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# A new joint channel equalization and estimation algorithm for underwater acoustic channels

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## Abstract

Underwater acoustic channel (UAC) is one of the most challenging communication channels in the world, owing to its complex multi-path and absorption as well as variable ambient noise. Although adaptive equalization could effectively eliminate the inter-symbol interference (ISI) with the help of training sequences, the convergence rate of equalization in sparse UAC decreased remarkably. Besides, channel estimation algorithms could roughly figure out channel impulse response and other channel parameters through several specific mathematical criterions. In this paper, a typical channel estimation method, least square (LS) algorithm, is applied in adaptive equalization to obtain the initial tap weights of least mean square (LMS) algorithm. Simulation results show that the proposed method significantly enhances the convergence rate of the LMS algorithm.

**Keywords:** Equalization, ISI, Sparse underwater acoustic channel, LMS, Channel estimation

## 1 Introduction

With further exploration of ocean resources, underwater communication is playing a more critical role in both military and civilian aspects. Owing to the fact that electromagnetic wave attenuates severely in underwater channels, sound wave becomes the only effective communication mode. But compared with electromagnetic wave, sound velocity is extremely slow which would cause a severe propagation delay. When transmitting signals, sound wave would continually reflect between sea surface and bottom owing to restrained underwater channel. As a result, transmitted signals in underwater acoustic channel (UAC) have more severe inter-symbol interference (ISI) due to complex multi-path propagation in contrast to other kinds of communication channel. Besides, underwater channels have variable and unknown impulsive ambient noises which are often related to wind, rainfall, tide, vessels, and so on [1].

Adaptive equalizers are often utilized to effectively mitigate the inter-symbol interference (ISI), but they have a considerably low convergence rate in UAC. Therefore, information frame needs to carry longer training sequences to guarantee that iterations could reach the steady state of convergence during training mode. But it would occupy more bandwidth and reduce communication effectiveness, and this would be a deadly drawback for the fact that underwater acoustic channel is badly band-limited due to low-frequency ship noise and absorption of high-frequency energy [2]. It can be concluded that enhancing convergence rate of equalizer is a better option than enlarging the training sequences in underwater acoustic communication.

In general, the convergence rate of standard least mean square (LMS) adaptive equalizer mainly depends on the step size of each iteration. Therefore, a series of variable step-size least mean square (VSSLMS) algorithms [3–5] were proposed, which adjusted the variable step-size by minimizing the error at each iteration. Tong et al. [6] proposed a data reuse least mean square (DR-LMS) algorithm, which reuse the known training sequences to achieve a better equalization performance. Cui et al. [7] combined LMS with recursive least square (RLS) algorithms to realize a faster convergence rate and simplify complexity of implementation at the same time. However, the initial coefficients of equalizer tap weights are always neglected among improved equalization

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methods, which are also critical to the whole iterations and convergence rate.

Channel estimation is another way to impede and compensate channel fading, which obtains an approximate channel response through a series of mathematical analysis and calculations. But those estimation algorithms would get poor performances in sparse underwater acoustic channels. This paper aims to exploit the typical channel estimation algorithm—least square (LS) [8] to obtain the initial coefficients of equalizer tap weights. Simulation results under UAC reveal that our proposed algorithm improves the convergence rate and BER compared with the traditional LMS adaptive equalizer, especially in a low SNR region.

## 2 UAC communication model

### 2.1 Sound velocity

In general, the sound velocity would be influenced by temperature, salinity, and static pressure, and its empirical formula can be written as [9]:

$$c = 1450 + 4.21T - 0.037T^2 + 1.14(S - 35) + 0.175P \tag{1}$$

where $c$ is the corresponding sound velocity, $T$ stands for temperature, $S$ is salinity (‰), and $P$ stands for pressure (atm). However, those environmental factors are slow time-varying during the communication, and sound velocity is usually considered as a constant, which is 1500 m/s.

### 2.2 Ray model

In an underwater acoustic environment, glancing angle and reflection loss are literally small, so the amplitude of multi-path is too large to ignore. In this paper, we apply ray model to simulate underwater acoustic channel [9], and the specific schematic plot can be seen in Fig. 1. The multi-path signals could be classified into five categories, which are mainly based on the reflecting border (sea bottom or sea surface) of the first time and the last time. Then, the transmission route from a communication sender to a receiver would be easily obtained so that propagation distance of each path could be roughly calculated according to specular reflection principle.

