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Feedback strategies for iterative channel estimation in OFDM underwater acoustic communications①

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Abstract

The extremely limited bandwidth in underwater acoustic communication makes channel estimation using fewer pilot symbols more challenging. Iterative channel estimation (ICE) can be used to refine channel estimation with limited number of pilots, by coupling the channel estimator with channel decoder. In this paper, various feedback strategies in ICE are discussed. The performance of a decision feedback based on the cost function is improved by modifying the design and another four feedback strategies are summarized, including hard/soft decision feedback and their threshold-controlled versions. Simulation results show that ICE can achieve impressive gains over the non-iterative receiver and the gains are more significant with fewer pilots. Furthermore, soft decision feedback outperforms hard decision feedback; while the feedback based on the cost function and soft decision feedback have quite close performance.

Key words: underwater acoustic communication, orthogonal frequency division multiplexing (OFDM), iterative feedback, sparse channel estimation

0 Introduction

Communication through acoustic channel is the most intricate among all wireless communication channels because of its extremely limited bandwidth, selective frequency fading, large propagation attenuation and severe multi-path spread[1]. The channel estimation for underwater acoustic channels is quite challenging and usually requires pilot symbol assisted modulation (PSAM). Acoustic channel estimation methods mainly include least squares (LS) estimation, minimum mean square error (MMSE) estimation, adaptive channel estimation[2], etc. In fact, underwater acoustic channels have sparse structures, which means the channel response can be modeled by several dominant paths[3]. Compressed sensing-based approaches are proved suitable especially for sparse channels and have been widely used in underwater acoustic channel estimation[4-6].

The performance of channel estimation can be improved by more pilots, however that will reduce the communication rate. Compared to the traditional channel estimation, Iterative channel estimation (ICE) has an additional iteration loop from the decoder to the channel estimator for updating the channel state information. ICE is equivalent to obtain an extra part of the data information as pilots to re-perform channel estimation. Therefore, more accurate channel estimation results can be obtained without increasing the number of pilots.

ICE has been extensively studied in wireless communications. In Refs[7-9], different hard/soft decision feedback methods with PSAM over flat-fading channels were investigated. Ref. [10] proposed a new threshold setting method, using a cost function comparison as the test threshold to choose between current iteration and previous channel estimation results. For underwater acoustic communication, hard decision feedback was studied and tested for OFDM with experimental data in Ref. [11], a turbo-detection scheme using soft decision feedback was proposed for single-carrier MIMO UWA communications in Ref. [12]. Furthermore, for MIMO-OFDM systems, various feedback strategies were considered in Ref. [13].

In this paper, four feedback strategies are summarized and more detailed simulations are given, including full hard/soft decision feedback and their threshold-controlled versions, meanwhile the feedback strategy proposed in Ref. [10] is improved, named as decision feedback based on the cost function.

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This paper is organized as follow. Section 1 defines a system model and explains several channel estimation methods. Section 2 compares these methods and provides numerical simulation results. Section 3 concludes the work.

1 System model

1.1 System and channel model

Considering an OFDM system with K subcarriers, its OFDM symbol duration is T, the cyclic prefix interval is T_{cp}, so the total OFDM block duration is $T' = T + T_{cp}$. The system bandwidth is B and the subcarrier spacing is $\Delta f = 1/T = B/K$. The frequency of mth subcarrier is f_m, which can be represented by the system center frequency f_c, $f_m = f_c + m/T$, where $m = -K/2, \cdots, K/2 - 1$.

Let $s(m)$ donates the transmitted information on the kth subcarrier, and the passband signal can be expressed as

$$x(t) = 2\mathrm{Re}\{\sum_{m=-K/2}^{K/2-1} s(m)\exp(j2\pi f_m t)\}, \quad t \in [0, T] \tag{1}$$

The acoustic channel is a multipath channel, assuming that the channel is time-invariant within an OFDM symbol, the channel impulse response can be given by

$$h(\tau) = \sum_{l=1}^{N_\tau} \xi_l \delta(\tau - \tau_l) \tag{2}$$

where, N_τ is the number of channel multipath, τ_l and ξ_l are the delay and amplitude of the lth path, respectively.

The received signal can be obtained as

$$y(t) = \sum_{l=1}^{N_\tau} \xi_l x(t - \tau_l) + w(t) \tag{3}$$

where $w(t)$ is the additive noise.

