol detection in the second data block, the BER increases to 17.3% for the LS method at the 2km range. The BER of the last data block is increased to 28.7% when the LS method is used to track channel changes, which is over three times higher than the BER of the first data block. Interestingly, the OMP method can partly overcome the error-propagation effect as the BER of each block increases at a slower rate than that of the LS method.

TABLE III
AVERAGE BER OF EACH BLOCK AT THE 2KM RANGE USING THE FORWARD DECISION-DIRECTED METHOD.

Channel tracking method	1^{st} block	2^{nd} block	3^{rd} block	4^{th} block
LS	9%	17.3%	23.3%	28.7%
OMP	9%	12.2%	14%	15.3%

TABLE IV
AVERAGE BER OF EACH BLOCK AT THE 8KM RANGE USING THE FORWARD DECISION-DIRECTED METHOD.

Channel tracking method	1^{st} block	2^{nd} block	3^{rd} block	4^{th} block
LS	9.4%	15.4%	21%	26%
OMP	9.4%	9.6%	10%	11%

Figs. 5 and 6 compare the BER of the fourth block and the third block, respectively, at various communication distances with different channel estimation methods. The improvement of the system BER using the backward decision-directed method can be clearly seen from Figs. 5 and 6. Tables V and VI show the detailed BER of the third and fourth data blocks at the 2km and 8km ranges, respectively, using the proposed backward decision-directed method. It can be seen that the system BER has been significantly reduced compared with

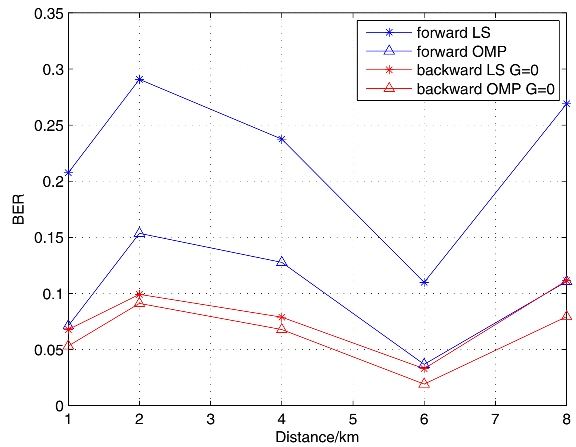

Fig. 5. BER of the fourth block.

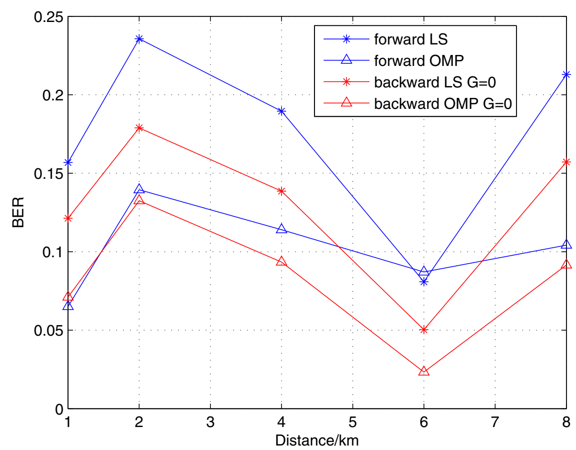

Fig. 6. BER of the third block.

TABLE V
AVERAGE BER OF THE THIRD AND FOURTH BLOCKS AT THE 2KM RANGE USING THE BACKWARD DECISION-DIRECTED METHOD.

Channel tracking method	The 3^{rd} block	The 4^{th} block
LS with $G = 11$	17.45%	9.91%
LS with $G = 0$	17.89%	9.92%
OMP with $G = 11$	13.31%	9.17%
OMP with $G = 0$	13.25%	9.11%

TABLE VI
AVERAGE BER OF THE THIRD AND FOURTH BLOCKS AT THE 8KM RANGE USING THE BACKWARD DECISION-DIRECTED METHOD.

Channel tracking method	The 3^{rd} block	The 4^{th} block
LS with $G = 11$	15.4%	11%
LS with $G = 0$	15.7%	11.2%
OMP with $G = 11$	9%	7.8%
OMP with $G = 0$	9.2%	7.9%

that of the forward decision-directed method. For example, in the 8km range the BER of the fourth block is around 11% using the backward LS-base channel tracking, which is less than half of that with the forward LS tracking method (26%).

It can also be seen that for most of the scenarios, the BER of the fourth data block using the backward method is only slightly higher than the BER of the first block with the forward method. For the OMP method at the 8km range, the BER of the fourth block is even lower than that of the first block. Interestingly, the tradeoff between a smaller G (leading to a larger interference) and a larger G (resulting in a larger mismatch between the estimated and real CSI) does not play an important role in terms of the system BER.

VIII. Conclusions

A forward-backward block-wise decision-directed channel tracking method is proposed in this paper. To equalize data blocks that are far away from the pilot sequence of the current frame and near the next frame, the proposed method uses the pilot sequence of the next frame or the detected data of the next block to estimate CSI for the block instead of previously detected data blocks. It is shown by our experiment that the proposed method can reduce the effect of error propagation and thus lead to a better BER performance both in LS-based and CS-based channel estimation. The average uncoded BER of the last block is much lower than the BER using the forward method and is only sightly higher than the BER of the first block for most scenarios.

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