### 2.3 System mode for simulation

For practical purpose, a one-way transmission scheme with a relay node is established for simulation, which is as shown in Fig. 2. Taking long communication distance and severe ISI into account, the relay transmission node, which would forward the information sequences, is added to guarantee the communication quality to some extent. In order to simplify the communication model, the complex ambient noises are substituted for independent additive white Gaussian noise. And a typical channel response [10] is applied to simulate the unknown underwater acoustic sparse channel (as shown in Fig. 3).

Note that error correction coding and orthogonal frequency division multiplex (OFDM) could improve system performance. However, it would impede the understanding of how efficiently the receiver equalizer mitigates the ISI. For this reason, channel coding is omitted and OFDM is replaced by binary ASK modulation in this paper. For more details, the modulation frequency is 8 kHz and each transmitting frame consists of 400 training symbols and 1000 data symbols.

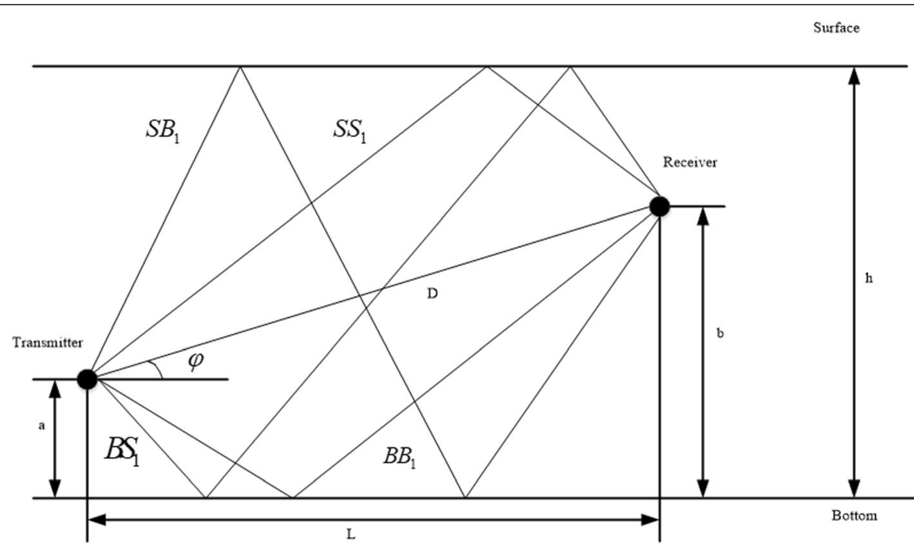


**Fig. 1** The ray model in underwater acoustic channel

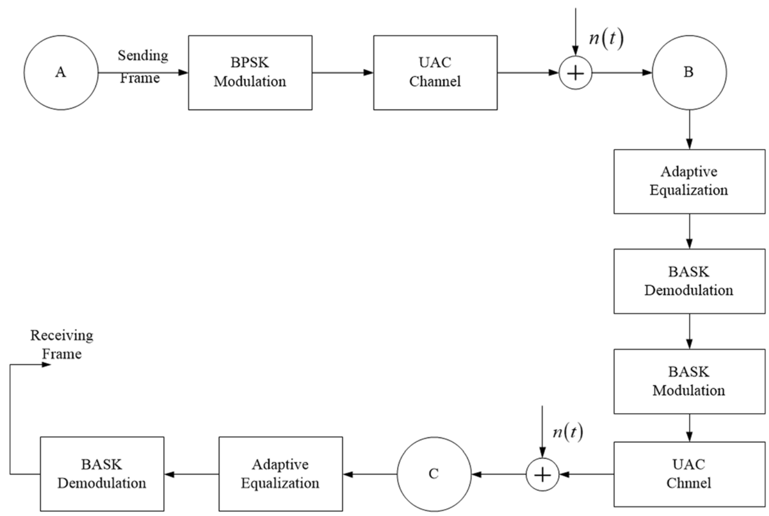


**Fig. 2** Established one-way transmission scheme

## 3 Related works: channel equalization and estimation

Channel equalization and estimation are two common ways to overcome multi-path effects and mitigate ISI. However, their fundamental principles are entirely opposite. It is obvious to see in Fig. 4 that the former is to compensate channel's loss and attenuation, while the latter attempt to calculate channel response.