1.2 Orthogonal matching pursuit based on compressive sensing

Compressive sensing can reconstruct sparse signals by matching the received signals with suitable elements from the dictionary which is composed of parameterized signals[14]. Exploiting the sparsity of underwater acoustic channel, channel estimation can be transformed into the reconstruction of sparse signals. At present, there are two main methods for estimating the underwater acoustic channel under the theory of compressive sensing, orthogonal matching pursuit (OMP) algorithm and basis pursuit (BP) algorithm. In general, the OMP algorithm can recover highly sparse signals efficiently and has less computational complexity than BP algorithm, thus it is more suitable for real-time processing system[11]. In this paper, OMP algorithm is used to estimate sparse channel. The processing steps of the OMP algorithm applied to underwater acoustic channel estimation are as follows.

Firstly, define the path delay parameter set as

$$\tau_l \in \left\{\frac{T}{\lambda K}, \frac{2T}{\lambda K}, \cdots, T_g\right\} \tag{4}$$

where, λ is time oversampling factor, and the total number of candidate paths is $N_\tau = \lambda K T_g / T$.

A linear model is usually used for sparse signals:

$$\boldsymbol{y} = \boldsymbol{A}\boldsymbol{x} + \boldsymbol{\eta} \tag{5}$$

For channel estimation, $\boldsymbol{y}$ is the received pilot information, $\boldsymbol{\eta}$ is the noise vector, $\boldsymbol{x} \in R^M$ is the channel information to be estimated, and $\boldsymbol{A}$ is the dictionary constructed which can be written as

$$\boldsymbol{A} = [\boldsymbol{a}_1, \boldsymbol{a}_2, \cdots, \boldsymbol{a}_{N_\tau}] \tag{6}$$

where $\boldsymbol{a}_i (i = 1, 2, \cdots, N_\tau)$ is a $K_p \times 1$ vector.

Assume $\boldsymbol{r}_p$ is the signal residual after p iterations with the initial value $\boldsymbol{r}_0 = \boldsymbol{y}$. For the searching of the element in dictionary, which has the largest inner product of residual, the index of the element could be got:

$$s_p = \arg \max_{j=1,\cdots,N_\tau, j \notin \boldsymbol{I}_{p-1}} \frac{|\boldsymbol{a}_j^H \boldsymbol{r}_{p-1}|^2}{\|\boldsymbol{a}_j\|_2^2} \tag{7}$$

where, $\boldsymbol{I}_{p-1} = \{s_1, s_2, \cdots, s_{p-1}\}$ is the index set obtained from the previous $p - 1$ iterations.

After Schmidt orthogonalization, the selected element is

$$\boldsymbol{u}_{s_p} = \boldsymbol{a}_{s_p} - \sum_{i=1}^{p-1} \frac{\langle \boldsymbol{a}_{s_p}, \boldsymbol{u}_i \rangle}{\langle \boldsymbol{u}_i, \boldsymbol{u}_i \rangle} \boldsymbol{u}_i \tag{8}$$

where, $\boldsymbol{u}_i$ is the ith selected element after orthogonalization. Then the estimation of signal $\boldsymbol{x}$ can be obtained:

$$\hat{x}_p = \frac{\langle \boldsymbol{u}_{s_j}, \boldsymbol{r}_{p-1} \rangle}{\|\boldsymbol{u}_{s_p}\|_2^2} \tag{9}$$

The residual signal is

$$\boldsymbol{r}_p = \boldsymbol{r}_{p-1} - \hat{\boldsymbol{x}}_p \boldsymbol{a}_{s_p} \tag{10}$$

when $\|r_p\|_2^2 < \varepsilon$ (ε is the preset threshold), the iterations stop.

