Dual-mode genetic blind equalization algorithm based on error signals

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Abstract: Direct decision (DD) is the most frequently-used blind equalization algorithm with advantages of fast convergence and small residual errors. Genetic blind equalization is an effective method for blind equalization, which makes use of a genetic algorithm to solve blind equalization problems and has better global optimization characteristics. By studying characteristics of the DD algorithm and genetic blind equalization, this paper provides a dual-mode genetic blind equalization algorithm by using error signals. The proposed method combines advantages of DD and genetic blind equalization, and significantly improves operation efficiency. It also enhances convergence performance and avoids a larger operand in the genetic blind equalization algorithm. Effectiveness of the algorithm is verified in computer simulation.

Key words: blind equalization; dual-mode; error signal

0 INTRODUCTION

The available bandwidth of an underwater acoustic channel[1] is severely restricted by transmission loss (TL), resulting in low transmission rate and poor reliability. A blind adaptive equalization algorithm needs to transmit a training sequence repeatedly and takes a large bandwidth, which is much limited. On the other hand, by using a blind equalization algorithm instead of the traditional adaptive equalization algorithm, there is no need to send a training sequence, and therefore can effectively improve the transmission rate. Thus, it is necessary to develop a blind equalization algorithm for underwater acoustic channel.

Direct decision (DD)[2] is a common blind equalization algorithm with advantages of fast convergence and small residual errors. However, when the rate of wrong judgment is high, the algorithm does not converge. Genetic blind equalization proposed by T. Schirtzinger[3] is a search algorithm with a fast convergence rate but a larger operand. By simulation comparison of the two algorithms, we combine the two algorithms using features of error signals to solve the blind equalization problem effectively, and make it suitable for underwater sound communications.

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1 DIRECT DECISIONAND GENETIC BLIND EQUALIZATION

1.1 Signal Processing Model

A typical linear QAM equalizer[4]for signal processing is shown in Figure 1. The channel input signal $x(k)$ is an independent and identically distributed random signal. The channel transmission function $h(k)$ has no zeros in the unit circle. It can be considered that the signal-to-noise ratio (SNR) of the channel output is high without additional disturbance. At the in put to the equalizer, a signal $y(k)$ is received from output of the transmission channel, with added white noise. A recovery sequence $\hat{x}(k)$ is obtained at the output of the equalizer.

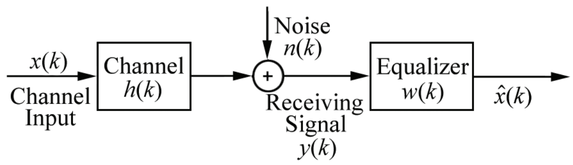

Fig.1 Signal processing model

From the signal processing model we have:

$$y(k)=h(k)*x(k)+n(k) \tag{1}$$

$$\hat{x}(k)=w(k)*y(k)=w(k)*h(k)*x(k)+w(k)*n(k) \tag{2}$$

The purpose of blind equalization is to acquire an optimal estimation of the channel input so as to complete channel transmission perfectly. Therefore, for the recovery sequence:

$$\hat{x}=x(k-D)\mathrm{e}^{\mathrm{j}\phi},\ w(k)*h(k)=\delta(k-D)\mathrm{e}^{\mathrm{j}\phi} \tag{3}$$

Taking Fourier transform, we obtain:

$$W(w)\cdot H(w)=\int_{-\infty}^{+\infty}\delta(k-D)\mathrm{e}^{\mathrm{j}\phi}\mathrm{d}k=\mathrm{e}^{\mathrm{j}(\phi-\omega D)} \tag{4}$$

Thus, $W(w)=\dfrac{1}{H(w)}\mathrm{e}^{\mathrm{j}(\phi-wD)}$

1.2 Direct Decision Algorithm

The DD algorithm uses a *threshold value decision device* to act as memoryless nonlinear function. When the eye pattern is expanded, *i.e.*, the blind equalization algorithm converges, the step length in the LMS adaptive algorithm is fixed. In this case, the equalizer can work in a direct decision mode, and the minimum mean square error of the filter tapping vector can be controlled like a common adaptive automatic equalizer.

The threshold value decision device for the source signal $x(k)$ can judge $\hat{x}(k)$ to make the result of judgment equal to the proximal $x(k)$ so that

$$\hat{x}(k)=dec[\hat{x}(k)] \tag{5}$$

Here, $dec[\ ]$ means the judgement. For example, in a simple case of data sequence with binary uniform probability, the data and decision value are shown as follows, respectively:

$$x(k)=\begin{cases}+1, & symbol\ 1\\ -1, & symbol\ 0\end{cases} \tag{6}$$

$$dec[\hat{x}(k)]=\mathrm{sgn}[\hat{x}(k)] \tag{7}$$

Here $\mathrm{sgn}(\cdot)$ is a sign function.