Figure 5 depicts a simple kind of adaptive equalizer, linear transversal equalizer (LTE) which consists of $N$ delay units and $N$ tap coefficients [11]. If we just define the input signal as $x(n)$ and the corresponding tap weights as $w_i(n)$, then the output signal $y(n)$ can be defined as:

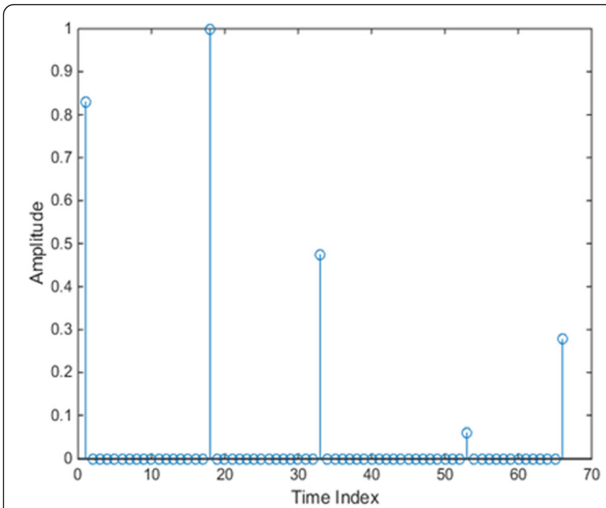


**Fig. 3** The typical underwater acoustic sparse channel response

$$y(n) = \sum_{i=0}^{N\text{-}1} w_i(n)x(n-i) \tag{2}$$

While channel estimation generally use complex probability theory and information theory to approximately deduce channel response with the aid of training sequences or pilot signal, those algorithms vary in time domain and frequency domain, and least square is the most conventional principle. The specific equations would be illustrated in the next section.

## 4 The proposed algorithm

Our new algorithm effectively combines channel equalization with estimation methods, which make a better use of training sequences.

In general, the unknown UAC communication system is simplified by an $N$th order finite impulse response (FIR) filter with an impulse response which is $h = [h_0, h_1, \cdots, h_{N-1}]^T$. In addition, the corresponding input vector regression of the adaptive equalization filter is assumed as $x(n) = [x(n), x(n-1), \cdots, x(n-M+1)]^T$ and the tap weight vector is $w(k) = [w_0(k), w_1(k), \cdots, w_{M-1}(k)]^T$, where $n$ is the time index and $M$ is the length of the equalizer taps, given that $s(n)$ is the initial training sequences and $v(n)$, which is to substitute the ambient noise of real underwater environment, is the independent white Gaussian noise with zero mean and variance $\delta_n^2$. Besides, the inner structure of training sequences is $[0, 1, 0, 1, \cdots, 0, 1]$, because changeable sequences could better track channels. Finally, the desired output sequences $d(n)$ can be defined as