Multi-path delay estimation τ_p can be obtained according to the final index set and Eq. (5). Then coupled with multi-path gain $\hat{\boldsymbol{x}}_p$, the matrix of channel frequency response can be written as

$$\boldsymbol{H} = \sum_{p=1}^{N} \boldsymbol{A}_p \boldsymbol{\Lambda}_p \tag{11}$$

where $\boldsymbol{\Lambda}_p$ is a diagonal matrix with

$$[\boldsymbol{\Lambda}_p]_{m,m} = e^{-j2\pi\tau_p m/T} \tag{12}$$

1.3 Iterative channel estimation

The structure of receiver with ICE is shown in Fig. 1. Here, low-density parity check (LDPC) codes are used, which have superior error-correcting performance that can achieve performance close to capacity limit predicted by Shannon theory[15]. In recent years, more LDPC codes have been applied in underwater acoustic communications[16-18]. In Fig. 1, received signal z is sent to the channel estimator to obtain the initial channel estimation. Then the output of the estimator is passed through the channel equalizer, the de-interleaver and finally to the LDPC decoder. In the feedback loop, the LDPC decoder yields log-likelihood ratio (LLR) of the code information symbols to update the expectation of each symbol, which will be fed back to channel estimator. The computation of LLR for ICE can refer to Ref. [19].

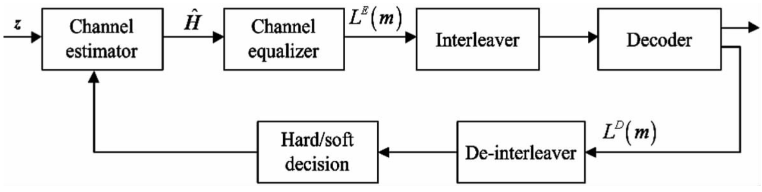

Fig. 1 Receiver with ICE

The followings are four main and an improved feedback strategies.

Method 1: Soft decision feedback

$$\hat{s}(m) = \sum_{i=1}^{M} P(s(m) = q_i) q_i \tag{13}$$

where P is the probability of symbol.

Method 2: Hard decision feedback

$$\hat{s}(m) = q_{i^*}, \quad i^* = \underset{i}{\arg\max} P(s(m) = q_i) \tag{14}$$

This feedback strategy selects the symbol with the maximum probability from the decoding results.

Method 3: Threshold-controlled hard decision feedback

$$\hat{s}(m) = \begin{cases} \hat{s}(m) & H(s(m)) < \Gamma_h \\ 0 & \text{otherwise} \end{cases} \tag{15}$$

where $H(s[m])$ is the information entropy calculated by the probability of symbol. The hard threshold Γ_h lies in [0,1]. Threshold-controlled feedback utilizes the probabilities of decoded symbols as thresholds. The selected threshold has an influence on system performance. If the threshold is too high, symbols fed back to channel estimator are few, while if it is too low, the information fed back may not be reliable. We will discuss this question in the simulation section below.

Method 4: Threshold-controlled soft decision feedback

$$\hat{s}(m) = \begin{cases} \hat{s}(m) & |\hat{s}(m)| > \Gamma_s \\ 0 & \text{otherwise} \end{cases} \tag{16}$$

where the soft threshold Γ_s lies in [0,1]. Only when the expectation of a symbol is higher than Γ_s, it will be fed back to channel estimator.

Besides the above four feedback strategies, a new feedback using cost function as the threshold is proposed in Ref. [10]. The threshold is tested by comparing the cost function of current ICE and initial channel estimation. We propose an improved method based on Eq. (5) in Ref. [10]. In the improved method, for threshold test, the cost function of current ICE is compared with previous ICE, instead of the initial channel estimation. The benefit of this improvement is that the cost function can be updated utilizing the result of the previous iteration. Besides, pilot-aided channel estimation with linear interpolation in Ref. [10] is replaced by OMP channel estimation in this paper. The improved feedback is referred to as Method 5.

Method 5: Feedback based on cost function

$$H_m^{(j)} = \begin{cases} \dfrac{Y_m}{\hat{X}_m^{(j)}} & \zeta\left(\dfrac{Y_m}{\hat{X}_m^{(j)}}\right) \leqslant \zeta(\hat{H}_m^{(j-1)}) \\ \hat{H}_m^{(j-1)} & \text{otherwise} \end{cases} \tag{17}$$

where, j donates the jth iteration, $\zeta\left(\dfrac{Y_m}{\hat{X}_m^{(j)}}\right)$ and $\zeta(\hat{H}_m^{(j-1)})$ are the cost function of the current and previous ICE on the mth subcarrier, respectively.

2 Simulation analysis

2.1 Performances comparison between hard/soft feedback decision

An OFDM system with the simulation parameters is shown in Table 1. The transmitted data is encoded by a rate 1/2 LDPC code and modulated using QPSK.