By comparison between direct decision and the Bussgang algorithm[5], it is observed that the direct decision algorithm is indeed a Bussgang algorithm of a memoryless nonlinear function with $g(\cdot)=\mathrm{sgn}(\cdot)$.

1.3 Genetic Blind Equalization Algorithm

Genetic algorithm[6](GA) is an optimal method whose basic idea is to simulate the natural law, that is, “selecting the superior and eliminating the inferior, and letting the fittest survive”. As a general optimization method, GA explores an optimal search method in the parameter space, and acquires optimal and secondary optimal results. Unlike a traditional calculus method, it does not need many requirements in solving a problem. It is applicable to various complicated engineering problems, especially for computer realization. GA is a global search algorithm using a group of codes to simulate biological chromosomes, generate a certain number of biotic communities at random, simulate the evolutionary process of biology, use the fitness evaluation function to evaluate every individual, confirm probability for every individual to save to the next generation, and conduct selective copy, intersection and mutation operation. This way, it makes every chromosome pattern with the highest fitness to be saved to the end until a globally optimal solution is obtained. GACMA[3] is used to conduct decoding, selection, intersection, and variation in the solution space based on GA and the error functions, i.e., error signals, to obtain the optimal solution.

In this paper, the proposed parameter is the number of population 40, and encoding length is 8-bit, while the critical cost function is selected as follows:

$$E_i=\frac{1}{N}\sum_{k=i}^{N}\left[\left|z_i(k)^2\right|-\left|\delta\right|^2\right] \tag{8}$$

It is observed that this algorithm basically borrows the error signals in the CMA algorithm.

We use a radial model to obtain the propagation characteristics of an underwater acoustic channel. The model is described as follows. A typical shallow water gradient sound speed profile is selected. The sea depth is 54.9 m. Sound speed is 1475 m/s on the surface and 1467 m/s at the seabed. The source launches a 15 kHz signal, propagating over 5 km. In the simulation, the iterative step is 5×10^{3}, the equalizer has the weight length of 11, and the central tap is initialized. The simulation result is shown in Figures 2 and 3.

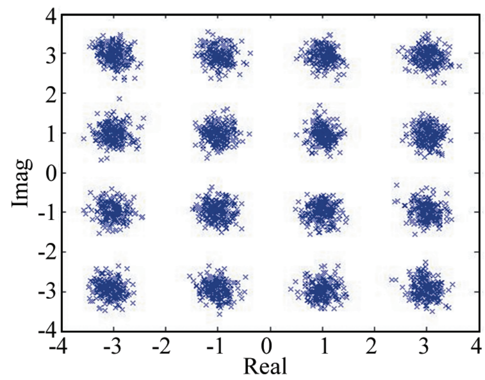

Fig.2 Constellation diagram of GACMA

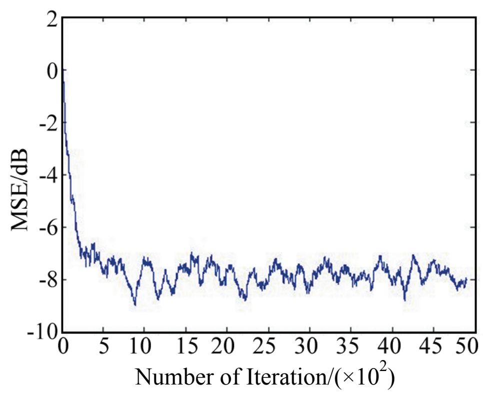

Fig.3 Performance of GACMA

It is observed from the constellation diagram and error curve that GACMA has faster convergence rate but greater steady-state errors, and after convergence it has bad stationarity. This is basically consistent with the results obtained by Schirtzinger et al.

2 DUAL-MODE GENETIC BLIND EQUALIZATION ALGORITHM BASED ON ERROR SIGNALS

2.1 Proposed Algorithm

Whether in DD widely-used for a long time and genetic blind equalization, disadvantages as mentioned in the above are intolerable. The problem can be solved when the two algorithms are combined with the characteristics of each being supplemented. Combination of DD and genetic blind equalization, that is, a dual-mode genetic blind equalization algorithm, can inherit advantages of both algorithms while overcome disadvantages, thus providing a perfect solution to the blind equalization problem.

The dual-mode genetic blind equalization algorithm uses a genetic blind equalization algorithm in the initial stage, and uses DD after convergence. It takes full advantage in rapid convergence of GA and steady characteristics of DD. The key of the proposed algorithm lies in the right time of algorithm switching. To this end, the characteristics of error signals are used.