$$d(n) = s(n) \cdot h + v(n) \tag{3}$$

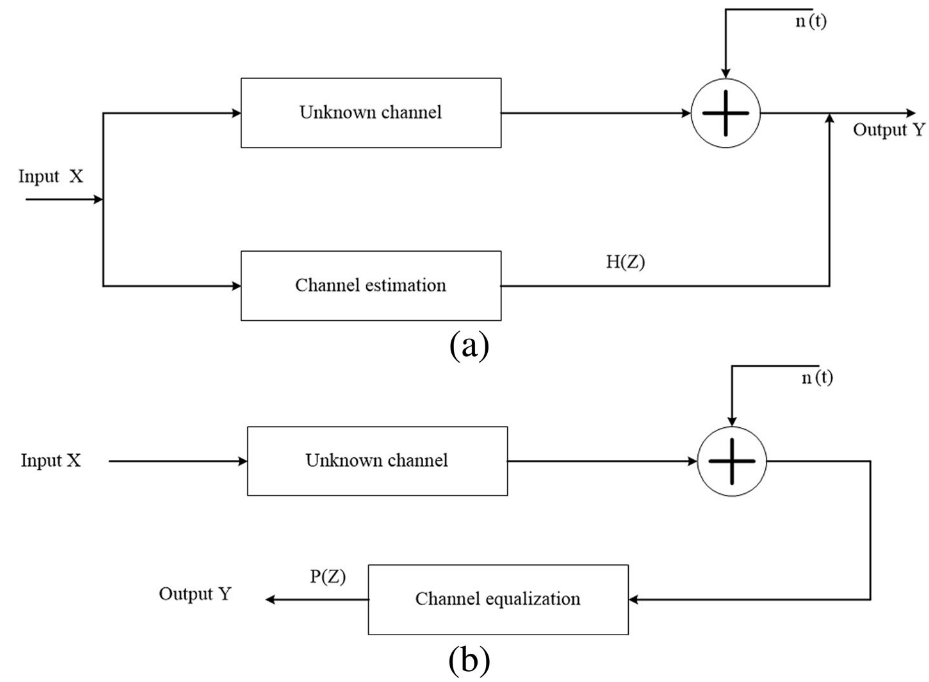


**Fig. 4** The comparison between channel estimation and equalization: **a** estimation and **b** equalization

where $d$ is the outcome of the training sequences $s$ influenced by channel response $h$ and $v(n)$.

Prior to starting with iterations and updating the tap weights, a significant step needs to be done, which is roughly estimating the tap weights with the aid of LS channel estimation algorithm. Firstly, we need to cut out $s$ and $d$ so that they are in the same length of equalizer taps, then we obtain $\overline{s} = [s(0), s(1), \cdots, s(M-1)]$ and $\overline{d} = [d(0), d(1), \cdots, d(M-1)]$. Next, a discrete fast Fourier transform is conducted on both of them as

$$\overline{S}(k) = \sum_{n=0}^{M-1} \overline{s}(n) W_M^{kn} \tag{4}$$

$$\overline{D}(k) = \sum_{n=0}^{M-1} \overline{d}(n) W_M^{kn} \tag{5}$$

where $W_M = e^{-j\frac{2\pi}{M}}$ and $k = 0, 1, \cdots, M-1$.

Then, we can use the following formula to calculate the estimated frequency domain channel response $\overline{H}$.

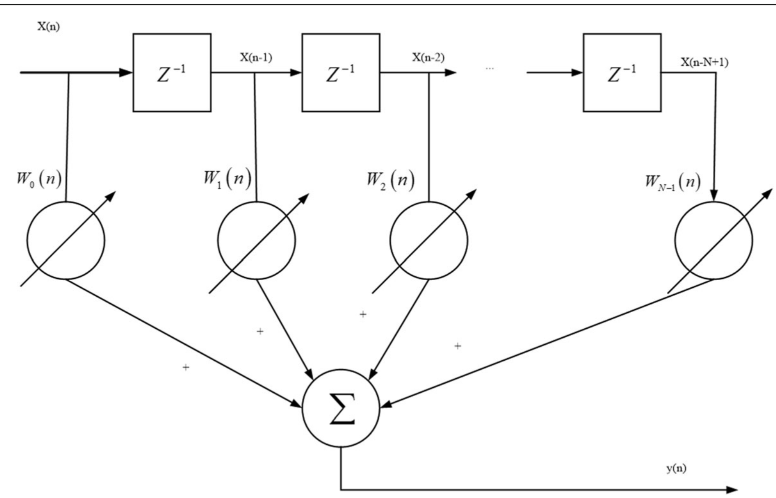


**Fig. 5** The inner structure of linear transversal equalizer

$$\overline{H}(k) = \frac{\overline{D}(k)}{\overline{S}(k)} \tag{6}$$

Subsequently, we conduct an inverse Fourier transform on $1\overline{H}$ to gain original equalizer weights $w_0$ which is as follows:

$$w_0 = \sum_{k=0}^{M-1} \frac{1}{\overline{H}(k)} W_M^{-kn} \tag{7}$$

Since the initial coefficients of tap weights $w(n)$ are obtained, we can utilize the general LMS algorithm to recursively update them as follows:

$$w(n+1) = w(n) + 2\mu \cdot e(n) \cdot s(n) \tag{8}$$

$$e(n) = s(n) - w^T(n) \cdot d(n) \tag{9}$$

where $\mu$ is the step size of updating tap weights and $e(n)$ is the error calculation output.