Table 1 Parameters of OFDM system

Parameter	Value
Sampling rate	48 kHz
System bandwidth	6 kHz – 12 kHz
Total number of subcarriers	1 024
Number of data subcarriers	851
Number of pilot subcarriers	125
Number of null subcarriers	48
OFDM symbol duration	171 ms
Cyclic prefix interval	35 ms

Ray acoustics model Bellhop[20] is used to generate a shallow sea channel impulse response. The main parameters that Bellhop model requires are shown in Table 2, in which the sound speed profile is measured from a depth of 69m shallow water area in the South China Sea. Fig. 2 shows the channel speed profile and impulse response in simulations.

Table 2 Parameters for Bellhop model

Parameter	Value
Water depth	69 m
Sound speed profile in water	measured
Sound speed in sea bottom	1 546 m/s
Sea-bottom density	1 469 kg/m^3
Transmitter depth	20 m
Hydrophone depth	25 m
Range	800 m

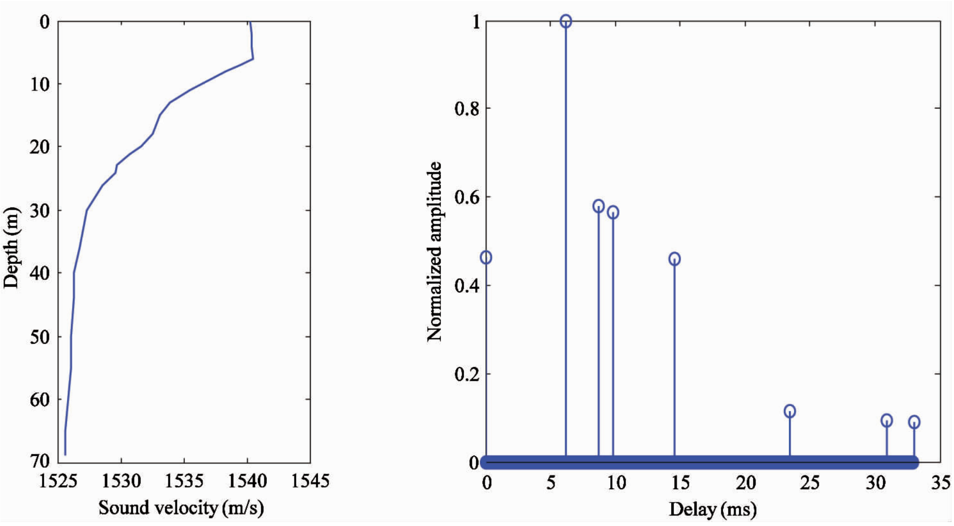

Fig. 2 Channel speed profile and impulse response

The performance is compared between hard and soft feedbacks at SNR = 9.5 dB with different thresholds, as shown in Fig. 3. Both the hard and the soft feedbacks have significant gains over the non-iterative receiver. When the threshold value is lower than 0.7, the performances of the two feedbacks are relatively close, while when the threshold value is higher than 0.7, soft feedback performs better. It can be concluded that soft decision feedback outperforms hard decision feedback. This is because, in general, soft decision feedback can make full use of statistics information.

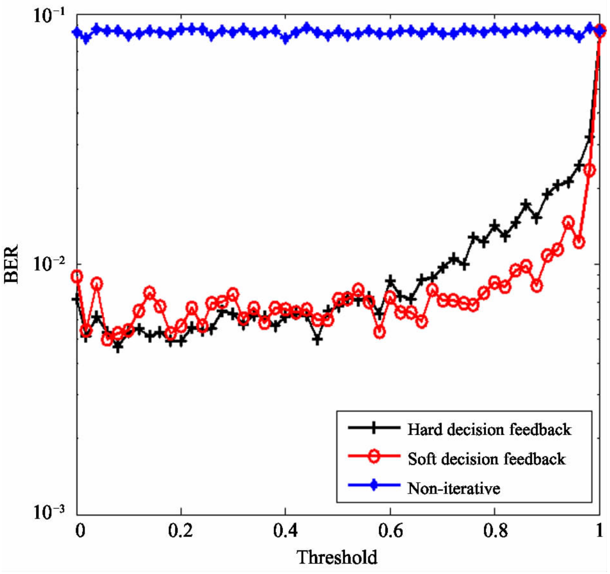

Fig. 3 BER performance for different feedback methods with varying threshold

2.2 Performances under different number of iterations

The soft decision feedback performances under different iterations are shown in Fig. 4 and Fig. 5. The BER and the normalized mean square error (NMSE) of channel estimation are compared respectively. NMSE is defined as