In reality, there are two factors that affect convergence of the error function in a blind equalization algorithm[7]. The first factor is, $\hat{d}_k=|y_k|^2-R$ frequently used in a general algorithm. The other is $\hat{d}_k=|y_k|^2-|\hat{a}_k|^2$. In fact, it can also optimize convergence of the equalizer. The difference between the two factors is that $\hat{d}_k$ plays a leading role in the initial stage of convergence, and $\hat{d}_k$ becomes important when convergence is nearly achieved. It is similar to the role of changing step length. The algorithm is described as follows:

$$W(k+1)=W(k)+\mu\cdot e_k\cdot X^*(k) \tag{9}$$

Here $e_k=k_1\cdot\hat{d}_k+k_2\cdot\hat{d}_k$. In the initial stage of convergence, $\hat{d}_k$ can ensure preliminary convergence of the equalizer and make sure that the algorithm can converge rapidly due to large disturbance between codes. When the equalizer converges, disturbance between codes becomes smaller, and therefore it is difficult to further reduce disturbance between codes by using $\hat{d}_k$. However, due to improvement of decision device's accuracy, $\hat{d}_k$ is further used to reduce disturbance between codes. Therefore, both of them can be overlapped in calculation. Moreover, the proportion can be adjusted appropriately in line with disturbance between codes in different stages of convergence. Therefore, convergences in different stages can be used to speed up convergence, and it needs a convergence coefficient to control the coefficients k_1 and k_2. The convergence coefficient is given by

$$m_k=(i-1)/i\cdot m_{k-1}+1/i\cdot\hat{d}_k \tag{10}$$

$$k_1=\begin{cases}1 & m_k\geq m_{\max}\\ \dfrac{m_k-m_{\min}}{m_k-m_{\max}} & m_{\min}<m_k<m_{\max}\\ 0 & m_{\min}\leq m_k\end{cases} \tag{11}$$

$$k_2=b(1-k_1) \tag{12}$$

In these formulas, $m_{\min}$ and $m_{\max}$ are two threshold constants. When m is between $m_{\min}$ and $m_{\max}$, k_1 and k_2 change with m linearly. The parameter b is an adjustment factor. By using the characteristics of error signals, the convergence rate of genetic blind equalization algorithm can be accelerated effectively. When k_1=0, and after the continuous step length is greater than a certain value, judgement can be made from the eye pattern that is wide open to switch the algorithm to DD. This way, dual-mode blind equalization is realized.

2.2 Simulation Results and Comparison

In the simulation, parameter values in Section 2.4 are used. Simulation results are given in Figures 4 and 5 to show comparison between convergence performances of the dual-mode genetic blind equalization algorithm and GACMA.

It is clear that, with the same fast convergence as GACMA, the dual-mode genetic blind equalization algorithm has lower steady errors, especially for DD after convergence. The proposed algorithm is more

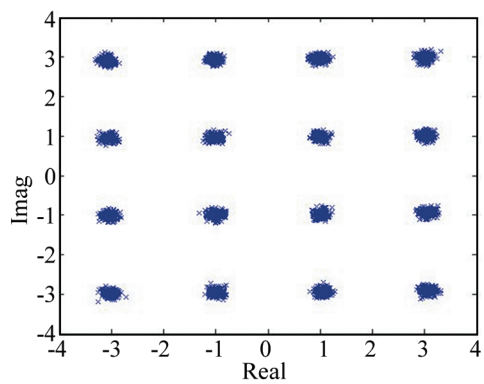

Fig.4　Constellation diagram of DDGACMA

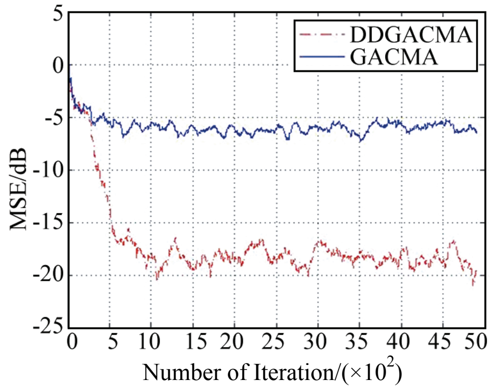

Fig.5 Performance of DDGACMA and GACMA

stable. The dual-mode genetic blind equalization algorithm based on error signals takes advantages of both algorithms, i.e., it converges fast, and has lower residual error and a moderate operand.

3 CONCLUSIONS

This paper introduces the DD algorithm and genetic blind equalization algorithm. After comparing their advantages and disadvantages by simulation, the paper proposes a dual-mode genetic blind equalization algorithm based on error signals. The algorithm has a fast convergence rate and low residual errors. It is applicable to practical systems.

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基于误差信号的双模式遗传盲均衡算法研究

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摘要：DD 算法具有收敛速度快，稳态剩余误差小的优点，是一种最常用的盲均衡算法。遗传盲均衡算法是一种新的盲均衡算法，它利用遗传算法来解决盲均衡问题，具有较好的全局优化特性。在综合研究了 DD 算法及遗传盲均衡算法的特性后，利用误差信号的特性，给出了一种新的双模式遗传盲均衡算法，有效的结合了 DD 算法以及遗传盲均衡算法的优点，大大提高了算法的运算速度，提升了收敛性能，解决了遗传盲均衡算法运算量大的问题，并通过计算机仿真验证了该算法的有效性。

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