## 5 Simulation results and discussions

During the simulation, convergence rate of the proposed algorithm is compared with the traditional LMS algorithm. Figure 6 shows the MSE learning curves of two algorithms when $\mu(n)$ is set to a constant, 0.005, and the length of the equalizer taps is 70. The final outcome shows that the proposed algorithm has a faster convergence rate with less than 2000 iterations to reach the steady state. Since the ambient noises are neglected during this simulation, the MSE in steady state approximately reaches − 600 dB.

The spectrogram of received signals is shown in Fig. 7. It is obvious that the received signals in frequency domain reach the peak roughly at − 8 and 8 kHz, which is mainly determined by the modulation.

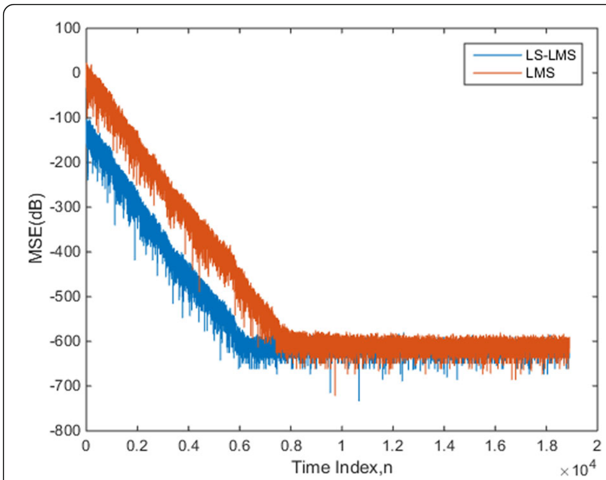


**Fig. 6** The MSE learning curves

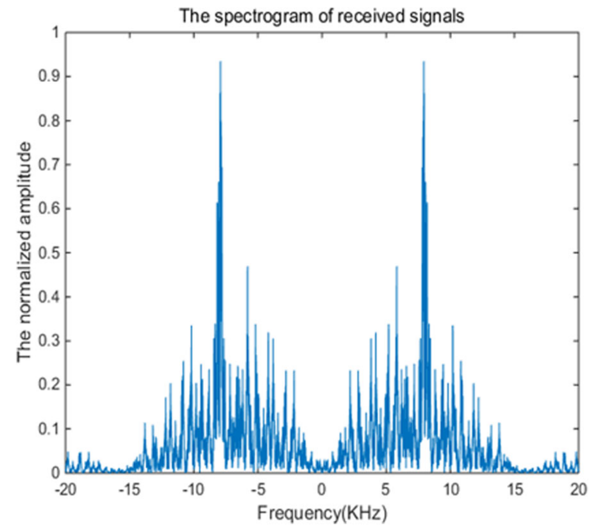


**Fig. 7** The spectrogram of received signals when the SNR is 5 dB

In general, the unknown and variable errors in the steady state are mainly caused by the additive noise [7]. Hence, the bit error rate (BER) becomes another performance metric to further identify the robustness of this new method. In Fig. 8, the BER performances of the two methods are plotted, where the results are averaged over 500 independent trials. And the results show that our proposed algorithm has 0.5 dB better BER performance than LMS algorithm in a low SNR environment.

In addition, Fig. 9 demonstrates that the length of training sequences could be effectively decreased when utilizing DR-LMS algorithm. During this simulation, the length of training sequences was cut down to one sixth of its original length.