$$NMSE = E\{ \| H - \hat{H} \|^2 / \| H \|^2 \} \tag{18}$$

In Fig. 4, ICE improves the performance significantly over the non-iterative receiver. And the gain of the first iteration is more obvious, which is about 1dB. As the number of iterations increases, the performance of the system improves continuously and tends to converge after 4 times. Fig. 5 shows the corresponding NMSE of ICE. It can be seen that as the iteration increases, the NMSE gradually decreases, which means that the channel estimation result becomes more accurate.

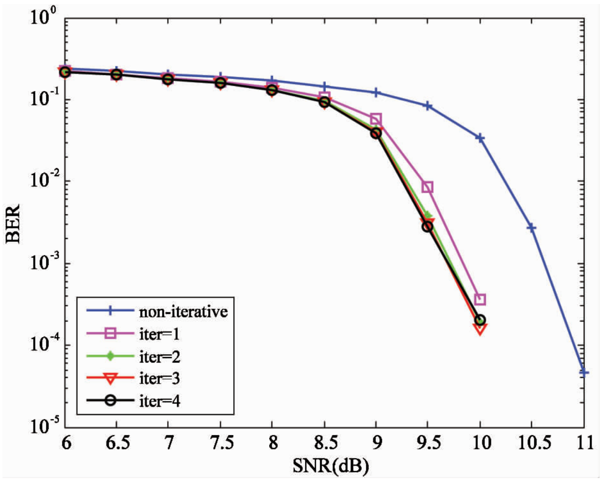

Fig. 4 BER performance with different iterations (Method 1)

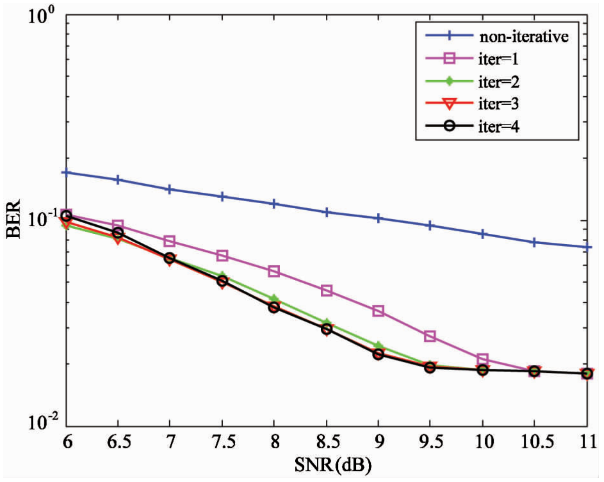

Fig. 5 NMSE performance with different iterations (Method 1)

2.3 Performances of ICE with different pilot intervals

Fig. 6 compares the performance of ICE at different pilot intervals 4, 8 and 12. Method 1 is used and the number of iterations is 4. It shows that as the pilot interval increases, ICE performance decreases and the gain between iterative and non-iterative channel estimation is more significant. Because in the case of fewer pilots, the additional pilots fed back are more valuable for channel estimation. In addition, the performances of the two cases (pilot interval = 4, 8) have a significant difference with non-iterative channel estimation, while becoming very close after ICE, which further shows that iterative strategy can save the number of pilots.

2.4 Performances comparison between soft decision feedback and the decision feedback based on cost function

Fig. 7 and Fig. 8 show the performance of BER and NMSE, respectively, using the decision feedback based on the cost function. A similar conclusion with Method 1 can be drawn, Both BER and NMSE of ICE perform better than the non-iterative receiver. Besides,

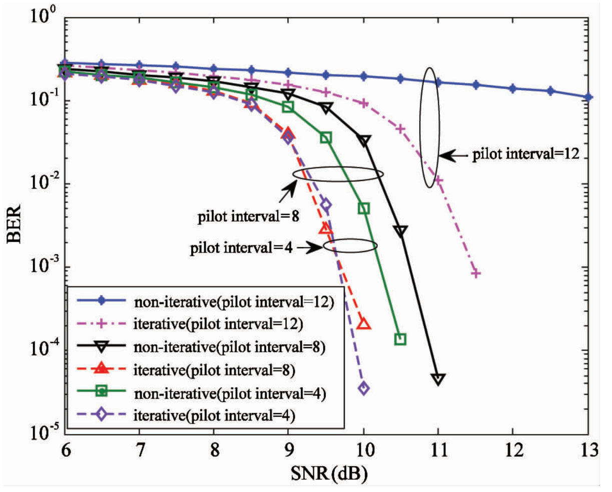

Fig. 6 Performance of ICE with different pilot interval (Method 1)

