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The study of CMA based ongenetic algorithm for underwater acoustic channel

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Abstract: Considering the significance of initialization in CMA, this paper proposes a new algorithm to improve the performance of CMA with the genetic algorithm. In the new algorithm, the idea of stylebook iteration is introduced in respect that the ultimate step of the new algorithm can reach an optimum value with a residual error reaching the minimum simultaneously. Simulation results confirm the effectiveness of the proposed techniques to lead superior performance to CMA.

Key words: blind equalization; CMA (Constant Modulus Algorithm); genetic algorithm; initialization

1 INTRODUCTION

Equalizing a communication channel without training mode is known as blind equalization. Blind Equalization algorithm does not depend on a training sequence for start-up period or restarting after system breakdown. Especially for acoustic channel, the complicated acoustic environment will bring a variety of noise into the received signal, so the situation is very unacceptable for high-precision underwater communication. To overcome the intersymbol interference, an important way is the algorithm of blind equalization. It can s-ave bandwidth and improve the communication rate so it has become a hotspot of communications research. In many blind equalization algorithms, the Constant Modulus Algorithm (CMA) advanced by Godard and Triechiar[1,2] is a widely applied method.

Many researchers [3,4] are paying their attentions to the CMA, such as its convergence properties and convergence rate. Most of them are focusing on the update of the tap wei-ghts vector. Few people concerned the initialization of the CMA, and they directly adopted the model of central tap initialization. In this paper, we bring in the idea of small swatch repetition and utilize the genetic algorithm to optimize the CMA initialization. The results have proved that the new algorithm achieved the performance improvement.

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2 INITIALIZATION OF CMA

CMA, a special case of the Godard algorithm, was developed by Treichler et al. independently of Godard to equalize constant modulus signals such as FM and Mary PSK signal in a multipath environment. Many researchers are involved in the studies of CMA. Figure 1 is a model of simple discrete channel and equalizer, where $x(k)$ indicates the transmitting signal sequence which is i.i.d. random variable, $n(k)$ is the noise sequence, $w(k)$ is the weight, $h(k)$ indicates the impulse respo-nse of the baseband which length is N_b, $dec(\cdot)$ indicates the judge equipment, $\hat{x}(k)$ is the estimate of the original signal and $e(k)$ in-dicates the error signal.

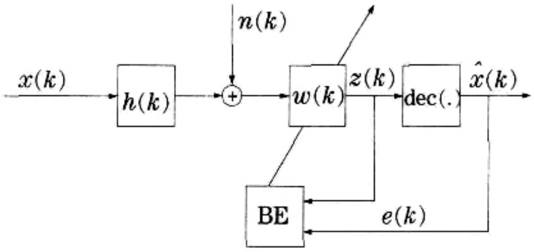

Fig.1　Blind equalizer diagram

In the coherent underwater acoustic communication, the transmitting signal waveform has constant envelope, such as PSK (phase-shift keying) signal. CMA is very appropriate for the equalization of this kind of signals. The cost function of the algorithm is defined as:

$$J_{CMA}(k)=\frac{1}{4}E[(|z(k)|^2-R_2)^2] \tag{1}$$

where R_2 indicates the module,

$$R_2=\frac{E[|x(k)|^4]}{E[|x(k)|^2]} \tag{2}$$

$$w(k+1)=w(k)+\mu\hat{\nabla}J_{CMA}(k)=w(k)+\mu e(k)y^*(k) \tag{3}$$

where μ is the step-parameter, the error of signal is expressed as:

$$e_R(k)=z(k)(R_2-|z(k)|^2) \tag{4}$$

The results of the different initializations of CMA are compared as follows:

The first initialization is the most common method: the central tap initialization. The channel is the uniform media channel; the number of taps is 11; the tap weights vector is [0 0 0 0 0 1 0 0 0 0 0], and the result is shown as Figure 2 (the error convergence chart A).

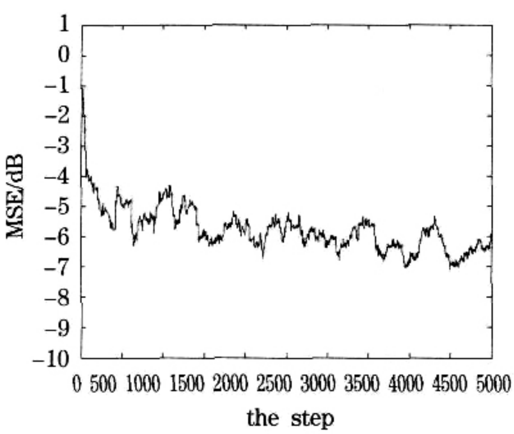

Fig.2　The convergence chart A

In Figure 2, we can find that the equalization effect is not very satisfactory: the convergence rate is slow, the steady-state mean square error (MSE) is higher and it has greater disturbance. This is because the central tap initialization method is not suitable for all acoustic channels. The following error convergence chart B and C, Figure 3 and Figure 4, are the results of tap initializations different from Figure 2.