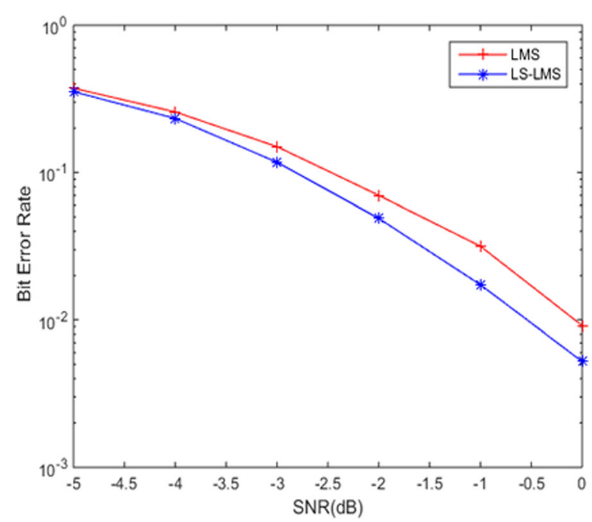


**Fig. 8** BER performances comparison between the referred two algorithms

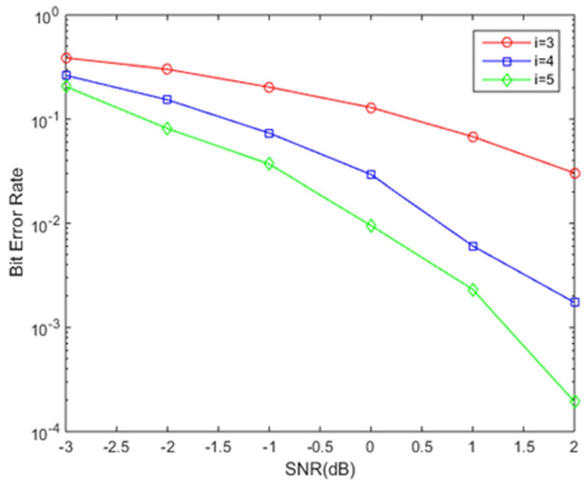

**Fig. 9** BER performances among different reuse times *i*

## 6 Conclusions

In this paper, a novel equalization algorithm is proposed which utilize channel estimation to define the initial values of receiver equalizer taps. Simulations show that our new method has better performances both in convergence rate and BER compared with the original LMS algorithm. In addition, the proposed method could lessen the transmission of training sequences and save energy for underwater communication devices.

In future work, MIMO channel equalization will gain more attention. And the relevant simulations would take more practical factors into account. Furthermore, we would attempt to figure out the optimal inner structure of training sequences by virtue of mathematical derivation and computing experiments.


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### Authors' contributions
BL and GL conceived and designed the experiments; HY performed the experiments; XP contributed the simulation tools; and BL wrote the paper. All authors have read and approved the final manuscript.

### Competing interests
The authors declare that they have no competing interests.

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### References

1. S Chen, J Xiang, J Shi, in 2006 IET International Conference on Wireless, Mobile and Multimedia Networks. Modified decision feedback equalizer (DFE) for sparse channels in underwater acoustic communications, (2006), pp. 1–4
2. K Pelekanakis, M Chitre, Robust equalization of mobile underwater acoustic channels. IEEE J Oceanic Engi. **40**(4), 775–784 (2015)
3. Y Chien, W Tseng, in IEEE International Conference on Consumer Electronics. A new variable step-size method for the M-max LMS algorithms, (2014), pp. 21–22
4. J Okello, Y Itoh, Y Fukui, I Nakanishi, In IEEE International Symposium on Circuits and Systems. A new modified variable step size for the LMS algorithm, (1998), pp. 170–173
5. J Sanubari, in 2004 IEEE Asia-Pacific conference on circuits and systems. A new variable step size method for the LMS adaptive filter, (2004), pp. 501–504
6. F Tong, B Benson, Y Li, R Kastner, in IEEE International Conference on Sensor Networks, Ubiquitous, and Trustworthy Computing. Channel equalization based on data reuse LMS algorithm for shallow water acoustic communication, (2010), pp. 95–98
7. P Cui, Y Yu, Y Liu, W Lu, H Zhu, in IEEE International Conference on Wireless Communications & Signal Processing. Joint RLS and LMS adaptive equalization for indoor wireless communications under staircase environments, (2015), pp. 1–5
8. M Ran, J Huang, H Fu, Sparse channel estimation based on compressive sensing for OFDM underwater acoustic communication. Sys Engi Elec. **33**(5), 1157–1161 (2011)
9. A Zielinski, Y Yoon, L Wu, Performance analysis of digital acoustic communication in a shallow water channel. IEEE J. Oceanic Engi. **20**(4), 293–299 (1995)
10. Y Luo, J Xu, Z Liu, J Xiao, S Wu, Self-adjusting underwater acoustic channel estimation and communication algorithms based on decision feedback equalizer. J. Shanghai Jiaotong Univ. **48**(5), 685–692 (2014)
11. B Zhao, *The Research of Adaptive Equalization in Time-Varied Multipath Channel* (Xidian University, Xi'an, 2013)