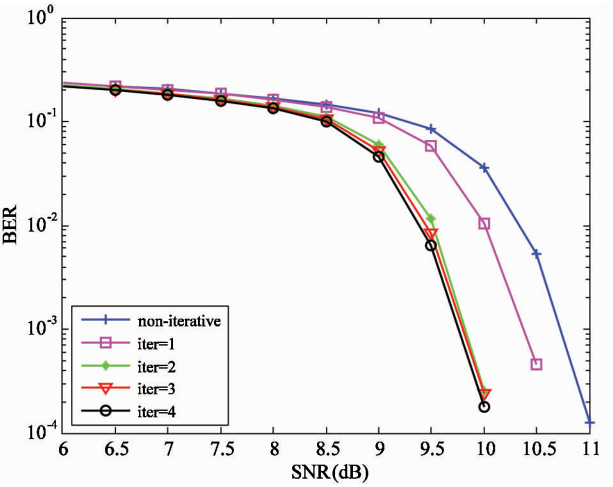

Fig. 7 BER performance with different iterations (Method 5)

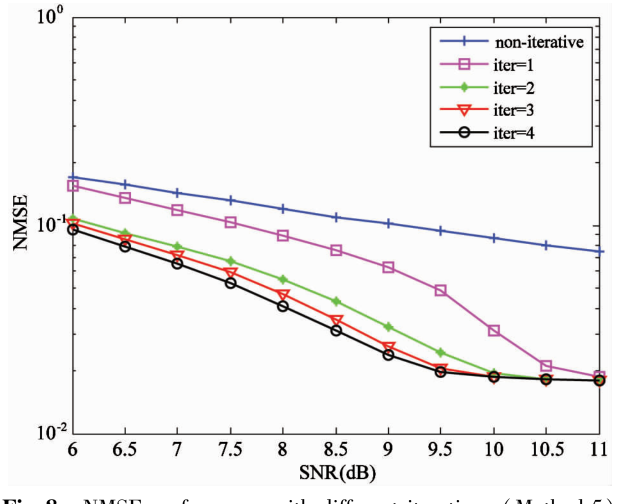

Fig. 8 NMSE performance with different iterations (Method 5)

as the iteration progresses, the system performance gradually promotes until it reaches stability.

Finally, the two feedback Methods 1 and 5 are compared when the system performance achieves stability (the number of iterations is 4), as shown in Fig. 9. It can be seen that the performances of the two methods are quite close.

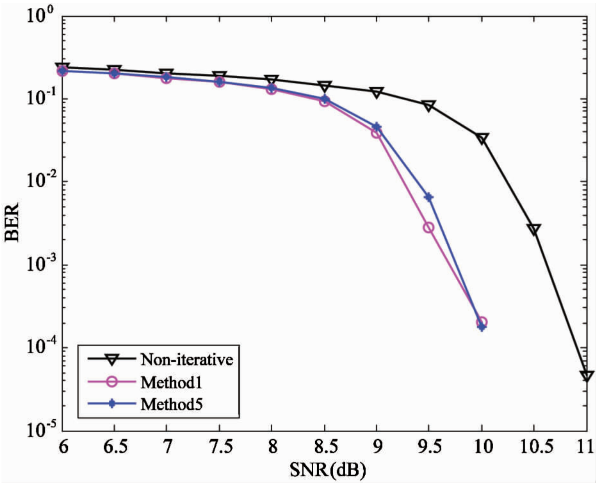

Fig. 9 Performance between Method 1 and Method 5 when iteration reaches a steady state

3 Conclusion

This paper investigates ICE that couples channel estimator and decoder for underwater acoustic OFDM. Five feedback strategies are considered to improve performance and are compared through numerical simulations. It is found that ICE has pronounced gains over the non-iterative receiver and the gains are more significant when pilots are fewer. Among these feedback strategies, soft decision feedback outperforms hard decision feedback generally. The performances of soft decision feedback and feedback based on cost function are quite close.