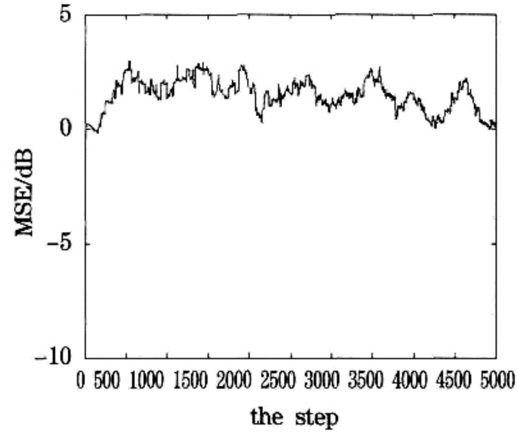

Fig.3　The convergence chart B

The differences of initializations are: the central value is 1 for Figure 2, 1+0.4j for Figure 3 and 1+0.4j for Figure 4. In Figure 3 the error can't convergence, however, in Figure 4 the error converges about at Step 300. Obviously, the tap weights vector for Figure 4 is better. So, it can be seen that the different tap weights vectors educe the different convergence performances, and that the conventional central tap initialization need to be improved.

3　GENETIC ALGORITHM

To solve the initialization of the CMA, the genetic algorithm is introduced. The basic idea is to utilize optimization characteristics of the genetic algorithm to find out the most suitable tap carryweights vector for the real-time acoustic channel initialization. This will speed up the convergence and reduce the MSE without increasing the calculation amount.

3.1　Conception and development of GA

The genetic algorithm (GA) proposed by Holland in American Michigan University[5] is

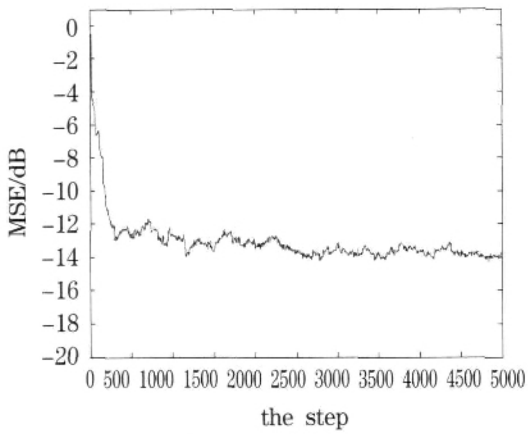

Fig.4 The convergence Chart c

one of random optimization algorithms. Its main features are the search strategy in groups and the exchange of information between the individuals in groups. The Genetic algorithm is applicable to the complex and nonlinear problems, which the traditional method can't resolve. It can be used in combinatorial optimization, machine learning, adaptive control, planning, artificial life and other fields.

The Genetic algorithm can be described with the following example of human evolution. Assume that the natural world is managed by a group of people, the first step of GA is the selection to keep the good and abandon the bad; the second step is the crossover as the human marriage and parenthood and the third step is the variation as the occasional variation in nature. (the occasionally reversion is also a kind of phenomena of variation). GA will produce more adaptive individuals, as human evolution incessant.

3.2 GA flow

GA is comprised with three steps: selection, crossover and variation. Different types of these steps result in different types of GA. Here is a simple genetic algorithm, LGA(Little Genetic Algorithm), and the flow is as follows:

1) According to optimization problem, define the cost function of the target;

2) Producing random binary codes, the total length of $A=\sum_{k=1}^{M} l_k$, where M is the total number of optimization parameters, l_k is corresponding to the binary coding length of k_{th}(unknown parameter);

3) Calculating the value of the code;

4) Calculating the cost function of each code, and utilizing the probability selection formula to choose the code, which can enter the crossover operation;

5) In accordance with the crossover probability to operate the crossover step and form a new code, and then return to (4). Repeating (4) and (5) until the number of code chains is N;

6) Varying the existing code;

7) Increasing the number of iterations, repeat (3) to (6) until the generation reaches the max generation, the best adaptive code in the N codes is the optimization parameter.

3.3 Technology of small swatch repetition

In order to improve the rate of convergence, we bring in the technology of small swatch repetition. In the initial phase of the equalization, we sample a small swatch from the receiving data. Then utilize the swatch and the genetic algorithm to adjust the tap weights vector until we get the optimized par-ameters. Then the optimized parameters will be the initial tap weights vector to work out the CMA.

The new algorithm is called GACMA. The difference of GACMA from CMA is the data repetition. GACMA will utilize 50 data from the equalizer output, and the data will be the input of the genetic algorithm. We select the steady-state error to be the cost function for the GA, and select, cross and vary the tap weights vector to get the optimi-zed tap weights vector of GACMA. Then we employ the tap weights vector as the initial coefficients to run the GACMA.