References

[1] Yang T C. Properties of underwater acoustic communication channels in shallow water[J]. *Journal of the Acoustical Society of America*, 2012, 131(1): 129-45

[2] Stojanovic M. Adaptive channel estimation for underwater acoustic MIMO OFDM systems[C]. In: Proceedings of the IEEE Digital Signal Processing Workshop and IEEE Signal Processing Education Workshop, Marco Island, USA, 2009. 132-137

[3] Li W, Preisig J C. Estimation of rapidly time-varying sparse channels[J]. *IEEE Journal of Oceanic Engineering*, 2008, 32(4): 927-939

[4] Berger C R, Zhou S L, Preisig J C, et al. Sparse channel estimation for multicarrier underwater acoustic communication: from subspace methods to compressed sensing [J]. *IEEE Transactions on Signal Processing*, 2010, 58 (3): 1708-1721

[5] Kim S. Angle-domain frequency-selective sparse channel estimation for underwater MIMO-OFDM systems [J]. *IEEE Communications Letters*, 2012, 16(5): 685-687

[6] Kang T, Iltis R A. Matching pursuits channel estimation for an underwater acoustic OFDM modem[C]. In: Proceedings of IEEE International Conference on Acoustics, Speech and Signal Processing, Las Vegas, USA, 2008. 5296-5299

[7] Niu H, Ritcey J A. Iterative channel estimation and decoding of pilot symbol assisted LDPC coded QAM over flat fading channels[C]. In: Proceedings of the 37th Asilomar Conference on Signals, Systems & Computers, Pacific Grove, USA, 2003. 2265-2269

[8] Valenti M C, Woerner B D. Iterative channel estimation and decoding of pilot symbol assisted turbo codes over flat-fading channels[J]. *IEEE Journal on Selected Areas in Communications*, 2001, 19(9): 1697-1705

[9] Niu H, Shen M, Ritcey J A, et al. A factor graph approach to iterative channel estimation and LDPC decoding over fading channels[J]. *IEEE Transactions on Wireless Communications*, 2005, 4(4): 1345-1350

[10] Auer G, Bonnet J. Threshold controlled iterative channel estimation for coded OFDM[C]. In: Proceedings of 2007 IEEE 65th Vehicular Technology Conference-VTC2007-Spring, Dublin, Ireland, 2007. 1737-1741

[11] Tropp J A, Gilbert A C. Signal recovery from random measurements via orthogonal matching pursuit[J]. *IEEE Transactions on Information Theory*, 2007, 53 (12): 4655-4666

[12] Chen Z, Zheng Y R, Wang J, et al. Frequency domain turbo equalization with iterative channel estimation for single carrier MIMO underwater acoustic communications [J]. *IEEE Journal of Oceanic Engineering*, 2017, 42 (3):711-721

[13] Huang J, Huang J, Berger C R, et al. Iterative sparse channel estimation and decoding for underwater MIMO-OFDM[J]. *Eurasip Journal on Advances in Signal Processing*, 2010(1): 1

[14] Baraniuk R. Compressive sensing[C]. In: Proceedings of the Conference on Information Sciences and Systems, Princeton, USA, 2008. 4-5

[15] Mackay D J C. Good error-correcting codes based on very sparse matrices [J]. *IEEE Transactions on Information Theory*, 2001, 45(2): 399-431

[16] Rafati A, Lou H, Xiao C. Soft-decision feedback turbo equalization for LDPC-coded MIMO underwater acoustic communications[J]. *IEEE Journal of Oceanic Engineering*, 2014, 39(1): 90-99

[17] Huang J, Zhou S, Willett P. Nonbinary LDPC coding for multicarrier underwater acoustic communication [J]. *IEEE Journal on Selected Areas in Communications*, 2008, 26(9): 1684-1696

[18] Liu S, Song A. Optimization of LDPC Codes over the Underwater Acoustic Channel [M]. Abingdon: Taylor & Francis, Inc., 2016. 1-10

[19] Zhou S, Wang Z. Data Detection[M]. Hoboken: John Wiley & Sons, Ltd, 2014. 137-156

[20] Porter M B, Bucker H P. Gaussian beam tracing for computing ocean acoustic fields[J]. *Journal of the Acoustical Society of America*, 1987, 82(4): 1349-1359

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