This new algorithm has intergraded the idea of CMA, the genetic algorithm and the small swatch repetition. As the swatch is very small, it dosen't increase the load of the calculation, but speed up the convergence and reduce the

MSE of CMA.

4 COMPUTER SIMULATION

4.1 Simulation model

Assume that the source uses a 4-QAM signal with an additive Gaussian noise, the SNR is about 25 dB, the carrier frequency is 10kHz, the signal transmission rate is 2,000 bit/s, and the sampling frequency is 100kHz. The channel is expressed in paper[6], as a negative gradient channel with the acoustic parameters shown in table 1, and the channel impulse response is calculated from Equation (5)

Table 1 Acoustic channel parameters

Acoustic Thread	Amplitude	Relative delay
1	1.000000	0.00000
2	0.263112	0.00070
3	0.151214	0.00392
4	0.391599	0.00671

$$h(t)=\sum_{i}\alpha_i p(t-\tau_i) \tag{5}$$

Where α_i is the amplitude of sound pressure along the different i th acoustic path, τ_i is the relative time delay, p(t) is the impulse of the coefficient equal to 0.5:

4.2 Simulation results

Here, the first is the ordinary CMA convergence chart:

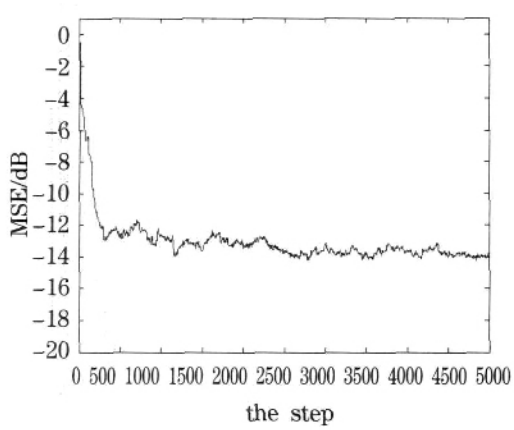

Fig.5 CMA convergence chart

From Figure 5, we can find that CMA the error converges about at Step 300 for CMA, and the steady-state error in general is - 12dB. The second is the convergence performance chart of GACMA.

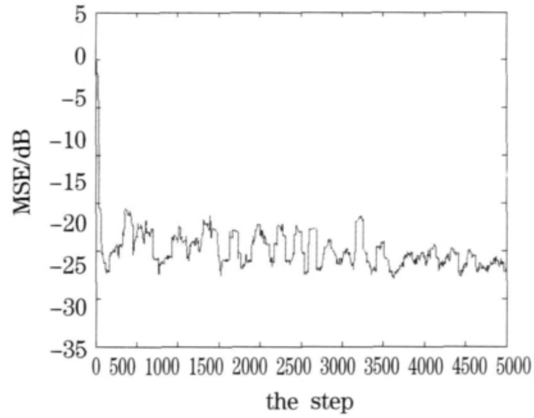

Fig.6(a) GACMA convergence chart

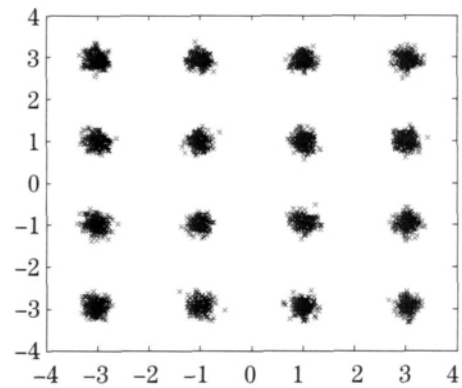

Fig.6(b) GACMA constellation

In Figure 6(a), the convergence rate of GACMA is almost twice of CMA, and at about Step 200, GACMA has converged with a drop of about 6dB in the steady-state error shown in Figure 5. This is mainly attributed to the genetic algorithm. Also, from Figure 6(b) it can be seen that the output constellation of GACMA behaves well. The simulation showed that the time spent on GACMA is nearly the same as the time on CMA for underwater acoustic communication, so that it can meet the needs for real-time processing.

5 CONCLUSION

Based on CMA's adva-ntages and disadvantages, the problem of the initialization of CMA is discussed, and the Genetic Algorithm has been brought in to work out the initialization. Through computer simulation it can be sure that GACMA is suitable for most underwater acoustic channels due to fast convergence speed a-nd lower steady-state error.

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基于遗传算法的水声信道常模类盲均衡算法研究

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摘要：为了解决CMA盲均衡算法收敛速度缓慢、稳态误差大的问题，考虑到初始化权值对CMA算法的重要影响，利用了遗传算法对CMA算法进行有效改进，引入了小样本重用的思想，给出了一种新的适用于水声信道的常模类盲均衡算法，计算机仿真研究证明，该算法不仅大大加快了收敛速度，而且有效的降低了稳态误差。

关键词：盲均衡；CMA；遗传算法；初始化

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